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Stock Price Prediction Using Time Series

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Abstract: Predicting Stock price of a company has been a challenge for analysts due to the fluctuations and its changing nature with respect to time. This paper attempts to predict the stock prices using Time series technique that proposes to observe various changes in a given variable with respect to time and is appropriate for making predictions in financial sector [1] as the stock prices are time variant.
Keywords: Stock prices, Analysis, Fluctuations, Prediction, Time series, Time variant

I. INTRODUCTION

Any Investor, individual or firm expects a good or reasonable number of returns on their investments. Investing in Stocks is one of the better options to get a good ROI (Return on investment). This requires investors to have a good understanding of various stocks and their current prices. To maximize the profits and minimize the losses requires a good prediction of the price when to buy a stock and when to sell the same. Some of the Forecasting principles are discussed in Efficient Market Hypothesis and Eliot Wave Theory [6]. In general, the stock prices are mainly determined by the actions of the institutional investors, we call them big buyers and big sellers. The Price Auction will be high for that day if the buyers are more and less when sellers are more. Finally, the price will be at the point of control that is mean price or most of the price at which most of the time of the price holds. Most of the time the price is normally distributed. So based on the price of the auction the entry point and exit point should be identified to get maximum profit and the stop loss point to be predicted properly to have efficient risk analysis. For achieving the same popular statistical techniques like Auto Regression and Moving Averages are being used extensively.

Modern computing technics like machine learning facilitates prediction with more accuracy with Hybrid models like Auto-Regressive Integrative Moving, Exponential Smoothing, ARIMA (Auto Regressive Integrated Moving Average') [7], Naïve Forecasting, Seasonal Naïve Forecasting or Neural Networks. Our current proposed model will use all the modern techniques and predict the stock price at a given point and ranks each of the models to facilitate the user to make a decision when to buy or sell a particular stock, doing a short-term trade or long term to maximize their profits. This model uses all the modern techniques and is different from the traditional approaches having a high probability of accurate prediction.

II. METHEDOLOGY

The proposed steps for achieving the objective are as follows, Initially, the data needs to be fed to the system that is extracted from Yahoo! Finance on monthly basis and the data imported is cleaned by making sure that outliers are removed and a filter is applied to reject the null values in the data. Then data is converted into time series objects and the ADF test is applied to make sure the data is stationary. Then the time series object is decomposed as the results depend on many factors to achieve accurate results the time series object must be decomposed to observe various seasonality factors and trends. Then the time series objects are fed to various algorithms like ARIMA, Exponential Smoothing, Naïve Forecasting, Seasonal Naïve Forecasting, Neural Networks etc. figure 2.1 demonstrates the workflow.

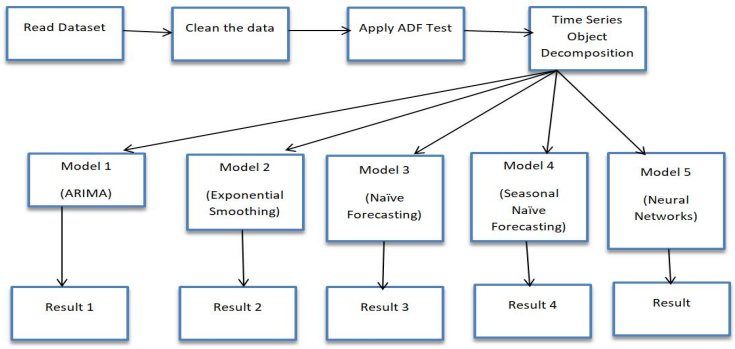


Fig 2.1 Methodology

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III. ALGORITHMS USED

A. *ARIMA*

Arima model, which is introduced by George Box and Gwilym Jenkins, is also referred as Box-Jenkins model [2]. The Combination of the models Auto regression and moving average results in a Hybrid model called Auto Regressive Integrated Moving Average which has the following equation.

$$y'(t)=c+\phi 1y'(t-1)+\cdots+\phi py'(t)-p+\theta 1\varepsilon(t-1)+\cdots+\theta q\varepsilon(t)-q+\varepsilon(t) \quad (1)$$

Where y't is dependent variable and differenced (Can be differentiated more than once), on the other side we have predictors carrying lagged values of y(t) and lagged errors.

This model is known as ARIMA (p, d, and q) model.

Where p and q are the orders of Auto regression and Moving Average parts and d is the degree of differentiation involved [3].

B. *Exponential Smoothing*

This forecast technique in which the past data is assigned with some weights in such a way that, they are exponentially decaying with respect to time. The latest weights are at the top and as time factor is increased, they start decaying.

C. *Naïve Forecasting*

The forecast is set to previous data without applying any predictions and is achieved through following equation.

$$y'(T+h)\,|T = y(T). \quad (1)$$

Where, (T + h) refers to the forecast related to past data

(T), refers to the forecast related to current data

D. *Seasonal Naïve Forecasting*

This forecasting technique is similar to naïve forecasting but the forecast is set to past data from same season, we can achieve seasonal naïve forecasting through following equation.

$$y'(T+h)|T = y(T+h) - m(k+1) \quad (1)$$

Where, m is the seasonal period

T + h refers to forecast related to past data

E. *Neural Networks*

This type of forecasting is used in nonlinear and complex forecasting scenarios and denoted as NNAR (p, x) where p is number of lagged inputs and x is number of hidden layers. The architecture of Neural Networks is shown in the figure 3.1 [5].

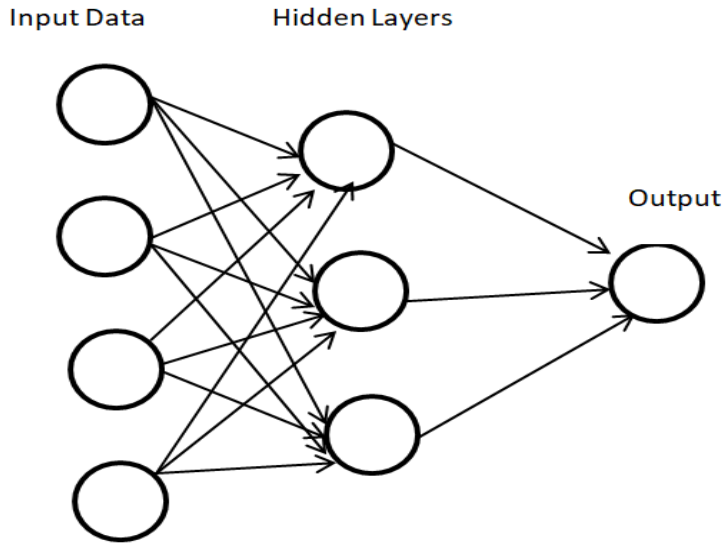


Fig 3.1 Neural Networks

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IV. EXECUTION AND RESULTS

A. *Gathering Data and Performing Various Analysis on It*

1) *Importing and Reading the Data:* We use quant mod library to pull the stock data from Yahoo and return the dataset as time-series objects. We have generalized the logic to pull the data from a given stock symbol for a period (from and to dates). We will use stock monthly data of Apple (Switching to other company can be done by just changing the stock symbol), Downloaded from Yahoo Finance

2) *Plotting the Apple Stock Prices Time Series:* Plotting the time series object for apple stock prices, the data received from yahoo finance in fig 4.1.2

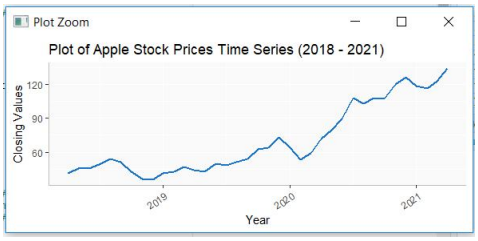


Fig 4.1.2 Plotting data received from yahoo finance (Apple stock index)

3) *Decomposition of Plots:* Decomposition of plots is required to know about various trends in the current market [5]. Is shown in fig 4.1.3

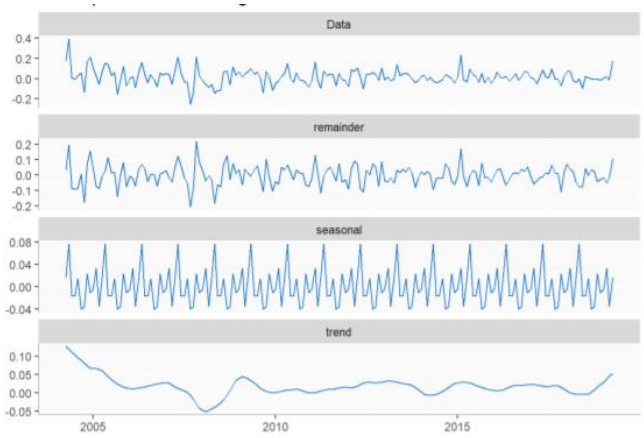


Fig. 4.1.3 Decomposition of plots

4) *Analysing the seasonality of Apple Stock Index:* To observe the various patterns of apple stock prices in the previous years and the current year as shown in figure 4.1.4



Fig. 4.1.4 Seasonality of Apple stock Prices

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5) *Applying Augmented Dickey Fuller Test (ADF):* ADF test is applied to check whether the time series is stationary, the results of ADF can be viewed in figure 4.1.5 The ACF and PACF plots are used to compare current data with past data including their residuals [4].

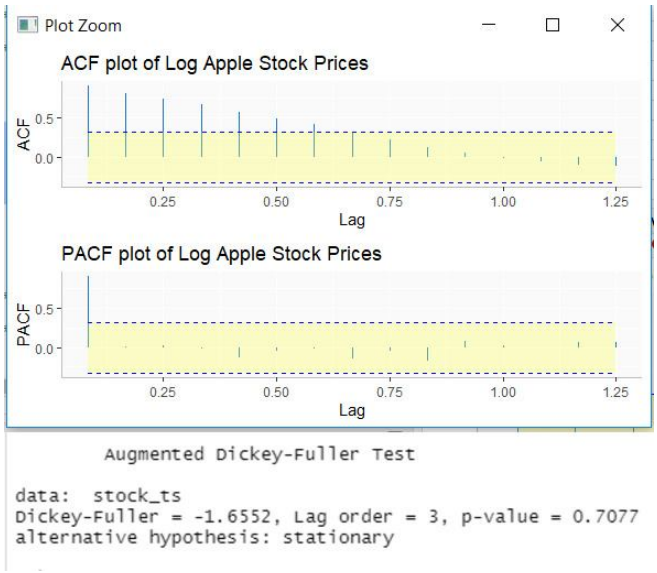


Fig. 4.1.5 ADF Test Results

6) *Splitting Data into Train and Test Datasets:* Generally, before building a model we need to spit the data into train and test sets, with the help of training set, model needs to be built and with the help of test set the model needs to be tested for its performance.

B. Results from Various Algorithms

Initializing the algorithm and feeding them with apple stock prices then return the predictions made by respective algorithm.

1) ARIMA

Forecast values, predicted by ARIMA model can be observed in figure 4.2.1.1

```
> print('Arima Forecast: ')
[1] "Arima Forecast: "
> print(arima$forecast)
         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
May 2021       120.7014 109.9755 131.4274 104.2975 137.1053
Jun 2021       120.7014 109.9755 131.4274 104.2975 137.1053
Jul 2021       120.7014 109.9755 131.4274 104.2975 137.1053
```

Fig. 4.2.1.1 Stock Price Predicted values using Arima

Visualizing Stock Prices predicted by ARIMA Model

Visualizing the apple stock prices predicted by ARIMA Model in figure 4.2.1.2

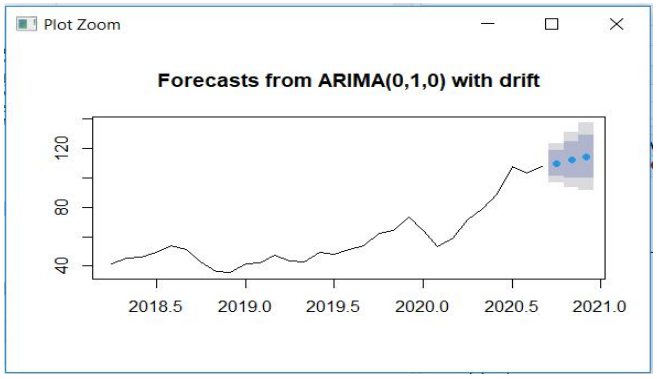


Fig. 4.2.1.2 Visualizing stock prices predicted using Arima

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2) Exponential Smoothing

Forecast Values predicted by ETS can be observed in the figure 4.2.2.1

```
> print('Exponential Smoothing Forecast: ')
[1] "Exponential Smoothing Forecast: "
> print(exp_smoothing$forecast)
         Point Forecast    Lo 80    Hi 80     Lo 95    Hi 95
May 2021       134.1088 120.1296 148.0881 112.72939 155.4883
Jun 2021       134.1088 114.3075 153.9102 103.82529 164.3924
Jul 2021       134.1088 109.8175 158.4001  96.95848 171.2592
>
```

Fig. 4.2.2.1 Stock prices predicted values using Exponential Smoothing

Visualizing Stock Prices predicted by Exponential Smoothing

Visualize the apple stock prices predicted by Exponential Smoothing in figure 4.2.2.2

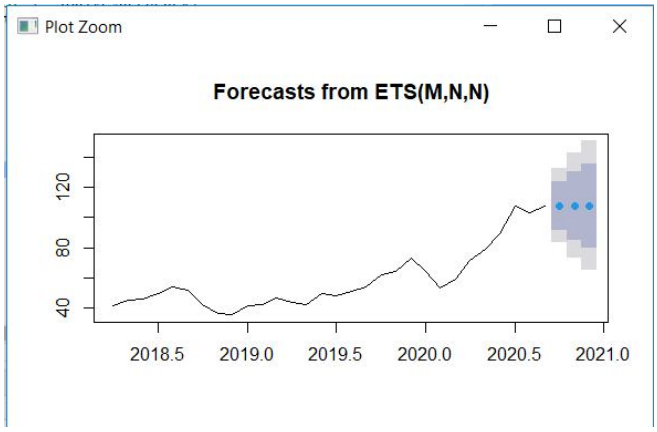


Fig. 4.2.2.2 Visualizing stock prices predicted using Exponential Smoothing

3) Naïve Forecasting

Forecast values predicted by Naïve model can be observed in the figure 4.2.3.1

```
> print('Naive Forecast: ')
[1] "Naive Forecast: "
> print(naive$forecast)
         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
May 2021         134.11 123.0774 145.1426 117.2371 150.9829
Jun 2021         134.11 118.5075 149.7125 110.2481 157.9719
Jul 2021         134.11 115.0009 153.2191 104.8852 163.3348
>
```

Fig. 4.2.3.1 Stock Price Predicted values using Naïve Forecasting

Visualizing Stock Prices predicted by Naïve Forecasting

Visualize the apple stock prices predicted by Naïve Forecasting in figure 4.2.3.2

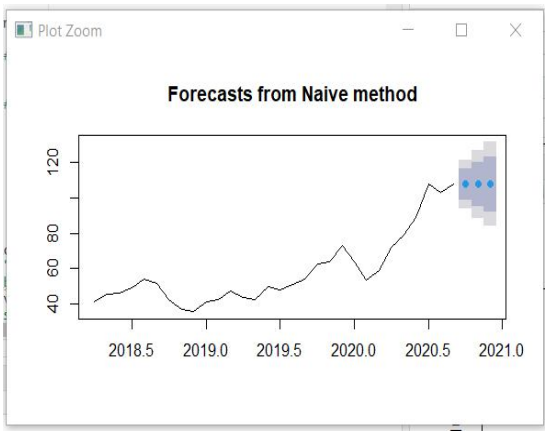


Fig. 4.2.3.2 Visualizing stock prices predicted using naïve forecasting

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4) Seasonal Naïve Forecasting

Forecast values predicted by Seasonal Naïve can be observed in the figure 4.2.4.1

```
> #print('Seasonal Naive Forecast: ')
> print(snaive$forecast)
         Point Forecast Lo 80 Hi 80 Lo 95 Hi 95
May 2021         107.32   NaN   NaN   NaN   NaN
Jun 2021         120.01   NaN   NaN   NaN   NaN
Jul 2021         126.38   NaN   NaN   NaN   NaN
```

Fig. 4.2.4.1 Stock Price predicted values Seasonal Naïve Forecasting

Visualizing Stock Prices predicted by Seasonal Naïve

Visualizing the apple stock prices predicted by Seasonal Naïve.

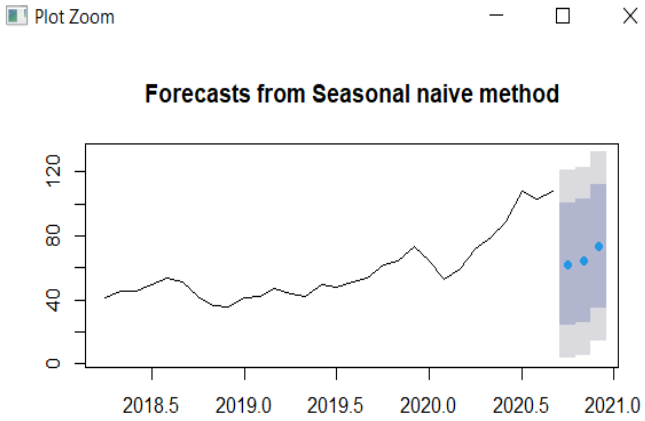


Fig. 4.2.4.3 Visualizing stock prices predicted using seasonal naïve forecasting

5) Neural Networks

Forecast values predicted by Neural Networks can be observed in the figure 4.2.5.1

```
> #print('Neural Net Forecast: ')
> print(nnet$forecast)
          Feb      Mar      Apr
2021 72.55306 69.80062 68.06135
```

Fig. 4.2.5.1 Stock Price predicted values by Neural Networks

Visualizing Stock Prices predicted by Neural Networks

Visualizing the apple stock prices predicted by Neural Networks in figure 4.2.5.2

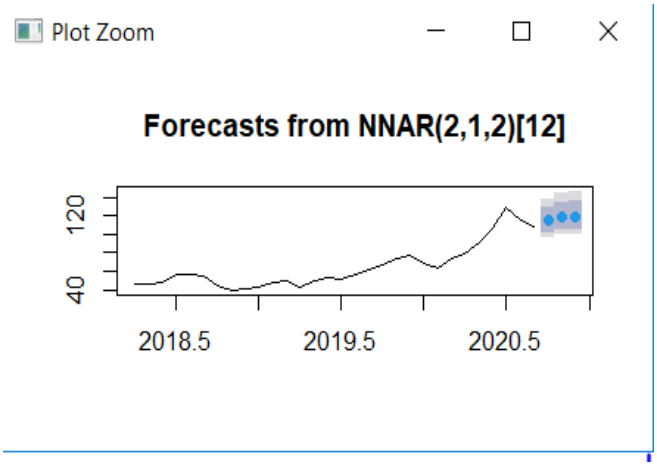


Fig. 4.2.5.2 Visualizing stock prices predicted by Neural Networks

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C. Comparing all the Algorithms

Based on the accuracies of the algorithms, they were given ranks in figure 4.3.1

```
> result[nrow(result) + 1,] <- append(list(Forecast = "Neural Network"), accuracy_nnet)
> result[nrow(result) + 1,] <- append(list(Forecast = "ARIMA"), accuracy_arima)
>
> print(result[order(result$RMSE),])
                Forecast            ME       RMSE        MAE  MPE MAPE      MASE        ACF1
4         Neural Network  2.476195e-02 0.06551681 0.05380686 -Inf  Inf 0.7481078  0.17716476
1   Exponential Smoothing  2.095968e-06 0.07276195 0.05601089 -Inf  Inf 0.7787518 -0.01588138
5                  ARIMA  2.838887e-02 0.07810058 0.06645958 -Inf  Inf 0.9240260 -0.01588145
3 Seasonal Naive Forecast  1.589091e-02 0.09513267 0.07192393  Inf  Inf 1.0000000 -0.15912276
2         Naive Forecast -2.969424e-03 0.10527330 0.07968441  Inf  Inf 1.1078985 -0.42053362
> |
```

Fig. 4.3.1 Comparison between algorithms

D. Today's Apple Stock price

The results of the apple stock price displayed from Google could be noticed below [8] in figure 4.4. As per rankings Exponential Smoothing proved to be most accurate, It could be noticed that exponential smoothing's result (Hi 80) equalizes today's apple stock price.



Fig 4.4 current day's apple stock price

V. CONCLUSION

Stock price has been predicted, in this case Exponential smoothing outperformed other models but depending on situation and data the performance might vary, when we receive data, it's recommended to feed the data to all the models, compare the results and consider the accurate result depending upon the ranks.

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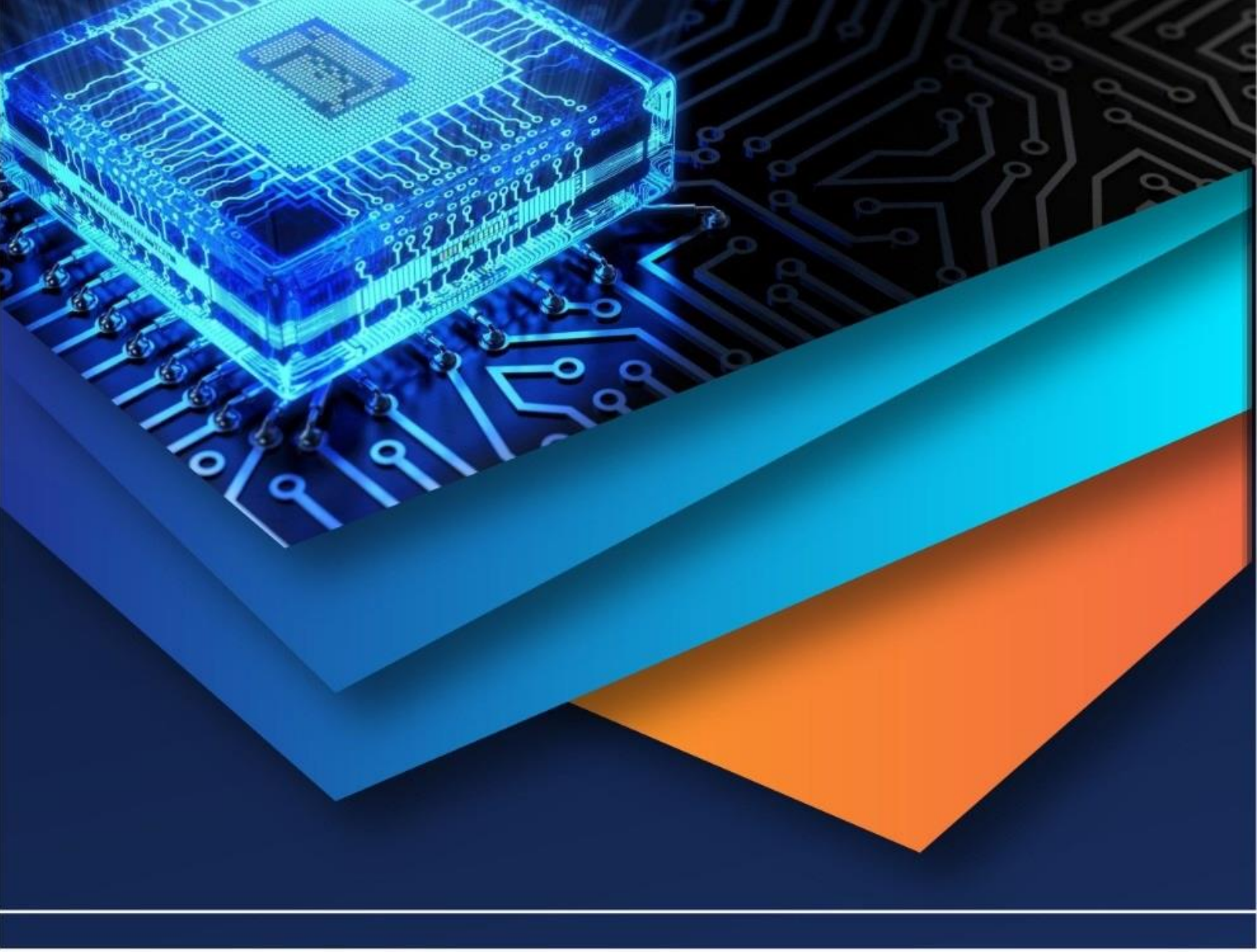
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