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## Stock Price Prediction and Stock Behaviour using GA and LR with NIFTY50 index Based on Daily Charts



**Abstract:** - The price of a company's stock, which can increase in lockstep with the price of a single share, is the one of the indicator to measure its performance. Clients or stockholding companies find it challenging to make long-term projections regarding the value of specific stocks due to the unpredictable nature of stock prices. Consequently, there is no business-related subject more talked about than stock market predictions. It is crucial to resolve this issue in a way that benefits buyers and investors because they frequently experience investment losses. Machine learning is useful in developing model for stock value predictions. We are utilizing Python and Linear Regression, one of the Machine Learning statistical techniques for predictive analysis, to create a stock price prediction website in order to address this issue. Our study primarily focuses on the NIFTY50 index's performance in distributed lag with the purpose of predicting stock prices in the Indian stock market. Several useful characteristics of the NIFTY50 lag index were extracted by means of a genetic algorithm. After that, we uncovered hidden correlations between the stock index and a given stock's trend by using the linear regression classifier. For the purpose of testing our approach, we used it to forecast the future of three distinct equities. In comparison to state-of-the-art forecasting methodologies, our experimental results demonstrated an accuracy of 82.55%. For the purpose of predicting daily changes in stock prices, the NIFTY50 stock index proved to be useful.

**Keywords:** Accuracy, Genetic Algorithm, Linear Regression, NIFTY50, Stock price prediction

### I.INTRODUCTION

Among the most challenging tasks in financial time series today is stock market prediction. Stock price predictions based on past trades are useless, says the Efficient Market Hypothesis. The ability to forecast stock prices is still a contentious topic, and several models have attempted to capture the nonlinear dynamics of the stock market. The use of machine learning strategies for predicting stock prices is a new but rapidly growing field of technology. Pattern recognition, function estimation, and time series prediction are three areas where machine learning methods like linear regression have made great strides. It is well-grounded in theory. Investors might be more cautious with their money when accurate stock price forecasts are available. Despite this, there has been little research about the future of the Indian stock market, especially in the wake of the financial crisis of 2008.

The stock market is a public or private venue where investors can buy and sell equities in a controlled market. The stock market attracts investors on a regular basis since it is a common means for corporations to acquire capital for expansion. Forecasts based on past market trends help a lot of investors make smart choices. Predicting the stock

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market's future value or price is crucial due to the market's volatility and the rapid changes it has experienced in the past few years.

Stock market prediction is a classic example of a problem that arises at the intersection of computer science and finance. The well-known efficient market hypothesis (EMH), which holds that investors would not consistently make above-average profits from technical or fundamental research, or from any analysis, provides a gloomy assessment of this issue and suggests that the financial market is efficient [1]. It maintains that stock prices already take into account all relevant information and cannot consistently increase. No trader, investor, or fund manager could produce returns greater than the market average as a result of this hypothesis. This is a result of the absence of overvalued or undervalued stocks.

For example, unexpected reactions frequently follow the release of shocking news. EHM asserts that no investor may obtain a competitive advantage and that normal market operations will return because all traders respond to fresh information in the same manner. However, EMH is not supported by numerous researches [2]. Successful stock market prediction models are covered in this study, which also seeks to quantify the efficiency differences between developing and existing markets.

Many things affect stock market fluctuations: company policy, currency rates, political and geopolitical events, other stock market movements, economic conditions, and investor psychology [3]. If stock markets are to function efficiently, the efficient market hypothesis [4] states that they must reflect all relevant information. In the weak-form market efficiency model, stock prices take into account all price data from the past. In a semi-strong market efficiency form, stock prices reflect all information that is publicly available. Uptrend forecasting, in contrast to market efficiency, takes into account real-time data that differs from theoretical situations.

Figure 1 shows the starting point for the endeavours: the tales of the technical and basic analyses.

In contrast to fundamental analysis, which relies on determining the stock's intrinsic or fair value, technical analysis evaluates the stock using charts and patterns. Using experience-based technical indicators to create unique input features can also improve machine learning models. Afterwards, we offer ARIMA [5] and GARCH [6] as linear models for stock market prediction. There are machine learning techniques that can predict stock market movements, like support vector machines and logistic regression [7].

Because of nonlinear stock price movements, constantly shifting marketplaces, and the complexity of predictors, predicting the course of a stock is difficult. If there was a reliable method for predicting stock market movements, it might encourage more people to trade stocks [8]. Stock forecasting ML methods primarily include artificial neural networks (ANNs) and support vector machines (SVMs) [9, 10]. Predicting the closing price of the following day is a typical task for numerous ANNs [11]. Adding more algorithms to different models that use artificial neural networks has improved the accuracy of predictions [12]. A system that predicts the movement of stocks using Support Vector Machine has also been developed [13]. Finding the optimal network architecture, input properties, and machine learning parameters often requires a combination of approaches, such as meta-heuristics, artificial neural networks (ANNs), and support vector machines (SVMs) [14,15].

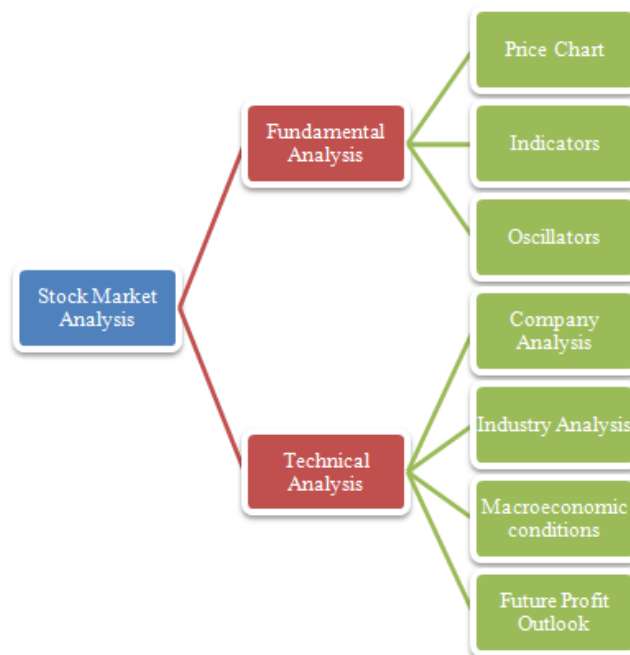
Recent stock studies have shown potential for several deep learning methods, including recurrent neural networks (RNNs), generator adversarial networks (GANs), convolutional neural networks (CNNs), and long short-term memory (LSTM) [16]. The selection of features is an important part of the information discovery process. The ability to streamline datasets and choose pertinent factors allows the prediction model to grow in efficiency and precision [17]. However, one limitation of feature selection models is that they rely on individual features to forecast trends. Prevailing research does not adequately address stock trend models that employ feature selection and global market indexes to forecast trends. These models can grasp the essence of global market movements, unlike feature-only ones. That kind of model is laid out in this book.

Predictive analysis frequently makes use of guided machine learning as well as the mathematical technique of linear regression. Since it generates linear correlations between the independent and dependent variables, the linear regression model is frequently consistent with the continuous/real values of mathematical variables.

Following its initial training on the training data set, the algorithm then uses the provided recommendations to create predictions. Also, front-end technologies like CSS and HTML are used in the given model. The scikit-learn package is used because it offers all the algorithms and functions needed for machine learning. The backend makes use of the web services and other resources accessible through the Python programming language's built-in Django framework.

When used to feature selection problems, GA performs well. The issues of noise and collinearity can be successfully resolved by using population-based GA [18]. Consequently, this article uses genetic algorithm (GA) for feature selection of several parameters. Surprisingly, when tested experimentally, this method boosted the accuracy of stock prediction. In this work, we utilise a linear regression model to predict the direction of the NIFTY50 and the movements of equities stocks, together with their prices. The second step in determining how accurate the model is is to calculate the Hit Ratio.

The following is the outline for the remainder of this essay: In Section 2, the methods of review are detailed. In Section 3, we lay out the whole approach for conducting experiments and the two-stage GA and Linear Regression model that we used to forecast stock prices. Section 4 details how the feature selection process and experimental comparison helped find the best feature variables to couple with one another. Section 5 provides a summary of the investigation's findings and suggests areas for future research.



**Figure 1. Stock Market Analysis parameters**

## II. REVIEW

This Section focused on developing machine learning models to predict stock prices. A number of studies, such as [19], have proposed ANN-based prediction models. But, Artificial Neural Networks converge towards less-than-ideal outcomes due to the unpredictable stock market [20]. To solve this problem, [21] suggested removing superfluous attributes using a Support Vector Machine preprocessing model. To forecast stock prices in large and small capitalizations about stock trend prediction, [22] offered a Support Vector Machine and Radial Basis Function method. They train their predictor to use the past data to make predictions about the data that will be available the following day. Numerical results showed how efficient the technique was, however the method has a few limitations, such as assuming four fixed qualities without optimisation or engineering. The experiments rely on it, regardless of how good the internet data is.

More than a hundred articles on neural and neuro-fuzzy approaches to stock market forecasting were reviewed by [23]. Performance evaluation, input data classifications, performance measures, and forecasting methodologies were among the many topics covered in the publications. [24] provides research on the use of ANNs for the purpose of predicting future prices in the financial markets. This includes predictions for the value of currencies, banks, financial crises, stock prices, and the price of options. As stated in [25], a small number of seminal research have collected qualitative information on companies using text mining algorithms. Based on the quality of the news these companies receive, these studies use this information to predict how the stock prices will behave in the future.

The three main categories of classical feature selection approaches are wrapper, embedding, and filter. By merging principal component analysis (PCA) with support vector machines (SVMs), we were able to get trustworthy model predictions by eliminating extraneous dimensions from the feature data [26]. [27] A two-stage attention-reliant recurrent neural network (DA-RNN) was proposed for feature extraction and sequential prediction. To begin, we built an input attention technique using the encoder's hidden state. This allowed us to adaptively extract important driving series at each time step. Secondly, they used a temporal attention approach to select relevant encoder hidden states for each time step. Because of this two-stage attention strategy, their model's predictions are absolutely accurate.

In their publication, the writers of [28] detailed numerous optimisation methods. Discovering the best Neural Network hierarchy for twelve ETFs is the objective. To find the best solution, they looked into genetic algorithms, particle swarm optimisation, and differential evolution. They go by a few different names: radial basis function neural networks, three-layer perceptrons, and recurrent neural networks. Their research led them to the conclusion that differential evolution provided the best results in terms of both effectiveness and predicted accuracy.

The work of [29] is the most relevant to this investigation. There was an effort to forecast the daily movement of stock prices in this research. The writers saw the problem of predicting stock movements as one of binary classification. Three Asian indices—Nikkei225, Hang Seng, and All Ords—along with four hundred sixty-three equities and components of the S&P 500 were examined. The NYSE Composite, Dow Jones Industrial Average, S&P 500, and two European indices—the DAX and the FTSE 100—were among the international indices.

The mean price direction was up-trending when the daily return was positive, meaning it was greater than zero. If the daily return is negative, or less than zero, then the average price trend is downward. After that, they extracted more data from stock indexes using a lag operator; this data, together with over 200 technical indicators, was subsequently input into a classifier. The chosen elements were inputted into a classifier using a feature selection method that relies on a genetic algorithm. The authors decided how well they could predict results by applying each of the four classification methods. The logistic regression, Random Forest, Artificial Neural Network, and Gradient Boosted Tree classification methods were among those employed.

In [6], a model was presented with the purpose of providing forecasts for the near future. For each of the eight scripts, we utilised six variables—Opening Price, Closing Price, Highest Price, Lowest Price, Volume, and Adjusted Closing Price—to predict their pricing utilising the Genetic Algorithm and evolutionary approaches. In all eight screenplays, American companies are the main characters. None of the other worldwide marketplaces are addressed in this study. Additionally, the specific rationale for selecting these six criteria remains unexplained.

Although we utilised worldwide stock indexes in our research to predict market movements, we did not review their usefulness [29]. We also suggested an evolutionary algorithm-based method for choosing useful traits. We analysed the past performance of every worldwide stock index and identified ten lag characteristics to foretell a company's future. Additionally, they classified stock patterns as uptrends or downtrends based on the daily return price change being greater than zero or less than zero. Our research indicates that a daily return price change of more than half a percentage point (0.5%) indicates an uptrend in stock movements. Not-Uptrend market conditions were defined as daily return price movements below half a percentage point. Our goal was to save the trader from going bankrupt. Unlike [29], our method took into account the potential that global stock indices could help forecast market swings.

### III. PROPOSED METHODOLOGY

In order to make the stock price prediction system more accurate, the authors have created the suggested model. In this case, we use linear regression with a number of stock-size-related characteristics to examine the NIFTY50 and stock graphs. Finding the right traits and selecting them are both handled by the genetic algorithm. You can see how the model operates in the figure. 2. The offered architecture begins with a genetic algorithm that selects features for preprocessing the given data. The stock price prediction model that relies on linear regression makes use of the genetic algorithms highly correlated feature subset. As stated in the architecture, there are two critical processes that we should examine:

- i. Genetic Algorithm (GA)
- ii. Linear Regression (LR)

#### i. Genetic Algorithm:

Combining genetic evolution with natural selection is one way that GA [20] uses for adaptive heuristic search. Two common uses include optimizing feature selection and solving optimization problems with a big search space by projecting the optimal answer. Inherent traits make each person special, and GA gives them the ability to find solutions to issues.

This data is aggregated into populations by the algorithm for GA optimization purposes [30]. Chromosomes, which are collections of genes, are the main vehicles for genetic information. Here, chromosome represents the set of features in a stock market dataset, where each gene represents the feature in a dataset. The chromosomes are generated to the initial population value and then subsequent generations will be generated and appended to find the optimal feature set for the stock market dataset. The combination of genes that are expressed internally determines how an individual's form appears externally. Take black hair as an example; its unique traits are encoded by a complex network of genes on the chromosome. Thus, starting the encoding process, which involves mapping phenotype to genotype, early on is crucial. The intricacy of genetic code often leads to its representation as binary strings for the sake of simplicity [31]. As a chromosome gets closer to its ideal state, its replication probability rises. As a result of natural selection favoring the best hypotheses, successive generations of approximations to the original solution have become increasingly accurate. To create the population that stands for the new set of answers, we use genetic operators to mix variation and crossover. In each new generation, individuals are chosen based on how effectively they address the issue at hand. This process will cause populations to evolve, which is quite similar to the way populations evolve in nature. The ability to adapt to one's surroundings would be enhanced in successive generations [32]. After that's out of the way, the greatest candidate from the most recent generation can be considered. This GA processing includes encoding solutions during initialization, evaluating them during fitness, checking them during termination condition checking, selecting them during selection, crossover, and mutation [33].

The full GA process is illustrated in Figure 3. The set of initial features is denoted as  $\{\alpha_1, \alpha_2, \dots, \alpha_n\}$ . At the outset, it generates a binary encoding for each chromosome  $\beta$ , representing a potential fix for the problem; put differently, the binary encoding of each chromosome contains all conceivable feature combinations. In the initialization step, a randomly generated original population  $\{\beta_1, H_2, \dots, \beta_n\}$  is generated once the population size is selected. The fitness of each chromosome is then calculated based on the previously defined fitness function. The fitness function is a measure for evaluating the efficiency of the chromosomes. The fitness function definition is a key component that affects GA performance [34]. The process of calculating the fitness function will store the best response for future replications. Chromosomes with high performance are more likely to be selected again, whereas those with low performance are more likely to be removed. To deal with the premature convergence on suboptimal feature sets, the restricted selection is used where as explained the fittest individuals will go to next iterations. More frequently, high-performing chromosomes will be chosen for further selection, while low-performing ones will be eliminated. We finally reach the perfect chromosome after multiple rounds of crossing, mutation, and selection. This work uses the GA fitness function as the  $r^2$  determination coefficient. The determination coefficient, which measures the extent to which changes in the characteristic variable X may

explain variations in the goal value Y, is another name for this measure. Here is the definition of the determination coefficient:

$$r^2 = \frac{\sum(y-\hat{y})^2}{\sum(y-\bar{y})^2} \dots\dots\dots(1)$$

Where  $r^2$  has a value range of [0, 1],  $y$  is the label value,  $\hat{y}$  is the predicted value, and  $\bar{y}$  is the average value.  $r^2$  is the notation for the determination coefficient. The higher the  $r^2$  value, the better X's ability to explain Y of this chromosome and the greater chance that it will be passed down to the next generation. Chromosome crossing and mutation are important processes for GA. Expanding the population's genetic diversity is beneficial for exchanging suitable chromosomal segments and gene combinations to produce new offspring.

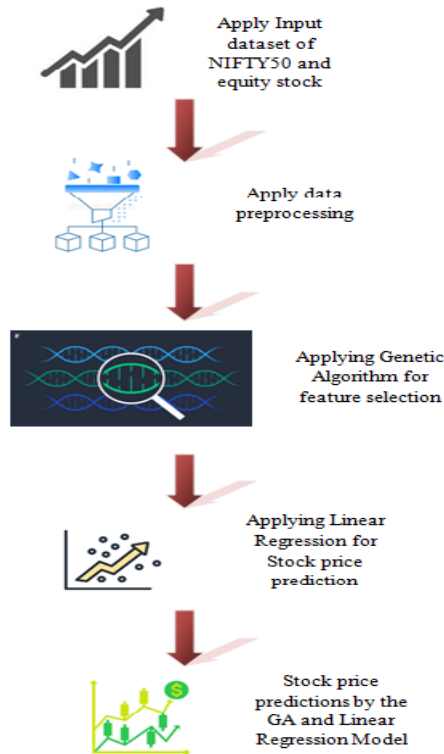


Figure. 2: Architecture of Stock Price prediction using Genetic Algorithm and Linear Regression

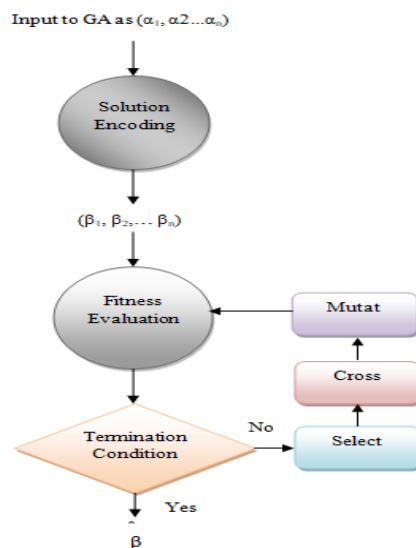


Figure. 3: Genetic Algorithm Flowchart

## ii. Linear Regression

By establishing relationships between the dependent and independent variables using elementary mathematical principles, linear regression finds the best fit or the path of least resistance. Here, tagged data is utilized in a supervised learning context. If you want to make stock forecasts using graph or curve analysis, this line will help you out. Since it relies on commonplace computing and mathematical ideas and is simpler to apply, linear regression is superior to other methods. A straight line with a slope of (m) and an error of (e) can be shown using the data points for the independent variable (x) and the dependent variable (y) as shown in Equation (2).

$$y = mx + c + e \quad \text{-----}(2)$$

Here, given numerous data sets with slopes of  $m_1, m_2, \dots, m_k$ , "c" represents the intercept produced on the dependent axis y as shown in equation (3).

$$y = m_1x + m_2x \dots m_kx + c + e \quad \text{-----}(3)$$

The linear regression is applied to the data with features generated by the genetic algorithm. The feature selection using genetic algorithm is implemented with restricted selection, which ensures the optimal features which have strong relationship with the dependent variable will be selected for implementation of the linear regression model. Hence, with GA for feature selection helps in analyzing the linear regression assumption of relationship between the independent and dependent variable. This data is used for linear regression. The data is normalized and then applied to the linear regression model. The optimal stock prediction values are obtained by minimizing errors and getting the best predictions.

## IV. RESULTS AND DISCUSSION

The dataset structure and the findings of the stock value prediction study are covered in this part.

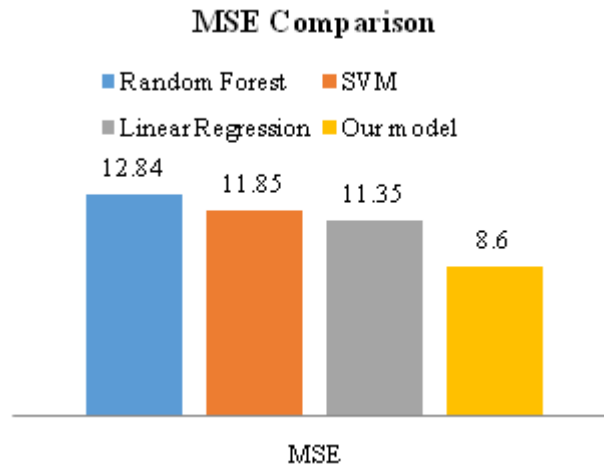
- **Data Set:**

The main objective of this data-driven analysis is to forecast the ultimate value of the NIFTY 50 stocks. The research made use of data obtained from the Bloomberg database for the period of February 11, 2005, to March 5, 2021. The data includes the highs and lows of the Indian stock market during the last fifteen years, which can help with research and forecasting. In order to conduct the investigation, reliable historical data was needed, along with input data that was pertinent and appropriate for the upcoming cost estimate. Based on its reliability and availability of the required format for historical security data, Bloomberg was chosen as the primary source of financial data for this study. The study applied technical analysis data, which included daily HOLC (high, open, low, and close) trading data, for a period of fifteen years. The RSI over 14 periods and the daily volume of NIFTY 50 stocks are two of the factors that are considered. The data presented before was used to train a model that can forecast the closing prices of the NIFTY 50 stocks.

It is necessary to pre-process the dataset in order to remove noisy values before the evolutionary algorithm can be used for feature selection. The training process makes use of around 80% of the data, while the testing of linear regression models accounts for the remaining 20%.

- **Results of the stock price prediction model**

Figure 4 compares results with and without a genetic algorithm for feature selection after applying linear regression. The comparison for the MSE is shown for the NIFTY50 stocks dataset.

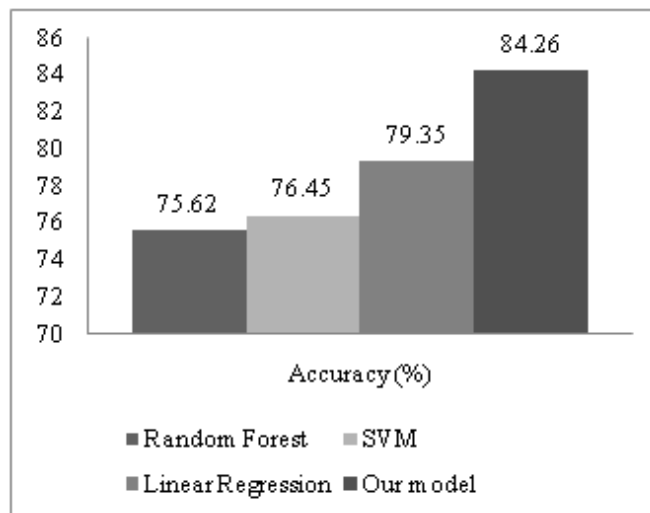


**Figure. 4: MSE comparison of Our model, i.e. Linear regression using genetic algorithm with existing systems**

Also, the accuracy percentage is better for stock price predictions. The accuracy comparison is shown in the graph of figure 5.

The data values are observed for a few of the NIFTY50 stocks, and the sample actual vs predicted values with the opening and closing levels are given in table 1.

The model calculates stock values in relation to the currency unit of the Indian stock market. Daily actual closing price vs. expected closing price and actual opening price vs. predicted opening price are displayed in table 1. The one step prediction intervals are used for predicting the values of the stock with 95% of the prediction interval. Accordingly the values for the given stocks are predicted.



**Figure 5. Accuracy comparison of Our model, i.e. Linear regression using genetic algorithm with existing systems**

These findings outperform the current methods, which bode well for Indian stock market traders and investors looking to minimize costs and safeguard their gains. The results of the linear regression are applicable as per the historic movements of the stock at given time intervals. In the uncertain events like news incidence, when market can show sudden bull or bear behavior, the model may not come up with given accuracy, but it can help the investors by predicting the values and cutting their positions to avoid the losses.



**Table 1: Stock prices actual Vs predicted as per NSE currency**

<b>Stock Name</b>	<b>Actual Opening Price</b>	<b>Predicted Opening Price</b>	<b>Actual Closing Price</b>	<b>Predicted Closing Price</b>
<b>HDFC BANK</b>	1053.40	1051.6	1044.95	1048.0
<b>AXIS BANK</b>	686	685.9	693.30	689.6
<b>UPL</b>	546.17	545.0	547.90	546.1
<b>SUNPHARMA</b>	424.50	425.4	414.65	420.6
<b>TATAMOTORS</b>	162.80	162.5	162.90	162.8
<b>EICHER MOTORS</b>	2043.30	2041.20	2015.52	2022.55
<b>ASIAN PAINTS</b>	1401.70	1400.00	1380.05	1388.50

## V. CONCLUSION

The machine learning approach is introduced to stock forecasting in this work. Several stock elements in the stock market explain changes in stock price. A wide variety of typical stock variables are chosen for this study. Nevertheless, as typicality does not imply universal applicability, GA is suggested as a feature selection method to identify the features more suited for the given scenario. Combining the linear regression model with the complex nonlinear interaction between variables and stocks allows for the forecasting of stock prices. The model outperforms the current state of the art in machine learning in terms of both accuracy and MSE. There are a few downsides to the stock price prediction model that is described in this research, despite its great resilience and ability to significantly boost forecast accuracy: First off, our experiment solely used NIFTY50 stock data; thus, data from other stock markets may be used in future studies. Second, rather than using a systematic approach to determine the ideal size of parameters, such as the choice of component count, trial and error is typically used in the design of the model parameters in this work. The best way to determine the model's parameters and make it easier to understand is to mix it with other machine learning technology. The model's implementation in real world trading system is possible in future with appropriate changes in the feature selection strategy and interface implementation.

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