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CRYPTO TRADING BOT USING MOVING AVERAGE, SUPPORT AND RESISTANCE

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Abstract

Crypto trading bot uses algorithms that follow a trend and defined set of instructions to perform a trade. The trade can generate revenue at an inhuman and enhanced speed and frequency. The characterized sets of trading guidelines that are passed on to the program are reliant upon timing, value, amount, or any mathematical model. Aside from profitable openings for the trader, algo-trading renders the market more liquid and trading more precise by precluding the effect of human feelings on trading. Our project aims to further this revolution in the markets of tomorrow by providing an effective and efficient solution to overcome the drawbacks faced due to manual trading by building an Crypto Trading Bot which will automatically trade user strategies alongside its own algorithms for day-to-day trading based on different market conditions and user approach ,and throughout the course of the day invest and trade with continuous modifications to ensure the best trade turnover for the day while reducing the transaction cost, hence enabling huge profits for concerned users be it Organizations or individuals.

Index Terms **Algorithmic Trading, Finance, Random Forest Regression, Moving average Bollinger bands , Support and Resistance Rsi , Multiple data of currencies.**

INTRODUCTION

Crypto trading bot is a technique for executing orders utilizing mechanized pre-modified trading guidelines representing factors like time, cost, and volume. This kind of trading endeavors to use the speed and computational assets of PCs comparative with human brokers.Just one of every five-day investor is productive. Crypto trading bot improves these chances through better technique configuration, testing, and execution The USP of a trade bot is that it simplifies the work of traders and helps the trader to make quick money with the minimum efforts.Algo trading is now a 'prerequisite' for surviving in tomorrow's financial markets. In order to get rid of the human variable, we have to automate trades. This project uses a python trading bot to make most of the trades. The strategy is based on two indicators. The indicators are Moving averages Bollinger bands ,Support and resistance RSI. The bot will check at these two indicators, and make appropriate moves, and take appropriate strategy in order to maximize profit.

Few Advantages of Crypto Trading Bot !

1.Quick, Fast and Reduced Cost Trading

2.Enhanced Precision and Diversity in Trading

3.Backtesting enabling traders to assess and tweak a trading idea.

- The global algorithmic trading market is expected to grow significantly between 2018 and 2026.
- Our project aims to further this revolution in the markets of tomorrow by providing an effective and efficient

solution to overcome the drawbacks faced due to manual trading like:

- Trades are executed at the best possible prices. " Trade request situation is instant and precise (there is a high possibility of execution at the ideal levels). "
- Trades are coordinated effectively and immediately to keep away from huge value changes.
- " Reduced exchange costs. " Simultaneous automated checks with different market scenarios. " Reduced hazard of manual mistakes when trading. "
- Algo-trading can be back tested utilizing historical and live data to check whether it is suitable for trading. " Reduced the chance of errors by human traders as a result of emotional and psychological factors.

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 Crypto trading bot with Machine Learning. The existing algorithmic trading with Machine Learning methods includes Only Random Forest , Random Forests and Probit regression , Moving Averages ,Bollinger bands , Support and Resistance Rsi gives the summary of limitations of existing systems and software.

Existing Softwares –

A few softwares currently in use are –

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.

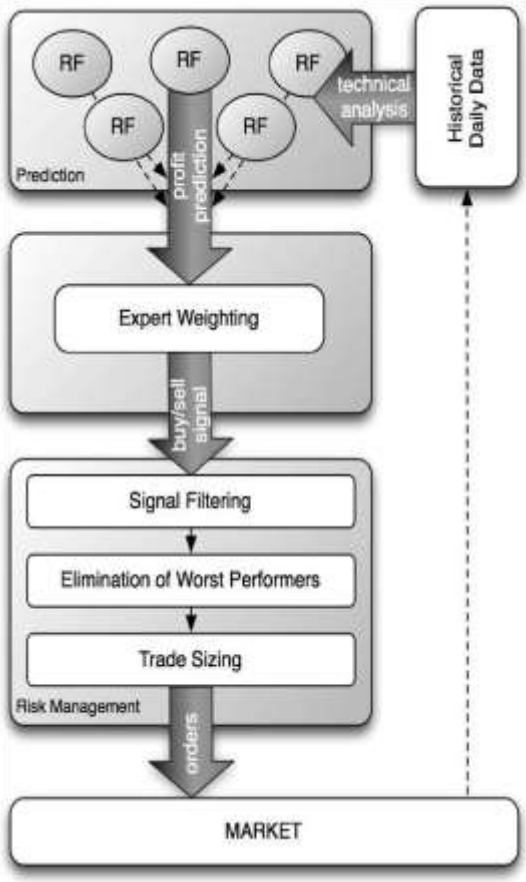


Figure 1 : Diagrammatic representation of the layered workings a fully automated expert trading system.

B . Moving Average and Bollinger Bands.

The main trading strategy used for this experiment was the Bollinger bands. The premise behind Bollinger bands was to look for proper places to take an entry.

Bollinger Bands are quite simple. They are composed of three different bands. These bands are dynamic and adjust themselves to changes in price. The most important band is the center line which is called the exponential moving average. The exponential moving average is used to signal a trend in the market. For example, when the market is strong then the Exponential Moving Average (EMA) will show a line going up and when the market trend is down the EMA will show a line going down. [3]. On top and below the center line there are two more bands, upper band, and lower band. They are located two standards deviations above and below the center band respectively. The simplest strategy to take using Bollinger bands is tracking when prices cross the upper or lower band. For example, when price action crosses the upper band the stock can be considered overbought. Therefore, this would be a good time to sell since the market is probably due for a correction; therefore, it will probably be on the way down soon. The converse is also true; for example, if the price action crosses the lower band to the downside, then the stock is due for the other type of correction, and it could soon see a rise in price action.

The chart in figure 2 is an example of a Bollinger Band. It includes the places to sell and to buy.

Figure 2 Moving average Bollinger bands example.

Overall, some form of intuition is needed to see where the price is heading for a specific currency. The way of doing this is to look at the price charts for that specific currency. From the price chart, we are able to draw the proper conclusions. The first step in doing this project is getting the Bollinger band charts for the price of Litecoin. The 1D time frame is used for this information. A Bollinger band chart is illustrated in Figure 2. In the figure, the blue line is the actual price, the green band represents the upper band, the red represents the lower band, and the middle band represents the 30-Day Moving Average. There were two different graphs we need to view; one is the recent monthly chart represented in Figure 3, and the other is the yearly chart. The yearly chart allows us to see a wider view of how the price has changed and fluctuated as depicted in Figure 4.

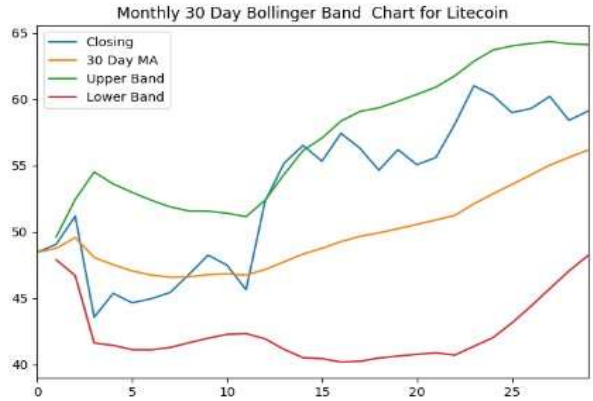


Figure 3 30 Day Moving Average Bollinger Band

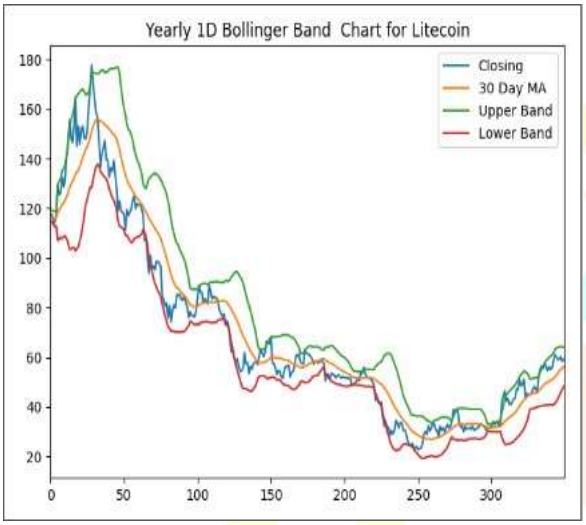


Figure 4 yearly 30-Day Moving Average Bollinger Band

C RSI Indicators

Relative Strength Index is what's called a momentum indicator. It shows you in what direction the market is heading towards. It compares the number of times that the price closed in an upwards trend vs the number of times it closed in a downward trend. From this information, the Relative Strength Index is assigned a score from 0-100.

The Relative Strength Index (RSI) tells you if something is being oversold or overbought. For example, if the RSI score is over 70 then the stock can be thought of as being overbought. This means it would be a good time to sell. However, if the RSI score is below 30 then the stock can be thought of as oversold [4]. In this case, it would be a good time to think about entering into a position.

This is very similar to what the Bollinger Band Indicators say. So both the Bollinger bands and the RSI Indicators can be used in conjunction to determine whether to enter into a trade or to leave it.

If the price is touching the lower Bollinger Band and the RSI is under 30 then the stock is probably oversold. This is where it would be a good idea to make a buy. The opposite is also true. For example, if the RSI is over 70 and the price is touching or approaching the upper band then it is probably under bought. This would be a good opportunity to make a sell.

In order to get the calculation of the RSI indicator, a specific formula is used. Basically, one needs to use the RSI calculations of the previous 30 days. Here, we used the RSI which goes as follows. RSI=100-100(1+RS) where RS is the average gain over the average loss of the last 30 days. The RSI basically relies on the fluctuations in the price of the cryptocurrency. It measures the average gain over the average loss.

$$RSI_{\text{step one}} = 100 - \left[\frac{100}{1+\frac{\text{Average gain}}{\text{Average loss}}}\right]$$

RSI formula

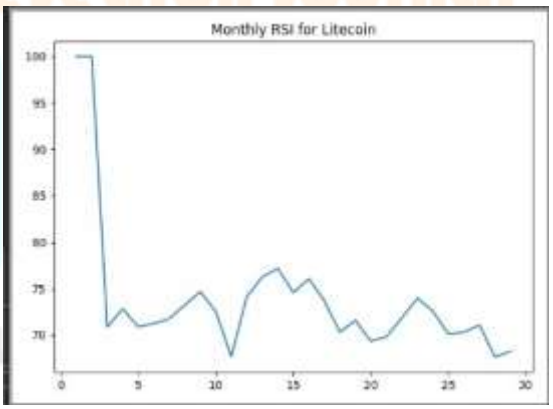


Figure 5 Monthly RSI

D. Using Genetic Algorithms like Deep MLP Neural Network

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

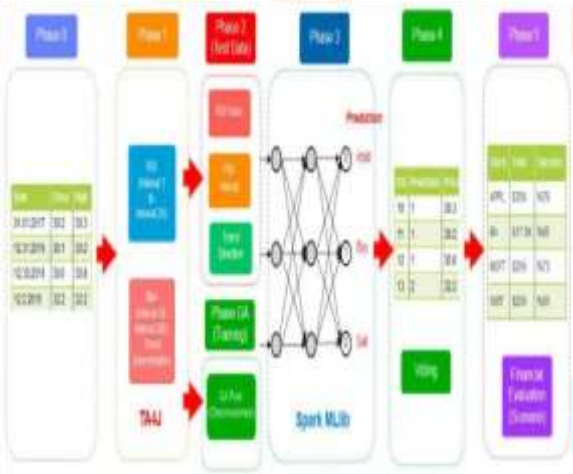


Figure 6 : Proposed Method (Genetic Algorithm and MLP)

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 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.

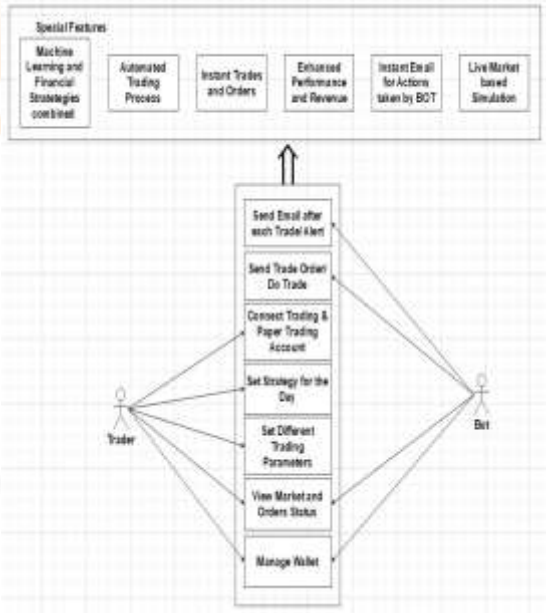


Figure 7 : Architectural Diagram for Crypto Trading Bot

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 days 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 Daily dataframe data set

The table 1 below shows the results of the Bollinger band for the last thirty days. It is based on the daily time frame since every row in the table represent a different day. From looking at this chart we can see overall the RSI is quite high for this time frame. Together from the Table chart and from the Bollinger band, we can see that price action is a bit high from the mean; therefore, it is a bit oversold, so taking a daily trade won't be a good idea. However, there is still profit to be made in the lower time frames. Together from the table chart in table 1 and from the Bollinger band we can reaffirm our hypothesis of the currency being oversold since it is touching the top band the RSI is quite high.

	Closing	30 Day MA	Upper Band	Lower Band	RSI
1	51.19	50.129999999999996	53.126132752230964	47.13186724776904	100
2	43.57	47.943333333333333	55.809242901421	40.077423765245655	88.82346968244 55
3	45.37	47.3	54.21884383405204	40.38115616594796	88.93154323421385
4	44.66	46.772	53.21237887084292	40.33162112915708	87.95846440867983
5	44.96	46.47	52.41740952011882	40.52259047988118	88.01584992652342
6	45.44	46.32285714285714	51.80762045328618	40.8380938324281	88.10975116581521
7	46.81	46.38375	51.4733240770436	41.29417592295 64	88.37892308866745
8	48.25	46.59111111111111	51.5118574411 35085	41.67036478108714	88.65843083631086
9	47.49	46.681	51.355027052648374	42.00697294735162	87.50793257853282
10	45.64	46.58636363636364	51.06474970929012	42.10797756343717	84.73569514082338
11	52.3	47.0625	52.45829044677001	41.66670955322999	86.34824786308068
12	55.17	47.68615384615384	54.535492200873665	40.83681549143403	86.96294856558404
13	56.51	48.31642857142857	56.4127548309798	40.22010231187733	87.24076814362712
14	55.33	48.784	57.385494222351305	40.18250577764869	85.57750762821509
15	57.43	49.324374999999996	58.69142638593072	39.957323614069274	86.06712714932554
16	56.3	49.734705882352934	59.41494639 1566	40.054465395549265	84.46898719554528
17	54.65	50.00777777777777	59.68061556457401	40.334939990981525	82.16174790194091
18	56.2	50.333684210526314	60.15397660383409	40.51339181721854	82.62353780487868
19	55.06	50.569999999999999	60.359283007680877	40.780716923191214	81.02571676057921
20	55.61	50.899999999999984	60.90968479690163	40.88431520309834	81.20731473294902
21	58.13	51.243999999999986	61.7674383014398	40.72056169856017	82.02375139650238
22	61.01	52.115999999999985	62.85015483398668	41.38184516601329	82.90294954668607
23	60.29	52.861999999999999	63.695479491591634	42.02852050840834	81.86620364604711
24	58.99	53.578499999999984	64.016209518856 16	43.140790481144805	79.96544220288885
25	59.29	54.294999999999998	64.19521477704289	44.39478522295707	80.10410854066862
26	60.21	55.033499999999998	64.3381253919333	45.728874608066654	80.44155657490509

Table 1 Daily Table

D : Hourly time frame data set

From Figure 8, we can see that the RSI situation has changed in the hourly time frame. For example, the RSI score has stopped being in the upper 70s and moved down under to the 50 and 60s. This is a good sign because now we can see that the momentum has slowed down a bit. Therefore, it is a good place to enter into a position.

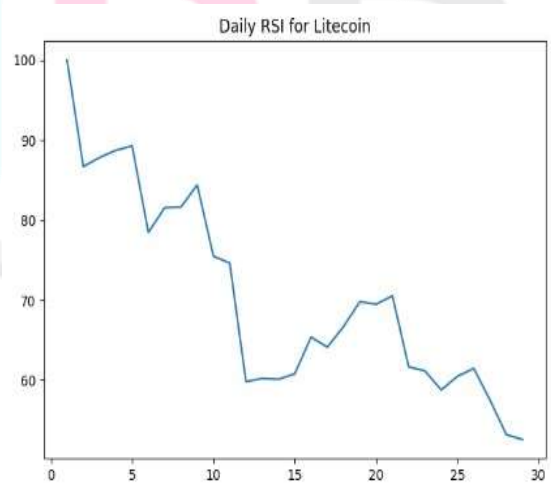


Figure 8 Hourly RSI

Table 2 confirms the appropriate market conditions. If we look at the chart, we can see that the RSI is falling as the closing price gets closer to the lower band.

	Closing	30 Day MA	Upper Band	Lower Band	RSI
0	58.89	58.89			
1	58.99	58.94	59.08142135623731	58.79857864376269	100
2	58.56	58.81333333333333	59.26337036884633	58.36329629782034	86.68730660154816
3	58.85	58.8225	59.19177857964896	58.45322142035351	87.81992185634495
4	59.11	58.87999999999995	59.29305690057386	58.46694309942633	88.71171889126268
5	58.29	58.94833333333333	59.44510960759234	58.45155705907432	89.27478300983184
6	58.81	58.92857142857143	59.39396424780103	58.46317860934183	78.46504947670901
7	59.48	58.99375	59.56084157738663	58.42665842261336	81.55007945479214
8	59.47	59.04666666666666	59.68488992730961	58.42844340602371	81.83523069455371
9	60.21	59.163	60.101653882488 7	58.22434611751129 8	84.39515745271548
10	59.65	59.20727272727272	60.14493326983045	58.2696121965824	75.50180163220757
11	59.59	59.23916666666667	60.18009340675301	58.31823992658032 6	74.62911243025214
12	58.36	59.17076923076923	60.18106947823124	58.16047351371534	59.82737647195635
13	58.41	59.11642857142857	60.16882823645373	58.06402890640341 5	60.22275096862506
14	58.4	59.06666666666665	60.14816037615535 6	57.98917296817797 4	60.12061221179658
15	58.5	59.033125	60.11408056675775	57.95216940424225	60.80903603351667
16	59.24	59.04529411764706	60.09672451589173	57.99386371940239	65.38835992858589
17	59.12	59.04944444444444	60.07008950114055	58.02879936377482 5	64.12982528411536
18	59.59	59.07789473684211	60.10032276087483	58.05546671280936	66.72782035821822
19	60.23	59.13549999999999	60.25612905266827	58.01487947331715	69.81109795754999
20	60.2	59.20099999999996	60.41080033153019	57.99119966849678	69.46408964144736
21	60.43	59.27299999999999	60.59602842392845	57.94997157607013	70.54597087731388
22	59.5	59.31999999999999	60.60254680042044	58.03745319157954 4	61.67517108697119
23	59.44	59.3495	60.61353658432	58.08546344156799 5	61.16127494044583 8
24	59.16	59.35200000000001	60.6142386128579 25	58.0897613871421	58.79349664285423
25	59.46	59.360500000000016	60.62327013785276	58.09772986214727 6	60.49082421223628 4
26	59.64	59.40200000000002	60.64296057870296	58.16103942129708	61.47690454259495
27	59.16	59.38750000000024	60.63268826090246	58.14213173909756 6	57.51243792786335
28	58.58	59.34300000000002	60.63548865435055	58.04745134564945	53.21752616841233

Table 2 Hourly Table

As the marketing conditions are right, this would be the appropriate time to enter a trade. Therefore, the bot enters into a trade at the price of 59.08. I hold the price for a few hours and then sells the price of 59.67. Therefore, it exits its position at the 1% profit margin. Therefore, it was a successful trade. It made another trader at 59.34 when the market made a pullback. It then sold at 59.55.

E. 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 predicted .

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.

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.

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

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)

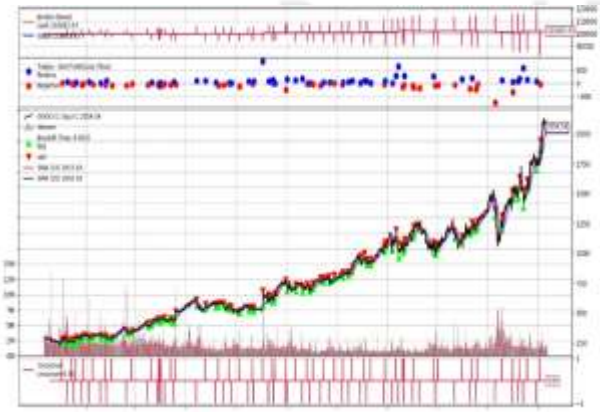
3. Backtesting Moving Average Crossover strategy - Table 3 shows the Back Testing results against parameters of Strike Rate and Profit Earned for 1-year and 10-year duration.

Table 3: Moving Average Evaluation

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

The Fig 9 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 year chart

Figure 9: Moving Average Back testing

4. Back testing RSI 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: RSI Evaluation

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

1 year chart

10 year chart

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

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