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Algorithmic Trading Bot

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Abstract: Algorithmic trading employs computer-driven instructions to execute trades by analyzing market trends and predefined strategies. This method allows for transactions at speeds and frequencies far beyond human capability. These trading instructions are typically based on parameters such as time, price, volume, or complex mathematical models. In addition to offering higher profitability opportunities, algorithmic trading improves market liquidity and eliminates emotional biases from trading decisions. This project is designed to advance the next generation of trading by developing an intelligent Algorithmic Trading Bot. The bot integrates user-defined strategies with built-in adaptive algorithms to conduct trades throughout the day, responding to varying market conditions. By continuously optimizing its operations and minimizing transaction costs, the system seeks to deliver consistent profits for both individual and institutional investors.

I. INTRODUCTION

• Algorithmic trading refers to the use of automated, pre-programmed instructions to execute trades, taking into account factors such as time, price, and volume. By leveraging the computational speed and analytical power of machines, algorithmic trading offers a distinct advantage over manual trading conducted by human brokers. Studies have shown that only about 20% of day traders achieve consistent profitability. However, algorithmic trading improves these odds through more effective strategy design, backtesting, and flawless execution.

• The key strength of trading bots lies in their ability to streamline the trading process, enabling users to earn profits quickly with minimal manual effort. As algorithmic trading becomes increasingly essential in the rapidly evolving financial landscape, it is no longer a luxury but a necessity for surviving in tomorrow's markets. According to industry analyses, the global market for algorithmic trading is projected to grow from $11.1 billion in 2019 to $18.8 billion by 2024, with further growth expected beyond 2026. This surge highlights the increasing reliance on automated systems in financial markets.

• Despite this growth, there remains a gap in accessible tools for the average individual investor. The absence of a simple, efficient, and user-friendly algorithmic trading bot for non-experts underscores the motivation for our project.

• **Benefits of Algorithmic Trading include:**
• Rapid and cost-effective trade execution
• Improved accuracy and diversified strategy deployment
• Ability to backtest strategies using historical data for performance optimization
• Our project seeks to address the shortcomings of manual trading by developing a smart Algorithmic Trading Bot. The bot will be capable of executing trades at optimal prices, placing orders quickly and precisely, and

responding in real-time to changing market conditions. It will also help reduce transaction costs, minimize manual errors, and automatically evaluate various market scenarios. Furthermore, the bot can be backtested with both live and historical data to ensure reliability and effectiveness, while eliminating emotional decision-making—one of the major drawbacks of human trading.

II. RELATED WORK

This section describes a literature survey of the various methods for algorithmic Trading with Machine Learning which are already proposed and implemented. It describes the survey of the existing system and software used for algorithmic trading with Machine Learning. The existing algorithmic trading with Machine Learning methods includes Only Random Forest , Random Forests and Probit regression , Genetic Algorithms like Deep MLP Neural Network , Support vector

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Machine Regression (SVR) and Random forests and Gradient boosted decision trees (using XGBoost) gives the summary of limitations of existing systems and software

Existing Softwares -

A few software's currently in use are [1]:

- Zerodha Streak: One of the most efficient trading platforms with Algorithmic Trading in India. The biggest benefit of Streak is that it lets the users perform algo trade without coding. The algos can be created even without the technical knowledge of programming.
- Omnesys Nest: It is one of the best algo trading platforms, provided by Thomson Reuters. It has all the excellent features of a state-of-the-art trading platform, including low latency rates and high levels of performance.
- Algonomics: It is a trading platform offered by NSEIT and is one of the best algo trading platforms. The differentiating feature of the platform is its ultra-low latency levels which are beneficial for high volume trades by the investment banks, fund managers and individual algo traders.

A. Using only Random Forest Algorithm [3]

Seasonality impacts and exact normalities in financial information have been very much archived in the monetary financial matters writing for more than seventy years. This methodology proposes a specialist framework that utilizations novel AI strategies to foresee the value return over these occasional occasions, and afterward utilizes these expectations to foster a beneficial exchanging technique.

In this methodology the creators present a mechanized exchanging framework dependent on execution weighted groups of irregular backwoods that improves the benefit and soundness of exchanging irregularity occasions.

An investigation of different relapse procedures is proceeded just as an investigation of the benefits of different strategies for master weighting. The outcomes show that recency-weighted troupes of arbitrary timberlands to create prevalent outcomes as far as both productivity and expectation exactness contrasted and other outfit strategies.

Figure 1 shows the diagrammatic representation of the system that was implemented.

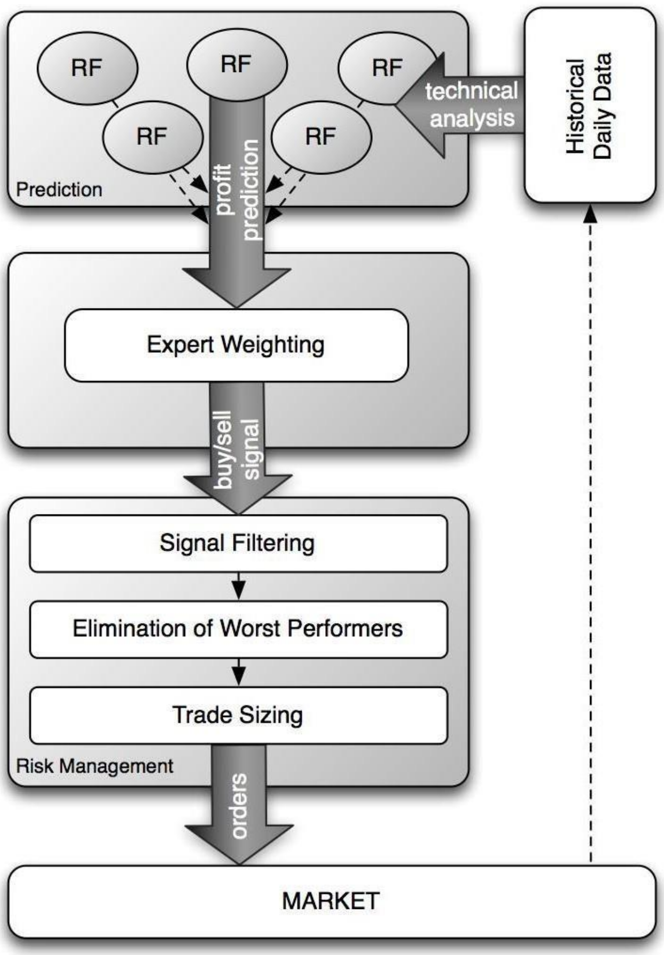

Figure 1 : Diagrammatic representation of the layered workings a fully automated expert trading system

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B. Using Random Forest and Probit Regression [4]

In Forex there are numerous money sets and many exchanging individuals and each pair is not the same as the other, and every individual thinks in his own specific manner. Tracking down the best exchanging methodology is actually a mind boggling distraction. Their methodology was to present an expectation and choice model that produces beneficial intraweek venture procedure. The proposed methodology permits improving exchanging results intraweek high-recurrence exchanging. Such outcomes are promising for research on sequential mix of numerous calculations to Forex portfolio the executives.

It is presumed that algorithmic exchanging dependent on blend of arrangement and Probit relapse can be powerful in improving the forecast exactness. This blend assists with recognizing the fun occasions to purchase or to sell money sets. Figure 2 shows the performance evaluation result of Random Forest plotted into a graph of real and predicted values. Figure 3 shows performance evaluation of Probit Regression used in this paper.

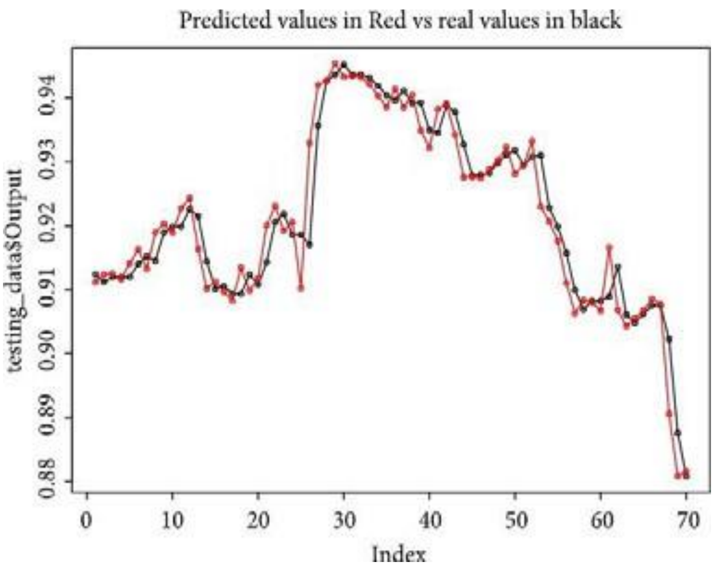

Figure 2 : Predicted values versus real values (predicted values in red, real values in black); for Random Forest regression using: 500 tree and 8 variables tried for each split.

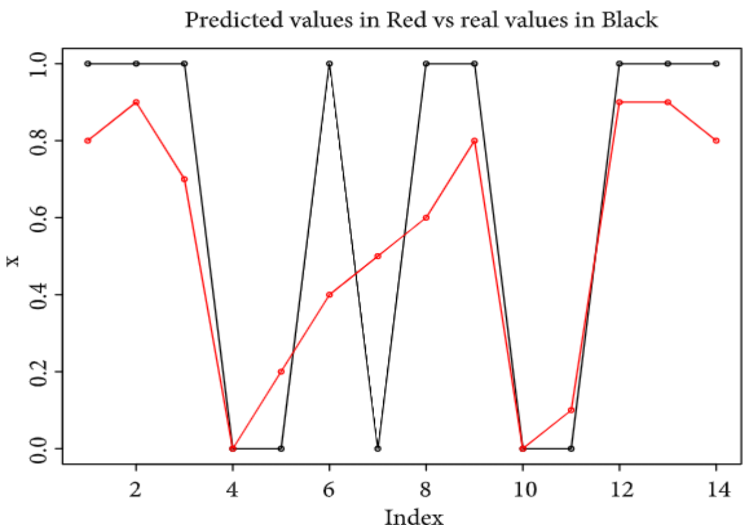

Figure 3 : Predicted values versus real values (predicted values in red, real values in black); for Probit regression.

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C. Using Genetic Algorithms like Deep MLP Neural Network [7] In this examination, we propose a stock exchanging framework dependent on advanced specialized investigation boundaries for making purchase sell focuses utilizing hereditary calculations. The model is created using Apache Spark huge information stage. Each Dow stock is prepared independently utilizing day by day close costs between 1996-2016 and tried between 2007-2016. The outcomes demonstrate that improving the specialized pointer boundaries upgrades the stock exchanging execution as well as gives a model that may be utilized as a choice to Buy and Hold and other standard specialized examination models.

At that point, we utilized those streamlined component esteems as purchase sell trigger focuses for our profound neural organization informational index. We utilized Dow 30 stocks to approve our model. The outcomes show that such an exchanging framework produces practically identical or better outcomes when contrasted and Buy and Hold and other exchanging frameworks for a wide scope of stocks in any event, for generally longer periods.

Figure 4 shows the implemented system for the Genetic Algorithm as per the research paper.

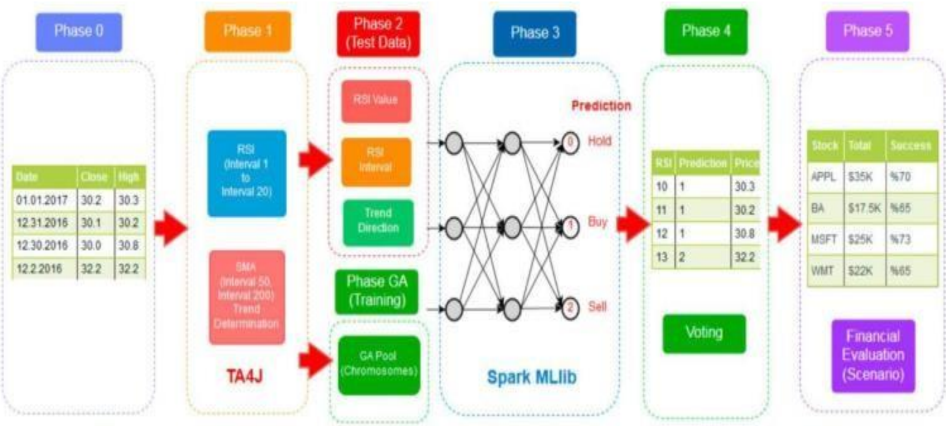

Figure 4 : Proposed Method (Genetic Algorithm and MLP)

D. Using only Support vector Machine Regression (SVR) [6]

This examination shows that utilizing a fixed training set on every day costs, it is feasible to acquire more modest forecast blunders in the test set than in the preparation set when utilizing a direct piece. Specifically, SVR acquired second rate prescient outcomes comparative with an arbitrary walk model for practically all stocks concentrated in regularly updated costs, utilizing fixed preparing, paying little heed to the embraced portion work. Steady model refreshing was additionally advantageous in the authorized value recurrence, and SVR models with direct and spiral bits accomplished preferable outcomes over the arbitrary walk model when this procedure was utilized. To accentuate the strength of the forecasts as time goes on, we prepared a 2-years up-to-the-minutes costs period for the chose Brazilian stocks, affirming better outcomes with a continually refreshed model.

The investigations introduced in this examination propose that occasionally refreshing the SVR model decreases the mean square mistake contrasted with utilizing an inflexible model without intermittent refreshing. A significant commitment of this investigation is an examination of value forecast consequences of the introduced SVR models with those of the arbitrary walk model, as per which markets are eccentric in the long haul. In this regard, the outcomes introduced here show that some SVR models, with occasional or fixed updates, may accomplish better compared to irregular prescient execution, particularly with the utilization of the direct piece. Another outcome which prompts further examination is the sign of a solid connection between SVR value forecast and unpredictability, thinking about a moving preparing window. The outcomes consequently don't straightforwardly discredit the EMH. Given that the focal point of the investigation isn't the recognizable proof of buying or deals methodologies that take into consideration phenomenal additions, the examination doesn't resolve issues, for example, exchange expenses or portfolio hazard levels. Figure 5 shows how the SVR algorithm performed when evaluation is done on real stock in the research paper.

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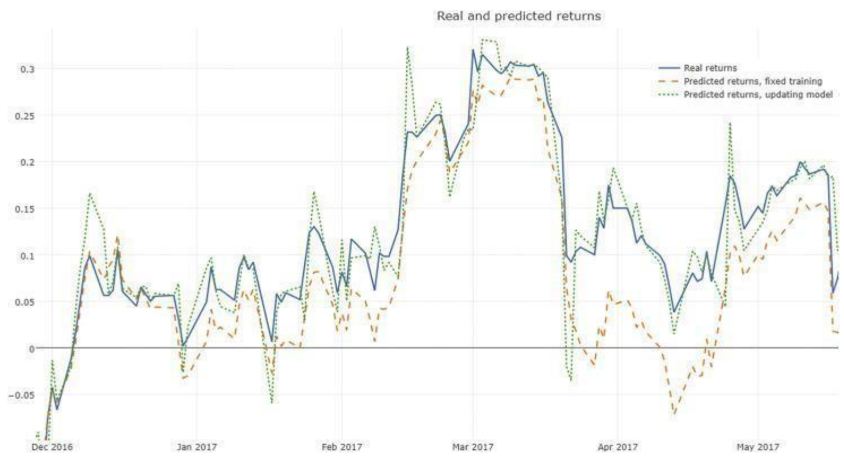

Figure 5 : Real returns and those predicted by the SVR model for the American stock BAC daily prices.

E. Using Random forests and Gradient boosted decision trees (using XGBoost) [5]

Creators think that utilization of AI procedures in stock value anticipating should be an all-around point of view and requests meticulously itemized execution. The proposed approach is a change in outlook in this class of issues by reformulating a customary estimating model as a characterization issue. Additionally, information disclosure from the examination ought to make new wildernesses or applications, for example, an exchanging methodology dependent on the qualities of the characterization exactness, researching the conduct of specific classes of stocks. In any case, outfit learning techniques have stayed unexploited in this field. In this paper, we have utilized Random Forests and XGBoost classifiers to fabricate our prescient model and our model has created amazing outcomes. The model is discovered to be powerful in anticipating the heading of stock development. The vigor of our model has been assessed by ascertaining different boundaries like exactness, accuracy, review, explicitness, and F-score.

Also, a significant piece of the curiosity of the current work lies in the cautious choice of specialized markers and their utilization as highlights. As the kind of the difficult that we're attempting to tackle is essentially that of monetary investigation, we enjoyed the benefit of adaptability of the use of different various highlights, each with its own understanding. Our model can be utilized for contriving new techniques for exchanging or to perform stock portfolio of the executives, changing stocks as per patterns expectation.

The proposed model is without a doubt a novel method to limit the danger of interest in financial exchange by anticipating the profits of a stock more precisely than existing calculations applied up until this point. Figure 6 shows comparison between different algorithms performance for trading. Figure 7 depicts how the used algorithm has performed on a real stock.

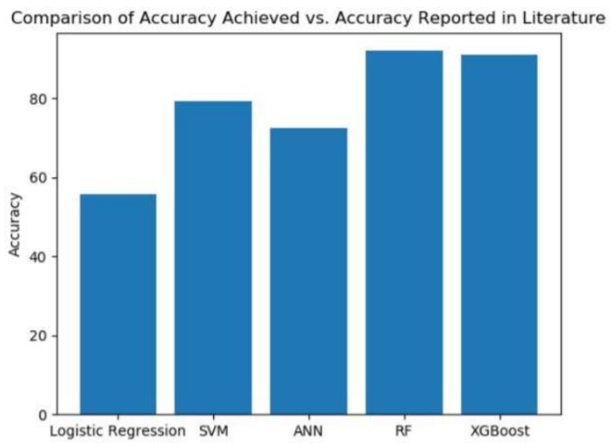

Figure 6 : Comparison of the accuracy achieved in this work to the accuracies achieved in available literature

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Figure 7 : Trading Strategy suggested by the model on AAPL data

III. DATASET

Alpaca API and Yahoo Finance is used to fetch past data and put it into a dataset. The dataset comprises Date , Open Price , High Price , Low Price , Close Price and Volume traded for that particular Stock day wise.

A. Database Splitting

The dataset is split in 60:40 ratio. Four variables i.e., X_train, X_test (for inputs) and Y_train, Y_test (for outputs) are created.

B. Annotation Description

The dataset consists of various columns as mentioned above. The columns that we require for our Random Forest Regressor and prediction is only Date and Close Price for the particular stock. The Close Prices will help us get a trend or a Moving Average for our Intraday trading of that particular stock. This will be integrated with Financial strategies to boost performance with greater accuracy owing to predictive power of Random Forest Regressor.

IV. PROPOSED METHODOLOGY

The Architectural diagram of our proposed solution. We have two types of roles i.e. Trader and Bot. The Trader has access to trade orders, viewing market statistics, setting up a day trade strategy via the bot and manage their account. The Bot will be validating and placing trades as per market and user statistics, will be sending notifications, and have access to user wallet to execute trade orders. A few special features have been listed on top in the diagram.

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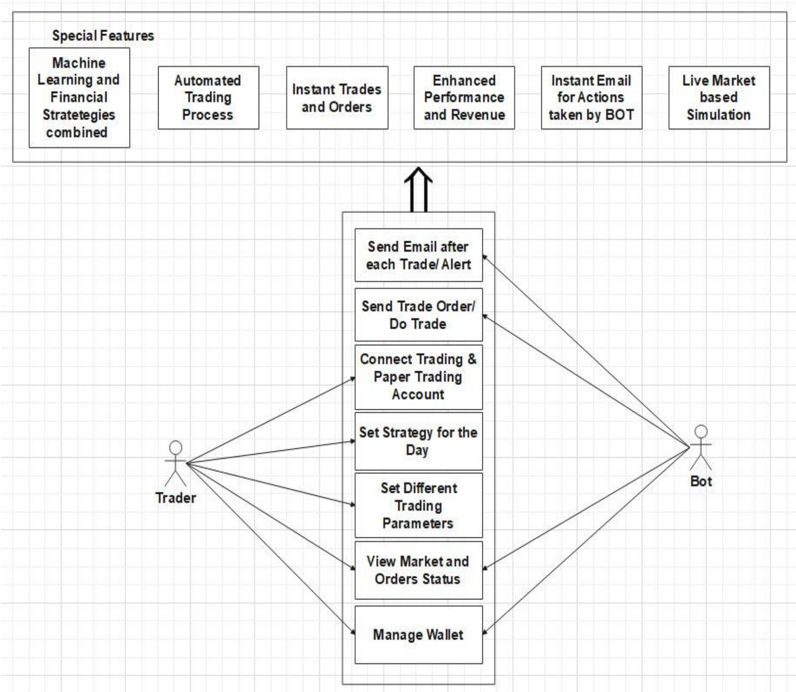

Figure 8 : Architectural Diagram for Algorithmic Trading Bot

A. Data Pre-processing

Data pre-preprocessing is applied on the dataset to get Intraday movements to pass into Random Forest Regressor.

a. We drop all other columns except Date and Close price.

b. To determine the actual trading signal, we assume that we traded on a prior day's close price, this is done by lagging the data by 1 day. We create a lag for 41 days.

c. We then clean the dataframe by dropping any NULL values.

d. Dataset is split as [0:33] data into X (inputs) and the rest into Y (outputs)

B. Splitting dataset into Test and Train dataset

Dataset spit into Training and Testing in the ratio 60:40. Four variables i.e., X_train, X_test (for inputs) and Y_train, Y_test (for outputs) is created.

C. Training the Random Forest Regression model on the training set

We import the RandomForestRegressor class and assign it to the variable regressor. We then use the .fit() function to fit the X_train and Y_train values to the regressor by reshaping it accordingly. Feature importance is calculated with regressor.feature_importances_ to help describe the importance of chosen features and to improve the model.

D. Predicting the Results

We predict the results of the test set with the model trained on the training set values using the regressor.predict function and assign it to 'Y_predicted'.

E. Visualizing the Random Forest Regression Results

A graph of Share Price (Both Y_test & Y_predicted) vs Date is plotted. The Actual values are plotted with "Red" color and the Predicted values with "Blue" color.

F. Integration of Financial Strategy Bot with Random Forest Model

Python Bot is coded which connects with a Paper Trading account via API. The strategy parameters are entered by the user , and once the Bot starts trading it will continue to do so until either Stop Loss is reached, Market is closed or User sends a Stop signal to Bot.

The Bot constantly checks Market conditions and current Positions in the market to decide its action. The Random Forest model is integrated as a joblib file with the bot and the Bot is made to take its decision on the basis of prediction from the model as well as the financial strategy.

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V. EVALUATION

Random Forest Regressor Model for Trading Analysis –

Evaluation Metrics –

1. Explained Variance Score - Explained variance regression score function.
Best possible score is 1.0, lower values are worse.

$$explained\_variance(y, \hat{y}) = 1 - \frac{Var\{y - \hat{y}\}}{Var\{y\}}$$

2. R^2 Score - computes the coefficient of determination.

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

3. Mean squared logarithmic error - computes a risk metric corresponding to the expected value of the squared logarithmic (quadratic) error or loss.

$$\text{MSLE}(y, \hat{y}) = \frac{1}{n_{\text{samples}}} \sum_{i=0}^{n_{\text{samples}}-1} (\log_e(1 + y_i) - \log_e(1 + \hat{y}_i))^2.$$

4. Random Forest Regressor Score - Return the mean accuracy on the given test data and labels.

regressor.score(X_test, y_test)
Mean accuracy of self.predict(X).y

VI. RESULT

1. Evaluation based on Metrics –

The Table shows the performance of our model against the evaluation parameters discussed earlier.

2. Random Forest Regressor Model:

Random Forest Regressor Model for Trading Analysis –
(Red: Actual Stock Price Movement, Blue: Bot predicted Stock Price Movement)
X axis: 'TSLA' Stock share prices of test dataset and predicted prices

Y axis: Dates of trade

The Fig 16 shows a plotted graph for Share Price vs Date depicting performance of the Random Forest Model.

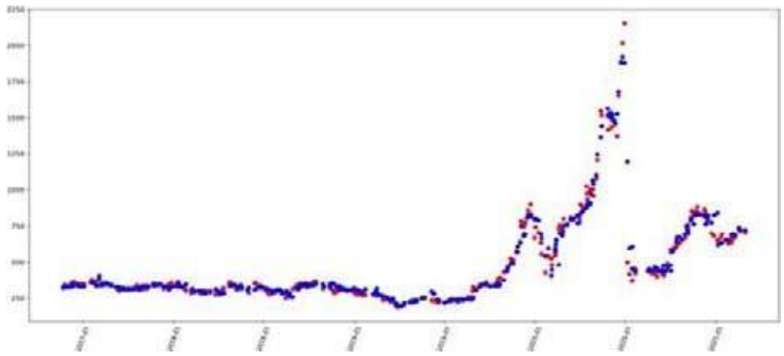

Figure 16: Share Price vs Date Graph

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3. Backtesting **Moving Average Crossover** strategy –

Table 3 shows the Back Testing results against parameters of Strike Rate and Profit Earned for 1-year and 10-year duration.

Table 3: Moving Average Evaluation

DURATION	STRIKE RATE	PROFIT EARNED
1 year	77.78%	$ 820.8
10 years	53.85	$ 1993.43

The Fig 17 shows the plotted graph of Moving Average Strategy for 1-year and 10-year duration depicting the behaviour of bot against actual trade movement.

1 Year Chart

10 Years Chart

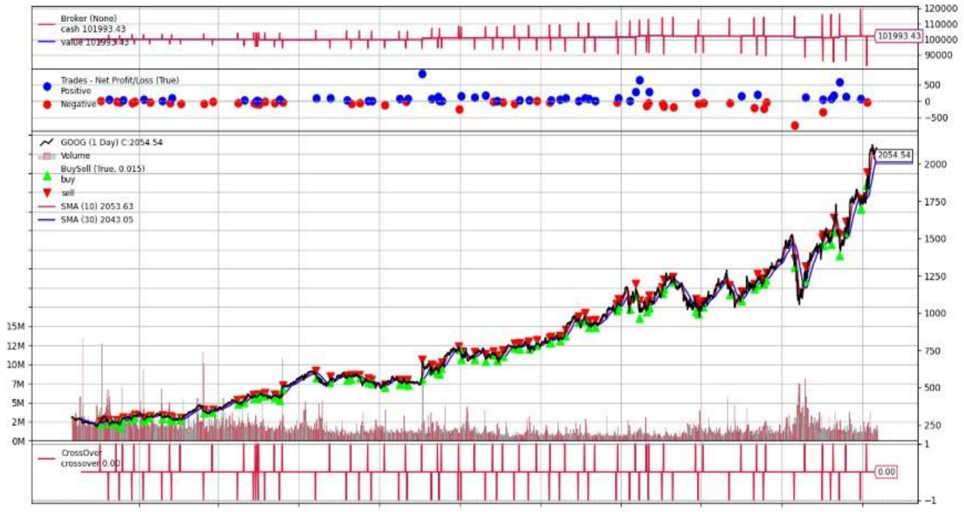

Figure 17: Moving Average Back testing

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4. Back testing **Donchian** strategy –

Table 4 shows the Back Testing results against parameters of Strike Rate and Profit Earned for 1-year and 10-year duration.

Table 4: Donchian Evaluation

DURATION	STRIKE RATE	PROFIT EARNED
1 year	26.3157%	$ -2053.89
10 years	31.0924%	$ -7859.13

The Fig 11 shows the plotted graph of Donchian Strategy for 1-year and 10-year duration depicting the behaviour of bot against actual trade movement.

1 Year Chart

10 Years Chart

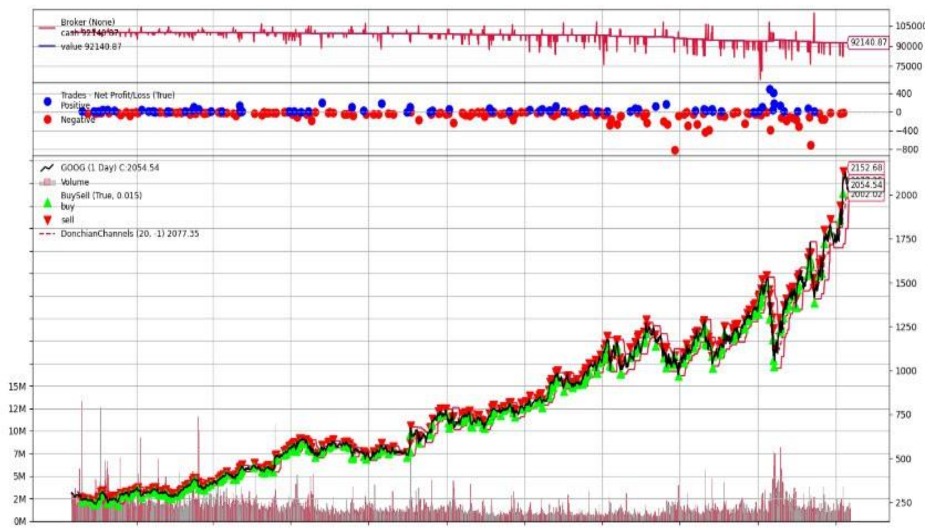

Figure 18: Donchian Back testing

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Back testing **Multiple Data's** strategy –

Table 5 shows the Back Testing results against parameters of Strike Rate and Profit Earned for 1-year and 10-year duration.

Table 5: Multiple Data's Evaluation

DURATION	STRIKE RATE	PROFIT EARNED
1 Year	50%	$ 3874.1
10 Years	41.81%	$ 14802.73

The Fig 12 shows the plotted graph of Multi Data's Strategy for 1-year and 10-year duration depicting the behaviour of bot against actual trade movement.

1 Year Chart

10 Years Chart

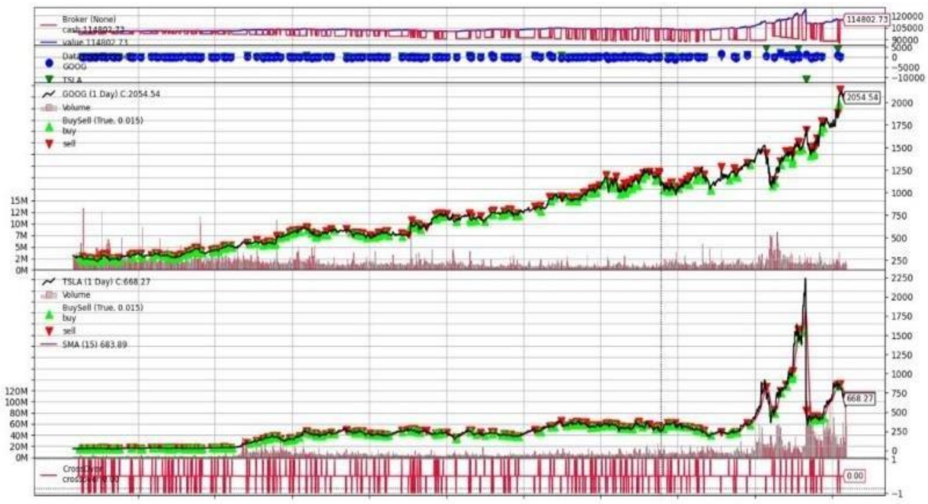

Figure 19: Multiple Data's Back testing

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5. Back testing **Gold Cross** strategy –

Table 6 shows the Back Testing results against parameters of Strike Rate and Profit Earned for 1-year and 10-year duration.

Table 6: Gold Cross Evaluation

DURATION	STRIKE RATE	PROFIT EARNED
1 Year	NA	NA
10 Years	50%	$ 214.15

The Fig 13 shows the plotted graph of Gold Cross Strategy for 10-year duration depicting the behaviour of bot against actual trade movement.

10 Years Chart

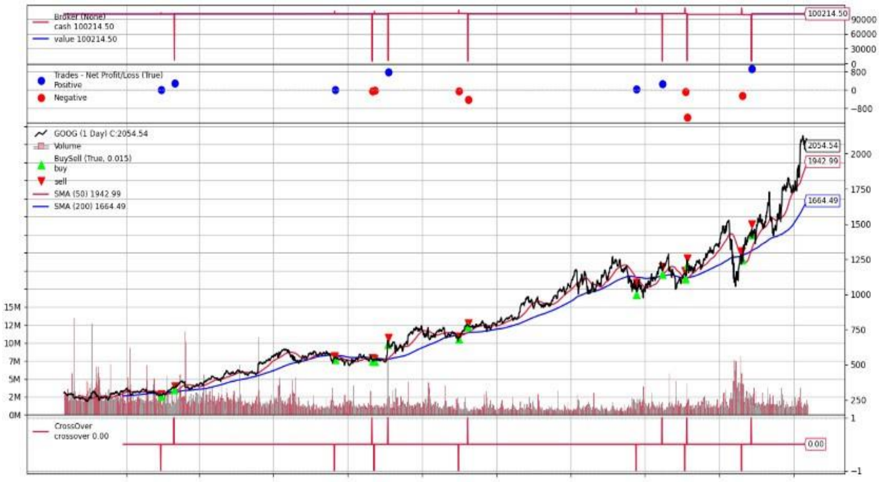

Figure 20: Gold Cross Back testing

VII. CONCLUSION

Algorithmic trading Bot not only provides Security, Cost, and Speed but is also a revolutionary technology for the future financial markets and economy. Algorithmic Trading Bot makes it easier for both new traders as well as established ones in getting profitable outcomes with minimized effort, time and loss.The integration of Financial Knowledge with Machine Learning is a demand of future Trading and enhances both Performance and Revenue.

VIII. ACKNOWLEDGMENTS

We would like to express our gratitude to our College, Ramrao Adik Institute of technology our Mentor, **Dr. Vanita Mane** Ma'am, and our Project Coordinator, **Dr. Sangita Choudhary** who have provided us with the opportunity to work on this project and given us support with guidance to make this project a success. We would also like to thank our teammates for their contribution and continued support and zeal towards this project. This project wouldn't be a success without their efforts.

REFERENCES

[1] https://www.adigitalblogger.com/algo-trading/algo-trading-platf orms/
[2] https://blog.quantinsti.com/growth-future-algorithmic-trading/

DOI: 10.17148/IARJSET.2025.125351

[3] Ash Booth, Enrico Gerding, and Frank Mcgroarty. 2014. Automated trading with performance weighted random forests and seasonality. Expert Syst. Appl. 41, 8 (June, 2014), 3651– 3661. DOI: https://doi.org/10.1016/j.eswa.2013.12.009

[4] Younes Chihab, Zineb Bousbaa, Marouane Chihab, Omar Bencharef, Soumia Ziti, and Miin-Shen Yang. 2019. Algo-Trading Strategy for Intraweek Foreign Exchange Speculation Based on Random Forest and Probit Regression. Appl. Comp. Intell. Soft Comput. 2019 (2019). DOI: https://doi.org/10.1155/2019/8342461

[5] Suryoday Basak, Saibal Kar, Snehanshu Saha, Luckyson Khaidem, Sudeepa Roy Dey, Predicting the direction of stock market prices using tree-based classifiers, The North American Journal of Economics and Finance, Volume 47, 2019, Pages 552- 567, ISSN 1062-9408, https://doi.org/10.1016/j.najef.2018.06.013.

[6] Bruno Miranda Henrique, Vinicius Amorim Sobreiro, Herbert Kimura, Stock price prediction using support vector regression on daily and up to the minute prices, The Journal of Finance and Data Science, Volume 4, Issue 3, 2018, Pages 183-201, ISSN 2405-9188,https://doi.org/10.1016/j.jfds.2018.04.003.

[7] Omer Berat Sezer, Murat Ozbayoglu, Erdogan Dogdu, A Deep Neural-Network Based Stock Trading System Based on Evolutionary Optimized Technical Analysis Parameters, Procedia Computer Science, Volume 114, 2017, Pages 473-480,ISSN 1877-0509, https://doi.org/10.1016/j.procs.2017.09.031.

[8] Maragoudakis, M and Serpanos, D. (2010), towards stock market data mining using enriched random forests from textual resources and technical indicators. AIAI 2010, IFIP AICT 339,pp. 278-286. https://link.springer.com/chapter/10.1007/978-3-642-16239-8_37

[9] https://www.investopedia.com/terms/c/conditional_value_at_risk. asp

[10] https://www.investopedia.com/articles/trading/05/scalping.asp

[11] Manoj Thakur and Deepak Kumar. 2018. A hybrid financial trading support system using multi-category classifiers and random forest. Appl. Soft Comput. 67, C (June 2018), 337–349.
DOI: https://doi.org/10.1016/j.asoc.2018.03.006

[12] M. Nabipour, P. Nayyeri, H. Jabani, S. S. and A. Mosavi, "Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; a Comparative Analysis," in IEEE Access, vol. 8, pp. 150199- 150212, 2020, doi: 10.1109/ACCESS.2020.301596

[13] M. H. L. B. Abdullah and V. Ganapathy, "Neural network ensemble for financial trend prediction," 2000 TENCON Proceedings. Intelligent Systems and Technologies for the New Millennium (Cat. No.00CH37119), 2000, pp. 157-161 vol.3, doi: 10.1109/TENCON.2000.892242.