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Forecasting of P/E Ratio for the Indian Equity Market Stock Index NIFTY 50 Using Neural Networks

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***Abstract:** The ratio of present price of an index to its earnings is known as its price to earnings ratio denoted by P/E ratio. A high P/E means that an index's price is high relative to earnings and overvalued. Its low value means that price is low relative to earnings and undervalued. A potential investor prefers an index with low P/E ratio. Therefore, the movement of the P/E ratio plays a crucial role in understanding the behaviour of the stock market. In this paper the modelling of the P/E ratio for the Indian equity market stock index NIFTY 50 using NNAR, MLP and ELM neural networks models and the traditional ARIMA model with Box-Jenkin's method is carried out. It is found that MLP and NNAR neural networks models performed better than that of ARIMA model.*

***Keywords:** Forecasting, Stock market, P/E Ratio, Neural Networks, Box-Jenkins Methodology*

I. INTRODUCTION

Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) are the two Indian stock exchanges which holds a prominent place in the world. The oldest among these two is BSE and its index known as SENSEX, which consists of 30 of the large and most actively-traded stocks. NSE is regarded as the best in terms of technology and sophistication. NSE also includes 22 significant sectors of the Indian economy. The index of NSE is known as NIFTY-50 and it consists 50 large and actively traded stocks. Investors and economists are attracted to invest in stock market because it involves high gains as well as high risks. But, usually, the information or data about the stock will be incomplete, complex, uncertain and vague which causes the prediction of the future economic performance a challengeable task. In general investors, invest in the stock market based on analysis of the available data. Trading in the stock market has gained wide popularity in the world and becomes part of daily routine for many investors to gain huge profits. Because of the incomplete data, analysing the stock movement behaviour becomes a tuff task.

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The advanced and robust predictive modelling can guide investors in classifying and identifying high performance securities to take the best investment decisions. Fundamental analysis, [7],[8] technical analysis, [9],[18],[25] and statistical analysis [11] like regression analysis [3] are used to estimate and gain from the market's direction. Further, ARIMA, NNAR and Neural Networks modelling are discussed in [24],[5],[2],[6],[23] and [16].

A. Price-to-Earnings Ratio (P/E)

The measure of the market value of a company is evaluated using the ratio of the present price per share relative to its earnings per share. This measure is known as the price to earnings ratio and is abbreviated as P/E ratio. It is used to calculate the fair value of the market by projecting future earnings per share. Usually, the companies yield higher dividends in the future if their future earnings are higher. A share's price increases/decreases over a period according to the demand and speculation of investors of the stock. This ratio is useful to investors to decide as what amount to be paid for a stock based on its earnings [4]. Because of this reason investors use this ratio to evaluate the worth of a share by its multiple earnings. The P/E ratio is evaluated by the following formula.

$$Price\ to\ Earnings\ Ratio\ (P/E\ Ratio) = \frac{Market\ value\ per\ share}{Earnings\ per\ share} \quad (1)$$

The price to earnings ratio is of two types, they are a) Trailing P/E ratio

b) Forward P/E ratio

B. The Trailing P/E Ratio

The P/E ratio which uses the previous 12 months earnings is known as the trailing P/E ratio. This is evaluated as the ratio of the present stock price to the previous 12 month's earnings per share (EPS) and is given by

$$\text{Trailing P/E Ratio} = \frac{\text{Present Share Price}}{\text{Trailing Twelve Months}'\text{Earnings per share}} \quad (2)$$

C. Forward P/E Ratio

If the predicted earnings per share are used to evaluate the price to earnings ratio, then it is known as forward price to earnings ratio. Because the estimates of the earnings per share are used, this ratio is not reliable when compared to current earnings data. The predicted earnings can be the next 12 months estimates or the estimates of the next fiscal year. The formula for this ratio is defined as

$$\text{Forward P/E Ratio} = \frac{\text{Market Value per Share}}{\text{Predicted Earnings per Share}} \quad (3)$$

II. LITERATURE REVIEW

Forecasting of stock returns has emerged as a vital field of research in recent times. Very frequently, a linear relationship has been established between the returns of the stock and economic variables. The nonlinearity [1] pattern in the returns of the stocks, has shifted the focus of research on predicting the nonlinear pattern of the returns of the stocks. Nonlinear statistical modelling on the stock returns requires that the model must be defined in advance to the estimation. Because the returns of stock market are uncertain and nonlinear in nature, Artificial Neural Network (ANN), emerged as a preferred method in identifying the association between the performance of a stock and its factors, more precisely than many other statistical models [27][32][33]. Kim and Chun [21] applied probabilistic neural network to estimate the stock market index. Neuro fuzzy approach was used by Pantazopoulos [25] for forecasting the IBM stock prices. Kim and Han [20] applied neural networks developed by genetic algorithm which reduces the complexity of the feature space. Siekmann [28] executed a adaptable fuzzy parameters network model which connects the first and second hidden layers of the network through the weights. Rong-Jun Li; Zhi-Bin Xiong [22] established a fuzzy neural network which works like a fuzzy inference system. Because this study is based on a neural network forecasting approach on NIFTY-50, will be useful in developing neural network as another tool for forecasting the hugely unstable Indian market. The self-similarity of this study is useful in understanding the microstructure of Indian stock market.

III. METHODOLOGY

Many forecasting models were developed by many researchers, economists and practitioners across the globe using fundamental [7],[8], and analytical techniques [9],[12],[17] which yields approximately accurate prediction. Traditional forecasting methods [11] are used along with these methods of prediction. In forecasting a time series, the previous data of the response variable is analysed and modelled to identify the behaviour of the historic changes. The future of the variable under study is then forecasted using these models. Time series modelling and forecasting has two main approaches i) linear approach ii) nonlinear approach. The commonly known methods which are linear in nature are trend line, time series regression, exponential smoothing, autoregressive model, moving average model and ARIMA. Among these linear models, the model proposed by Box and Jenkins [11] known as ARIMA is used widely. This model is flexible because it represents various kinds of time series. Because the variance between the forecasted and original values is very high, the returns of the stock are not ideally linear. This indicates that there exists nonlinearity in the stock market and studied by several financial analyst and researchers [26], [1]. In many nonlinear techniques, before estimating the parameters, the model must be specified in advance.

A. Time Series Models

a. Auto Regressive Model (AR)

The general approach for modelling a univariate time series $\{Z_t\}$ is the Auto Regressive (AR) model. In this model, the time series $\{Z_t\}$ depends on the linear combination of the previous **p** values of the time series $\{Z_t\}$ and an error term (random shock) e_t. Let $\{Z_t\}$ be a stationary time series with mean μ and let $\tilde{Y} = Z_t - \mu$. Then the equation of the autoregressive model denoted by AR(p) is

$$\tilde{Y}_t = \omega_1 \tilde{Y}_{t-1} + \omega_2 \tilde{Y}_{t-2} + \cdots + \omega_p \tilde{Y}_{t-p} + e_t \quad (4)$$

where e_t is error term. This model equation resembles a multiple linear regression model where the predictors are the lagged values of $\tilde{Y}_t$. Different time series patterns can be modelled by these AR(p) models.

b. Moving Average Model (MA)

Another application for modelling a univariate time series is the Moving Average model. In this model, the observed time series depends on the linear combination of previous **q** error terms. That is, at period t an error term e_t is activated which is independent of error terms of other periods. The time series is then generated by a considering the weighted average of present and previous shocks. Mathematically, a moving average model can be formulated as

$$\tilde{Y}_t = e_t + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} \quad (5)$$

The model parameter at time t is estimated by the mean of the previous q observations. q is the length of the moving average interval. Because this model assumes a fixed mean, the estimates of the forecast of any number of time intervals in the future is exactly same as the parameter estimate. This model provides a better estimate of the mean when the mean is constant or fluctuating slowly. If there is constant mean, then the largest value of q will provide a better estimate of the underlying mean. If the period of the moving average is longer, then it will average out the effects of variability.

c. Auto Regressive Integrated Moving Average (ARIMA)

The widely used general class of models for forecasting a time series is known as Auto regressive Integrated Moving Average model. This model is a generalization of autoregressive moving average [16] model. The ARIMA model is identified by the parameters p, d and q and where p tells about the order of AR process, d denotes the number of differencing needed to convert a non-stationary time series to stationary time series and q tells about the order of the MA process. Hence a ARIMA model, in general, is denoted by ARIMA (p, d, q). In this model, once the differencing process of order d is completed, the outcomes of the model must be integrated to produce the estimates and forecasts. This integration process in the ARIMA model is denoted by the letter “I”. The general equation of the ARIMA model can be written as:

$$\tilde{Y}_t = \omega_1 \tilde{Y}_{t-1} + \cdots + \omega_p \tilde{Y}_{t-p} + e_t - \theta_1 e_{t-1} - \cdots \theta_q e_{t-q} \quad (6)$$

where ω_k is the coefficient AR at lag k, θ_k is the coefficient of MA at lag k.

The optimum Arima model using Box-Jenkins methodology [11] consists the four steps:

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(1) Stationarity test.
(2) Identification of the model.
(3) Estimation of the parameters.
(4) Verifying model adequacy using diagnostic checking.

d. Neural Networks:

A new method of forecasting is the neural networks [23] method. These methods are based on the functioning of human brain which can be modelled using simple mathematical functions. These models address the complex nonlinear relationships which exists between the target and predictor variables.

e. Neural Network Auto Regressive NNAR(p.k):

This neural network model is based on a feed forward network and is denoted by NNAR(p,k) where p and k represents the lagged inputs and the nodes in the hidden layer respectively. This model is a 3 layered feed forward network consisting of an activation function and a linear combination function. The output (Y_t) and the inputs (Y_{t-1}, ..., Y_{t-p}) of the model are related and can be expressed using the mathematical equation: $Y_t = \Psi_0 + \sum_{j=1}^{m} \Psi_j * g\left(\Psi_{0,j} + \sum_{i=1}^{r} \Psi_{i,j} * Y_{t-i}\right) + e_t$ (7)
Where $\Psi_{i,j}$ (i = 0, 1, 2,…, n, j = 1, 2, …, h) and Ψ_j (j = 0, 1, 2, …, h) are model parameters, 'm' is number of hidden nodes and 'r' is number of input nodes. The activation function used for the output layer is a linear function and the transfer function used in the hidden layer is a sigmoid function given by $Sig(x) = \frac{1}{1+exp(-x)}$ (8)

f. Multi layer perceptron (MLP)

Another neural network model considered for modelling and forecasting is the multilayer perceptron (MLP) model. In this model training of the network is carried out using back propagation method [5],[2],[6],[15]. The MLP model comprises of an input layer, more than one hidden layer and an output. An Artificial Neural network performs well, only when the inputs and number of nodes in the hidden layer are selected carefully. It is important to identify the significant relationships which exists in the time series. To achieve this, the network is trained on the samples of the previous data points. To evaluate the forecasts Y_t, using previous observations, Y_{t-1}, .., Y_{t-p}, with 'h' nodes in the hidden layer, the prediction equation [13] [28] [29] [30] [31] for a feed forward neural network with one hidden layer is given by
$Y_t = G_o(\Psi_{co} + \sum_h \Psi_{ho} * G_h(\Psi_{ch} + \sum_i \Psi_{ih} * Y_{t-i}))$ (9)

Where Ψ_{ch} is the weight associated with the constant inputs and the neurons in the hidden layer, Ψ_{co} is the weight associated with the constant input and the output, w_{ih} is the connection weight between the inputs and the hidden neurons and w_{ho} is the connection weight between the hidden neurons and the output respectively. G_h and G_o are the activation functions which enables the mappings from inputs to hidden nodes and from hidden nodes to output(s) respectively. The sigmoid activation function used in NNAR model is also used in MLP.

g. Extreme learning machines (ELM)

A novel machine learning neural network algorithm used to model and forecast a time series is the extreme learning machines (ELM) algorithm proposed by Huang [19]. This algorithm well suits for single hidden layer feed-forward neural network (SLFN) [13], which is identical to the feed- forward neural networks. The main feature of ELMs is that the input weights and the hidden layer bias will be attributed randomly [10]. Therefore, the architecture of the network resembles to the resolution of a linear system. The unknown weights connect the hidden layer with the output layer. Moore-Penrose [14], generalized pseudo inverse, is used to obtain the solution to the linear system. The equation of the output function of the basic ELM for generalized SLFN can be expressed as
$f(x_i) = \sum_{j=1}^{L} \beta_j h_j(x_i) = h(x_i)\beta$ (10)

Where 'L' is the number of hidden layer neurons, $\beta = \left[\beta_1, \beta_2, \dots, \beta_j, \dots \beta_L\right]^T$ is the vector of the output weights associated with the hidden layer and the output nodes, $h(x_i) = \left[h_1(x_i), h_2(x_i), \dots, h_j(x_i) \dots, h_L(x_i)\right]$ is the output vector of the hidden layer with respect to the input vector 'X' which is the activation function in SLFN. Hence $h_j(x_i)$ expressed as $h_1(x_i) = g(w_j.x_i + b_j)$. Since each input variable x_i generates an equation, there will be 'n' equations which can be summarized as $H\beta = Y$ where H is the matrix with hidden layer output given by

$$H = \begin{bmatrix} h_1(x_1) & \cdots & h_L(x_1) \\ \vdots & \ddots & \vdots \\ h_1(x_n) & \cdots & h_L(x_n) \end{bmatrix} =$$

$$\begin{bmatrix} g(w_1 * x_1 + b_1) & \cdots & g(w_L * x_1 + b_L) \\ \vdots & \ddots & \vdots \\ g(w_1 * x_n + b_1) & \cdots & g(w_L * x_n + b_L) \end{bmatrix} \quad (11)$$

Where, $w_j = \left[w_{j1}, w_{j2}, \dots, w_{ji}, \dots, w_{jn}\right]^T$ is the weight vector connecting the jth hidden node and the input nodes, $w_j.x_i$ is the inner product of w_j and x_i and b_j is the threshold value of the jth hidden node. In ELM, the weights w_j and the threshold value b_j are assigned randomly and are not tuned. Once the random values are assigned, then the output matrix H will be fixed.

B. Test for Stationarity

Using Box-Jenkins methodology [11], to obtain a ARIMA model, the underlying time series should be stationary i.e., the properties of the time series are independent of time at which it is captured. This means that, the average, variance and auto covariance of the time series is independent of time. To find out the patterns, the ARIMA model uses lags of the data. In general, the differencing process converts a non-stationary time series into a stationary time series. These differences are evaluated by considering the differences between the values of two consecutive periods. That is, the differencing process eliminates trends or cycles (if any), from the time series to convert it into a stationary time series.

a. Augmented Dickey Fuller Test (ADF)

This test is used to test the stationarity of a time series. The null hypothesis assumed in this test is that the time series is non-stationary and the alternative that it is stationary.

The test statistic is given by $DF_{\gamma} = \frac{\hat{\gamma}}{S.E.(\hat{\gamma})}$ (12)

If, the contribution of the lagged value to the change is non-significant and there is an indication of a trend component, then the null hypothesis is accepted and it can be concluded that the time series is non-stationary otherwise reject the null hypothesis and conclude that the time series is stationary.

C. Model Identification

The appropriate model will be selected by determining the optimal model parameters. To select the optimal parameters of the model, one criterion is to use the plots of ACF and PACF, which must match with the theoretical or actual values. Another criterion is to use the accuracy measure, viz., R^2. The model with the highest R^2 is considered to be the best model.

D. Parameter Estimation

The method that is frequently used for estimating the parameters in ARIMA model is maximum likelihood (M.L.). The parameters are determined in such way that their maximum likelihood estimator values lead to the highest probability of producing the actual data, i.e., the parameter values which maximizes the value of the likelihood function L.

E. Diagnostic checking

The time series models which are identified, must be verified for the model adequacy. To test the adequacy of the model, residual ACF and PACF plots must be studied to see that any further structure is possible or not. The model will be considered adequate only when the autocorrelation and partial autocorrelation functions are small. The forecasts are then generated using the best model. The model will be re-estimated if any of the autocorrelations are large by adjusting the model parameters p and q. This process of verifying the residual ACF and PACF plots and adjusting the model parameters p and q should be continued until there is an indication that the resulting residuals do not exhibit any further structure. After obtaining the best model, it can be utilized to produce forecasts and associated probability limits. Alternatively, the model adequacy can be verified using Box-Ljung test. This test assumes that the model fit is good and will be tested for the possible rejection of the assumption. The test Statistic is given by

$$Q = n(n+2)\sum_{k=1}^{m} \frac{\hat{r}_k^2}{n-k} \quad (13)$$

where $\hat{r}_k$ is the estimated autocorrelation of the time series at lag k, and m is the number of lags being tested.

IV. RESULTS

A. Data

The data is obtained from the website www.nseindia.com. The period of the study is 01-04-2014 to 31-05-2019. The dataset consists of 1394 observations. The summary of the dataset is

Table 1: Descriptive Statistics of Data

Measure	Minimum	First Quartile	Median	Mean	Third Quartile	Maximum
PE	18.52	21.64	23.63	24.05	26.33	29.90

The dataset under study is divided into 2 datasets viz., train dataset consisting of 1255 (90%) observations and test dataset consists of 139(10%) observations. The time series models are fitted on train dataset and validated on test dataset using the R software.

B. Test for Stationarity

The plots of the dataset and the first differences (X) of the dataset are as follows:

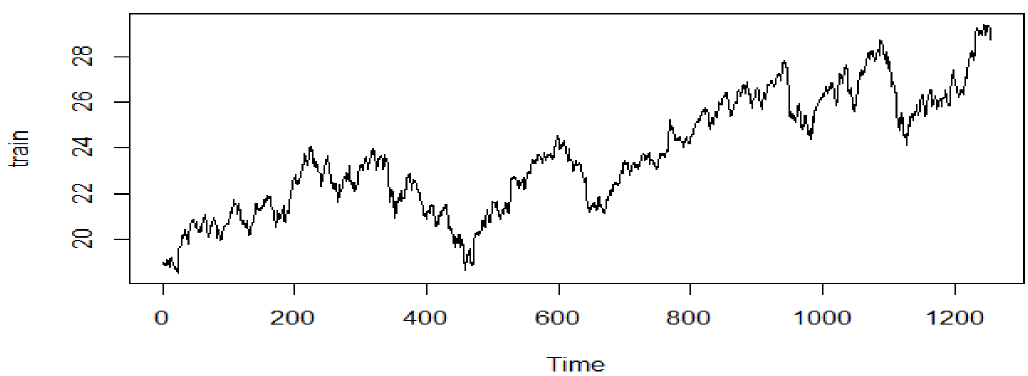


Figure 1: Time plot of the Data

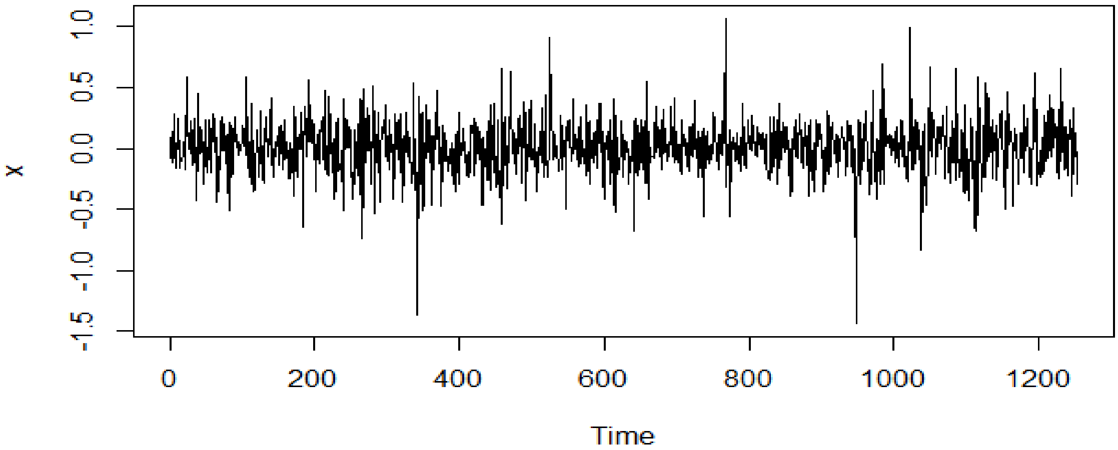


Figure 2: Time Plot of the First Differences of Data

It can be found from time plot of the data, that there exists a trend in the data, hence it can be concluded that the data is non-stationery. But the First differences (X) do not exhibit any trend. Hence it can be concluded that the First differences (X) is stationary in average and variance. The ADF test results about the stationarity of the data is follows:

Table 2: ADF Test Results of the Data

Test Statistic	Lag order	P-Value
-3.1049	10	0.1106

The P-value of the ADF test statistic is 0.1106. Since 0.1106 > 0.05, conclude that the time series exhibits non-stationarity.

The ADF test results on the first differences (X) of the dataset, is as follows:

Table 3: ADF Test Results on the Differences of Data

Test Statistic	Lag order	P-Value
-10.46	10	0.01

The P-value of the ADF test statistic on the first differences of the dataset (X) is less than 0.05, i.e., 0.01<0.05, hence accept the alternative hypothesis and conclude that the first differences of the dataset (X) is stationary.

C. Model Identification

In R software the auto.arima() function is used to obtain the optimum ARIMA. The optimum model is identified by considering the AIC value. The model with the smallest AIC value is considered as the optimum model for forecasting. For the data set used in this paper, the optimum model is identified as ARIMA (1,1,1).

The nnetar() function in R, is used to fit an NNAR(p,k) model where ‘p’ and ‘k’ values are selected automatically by the function. The optimal number of lags for the model is equal to that of a linear AR(p) model. The network uses the previous data points iteratively to forecast the future data points which are one-step ahead. The one step forecasts, so obtained, along with the previous data points are used as inputs to obtain the two step forecasts. For the data set used, the obtained the NNAR model is NNAR(2,2).

In R software, to fit multi-layer perceptron model and extreme leaning machines model, the package used is nnfor(). The nnfor() package is capable of producing extrapolative (univariate) forecasts and also includes explanatory variables. The function used to fit a MLP is mlp() and it requires the time series as input to model itself. For the data set used, the resulting network consists of 5 hidden nodes and it is trained 20 times. The network obtained generates different forecasts and those forecasts are combined using the median operator. For the data set used, the obtained multi- layer perceptron neural network model is MLP (2:5:1)

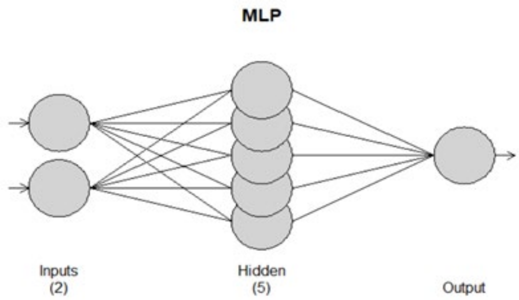


Figure 3: MLP (2:5:1)

The elm () function is used fit the extreme learning machines (ELM) model. The inputs of the model are mostly identical to that of mlp(). The ELM model assumes a very large hidden layer which will be pruned accordingly. For the data set used, the ELM model obtained is ELM (2:100:1)

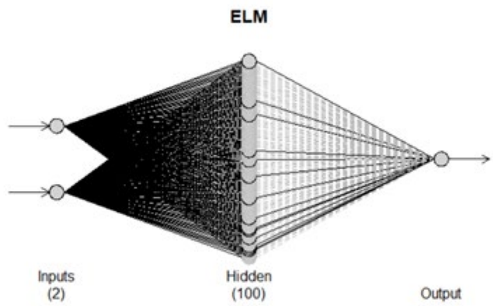


Figure 4: ELM (2:100:1)

D. Parameter Estimation

The parameters of the best ARIMA model are as follows:

Table 4: Parameter Estimates of ARIMA (1,1,1)

Variable	Coefficient	Standard Error	p-value
AR(1)	-0.6077	0.1852	0.001034
MA(1)	0.6722	0.1725	0.000097

Table 5: Accuracy Measures of ARIMA (1,1,1)

Measure	Value
Estimated σ^2	0.04623
Log likelihood d	149.12
AIC	-292.23
BIC	-276.83

The P-values of the parameters are less than the significance level 0.05, i.e., the AR(1) and MA(1) parameters are significance at 5% . According to the optimum ARIMA (1, 1, 1), the equation of the model is

$$\tilde{Y}_t = -0.6077 * \tilde{Y}_{t-1} + e_t + 0.6722 * e_{t-1} \qquad (14)$$

The R^2 measure for the four time series models is as follows:

Table 6: Comparison of the Four Time Series Models

S. No.	Model	R^2
1	ARIMA (1,1,1)	0.993
2	NNAR (2,2)	0.993
3	MLP (2:5:1)	0.992
4	ELM (2:100:1)	0.992

The accuracy measures of the best ARIMA (1,1,1) and the neural network models NNAR (2,2), MLP(2:5:1) and ELM(2:100:1) models on train data are as follows:

Table 7: Accuracy Measures of the Four Time Series Models

	RMSE	MAE	MAPE
ARIMA (1,1,1)	0.215	0.157	0.671
NNAR (2,2)	0.215	0.157	0.674
MLP (2:5:1)	0.215	0.158	0.675
ELM (2:100:1)	0.221	0.164	0.702

E. Diagnostic Checking

The time plot, ACF, PACF and Q-Q plot of the residuals of the four models are as follows:

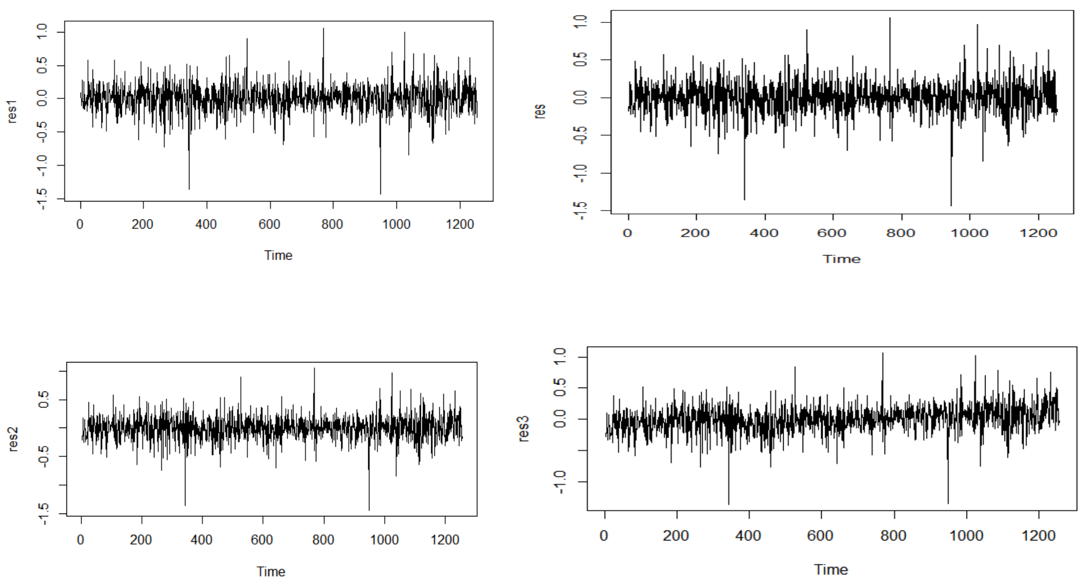
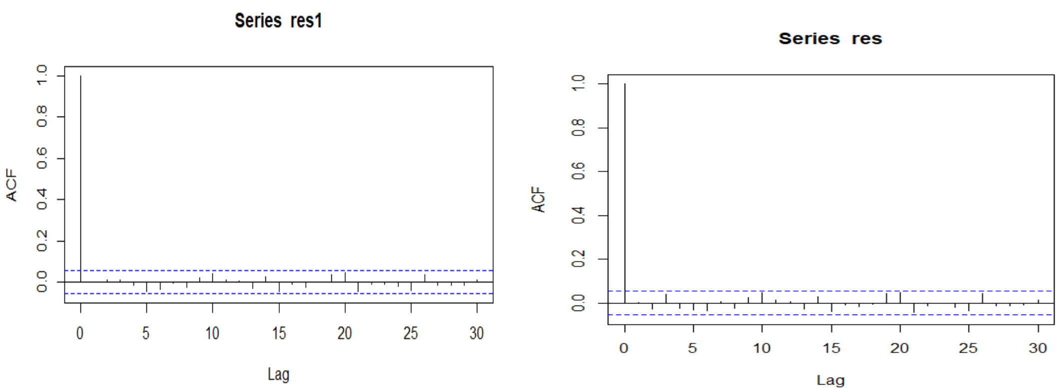


Figure 5: Time Plot of Residuals of the Time Series Models



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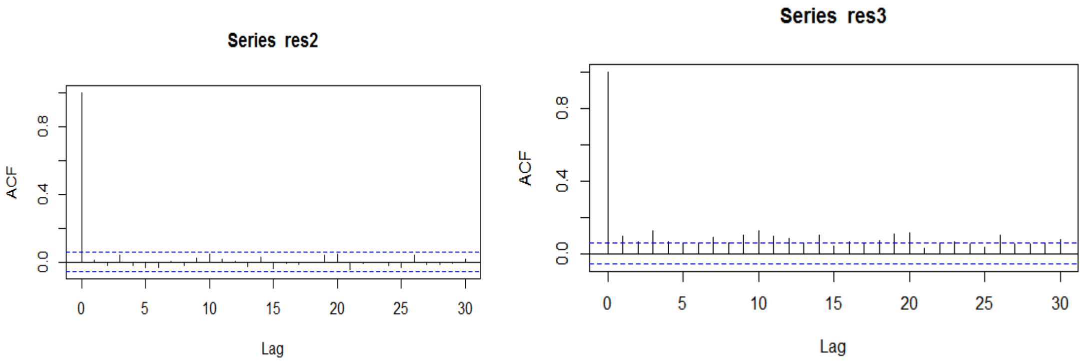

Figure 6: ACF of Residuals of The Time Series Models

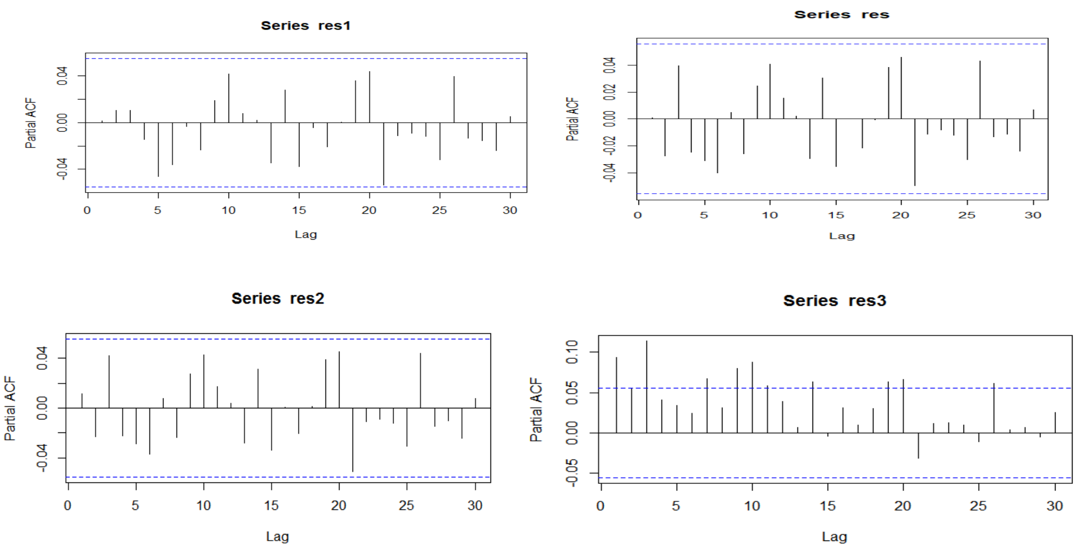

Figure 7: PACF of Residuals of the Time Series Models

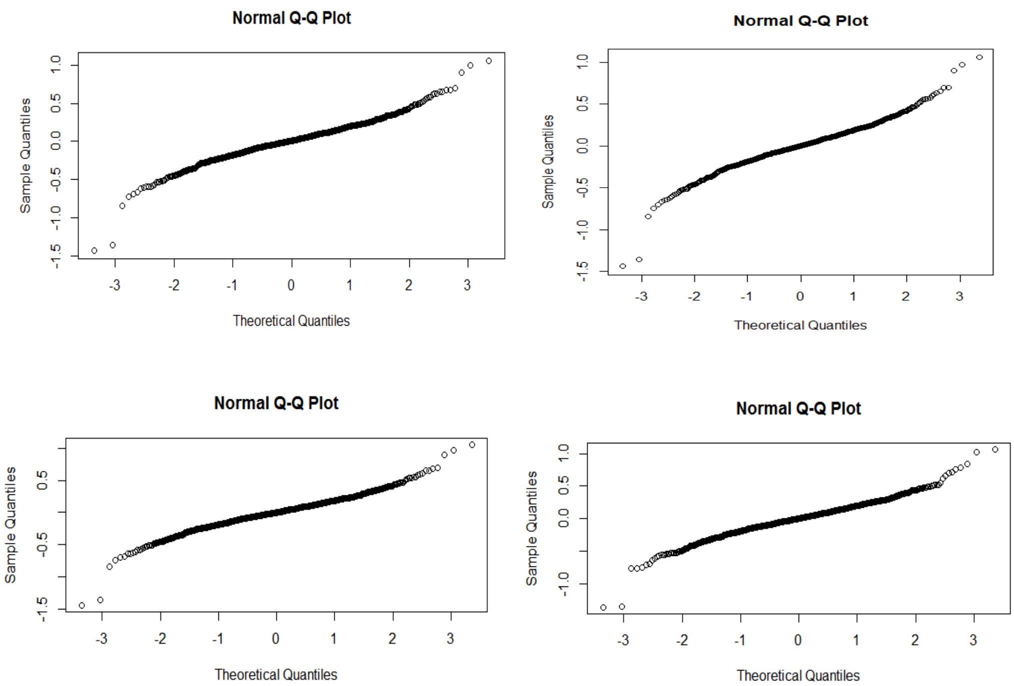

Figure 8: Normal Q-Q Plot of the Residuals of the Time Series Models

The time plot, q-q plots suggests that the residuals follow normal distribution. The ACF and PACF plots of the residuals obtained by the models ARIMA (1,1,1), NNAR(2,2) and MLP(2:5:1), suggests that the residuals are independently, identically distributed normal variates with mean zero (0) and variance σ_e^2 i.e., i.i.d $N(0, \sigma_e^2)$. The ACF and PACF functions of the residuals of ELM (2:100:1) model suggests that the residuals are not i.i.d $N(0, \sigma_e^2)$. The diagnostic test viz., Box-Ljung test, is applied on the residuals of all the four time series models in R. The output of the diagnostic test is as follows:

TABLE 8: Lung-Box test

MODEL	Statistic (χ^2)	DF	p-value
ARIMA (1,1,1)	0.0035	1	> 0.05
NNAR (2,2)	0.0011	1	> 0.05
MLP (2:5:1)	0.1108	1	> 0.05
ELM (2:100:1)	10.582	1	< 0.05

Since the probability corresponding to Box-Ljung Q-statistic is greater than 0.05, for the three models, ensures that the three models ARIMA (1,1,1), NNAR (2,2) and MLP (2:5:1) are adequate. The p-value of the ELM (2:100:1) is less than 0.05 indicates that the model is not adequate to the data set used in this study. Hence it can be concluded that the selected autoregressive integrated moving average ARIMA (1,1,1), Neural network autoregressive NNAR (2,2) and Multi-Layer Perceptron MLP (2:5:1) models are adequate for the time series data used in this study.

V. FORECASTS

The forecasted values obtained by the four models for the test data is shown in the following graph.

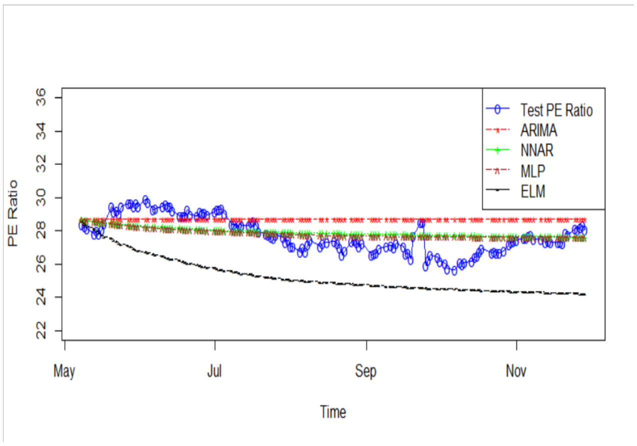

Figure 9: Forecasts Obtained by the Four Time Series Models for the Test Dataset

The accuracy measures of the four time series models for the forecasted values of test data are as follows:

Table 9. Accuracy Measures of Forecasted Values by the four Time Series Models

Model	RMSE	MAE	MAPE
ARIMA (1,1,1)	1.419	1.216	4.233
NNAR (2,2)	0.920	0.797	2.851
MLP (2:5:1)	0.900	0.769	2.762
ELM (2:100:1)	2.505	2.369	9.378

VI. CONCLUSION

In this study, the four models viz., ARIMA (1,1,1), NNAR (2,2), MLP (2:5:1) and ELM (2:100:1) were tested and compared to each other for modelling the Indian equity market stock index NIFTY-50. Of the four time series models considered, the ARIMA (1,1,1), NNAR(2,2) and MLP(2:5:1) are found to be adequate using the Ljung-Box test (Table 8). And of these three models, NNAR(2,2) and MLP(2:5:1) models performed better than ARIMA (1,1,1) model (Table 9) with respect to the forecasting capabilities. The errors in the forecasting procedure were much lower in the MLP model compared to the other models considered in the study (Table 9). Upon observing the accuracy measures Root Mean Squared Error (RMSE), Mean absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) (Table 9) for the forecasted values, it can be concluded that the MLP (2:5:1) model along with NNAR (2,2) out performs the other time series models considered in the study.

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