STOCK PRICE PREDICTION USING TIME SERIES

Mr.P.Ramu[1], Ms.A.Vani Priya[2], Ms.D.Roopa Sree [3], Ms.S.Sankeerthana[4]

[1]*Assistant Professor, Dept of Computer Science and Engineering from Sreenidhi Engineering College, JNTUH., (T.S.), INDIA.*

[234] *UG Scholar, Dept of Computer Science and Engineering from Sreenidhi Engineering College, JNTUH.,(T.S.), INDIA.*

Abstract - Analysts have found it challenging to estimate a company's stock price because of its volatility and shifting nature. Because stock values are time-dependent, this research aims to forecast stock values using the technique called Time series, which requires tracking many changes in a single variable over time and is particularly suited for financial forecasting. Using Time Series on a dataset will allow you to examine how a defined economic, currency, or meteorological variable changes over time, as well as how it changes in comparison to other similar variables over the same period. In this project, we will use time series models to forecast stock values using ARIMA and other forecasting approaches. Time Series is a basic statistical tool for analyzing continually changing variables such as stock prices, weather, currencies, and so on. A popular forecasting model called the ARIMA model that works with historical data to provide near-term projections and may be used as a foundation for more complex and complicated models. We'll gather stock market data and analyze it with ARIMA time series modeling and other forecasting techniques like Naive Estimate and Exponential Smoothing, to forecast future stock prices.

Key Words: Stock price, time changing, Data, ARIMA, Exponential smoothing, Naive, Seasonal Naive, statistics, Analysis

1 INTRODUCTION

This work is about the prediction of the stock price using time series. Every investor, whether an individual or a company, wants a good or reasonable return on their investment. Stocks are one of the best ways to get a good return on investment. This requires investors to fully understand many stocks and their current prices. To maximize profits and avoid losses, you need to make accurate price forecasts when buying and selling stocks. Both the Efficient Market Hypothesis and the Elliott Wave Theory test several predictive principles. The behavior of institutional investors, often known as large buyers and sellers, is generally a major contributor to equity value. If one day there are more buyers than sellers, the auction will be higher for that price. Finally, the price is displayed at the control point. This is the average price or the most constant price. Pricing is usually distributed in most cases. Therefore, you need to select entry and exit points based on the auction price to maximize profits and accurately predict stop-loss points for complete risk analysis. Extensive statistical techniques such as autoregressive and moving averages are often used to achieve the same goal.

With the latest computing technologies such as machine learning, ARIMA (autoregressive integrated moving average), exponential smoothing, autoregressive integrated moving, ARIMA (autoregressive integrated moving average), naive prediction, seasonal naive prediction, and neural networks several techniques such as are possible. The currently proposed model uses all new techniques to predict current stock prices and maximize profits. Each model is ranked to help users decide whether to buy or sell a particular stock, whether the transaction is short-term or long-term. Unlike the old approach, this model uses all the latest methods and is more likely to make accurate predictions.

1.1 RELATED WORK

From the literature survey, it had been observed that the appliance of machine learning techniques to securities market prediction is being undertaken thoroughly throughout the globe. Machine Learning techniques are proving to be rather more accurate and faster as compared to contemporary prediction techniques. Significant work has been done throughout the planet in this field.

Authors Naresh Kumar, and Seba Susan the objective of this think is to supply an assessment of forecast models based on COVID-19 cases, as well as to estimate the virus's effect in influenced nations and around the world [5]. On COVID-19 occurrences, demonstrate execution was assessed utilizing measurements such as cruel supreme mistake (MAE), root cruel square blunder (RMSE), root relative squared mistake (RRSE), and cruel supreme rate mistake (MAPE). For COVID-19 affirmed, dynamic, recuperated, and passing cases, we produce estimating discoveries. ARIMA outflanked the Prophet's show, concurring with the findings. COVID-19 occasion day-level information has been assembled from a GitHub store. The ESRI living chart book group, the Connected Material science Lab (APL), and the Center for Frameworks Science and Building (CSSE) at Johns Hopkins College, both of which are based within the Joined together States, bolster and keep up the asset [5]. Starting January 22, 2020, the store will contain worldwide COVID-19 detailed occurrences on an everyday premise.

1.2 METHODOLOGY

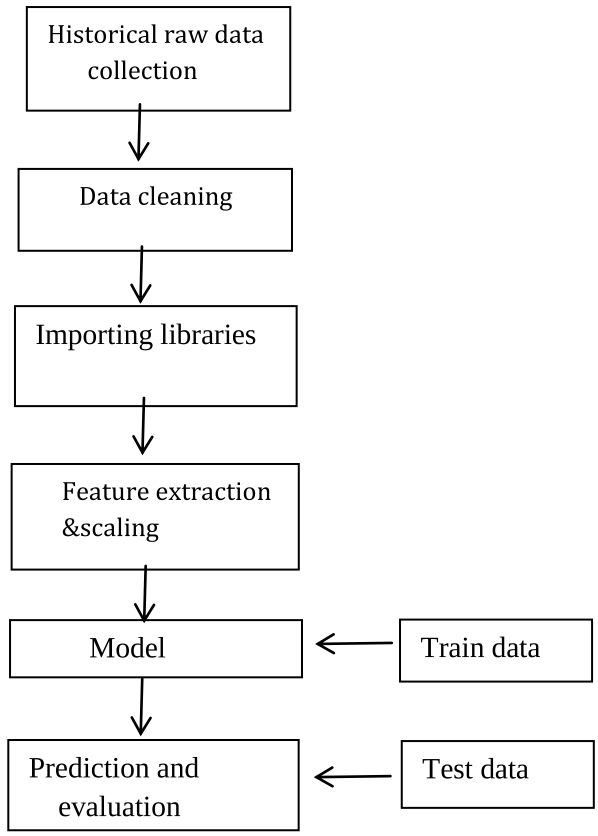
Stock price prediction is a big problem because it involves many factors that have yet to be addressed and it doesn't seem statistical initially. But by using accurate machine learning techniques, one can relate previous data to this data and train the machine to find out from it and make appropriate assumptions.

In the existing system stock showcase is one of a country's most imperative financial divisions. It gives financial specialists the chance to contribute and benefit from their cash. Analysts from an assortment of spaces, counting measurements, fake insights, financial matters, and funds, are all fascinated by anticipating the stock advertisement. Stock showcase determining precision brings down showcase risk[12].

When it comes to the stock market's consistency, there are numerous diverse perspectives. Concurring to the effective showcase theory (EMH), all open data is immediately completely coordinated into the current showcase cost, causing stock cost volatility. Many machine learning strategies have been utilized within the writing to assess stock cost heading. A few of these works are altogether inspected. Ampomah et al. (2020) explored the execution of tree-based AdaBoost gathering ML models in determining stock costs (specifically, AdaBoost-DecisionTree (Ada-DT), AdaBoost-RandomForest (Ada-RF), AdaBoost-Bagging (Ada-BAG), and Bagging (Ada-BAG), and Bagging-ExtraTrees (Bag-ET) [12]. The AdaBoost-ExtraTree (Ada-ET) model outperformed the other tree-based AdaBoost ensemble models, according to the findings.

Machine learning strategies such as direct discriminant examination, arbitrary woodland, manufactured neural arrange, SVM, and logit were utilized by the analysts Ernest Kwame Ampomah, Gabriel Nyame, and Zhiquang qin. The exploratory discoveries appeared that SVM beat all of the other classification techniques.

1.3 EXISTING METHODOLOGY



Flow chart -1: Existing method

In the proposed system in this time-series study, the entire cost of a face drilling rig utilized in the Swedish mining sector is estimated using an Autoregressive Integrated Moving Average (ARIMA) model [15].

Time series forecasting forecasts future data points based on data gathered over a specific period. Forecasted data points will serve as a foundation for production management and planning, as well as to optimize industrial processes and economic planning. The primary aim is to obtain the best prediction possible, which entails reducing the mean square difference between actual and anticipated values for each lead-time.

Time series forecasting approaches such as Box–Jenkins and the Autoregressive Integrated Moving Average (ARIMA) are based on the assumption that time series data is generated by linear processes. Some of the techniques were used. The authors Al-Douri, and Jan Lundberg used Multiple regression and neural network techniques to model and anticipate the future.

The data in a stable stochastic model have the same variance and autocorrelation. The difficulty in determining the parameters is the model's flaw. To address this issue and provide accurate forecasting, automated model selection processes are required. Zhang proposes combining ARIMA and Artificial Neural Network (ANN) models in a hybrid technique. The combination increases predicting precision. The results from three real-world data sets show that the hybrid model outperforms each component model. The ARIMA and ANN models share some commonalities. Both have a diverse range of models with varying model ordering. To create an effective model, both require a big sample size.

ARIMA, on the other hand, can deliver results based on the problem and data. The main portion of the ARIMA model is a complex polynomial that combines AR and MA polynomials. All of the TC data points are subjected to the ARIMA (p, d, q) model.[15]The mean of the time series data; p: the number of autoregressive delays; q: the number of moving average delays AR (autoregressive coefficients):

MA stands for moving average coefficients.

d: the number of differences produced by the white noise in the time-series data.

For TC (Z TC), the ARIMA model is stochastically implemented using default values for p, d, and q. (0,0,0), (0,0,1), (0,1,1), (1,0,0), (1,0,1), (1,1,1), (2,1,1) (2,0,3). For each scenario, all of the TC data from the previous 37 months is included [15].

2. ALGORITHMS USED

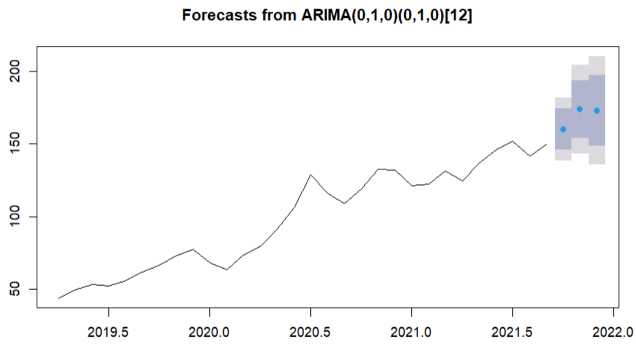
2.1 ARIMA (Autoregressive integrated moving average)

ARIMA may be a blend of two calculations: auto relapse and moving averages, as the title suggests. Autoregression could be a time arrangement demonstrate that employments past time step data as input to a relapse condition to anticipate values in the following time step[3]. It could be a clear strategy that can make solid forecasts for a wide extent of time arrangement issues. A moving normal could be time-arrangement information normal that advances through all the arrangements by subtracting the best things from the already found the middle value of gather and embeddings the another in each average.

The Arima model, in some cases known as the Box-Jenkins model, was presented by George Box and Gwilym Jenkins[22]. The ARIMA model, which contains the condition underneath, combines the autoregression and moving average models (3).

$$c+\phi_1 y'(t-1)+\cdots+\phi_p y'(t)-p+\theta_1 \varepsilon(t-1)+\cdots+\theta_q \varepsilon(t)-q+\varepsilon(t) = y'(t) \quad (3)$$

On the one hand, we have indicators with lagged y(t) values and lagged errors, while y′t could be a subordinate variable that can be shifted a few times. The ARIMA (p, d, and q) demonstrate is the title given to this show. The Auto regression and Moving Average component orders are p and q, individually, and the degree of differentiation is d.



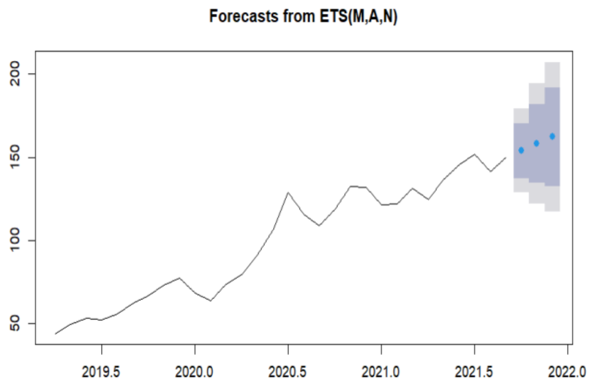
Graph 1: Arima results

2.2 Exponential smoothing

Exponential smoothing is a time series forecasting method for univariate data and can be extended to support data with systematic trends or seasonal components. This is a powerful predictive method that can be used as an alternative to Box Jenkins' popular ARIMA method family.

This determining method includes allotting weights to earlier information in such a way that they rot exponentially over time. The foremost later weights are on best, and as the time figure increments, they start to debase [3].

Arima is the autoregressive integrated moving average used for calculating moving averages.



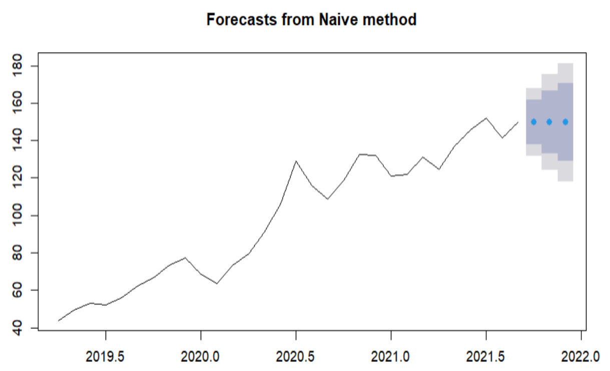
Graph 2: Results of exponential smoothing

2.3 Naive

The estimate is made by applying the taking after equation (1) to past information without making any expectations.

$$y\ (T) = y'\ (T + h)\ |T \qquad - (1)$$

The prior data prediction is (T + h), while the current data forecast is (T).



Graph 3: Results from Naive

2.4 Seasonal Naive

This estimating strategy is comparative to naive forecasting but the estimate is based on the previous information of the same season. The equation is as follows

$$y'(T + h)\ |\ T = y(T + h) - m(k + 1) \qquad -(2)$$

2.5 Neural Networks

NNAR (p, x) is a nonlinear and advanced forecasting scenario in which p is the no. of lagged inputs and x is the no. of hidden layers. It illustrates the architecture of neural networks.

3 FUTURE SCOPE

The no. of stock cost expectation calculations will be extended in future investigations. The taking after is a few cases of how the comes about of this think could be utilized to figure stock costs: To determine whether there's any drift or regularity within the information, the figure of each bank's stock cost must be tried on greater preparing datasets.

A set of conventional statistics and neural organized calculations based on slant or regularity must be built to decide the finest strategy for stock cost prediction. Any procedure's execution must be assessed utilizing the back-testing approach.

For a trade user's comfort, the assessed blunder terms can be spoken to as RMSE. The finest calculations for each stock cost can be built up due to the least RMSE esteem; these calculations ought to be utilized to estimate stock costs, and successful stock cost determination can result in impressive benefits.

4 CONCLUSION

The ARIMA demonstration and the EXPONENTIAL SMOOTHING show for stock cost expectations were given in this research. Each calculation distinguishes the stock information set of all five educates, concurring with the assessments of these two models. The ARIMA show test comes about and appeared that it can dependably anticipate stock costs within the brief term.

This may lead to advantageous speculation choices for stock advertising examiners. The ARIMA demonstrate may be prepared to compete with other short-term forecast models based on the discoveries obtained. A wide extent of recurrence values can be utilized utilizing exponential smoothing. The Exponential smoothing approach was chosen for a single-time arrangement that was taken after a design in terms of order choice. There are numerous well-known time arrangement strategies within the ARIMA. The plan area of ARIMA was basic, conveying an about straight line.

The data fed into the system is extracted every month from Yahoo! Finance, and the data is cleansed by removing outliers. The time series object is then deconstructed because proper findings are dependent on several factors. Following that, the time series objects are supplied to algorithms like ARIMA, Exponential Smoothing, Nave Forecasting, Seasonal Nave Forecasting, and Neural Networks, among others.

While the exactnesses of the other calculations like naïve, regular naïve, and neural systems are on a normal of 94.7%, ARIMA and Exponential smoothing have given 2.9% more exactness than the rest that's, 97.6% precision which straightforwardly shows that the mistakes in ARIMA and Exponential Smoothing are way less comparatively.

When the information had a solid regular slant, ARIMA and Exponential smoothing created a reliable demonstration. In this circumstance, ARIMA and Exponential smoothing beat other models, be that as it may, the execution and precision of these two models are subordinate to the information. We ought to nourish the information to all of the models, compare the outcomes, and select the foremost exact that comes about depending on the rankings.

When the RMSE for each bank's models was compared, it was found that factual strategies beat the Repetitive Neural Arrange (RNN) strategy, since the RNN strategy is way better suited for foreseeing stock advertise returns than measurable models, which must be adjusted in a case for stock cost prediction.

REFERENCES

[1] T. Huamin, D. Qiuqun, and X. Shanzhu, "Reconstruction of time series with missing value using 2D representation-based denoising autoencoder," in Journal of Systems Engineering and Electronics, vol. 31, no. 6, pp. 1087-1096, Dec. 2020, DOI: 10.23919/JSEE.2020.000081.

[2] Ariyo, A. O. Adewumi, and C. K. Ayo, "Stock Price Prediction Using the ARIMA Model," 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, 2014, pp. 106-112, DOI: 10.1109/UKSim.2014.67.

[3] Gupta and A. Kumar, "Mid Term Daily Load Forecasting using ARIMA, Wavelet-ARIMA, and Machine Learning," 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), 2020, pp. 1-5, DOI: 10.1109/EEEIC/ICPSEurope49358.2020.9160563.

[4] International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-5, March 2020. Retrieval Number: D1869029420/2020©BEIESPDOI: 10.35940/ijitee.D1869.039520