

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

R Gautham Goud, M. Krishna Reddy



Abstract: The ratio of the 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 the price is low relative to earnings and undervalued. A potential investor prefers an index with a 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 network models, as well as the traditional ARIMA model with the Box-Jenkins method, is carried out. It is found that the MLP and NNAR neural network models outperform the ARIMA model.

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

I. INTRODUCTION

The Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) are two prominent Indian stock exchanges that hold a significant place in the global financial market. The oldest of these two is the BSE, and its index, known as the SENSEX, consists of 30 of the largest and most actively traded stocks. NSE is regarded as the best in terms of technology and sophistication. The NSE also encompasses 22 key sectors of the Indian economy. The NSE index is known as NIFTY-50, and it comprises 50 large and actively traded stocks. Investors and economists are drawn to the stock market because it offers high returns, albeit with significant risks. However, the information or data about the stock is usually incomplete, complex, uncertain, and vague, making it a challenging task to predict the future economic performance. Generally, investors invest in the stock market based on an analysis of available data. Trading in the stock market has gained widespread popularity worldwide and has become part of the daily routine for many investors, who aim to generate substantial profits. Due to the incomplete data, analysing the stock movement behaviour becomes a challenging task.

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Advanced and robust predictive modelling can guide investors in classifying and identifying high-performance securities, enabling them to make informed 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 market value of a company is evaluated using the ratio of the present price per share 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. Typically, companies yield higher dividends in the future if their future earnings are expected to be higher. A share's price increases or decreases over a period according to the demand and speculation of investors in the stock. This ratio is helpful to investors to decide what amount to pay for a stock based on its earnings [4]. For this reason, investors use this ratio to evaluate the worth of a share by comparing its earnings multiple to that of other companies. The following formula evaluates the P/E ratio.

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

(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 last 12 months' earnings per share (EPS) and is given by

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

(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 the 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 estimated for the next 12 months or 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 of stock returns requires that the model be defined in advance of the estimation. Because the returns of the stock market are uncertain and nonlinear, 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]. Kim and Chun [21] applied probabilistic neural network to estimate the stock market index. Pantazopoulos used a Neuro-fuzzy approach [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 employs a neural network forecasting approach for NIFTY-50, it will be beneficial in developing neural networks as an additional tool for forecasting the volatile Indian market. The self-similarity of this study helps understand the microstructure of the Indian stock market.

III. METHODOLOGY

Many researchers developed many forecasting models, 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 have two main approaches: i) the linear approach and ii) the nonlinear approach. The commonly known methods, which are linear, include 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 has been studied by several financial analysts and researchers [26], [1]. In many nonlinear techniques, the model must be specified in advance before estimating the parameters.

A. Time Series Models

a. Auto Regressive Model (AR)

The general approach for modelling a univariate time series $\{Z_t\}$ is the Autoregressive (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

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

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

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 a period. t an error term e_t is activated, which is independent of the error terms of other periods. The time series is then generated by considering the weighted average of present and previous shocks. Mathematically, a moving average model can be formulated as

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

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 for any number of time intervals in the future are precisely the same as the parameter estimate. This model provides a more accurate estimate of the mean when the mean is constant or fluctuates slowly. If there is a continuous mean, then the most significant value of q will provide a better estimate of the underlying mean. If the period of the moving average is longer, 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 the Auto Regressive Integrated Moving Average (ARIMA) model. This model is a generalization of the autoregressive moving average [16] model. The ARIMA model is identified by the parameters p , d and q , where p tells about the order of the AR process, d denotes the number of differencing needed to convert a non-stationary time series to a stationary time series, and q tells about the order of the MA process. Hence, an 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:

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

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:

- (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 the human brain, which can be modelled using simple mathematical functions. These models address the complex, nonlinear relationships that exist between the target and predictor variables.

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

This neural network model is based on a feedforward network and is denoted by NNAR(p, k), where p represents the number of lagged inputs and k represents the number of nodes in the hidden layer. This model is a three-layer feedforward network consisting of an activation function and a linear combination function. The output (Y_t) and the inputs (Y_{t-1}, \dots, Y_{t-p}) of the model are related and can be expressed using the mathematical equation: $Y_t = \Psi_0 + \sum_{j=1}^m \Psi_j * g(\Psi_{0,j} + \sum_{i=1}^r \Psi_{i,j} * Y_{t-i}) + e_t$ (7)

Where $\Psi_{i,j}$ ($i = 0, 1, 2, \dots, n, j = 1, 2, \dots, h$) and Ψ_j ($j = 0, 1, 2, \dots, h$) are model parameters, 'm' is the number of hidden nodes and 'r' is the number of input nodes. The activation function used for the output layer is linear, 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 the back propagation method [5],[2],[6],[15]. The MLP model comprises an input layer, one or more hidden layers, and an output layer. An Artificial Neural Network performs well only when the inputs and the number of nodes in the hidden layer are selected carefully. It is essential to identify the significant relationships which exist 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}, \dots, Y_{t-p} , with 'h' nodes in the hidden layer, the prediction equation [13] [28] for a feed forward neural network with one hidden layer, the function 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 neurons, respectively? G_h and G_o The activation functions enable the mappings from inputs to hidden nodes and hidden nodes to output(s), respectively. The sigmoid activation function used in the NNAR model is also used in the 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 is well-suited for a 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 that of a linear system. The unknown weights connect the hidden layer with the output layer. Mooregeneralised4], 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, $\beta = [\beta_1, \beta_2, \dots, \beta_j, \dots, \beta_L]^T$ Is the vector of the output weights associated with the hidden layer and the output nodes? $h(x_i) = [h_1(x_i), h_2(x_i), \dots, h_j(x_i) \dots, h_L(x_i)]$ 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 $h_1(x_i) = g(w_j \cdot x_i + b_j)$. 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

$$H = \begin{bmatrix} h_1(x_1) & \dots & h_L(x_1) \\ \vdots & \ddots & \vdots \\ h_1(x_n) & \dots & h_L(x_n) \end{bmatrix} = \begin{bmatrix} g(w_1 * x_1 + b_1) & \dots & g(w_L * x_1 + b_L) \\ \vdots & \ddots & \vdots \\ g(w_1 * x_n + b_1) & \dots & g(w_L * x_n + b_L) \end{bmatrix} \quad (11)$$

Where, $w_j = [w_{j1}, w_{j2}, \dots, w_{ji}, \dots, w_{jn}]^T$ is the weight vector connecting the jth hidden node and the input nodes, $w_j \cdot x_i$ 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 They are assigned randomly and are not tuned. Once the random values are assigned, the output matrix H will be fixed.

B. Test for Stationarity

Using the Box-Jenkins methodology [11] to obtain an ARIMA model, the underlying time series should be stationary, i.e., the properties of the time series are independent of the time at which it is captured. This means that the average, variance, and autocovariance of the time series are independent of time. To identify patterns, the ARIMA model utilises 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 hypothesis is that it is stationary.

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

Suppose the contribution of the lagged value to the change is non-significant, and there is an indication of a trend component. In that case, 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 choose the optimal parameters of the model, one criterion is to use the plots of ACF and PACF, which must match the theoretical or actual values. Another criterion is to use the accuracy measure, viz., R^2 . The model with the highest R-squared value is considered the best model.

D. Parameter Estimation

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

E. Diagnostic checking

The identified time series models must be verified for model adequacy. To test the adequacy of the model, residual ACF and PACF plots should be examined to determine if any further structure is present. 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 changing 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 the Box-Ljung test. This test assumes that the model fit is good and will be used to test for the possible rejection of this 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 two datasets: a train dataset consisting of 1,255 (90%) observations and a test dataset consisting of 139 (10%) observations. The time series models are fitted on the training dataset and validated on the 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:

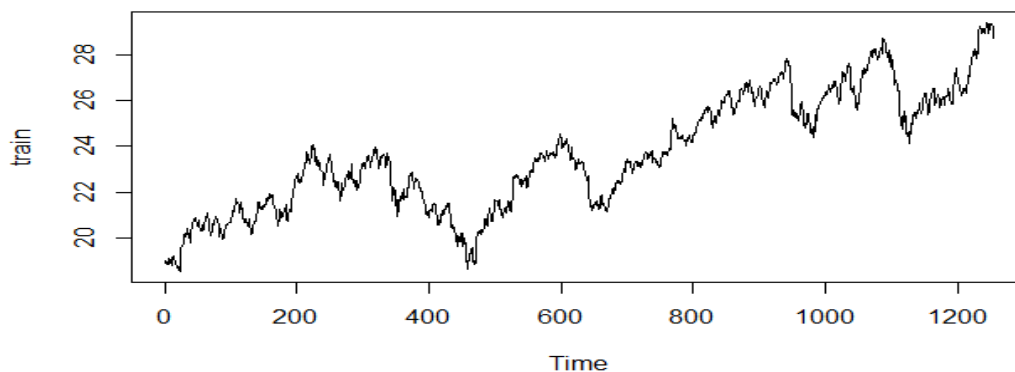


Figure 1: Time plot of the Data

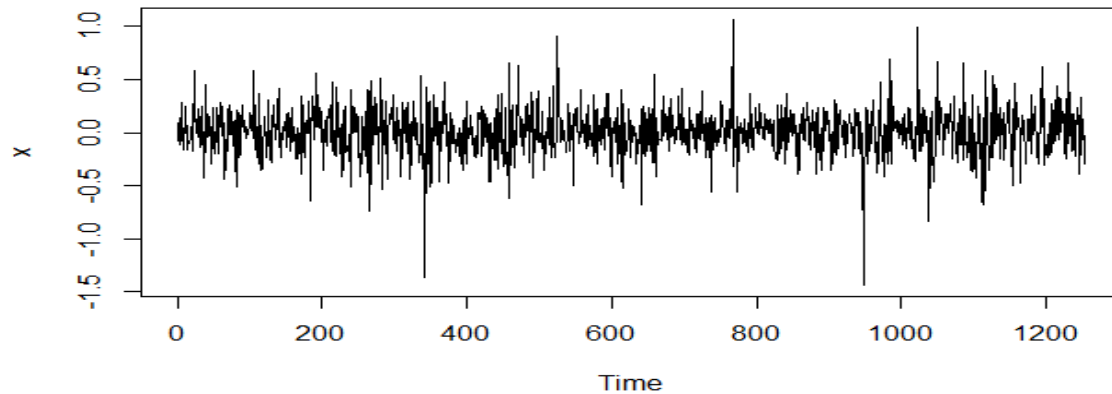


Figure 2: Time Plot of the First Differences of Data

It can be observed from the time plot of the data that a trend exists; hence, it can be concluded that the data is non-stationary. But the First differences (X) do not exhibit any trend. Hence, it can be concluded that the First differences (X) are stationary in terms of average and variance. The ADF test results about the stationarity of the data are as 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 are 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, we accept the alternative hypothesis and conclude that the first differences of the dataset (X) are 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 regarded as the optimal 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, obtained in this manner, along with the latest data points, are used as inputs to generate the two-step forecasts. For the data set used, the obtained NNAR model is NNAR(2,2).

In R software, to fit a multi-layer perceptron model and an extreme learning machine 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 an 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)

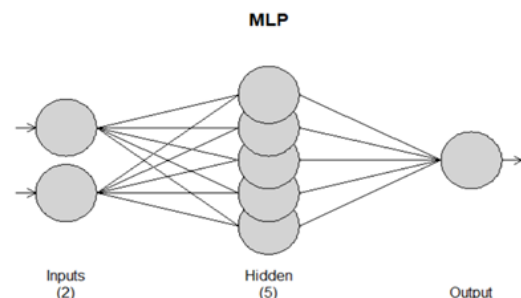


Figure 3: MLP (2:5:1)

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

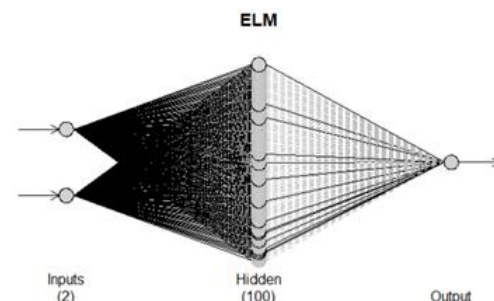


Figure 4: ELM (2:100:1)

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 of 0.05, i.e., the AR(1) and MA(1) parameters are significant at the 5% level. According to the optimum

ARIMA (1, 1, 1), the equation of the model is

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

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:

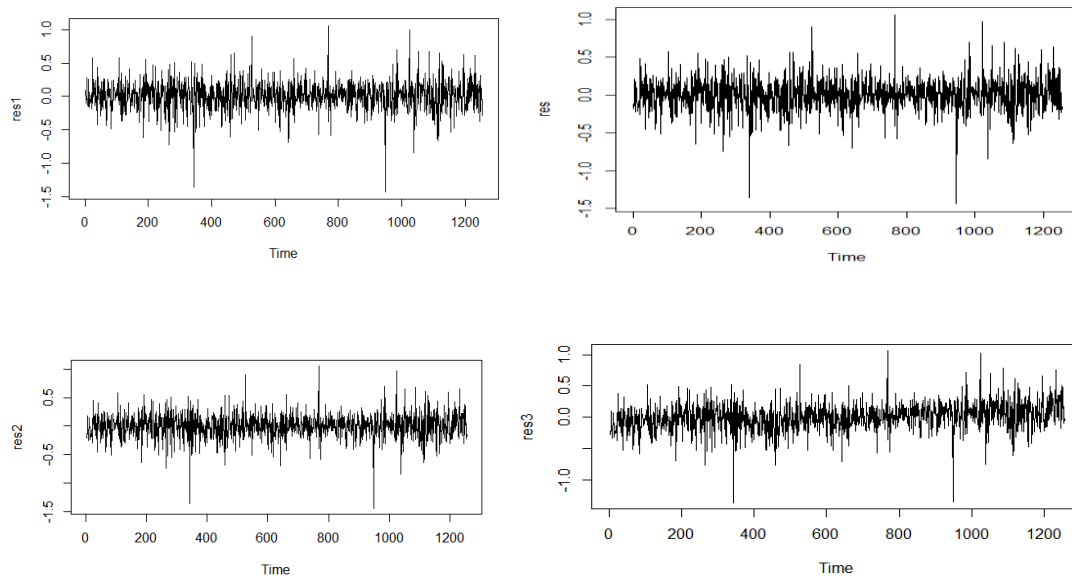
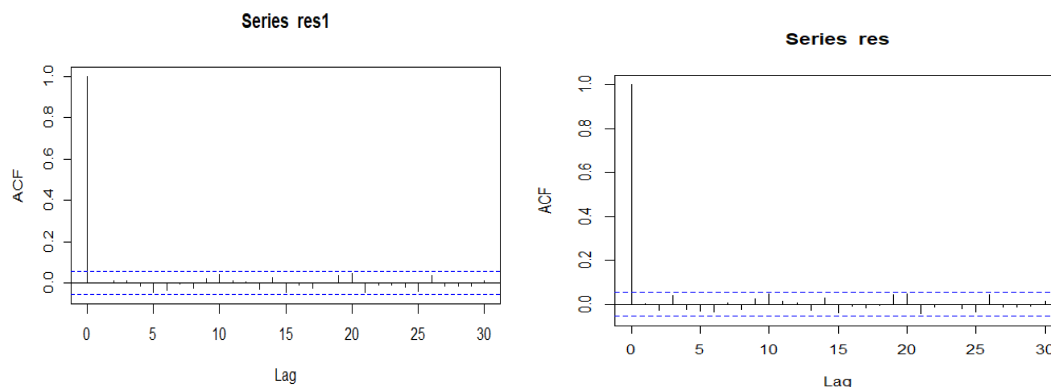


Figure 5: Time Plot of Residuals of the Time Series Models



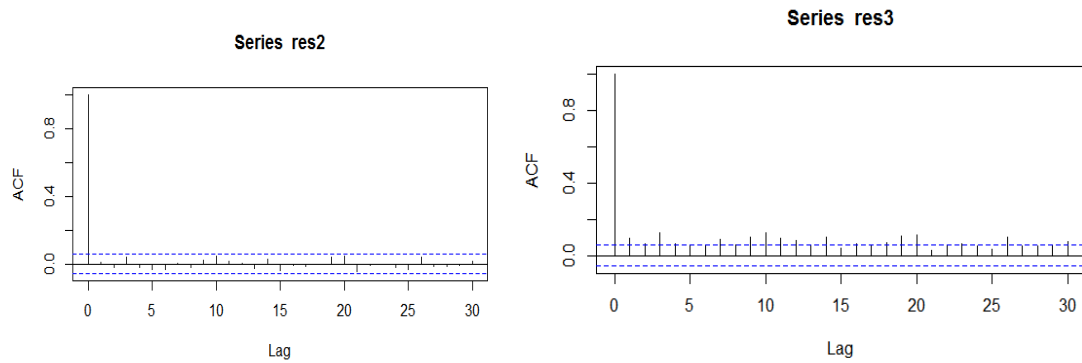


Figure 6: ACF of Residuals of The Time Series Models

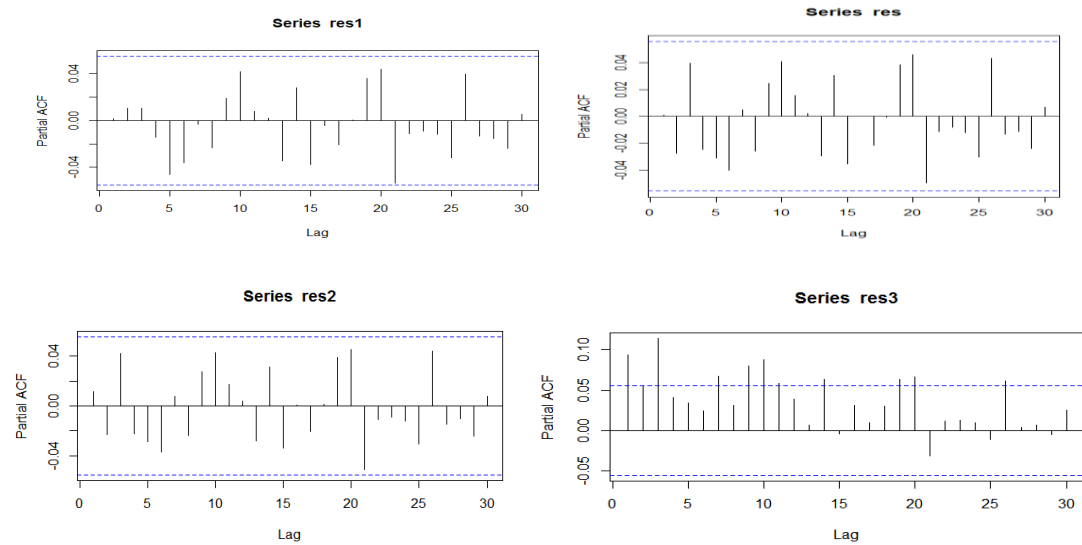


Figure 7: PACF of Residuals of the Time Series Models

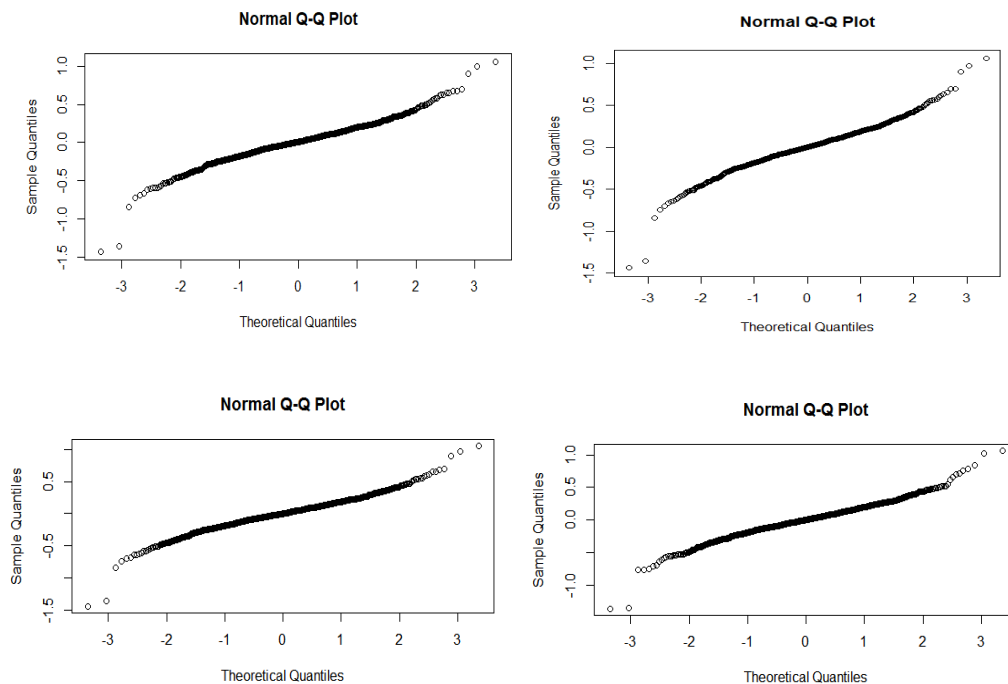


Figure 8: Normal Q-Q Plot of the Residuals of the Time Series Models

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

The time plot and q-q plots suggest that the residuals follow a 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) suggest 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 the ELM (2:100:1) model suggest that the residuals are not i.i.d. $N(0, \sigma_e^2)$. The diagnostic test, namely the Box-Ljung test, is applied to the residuals of all 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 the Box-Ljung Q-statistic is greater than 0.05, for 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, indicating that the model is not sufficient for 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 are shown in the following graph.

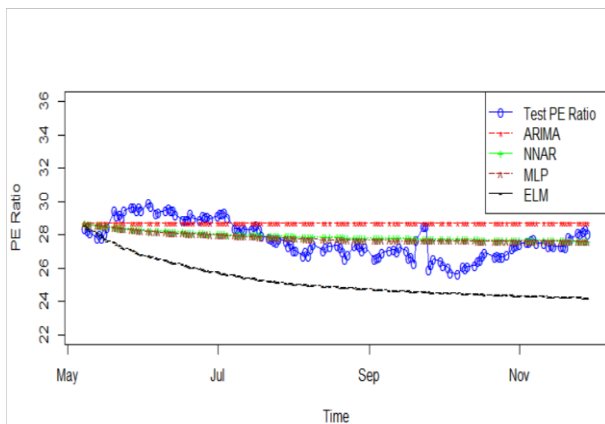


Figure 9: Forecasts Obtained by the Four Time Series Models for the Test Dataset

The accuracy measures of the four time series models for the forecasted values of the 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, four models —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). Of these three models, the NNAR(2,2) and MLP(2:5:1) models performed better than the ARIMA (1,1,1) model (Table 9) in terms of 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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REFERENCES

1. A. Abhyankar, L. S. Copeland, and W. Wong. Uncovering nonlinear structure in real-time stock-market indexes: the S&P 500, the DAX, the Nikkei 225, and the FTSE-100. *Journal of Business & Economic Statistics*, 15(1):1–14, 1997. <https://doi.org/10.1080/07350015.1997.10524681>
2. A. A. Adebiyi, A. O. Adewumi, C. K. Ayo, et al. Comparison of ARIMA and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*, 2014, 2014. <https://doi.org/10.1155/2014/614342>
3. M. U. Ahmad. An analysis of market p/e using auto regression and vector auto regression models. *SAMVAD*, 10:116–120, 2015.
4. K. Anderson and C. Brooks. The long-term price-earnings ratio. *Journal of Business Finance & Accounting*, 33(7-8):1063–1086, 2006. <https://doi.org/10.1111/j.1468-5957.2006.00621.x>
5. A. Aslanargun, M. Mammadov, B. Yazici, and S. Yolacan. Comparison of ARIMA, neural networks and hybrid models in time series: tourist arrival forecasting. *Journal of Statistical Computation and Simulation*, 77(1):29–53, 2007. <https://doi.org/10.1080/10629360600564874>
6. S. D. Balkin and J. K. Ord. Automatic neural network modelling for univariate time series. *International Journal of Forecasting*, 16(4):509–515, 2000. [https://doi.org/10.1016/S0169-2070\(00\)00072-8](https://doi.org/10.1016/S0169-2070(00)00072-8)
7. A. Basistha and A. Kurov. Macroeconomic cycles and the stock market's reaction to monetary policy. *Journal of Banking & Finance*, 32(12):2606–2616, 2008. <https://doi.org/10.1016/j.jbankfin.2008.05.012>
8. B. S. Bernanke and K. N. Kuttner. What explains the stock market's reaction to the Federal Reserve policy? *The Journal of Finance*, 60(3):1221–1257, 2005. <https://doi.org/10.1111/j.1540-6261.2005.00760.x>
9. L. Bonga-Bonga et al. Equity prices, monetary policy, and economic activities in emerging market economies: The case of South Africa. *Journal of Applied Business Research (JABR)*, 28(6):1217–1228, 2012. <https://doi.org/10.19030/jabr.v28i6.7337>
10. H. Bouzgou and C. A. Gueymard. Minimum redundancy–maximum relevance with extreme learning machines for global solar radiation forecasting: Toward an optimized dimensionality reduction for solar



- time series. Solar Energy, 158:595–609, 2017. <https://doi.org/10.1016/j.solener.2017.10.035>
11. E. Box George, M. Jenkins Gwilym, C. Reinsel Gregory, and M. Ljung Greta. Time series analysis: forecasting and control. San Francisco: Holden Day, 1976.
 12. J. Y. Campbell and R. J. Shiller. Stock prices, earnings, and expected dividends. the Journal of Finance, 43(3):661–676, 1988. <https://doi.org/10.1111/j.1540-6261.1988.tb04598.x>
 13. J. Faraway and C. Chatfield. Time series forecasting with neural networks: a comparative study using the airline data. Journal of the Royal Statistical Society Series C: Applied Statistics, 47(2):231–250, 1998. <https://doi.org/10.1111/1467-9876.00109>
 14. J. A. Fill and D. E. Fishkind. The Moore–Penrose generalised inverse for sums of matrices. SIAM Journal on Matrix Analysis and Applications, 21(2):629–635, 2000. <https://doi.org/10.1137/S0895547987329692>
 15. M. Gori, A. Tesi, et al. On the Problem of Local Minima in Backpropagation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 14(1):76–86, 1992. <https://doi.org/10.1109/34.107014>
 16. R. G. Goud and M. K. Reddy. Forecasting the P/E ratio for the Indian equity market's Nifty 50 stock index. International Journal of Agricultural & Statistical Sciences, 16(2), 2020. <https://doi.org/10.2139/ssrn.606263>
 17. C. S. Hansen and B. Tuypens. Proxying for expected returns with price-earnings ratios. Available at SSRN 606263, 2004.
 18. E. Hjalmarsson. Predicting global stock returns. Journal of Financial and Quantitative Analysis, 45(1):49–80, 2010. <https://doi.org/10.1017/S0022109009990469>
 19. G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew. Extreme learning machine: theory and applications. Neurocomputing, 70(1-3):489–501, 2006. <https://doi.org/10.1016/j.neucom.2005.12.126>
 20. K.-j. Kim and I. Han. A genetic algorithm approach to feature discretisation in artificial neural networks for predicting stock price indices. Expert Systems with Applications, 19(2):125–132, 2000. [https://doi.org/10.1016/S0957-4174\(00\)00027-0](https://doi.org/10.1016/S0957-4174(00)00027-0)
 21. S. H. Kim and S. H. Chun. Graded forecasting using an array of bipolar predictions: application of probabilistic neural networks to a stock market index. International Journal of Forecasting, 14(3):323–337, 1998. [https://doi.org/10.1016/S0169-2070\(98\)00003-X](https://doi.org/10.1016/S0169-2070(98)00003-X)
 22. R.-J. Li and Z.-B. Xiong. Forecasting the stock market with fuzzy neural networks. In 2005, International Conference on Machine Learning and Cybernetics, Volume 6, pages 3475–3479. IEEE, 2005.
 23. H. R. Maier and G. C. Dandy. Neural network models for forecasting univariate time series. 1996.
 24. A. Maleki, S. Nasser, M. S. Aminabad, and M. Hadi. Comparison of ARIMA and NNAR models for forecasting water treatment plant's influent characteristics. KSCE Journal of Civil Engineering, 22:3233–3245, 2018. <https://doi.org/10.1007/s12205-018-1195-z>
 25. K. N. Pantazopoulos, L. H. Tsoukalas, N. G. Bourbakis, M. J. Brun, and E. N. Houstis. Financial Prediction and Trading Strategies Using Neuro-Fuzzy Approaches. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 28(4):520–531, 1998. <https://doi.org/10.1109/3477.704291>
 26. A.-A. RE. Univariate modelling and forecasting of monthly energy demand time series using abductive and neural networks. Computers & Industrial Engineering, 54(4):903–917, 2008. <https://doi.org/10.1016/j.cie.2007.10.020>
 27. A. N. Refenes, M. Azema-Barac, L. Chen, and S. Karoussos. Currency exchange rate prediction and neural network design strategies. Neural Computing & Applications, 1:46–58, 1993. <https://doi.org/10.1007/BF01411374>
 28. S. Siekmann, R. Kruse, J. Gebhardt, F. Van Overbeek, and R. Cooke. Information fusion in the context of stock index prediction. International journal of intelligent systems, 16(11):1285–1298, 2001. <https://doi.org/10.1002/int.1060>



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