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Evaluating the Robustness of Neural Network and ARIMA Models in Predicting Stock Prices: A Case Study of Tata Consultancy Services

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Abstract

The present study focuses on evaluating the robustness of Artificial Neural Networks (ANNs) and Auto-Regressive Integrated Moving Average (ARIMA) models in forecasting stock prices. The analysis identifies a stochastic trend in the daily time series data from August 1, 2010, to August 1, 2024. The study period is characterized by high volatility, making this research distinct from existing literature. Empirical findings indicate that ARIMA is the most suitable model for this dataset. The selection of the best model is based on Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Although both models yield closely comparable results, ARIMA emerges as the superior choice for the data under consideration.

Keywords: ARIMA, ANNs, Stock Price, TCS, Forecasting

1. Introduction

Forecasting stock prices is a most important and challenging research of the modern time world (Stathatos & Vosniakos, 2019) . There are a plenty of numerous models which can be helpful to predict the future stock prices and provide the most precise and relevant information to the investors (Nguyen et al., 2024) . Recently, ANN (artificial nueral network) model has been introduced to predict most relevant stock prices. In a past research, Modular Nueral Network has been used to predict the buying and selling prices of stock prices in Japan (Majumder & Eldho, 2020) . Research results were showing that extreme profit has been achieved by the companies. Some other researches, a pattern has been developed which is a recognition technique to forecast the stock prices of Tokyo Stock Exchange (Hughes et al., 2020) . A new concept has been introduced for research which is mismatching patterns, for this prediction four layered neural network developed for predicting US stocks. Research results have challenged the results retrieve from multiple discriminant analysis method (Menteri Kesehatan RI, 2019) . Back- propagation neural network integrated with random optimization technique to predict the Japanese Stock prices (Albanesi, 2019) . Different types of forecasting models are complementary with each other because all are taking the patterns of data sets. These combinations of neural networks concluded that the combinations models prediction is more relevant than individuals (Nurhayati, 2016) . Further several networks and models have been developed. In some research ARIMA model and artificial neural network have combined to study the stock price predictions (Anisah & Crisnata, 2021) . These hybrid approaches are very popular for predicting the stock prices all over world. ARIMA model is helpful to understand into a given application, the dynamics of the time series data (Yudho Yudhoanto,

2019) . Different pre-processings and methods apply on the raw data when it has been retrieved for converting it into a calculative form (Jo et al., 2023) .

A Wavelet transformation has been used when it was required to forecast the data of global temperature. Some new techniques such as new classification and feature extraction has been introduced for electrocardiography data (Li & Ma, 2010) . Pre-processing on raw data is important for accurate predictions of the stock market. In comparison with ARIMA model, Artificial Neural Network (ANN) is more beneficial for different stock prices predictions (Saini & Sharma, 2022) . Forecasting of stock market can provide a benchmark for stock market investors and stock market distributors (Dixit et al., 2013) . It is a very good system that all data of the stock market record regularly so that researcher can conduct research and predict future of stock market easily (Sarangi et al., 2021) . Artificial Neural Network is a nonlinear technique for the prediction of stock prices and it is very advantageous for the stock traders and researchers (Jaiswal & Das, 2018) . ANN model do not need to convert the times series data into stationary, for this reason ANN model is more popular than ARIMA model for forecasting (Madhu et al., 2021) . According to the past analysis, ANN model is more adaptive than ARIMA model. Neural network also been used for predicting earthquakes in Chile, but according to all over researches, it has been concluded that not a single model predict the accurate results so that a combination of more than one model can improve the accuracy of the predictions (T. P. Nguyen et al., 2020) .

Hybrid of ARIMA-ANN model has been introduced by Usmani et al., (2018) which was proven to be an accurate result production? Along with ARIMA model and ANN model many other models are also used for stock market prediction (Darrat & Zhong, 2000a) . A few models are based on fuzzy logic and many others are based on support vector model. ARIMA model has also been modified to the SARIMA and FARIMA (Darrat & Zhong, 2000a) . A combination of ARIMA – GARCH and ANN model has also been used for predicting accurate values of the time series (Darrat & Zhong, 2000a) . Hybrid models can be used instead of single model with several decompositions, the accuracy may degrade due to a few limits and models will not be successful longer (Tawarish & Satyanarayana, 2019) . For retaining the simplicity of the model, it should be taken a limited number of single models. Instead of applying directly ARIMA-ANN model, volatility of time series data should be studied after that ARIMA-ANN model should be applied (Wijesinghe & Rathnayaka, 2020b) . The proposed method was applied to a time series data by adding non-linear and linear data. The performance of this method was better than the performance of the models (Panda et al., 2023) . The new hybrid of ANN-ARIMA model can be suitable for both multi-step ahead and one-step ahead (Raza, 2017) . By some researches a substitute also found which Univariate ARMIMA model for predicting securitized real estate series return in the Australia, in US and in the UK, a turning point has been found (Marcek, 1997) . In these studies, authors used exponential smoothing and ARIMA models. Spectral analysis with four years of cycle had been performed well in capturing the turning moments in the 3rd monthly series of real estate returns (Saluza, 2016) . The present study demonstrates the difference between the results of ARIMA model and the ANN model. A long run neutrality hypothesis has been proved by using Australian data.

2. Need for the Study:

Despite the availability of numerous forecasting models, there is no clear consensus on which model performs best under varying market conditions, particularly during periods of high volatility. This study seeks to address this gap by comparing the robustness of ARIMA and ANN models. The findings contribute to academic literature while providing practical insights for financial analysts and investors in choosing the most suitable model for stock price forecasting in volatile markets.

3. Literature Review

A perfect modelling for stock prices is always a challenging task stochastic stock returns behaviour studied by using AR (1) and GARCH Exponential and the GARCH-M and the results have been compared with the traditional models, as have not generated a big difference (Ks & Kalra, 2021) . As compared to traditional models Neural Network Model has been proved for better stock prices predictions over a discriminant model and logistic regression (Ks & Kalra, 2021) . Kihoro & Okango, (2014) examined approx. nineteen sectoral security indices through ANN model and concluded that the results are superior forecasted for the investors. Naliniprava tripathy, (2011) calculated the efficiency of ARIMA model and NN model to forecast the Indian stock market with a reference to five to six years of closing values of BSE Sensex by calculating Akaike Info Criterion (AIC) and the statistical values such as MSPE, MAPE, RMSE and AAR. A statistical comparison indicates that ARIMA model is outperformed ANN model. Uma Maheswari et al., (2021) employed a combination of NN and ARIMA model on a time series data and found that this combination of the models is more efficient for stock market prediction as compared to other independent models. Wijesinghe & Rathnayaka, (2020a) has used the NN and conventional models and investigated by using SEE (Standard error of estimate) and MAD (Mean absolute deviation), concluded that neural network models are more efficient for the prediction and compared with Box Jenkins method for the prediction. CHAREF & AYACHI, (2016) applied a comparative study with ARIMA model and NN model on stock indices from other countries and found these models are more effective for forecasting the options and future prices and other security prices. Gao, (2021) has done a comparative study on a dynamic NN model, ARIMA model and traditional models for predicting the events of time series data which showed that NN and ARIMA models are accurate. Darrat & Zhong, (2000b) while investigating the Indian Stock market by applying the NN model has been suggested that Random Walk theory has been proved to be better forecasting model as compared to other model.

Ampountolas, (2023) examined the weakest form of the efficient market and concluded that the efficient market hypothesis is not accurate as compare to the ANN model, it has been more effective than other models. A research done by Ampountolas, (2023) has employed the ANN model and ARIMA model along with the trained function, concluded that BFGS outperforms Rubi et al., (2022) found a better volatile stock market due to minimum error by using the ANN model along with trained functions. Johari et al., (2018) by using GARCH model to evaluate the Indian Stock market and found there is no significant impact of the stock prices , concluded that the date of the announcements of dividend does not has a significant impact on the changes of the stock market.

Chai & Nor, (2019) examined the GBP vs USD and USD vs JPY rate of exchange volatilities for predicting by applying the neural network regression and recurrent neural network for concluding that both of the models outstripped and predictably applied the GARCH models. The outcomes of Maniar, (2023) are proving that Artificial Neural Network model can be able to forecast the stock prices of Bombay Stock Exchange with more accuracy. Maniar, (2023) predicted in their research by employing the ARIMA model for Qatar Exchange with multilayer and modelling of ANN model, found that ANN model outperformed ARIMA model with 98 percent of predictive accuracy. Tanuwijaya et al., (2023) has applied feed forward neural network model with trained propagation for forecasting the daily return of NASDAQ stock exchange and concluded that ANN is more appropriate than other traditional models. The efficiency has been checked of NN model for non-linear time series to decode genetic protein sequences and deterministic chaos. Ayub & Jafri, (2020) for forecasting the options and future prices, found that NN model significantly outperformed the traditional Black-Scholes model for forecasting the prices of derivatives. Khashei & Hajirahimi, (2019) also examined that ANN models are more efficient for forecasting the prices of call options. Ma et al., (2023) studied the stock market of Australia and suggested that the prediction efficiency has enhanced by using ANN on the external variables. In the research, a comparative study has been done on Random walk, ARIMA and neural network models to predict the currency prices.

Pandji et al., (2019) concluded that NN modelling is more efficient than ARMA and Random Walk theory. Madhu et al., (2021) investigated the accuracy of ANN with different Random Walk models , concluded that multilayer perceptron is more efficient than all other models on different performance criteria. T. P. Nguyen et al., (2020) applied backpropagation volatility models along with neural network and EGARCH and MGARCH to predict the options and future prices, found that NN along with EGARCH provide better performance as compare to GARCH-M. Usmani et al., (2018) used ANN for estimating and modelling the macroeconomic parameters such as GDP (Gross Domestic Product), NGSD (Gross National Savings) , inflation ,population, unemployment rates, service tax and TX_RPCH (export of goods and services), TM_RPCH (volume of imports of services and goods) for the prediction and found that more significant results as compared to the results from the traditional model.

4. Methods and Models

ARIMA

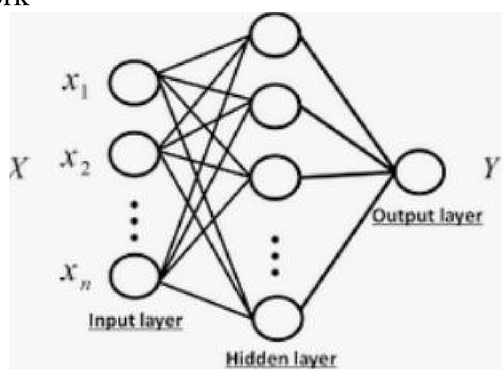
An autoregressive integrated moving average (ARIMA) model is widely used for forecasting future values in time series data. It is an extension of the autoregressive moving average (ARMA) model and is particularly effective for analyzing time series that are not stationary. The ARIMA model is characterized by three parameters: p, d, and q, where p represents the autoregressive component, d indicates the level of differencing required to achieve stationarity, and q denotes the moving average component.

To apply an ARIMA model, a non-stationary time series must first be converted into a stationary one by applying first-order, second-order, or higher levels of differencing until stationarity is achieved. The autoregressive (AR) component of the ARIMA model suggests that future values of the series depend on its past values, following a lead and lag pattern. The moving average (MA) component, on the other hand, indicates that the regression error is a linear combination of error terms from the current period and previous periods.
ARIMA models are typically estimated using the Box-Jenkins methodology. For stock price returns, the ARIMA model can be formulated as follows:

$$C(R)_t = a_0 + a_1 Ret_{t-1} + a_2 Ret_{t-2} + \cdots a_n E_{t-n} + a_{n+1} E_{t-2} \dots\dots a_{n+1+m} E_{t-n+1+m} + \varepsilon t \quad (1)$$

Where, $C(R)_t$ is Crude Oil Return, Ret_{t-1} *is* lagged return and E_{t-n} is the lagged error.

Artificial Neural Network: The analyst utilized an Artificial Neural Network to predict a wide range of time series data. In this study, a shallow neural network with a single hidden layer was applied. The model's input consisted of lagged values of Stock price returns.
Fig 1. Shallow neural network



Source: Course era

5. Empirical results

- **Analysis of the results of descriptive statistics**

The dataset of 3,458 daily price observations provides a detailed view of TCS stock prices over 14 years, with a recorded low of ₹416.025 and a high of ₹4,387.85, and an average price of ₹1,837.014. The significant variance (1,197,489.49) and standard deviation (₹1,094.3) highlight the stock's volatility, with prices frequently deviating from the mean. The negative kurtosis (-1.0221) indicates a platykurtic distribution, suggesting fewer extreme price movements than a normal distribution. While normality is less critical in time series analysis, the stationarity of the data remains a crucial aspect for accurate forecasting.

Table 1. Descriptive Statistics of TCS stock prices

Number of Realizations	3458
Lowest	416.025
Highest	4387.85
Mean	1837.014
Median	1316.41
Kurtosis	-1.0221
Quartile 1	1064

Quartile 3	3011
Standard Deviation	1094.3
Variance	1,197,489.49

Sources: Authors' work

- **Analysis of the Results of Stationarity**

Before forecasting time series data, ensuring that the data is stationary is crucial. Non-stationary data can lead to misleading results and inaccurate forecasts because traditional regression models assume that the statistical properties of the data, such as mean and variance, remain constant over time. If the data is not stationary, it may exhibit trends or seasonality that distort the relationships between variables, making the predictions unreliable.

As indicated in Table 2, the initial analysis of the data shows non-stationarity at the level, suggesting that the mean and variance change over time. However, the Dickey-Fuller test results presented in Table 3 reveal a p-value less than 0.05, which confirms that the data has achieved stationarity and is integrated at I(0) (Li & Ma, 2010) (Dixit et al., 2013) . This result validates that the data meets the necessary conditions for accurate forecasting and further analysis, ensuring that the subsequent modeling will be based on a stable and reliable time series.

Fig. 2

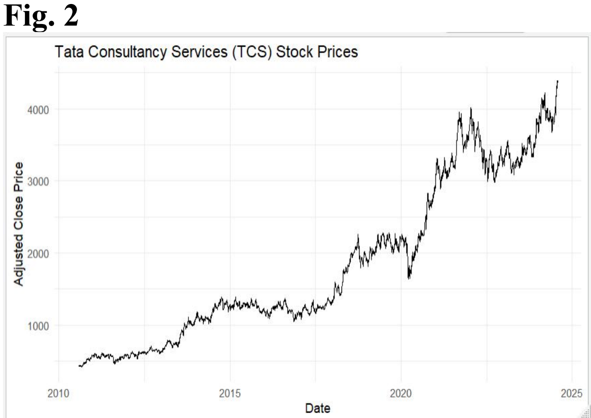


Table :2

Data: na,omit(TCS,NS$TCS,NS,Close)

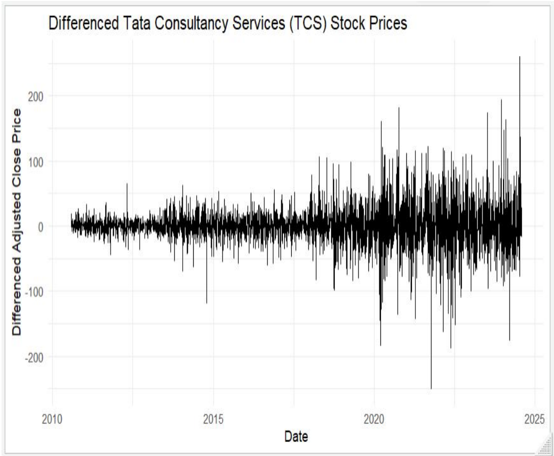
Dickey-Fuller = -1.4153

Lag order = 17

P – value = 0.826

Sources: Authors' work

Fig.3



Sources: Authors' work

Table : 3

Augmented Dickey-Fuller Test

Data: na,omit(tcs_diff)

Dickey-Fuller = -16.846

Lag order = 17

P – value = 0.01

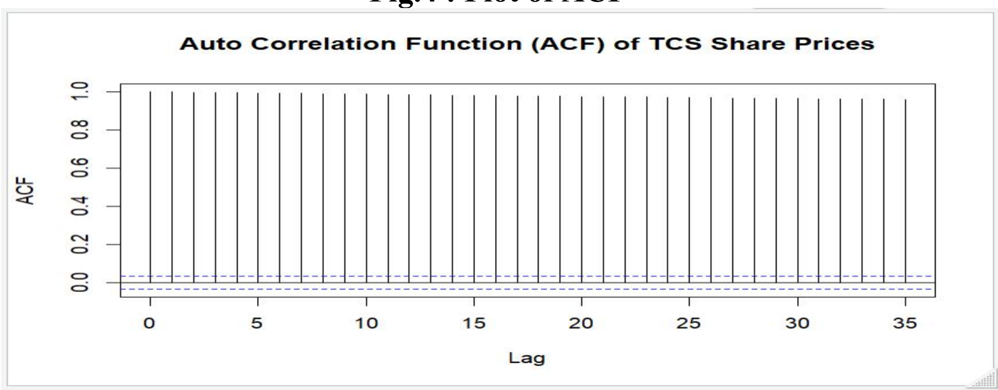
- **Analysis of the Results of ACF and PACF:**

Chart 3 and chart 4 displays the results of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). The Autocorrelation Function measures the correlation between a time series and its own lagged values whereas Partial Autocorrelation Function (PACF) is used to measure the relationship between the series and its lagged value after excluding the effect of intermediate lags. In chart 3 ,the X-axis and the Y-axis denote the various time lags and the autocorrelation values. For the development of an exact ARIMA model, it is essential to determine the appropriate lag for the moving average component in time series models which is done by analyzing the error term or the autocorrelation of residuals. After identifying the suitable lag,if it is found that the value of the autocorrelation exceeds above the upper bound or below the lower bound,the identified lag can be considered as significant. For forecasting the accurate model,it is important to recognize the most relevant past value.The ACF assists in improving the accuracy of the model by analyzing the data structure. Similar to the Autocorrelation Function , identification of suitable lag is also required in Partial Autocorrelation Function (PACF) for the autoregressive component in the ARIMA model. The X-axis in chart 4 represents various lags, and the Y-axis shows the partial autocorrelation values (Sarangi et al., 2021) .

In the PACF, prominent spikes occur at lags 6, 10, 17, 22, and 33 because these values are either above or below the threshold bounds (Darrat & Zhong, 2000) . For the development of an accurate ARIMA model, it is required to use both the ACF and PACF for selecting the parameters for the ARIMA model. The ACF is used to determine the "q" parameter (for the moving average component), whereas PACF advocates the "p" parameter (for the autoregressive component) (Usmani et al., 2018) .In order to develop the ARIMA model, auto.arima function is applied in the R Software.

There is an important tool in time series analysis i.e., the Autocorrelation Function (ACF) plot which is applied to find out the patterns of autocorrelation within a data set. In this study, the ACF plot shows the autocorrelation of TCS share prices at different lags. Based on the analysis, it was found that the first lag (lag 1) has a significant autocorrelation coefficient, which confirms the presence of a strong relationship between the current share price and its value in the previous period and the influence of past values on the current value diminishes over time, which approves that as the lag increases, the autocorrelation coefficients gradually decrease (Wijesinghe & Rathnayaka, 2020) . The ACF plot of TCS share prices supports this finding as it also confirms a strong autocorrelation at lag 1.

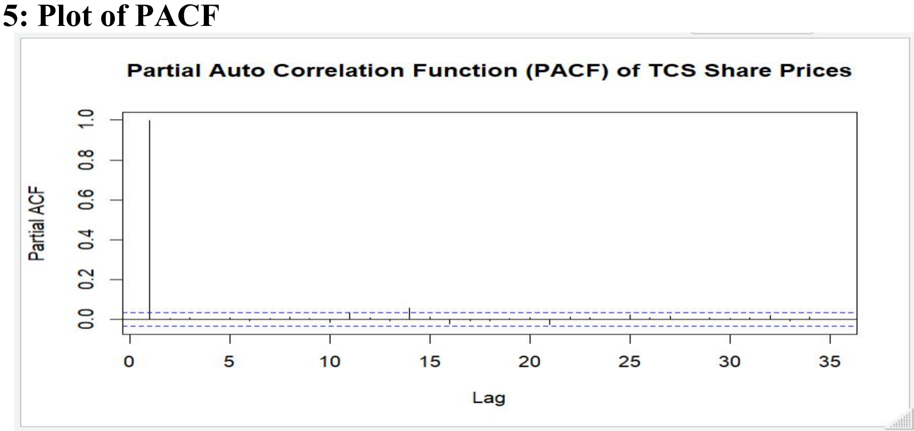
Fig.4 : Plot of ACF



Sources: Authors' work

The analysis of the Partial Autocorrelation Function (PACF) plot for Tata Consultancy Services (TCS) share prices matches the findings of the Autocorrelation Function (ACF) plot. The Partial Autocorrelation Function (PACF) plot provides crucial insights into the relationship between the current share price and its past values, while controlling for the effects of intervening lags. Similar to the Autocorrelation Function (ACF) plot, the Partial Autocorrelation Function (PACF) plot also confirms the presence of a significant autocorrelation term at lag 1 which means that that an ARIMA model with an autoregressive term (p=1) is well-suited for modeling the stock price movements of TCS share price. The analysis concludes that both the PACF plot and ACF plot of TCS share prices are confirming a strong direct relationship between the current value and the previous value.

Fig 5: Plot of PACF

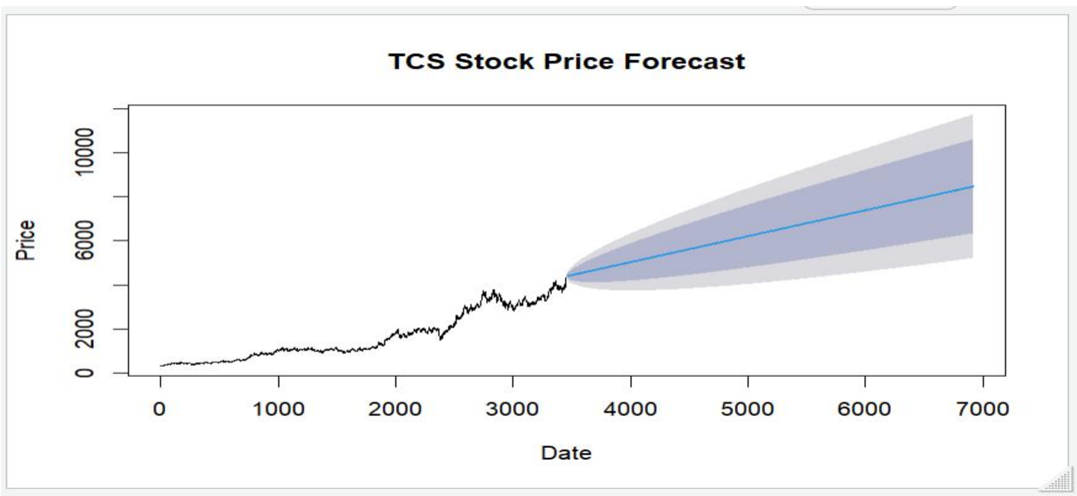


Sources: Authors' work

- **Predictive model in ARIMA**

ARIMA (AutoRegressive Integrated Moving Average) model is used to create a chart that visualizes a time series forecast for TCS (Tata Consultancy Services) stock prices and in the chart. There are two lines i.e. black and blue and a shaded area in a chart that denotes the historical stock price data, forecasted stock price, and the confidence intervals around the forecast. The range of potential future stock prices can be identified through the confidence intervals.The forecasting based on the ARIMA model believes that the share price of TCS will grow in a continuous manner, but at the same time, wide confidence intervals reflects that there is no certainity in the prediction of future market trends as time progresses. The good fit of the historical data to the confidence intervals indicates that the ARIMA model is reasonably well-suited for this time series.

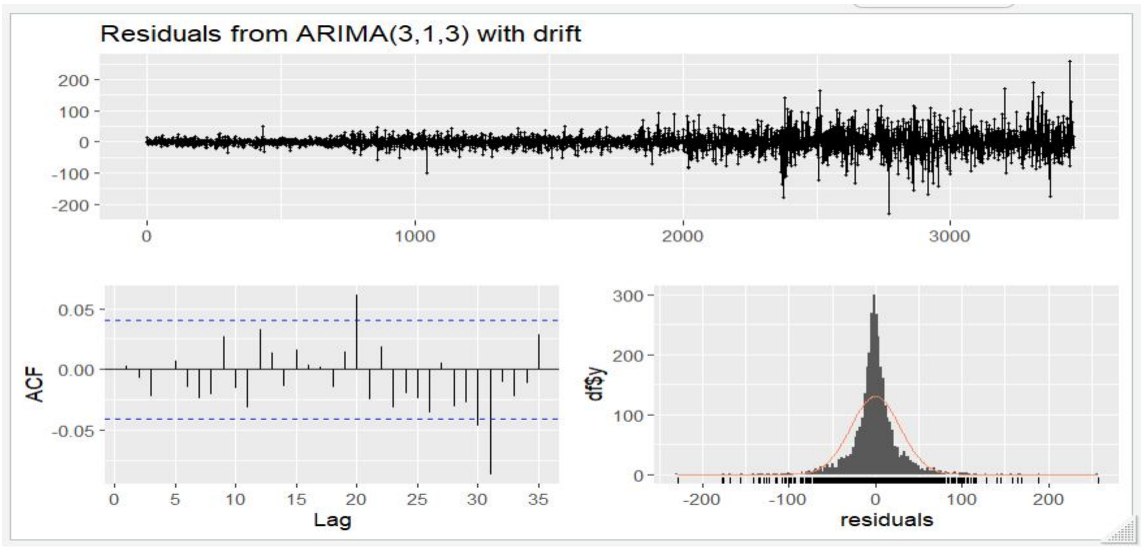
Fig.6



Sources: Authors' work

The image in Chart 6 shows the residuals from an ARIMA(3,1,3) model with drift, along with their ACF (Autocorrelation Function) and a density plot. The analysis of the residuals from the ARIMA(3,1,3) model suggests that it is a reasonable fit for the data.

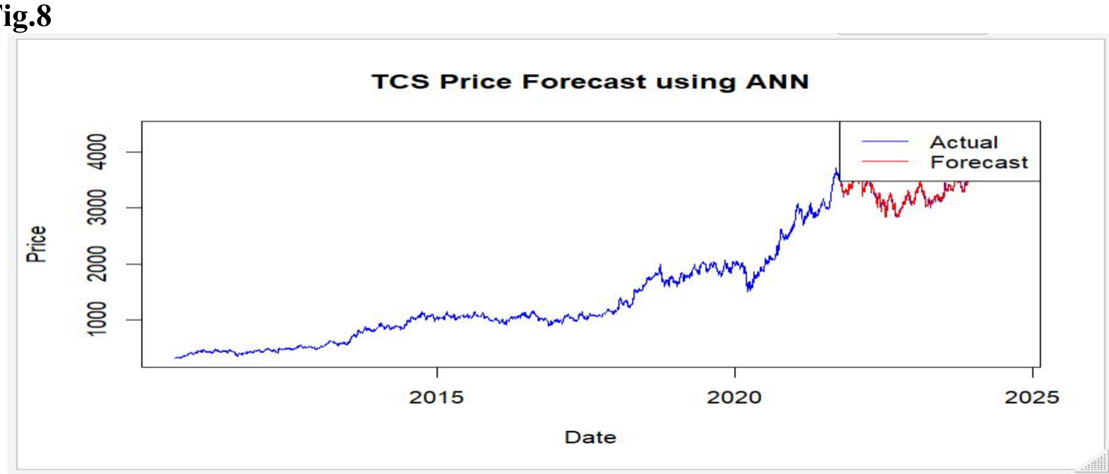
Fig.7



- **Predictive model in ANN**

The chart illustrates the results of a time series forecast for Tata Consultancy Services (TCS) stock prices using an Artificial Neural Network (ANN). The blue line represents actual historical prices, while the red line shows the forecasted prices. Both lines demonstrate an upward trend, indicating that the ANN model effectively captured the general direction of the stock price. The forecasted prices closely align with the actual prices up to 2020, suggesting strong model performance in predicting past price movements. Beyond 2020, the red line extends to predict future prices, showing continued growth. The model suggests a positive trend.

Fig.8



Sources: Authors' work

- **Comparison as a predictive model in ANNs & ARIMA**

The comparison between Artificial Neural Networks (ANNs) and the ARIMA (AutoRegressive Integrated Moving Average) model for stock price prediction reveals that both models exhibit nearly identical performance based on two key metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The results show only minuscule differences, with ANNs having an RMSE of 79.96309328 and MAE of 52.40972113, while ARIMA slightly outperforms with

an RMSE of 79.96304320 and MAE of 52.40970989. These nearly equivalent error levels indicate that both models are equally capable in terms of predictive accuracy.
Despite the similar error metrics, ARIMA is considered a more robust model due to its simplicity, interpretability, and consistent performance across various scenarios. Unlike ANNs, which are complex, non-linear models often regarded as "black boxes," ARIMA's linear structure allows for greater predictability and stability, particularly in handling trends and seasonality in time series data. This robustness, combined with its slightly better predictive accuracy, makes ARIMA a preferred choice for stock price forecasting, even when both models deliver similar performance.

Table 2 : Results of ANNs and ARIMA model

Predictive Model	RMSE	MAE
ANNs	79.96309328	52.40972113
ARIMA	79.96304320	52.40970989

Sources: Authors' work

6. Conclusion

It is important for any country, especially a developing country that its share market should be highly developed and for this, it is necessary that the investor can predict the stock price, hence this thing has been focused on in this study. The prediction of the stock price is based on the lagged value of the TCS share price. In this study, the data of more than ten years are analyzed, and found that the data is stationary which was a supporting factor for the development of the ARIMA model. Even though the data is not normally distributed, still it does not create any problem in developing the ARIMA model.In this study, both ACF plot and PACF plot were analyzed and their results confims that the future price of the TCS is influenced by the lagged value of the share price and their error term. The study's findings are consistent with previous research (Mo & Tao, 2016; Hale, 2018) but differ from other studies (Ahmed & Shabri, 2014; Moshiri & Foroutan, 2005). It was observed that while both ARIMA and Artificial Neural Networks (ANNs) models yielded similar results, the ARIMA model was slightly more accurate. However, both models were limited by their exclusion of exogenous variables, which rendered them somewhat static. Incorporating additional factors such as gold prices, interest rates, and supply and demand dynamics could make the models more dynamic and robust (Hale, 2018). This suggests a need for further in-depth research in this area.

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