Predicting Indian Stock Market Using Artificial Neural Network Model

Abstract

The study has attempted to predict the movement of stock market price (S&P CNX Nifty) by using ANN model. Seven years historical data from 1st January 2008 to 29th April 2014 are used to train and test the models. Training and testing is performed by using Multi-Layer Perceptron Network architecture. The forecasting performances of the ANN model is accessed by using back-propagation neural network of errors such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Normalized Mean Square Error (NMSE). Further the study has used Sign Correctness Percentage (SCP) to determine the correctness in the prediction of the direction of the stock market price (S&P CNX Nifty). The study finds that Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) at 5-day lag with sigmoid activation functions are 1.792 and 0.889 that gives highest accuracy predictions in the model. Further, the study finds that 82 percent data analysis is correctly predicted by the ANN model and the predictive power of the network model is more influenced by the previous day closing price. This study is quite useful to investors, professional traders and regulators for taking buy, sell and hold decision in the market while making investment decision. It will also guide that ANN is an effective tool in forecasting the daily stock market prices and direction.

Keywords: Stock Market, Artificial Neural Networks (ANNs), MAPE, MAE, NMSE and SCP

JEL classifications: G1, G17, C45

Introduction:
Prediction of stock market is a subject of interest to traders, market makers, investors and policy makers’ today. Stock market is typically considered to be a dynamic, non-linear, complicated, nonparametric, and chaotic in nature. Hence prediction of stock market returns is an important issue in finance literature. However stock analysts have been using some approaches for predicting stock market return. The random walk theory states that stock price fluctuations are independent of each other and price movements do not follow any patterns or trends. Stocks take a random and unpredictable path. The supporter of random walk believes that it is impossible to outperform the market without assuming additional risk. As per random walk theory long-term buy-and-hold strategy is the best and individuals are not required to attempt to time the markets. On the other hand, the efficient market theory states that it is impossible to beat the market because whatever information is available about a stock to one investor is available to everyone. The price of a security is reflecting about company's prospects and the direction of economy to everyone so individual investor cannot outperform the market. The weak-form efficiency asserts that future stock price cannot be predicted by analysing past stock price. Semi-strong-form efficiency proclaims that all publicly available information is fully reflected in stock prices and no excess returns can be earned by trading on that information. Strong-form efficiency assets that all information is fully reflected in securities prices. Even insider information is of no use.

On the other hand, technical analysts assume stock market price moves in trend and these trends can be captured. So, future market price can be forecasted by examining past stock prices. Technical analysts use tools such as charting patterns, technological indicators, and specialized techniques like Elliot Waves and Fibonacci series and believes that there are recurring patterns in the market behavior that are conventional. But most of the techniques used by technical analysts are lack of rational explanation for their use. However technical analysis is criticized due to its idiosyncratic nature and contradictory to Efficient Market Hypothesis. Fundamental analyst concerned more with company rather than actual stock. The analyst assumes that share’s current and future price depends on its intrinsic value and its expected return. The analysts make their decisions based on the past performance of the company, its earnings forecast, the particular industry sector and the overall economy. Fundamental traders do not rely on the market movements alone. Fundamental traders believe that the markets are reacting to events in certain ways and future market prices are forecasted based on these events. Critics of the theory, however, oppose that stocks do maintain price trends over time and it is possible to outperform the market by carefully selecting entry and exit points for stock investments. This theory states that stocks always trade at their fair value and inspire investors to make profit by purchasing undervalued stocks or sell stocks at inflated prices. Protagonists of this theory debates that it is meaningless to use fundamental and technical analysis to predict trends and search for undervalued stocks.

Markets are highly irrational and overreacted to the positive earnings news that drives prices up too high on good news and too low on bad news. Individual investors tend to overreact or underreact to news. It is commonly believed that investors in the market tend to move with the majority of investors sentiment. So when market is enthusiastic about a stock, the market’s herd mentality drives prices upward. The buying volume tends to reach peak and more people buy at higher price than at the low and vice-versa. This creates a tendency to buy high and sell low instead of the wiser opposite action. Hence the inefficiency of the markets often is caused by inefficiency of investors and traders. Some researchers arguing that a class of irrational investors has known as ‘noise traders’ move markets successfully. Noise traders are folks who tend to buy and sell on bad information. As the value of a stock rises or falls, people are inclined
to buy or sell that stock. This in turn further affects the price of the stock, causing it to rise or fall chaotically. Hence it is believed that the behavior of the stock market is chaotic, irrational and, at times, absolute inefficient.

The profitability of investing and trading in the stock market largely depends on the predictability. If the direction of the market is successfully predicted the investors may be better guided and earn good return. If any model predicts the trends of the dynamic stock market and eliminates uncertainties, it is not only helping to increase the investments in stock markets but also helping to the regulators to take corrective measures. Since presence of non-linearity in stock market enables the traders to make excess profits, the present study has been undertaken to investigate the same. Prediction of stock market by using non-linear model i.e. ANN model have not been extensively researched in the Indian stock market. Apparently this research would help to investors, economists, market regulators and policy makers in understanding the effectiveness of Indian stock market to take better investment decision and devise better risk management tools. In this context, we have raised three research questions. The first objective is to predict the stock exchange market index values by using ANN model. Secondly the study tries to determine the prediction accuracy of the model by using different forecasting performance measure i.e. Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Normalized Mean Square Error (NMSE). Thirdly the study tries to test the performance of the direction of the predicted value of the closing of the next day’s CNX S&P Nifty Index by using Sign Correctness Percentage (SCP) measure. Therefore, the present work offers a value addition to the existing literature and proves to be useful to the investors, researchers as well as to regulators. The structure of the paper is organized as follows: section 2 discusses the literature review, the data and methodology is presented in section 3, the empirical investigation is reported in section 4 and section 5 deals with concluding observations.

**Why Neural Network used?**

The direction of future change of the financial market is really desirable today. Many studies have established that non-linearity exits in financial market data series. Since linear models are failed to understand the data pattern and relationship between input and output data because of the complex, non-linear and chaos nature of the stock market, artificial neural networks are used to derive meaning from complicated or imprecise data. They are used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. ANNs have the capacity of performing nonlinear modeling without a priori knowledge about the relationship between input and output variables. The neural network is trained from a mass of historical data and tries to discover hidden dependencies to use them for predicting into future. Neural Network is a black box which takes some variables as an input, and gives other as an output and able to learn something. In other words, ANNs can generalize and correctly gather the unseen part of the data even if the sample data contain noisy information. Even if the underlying relationships among the data are hard to describe, ANNs capture the delicate functional relationships among them and provides a practical feasible way to solve real world problems. The Neural Network model can easily predict the direction of stock market return change when compared to actual value and enable to maximizing profits from investment trading. Thus ANNs are a more general and flexible modeling tool for forecasting. From statistical point of view, Neural Networks are analogous to nonparametric, nonlinear, regression model. Neural network model is appropriate for capturing all the nonlinear vibrant relationships in the stock market. So, Neural Network suits better than other
models in predicting the stock market returns. Today neural networks are more preferred over the other methods for stock market forecasting.

**Literature Review:**

Using artificial neural networks to predict stock markets has been an active research area during last decade. Phua, et.al (2000) uses Neural Network with Genetic Algorithm to the Singapore stock market and predicts the market direction with an accuracy of 81 percent. Qing Cao et.al (2005) uses Artificial Neural Networks to predict stock price movement for firms traded on the Shanghai Stock Exchange and compares the predictive power of univariate and multivariate neural network models. The study shows that Neural Network outperform the linear models and finds that Neural Networks are useful tool for stock price prediction in emerging markets like china. Thenmozhi (2006) applied Neural Networks to predict the daily returns of the Bombay Stock Exchange (BSE) Sensex and finds that the predictive power of the network model is influenced by the previous day. The study shows that satisfactory results could be achieved by applying MLP to predict the BSE Sensex. Asif Ullah et.al. (2008) compared a Back propagation Neural Network and Genetic Algorithm based back propagation Neural Network and shows that for stock rate prediction, Genetic Algorithm based back propagation Neural Network gives more accurate prediction. BirolYildiz et.al.(2008) developed an efficient three layer Neural Network with revised Back propagation Algorithm to predict the direction of Istanbul Stock Exchange National-100 Indices (ISE National -100) and finds that the model forecast the direction of ISE National -100 to an accuracy of 74.51 percent. H. Al-Qaheri, et al (2008), Bruce & Gavin (2009) Mitra (2009) Altay and Satman (2005) forecasting stock market volatility using Neural Networks and finds that ANNs are better than the results determined by linear and logical regression models. Zhao et al. (2009) predicts the stock price using BPNN by considering a single closing price as the time series vector. The authors uses two steps forecast approach. First, use Gray correlation analysis to choose the set of variable which can describe the characteristics of the state of the stock market from a number of technical indicators. Then classify the state of stock market by the Self-organizing feature map (SOFM) network. And based on this classification, BPNN is used for prediction. The result shows that the predictive accuracy of SOFM-BP model was better than that of the traditional BPNN model. Leandro and Ballini(2010)analyze Neural Networks for financial time series forecasting to predict future trends of North American, European, and Brazilian stock markets and finds that ANNs do indeed have the capability to forecast the stock markets and, if properly trained, robustness can be improved, depending on the network structure. S. M. Alhaj Ali, et.al. (2011) utilizes artificial neural network in the modeling of stock market exchange prices. The results finds that the use of ANN provides fast convergence; high precision, and strong forecasting ability for real stock prices which it turn will bring high return and reduce potential loss to stock brokers. Tripathy (2011) forecasting the next day’s close value of Stock price by using ANN Model and ARIMA Model in Indian Stock Market. The study finds that ANN model is very useful for predicting stock market price than the ARIMA models in India. Pete.,A.I, et al., (2012)predict the Nigerian stock market by using Artificial Neural Network and finds that artificial neural network can be used to predict future stock prices. Abbas (2012) predicts Tehran stock price using Artificial Neural Network for annual data from 2000 to 2008. The study shows that estimation and predictions of Tehran stock price with Artificial Neural Network is possible and gives stronger results.

**Data and Methodology:**
The data employed in the study consists of daily closing prices of S&P CNX Nifty Index. The required time series daily closing prices of indices have been collected for a period of 7 years from 1st January 2008 to 29th April 2014 from www.nseindia.com.

For forecasting, feed-forward with back-propagation neural network architecture has been used. These methods normally provide best results as compared to other ANN architectures. Selection of input variable for the neural network model is a critical factor for the performance of the neural network because it contains important information about the complex nonlinear structures of the data. The criticality in selecting the input variables lies in selecting the number of input variables and the lag between each. With less lag between input, the correlation between the lagged variable increases which may result in an over-fitting phenomenon. On the other hand, with increase in the lag between each input variable, the neural network may lose out essential information of input variables, resulting in under-learning. To handle with this dilemma of over fitting or under-learning and select an optimal structure, the study has considered various lagged structure (multiple lag input variable with different lag between each) and test the performance of the neural network on a trial and error basis. The input variables selected for this model are the lagged observation of the closing prices of Nifty Index. As neural networks are pattern recognizers, the quality of the data uses in the study largely influences the accuracy of the result. The input data uses in the neural network model facilitate de-trending of the data so as to facilitate proper network learning process. In order to improve the performance of the network a nonlinear scaling method is adopted. The closing price of Nifty index is scaled with linear scaling functions.

Further, if more than two hidden layers are taken, there is a chance that ANN model might create over-fitting i.e. the in-sampling error may become very low and out-sample error may go up. So the number of hidden layers is taken in our study is 2. The number of neurons in output layer is equal to the number of outputs required. In our study, there is only one output which is the estimated Nifty Returns. Hence, the number of output layers is 1. After the neural network model is constructed; training of the neural network is the next essential step of the forecasting model. The result of the training process of the network depends on the algorithm used for the purpose. The prediction is carried out by using different activation functions i.e. Sigmoid and Tan Hyperbolic functions. The predictions system predicts the next day’s value using the above closing price Nifty data. In neural network, data are normally normalized into range of (0, 1) or (-1, 1) according to the activation functions of neurons. In our paper the value of Nifty is normalized into the range of (0, 1) and networks are trained and tested using the back propagation algorithm.

Though ideal prediction in stock market is difficult one, nevertheless neural network is used to predict reasonably good prediction in number of cases. It is advisable to consider both short term (one day lag) and long-term (multi-lag) predictions to get healthier results. In one lag prediction, the next day value is expected to be based on actual past day value but on the other hand a few predicted values are also used to predict futures values.

**Artificial Neural Network Model:**

The basic structure in the human brain is called neuron. All neurons have four basic components, which are dendrites, soma, axon and synapses (connections). A neuron contains dendrites. Through dendrites neuron is able to receive signals from other cells. The axon carries outgoing signals from the cell. Where the outgoing axon meets the dendrite of another neuron, a connection is made in the form of an electrochemical device called a synapse. Basically, a
biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then output the final result. Artificial neurons are much simpler than the biological neuron. An Artificial Neural Networks process information in a similar way the human brain does.

Every ANN consists of a set of neurons and a set of connections between them. The connection between the neurons is attributed by a weight. The information sent to the neuron and multiplied by corresponding weights is added together and used as a parameter within an activation function. If these signals are sufficient, the neuron becomes activated. Each neuron takes a number of inputs and after processing with an activation function called transfer function yields a distinct output. The artificial neuron output a value based on inputs. The most commonly used transfer functions include, the hard limit, the pure linear, the sigmoid and the tan sigmoid function. Fig 1 shows a graphical representation of an artificial neuron.

Network structure with inputs \(x_1, x_2, \ldots, x_i\) are being connected to neuron \(j\) with weights \(w_{1j}, w_{2j}, \ldots, w_{ij}\) on each connection as shown in Figure 1. The neuron sums all the signals it receives then each signal is multiplied by its associated weights on the connection. This output \(h_j\) is then passed through a transfer (activation) function, \(g(h)\), that is normally non-linear to give the final output \(O_j\). The most commonly used function is the sigmoid (logistic function) because of its easily differentiable properties which is very convenient when the backpropagation algorithm is applied.

The overall input to the neuron is calculated by:

\[
\alpha = \sum_{i=0}^{n} w_i x_i
\]
Where \( x_i \) represents the inputs to the neuron and \( w_i \) represents the weights of the neuron. It signifies that the higher the weight of the connection more influence on the neuron.

In Neural Network bias plays an important role. Sometimes the threshold is called a bias value. The threshold is a real number that is subtracted from the weighted sum of the input values. So we take the bias as an input with value \(-1\) and its corresponding weight is the sum of the average of the other input weights. (where \( w_0 = \theta \) and \( x_0 = -1 \)) To normalize this sum into a standard range, functions called threshold functions, (sigmoid functions being the most widely preferred one) are used. Threshold Function is a simple function that compares the summed inputs to a constant, and depending on the result, may return a \(-1, 0, \text{ or } 1\).

The activation function \( f \) is typically of sigmoid form and may be a logistic function or hyperbolic tangent

A sigmoid function is defined

Logistic function \( f(\alpha) = \frac{1}{1 + e^{-\alpha}} \)

Hyperbolic function \( f(\alpha) = \frac{e^\alpha - e^{-\alpha}}{e^\alpha + e^{-\alpha}} \)

The Neuron Output (\( y \)): The artificial neuron computes its output according to the equation shown below. This is the result of applying the activation function to the weighted sum of its inputs, less the threshold. This value can be discrete or real depending on the activation function used. Then; the output of the neuron is defined by

\[ y = f \left( \sum_{i=0}^{n} w_i x_i - \theta \right) = f \left( \sum_{i=0}^{n} w_i x_i \right) \]

\( \theta \) is called the bias of the neuron, since \( \theta \) the bias is considered as an input, \( x_0 = -1 \) and the associated weight \( w_0 = \theta \). The quantities \( X_i \) and \( W_i \) denotes the inputs and weights respectively. It is almost always the case that a neuron output a value between \([0, 1]\) or \([-1, 1]\).

The network is composed of a large number of highly interconnected processing elements called neurones. These neurons are distributed in few hierarchical layers. Most of the neural networks are three layered: input, middle or hidden and output. Artificial neurons are arranged in these layers. Feed-forward networks were first studied by Rosenblatt (1961). Generally there is no data processing is happening at input layer. The input layer takes the inputs that feed into the network and passes to the middle layer. There are more than one middle layers/hidden layers. Hidden layers are then followed by an output layer. Artificial neurons reside in hidden layers. In middle (hidden) layer, all complexity resides and computations are made here. The results are achieved in output layers. In feed forward networks all connections are unidirectional. The layers of artificial neural network are shown in fig-2.
Machine learning approach is based on the principle of learning from training and experience so it is appealing for artificial intelligence model. ANNs are well suited for machine learning where connection weights adjusted to improve the performance of a network.

The closing price of Nifty index used as input of a traditional ANN for the training and prediction process. In training module, it involves Multilayer (MLP), random sampling of data set and the main core of this module is Back propagation Neural Network training. MLP is a feed forward Neural Network trained with error Back propagation which is a two-pass weight-learning algorithm to adjust the weights in-between nodes to reduce error of the output. The architecture of MLP is consisting of Input layer, hidden layer and output layer. During training, back propagation is the process of back propagating errors through the system from the output layer towards the input layer. It is necessary to use back propagation since hidden units have no training target value that can be used. So they must be trained based on errors from previous layers. The output layer is the only layer which has a target value for which to compare. As the errors are back propagated through the nodes, the connection weights are changed. Training occurs until the errors in the weights are sufficiently small to be accepted. It has observed from some studies that the sigmoid function works best when learning is approached towards average behavior and hyperbolic tangent function works best when learning deviation from the average.

**Performance Measurement:**

To measure the performance of the neural network model, the study used Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Normalized Mean Square Error (NMSE) and Sign Correctness Percentage (SCP). These tests are used for evaluating the prediction accuracy of the model. MAPE compute the mean error value. MAPE measure the residual errors. This normally gives an idea of the difference between the actual and predicted
value. The lower the MAPE values the better the model. The following equation shows the process to calculate the MAPE

\[
\text{MAPE} = \frac{100}{n} \left| \sum_{t=1}^{n} \frac{o_t - p_t}{o_t} \right|
\]

Where N is the total number of test data, Ot is actual stock price on day t and P t is forecast stock price on day t

The mean absolute error is an average of the absolute errors. The longer MAE means higher bias level and less accurate forecast to predict prices. But however MAE is a suitable model to predict stock market fluctuations. Smaller values of these measures shows more correctly predicted outputs.

\[
\text{MAE} = \frac{\sum_{t=1}^{n} |o_t - p_t|}{n}
\]

Where N total number of test data, Ot is actual stock price on day t and P t is forecast stock price on day t

Normalized Mean Square Error is used for evaluating the prediction accuracy of the model. The lower the value better is the model.

\[
\text{NMSE} = \frac{\sum_{t=1}^{n} (o_t - p_t)^2}{\sum_{t=1}^{n} (o_t - \bar{p})^2}
\]

Where O_t is the actual stock price of the data series, P_t is the predicted value for the same day's closing price and \( \bar{p} \) is the mean of actual value of stock price.

The correctness in predictability of the direction of the movement of the index is preferred over the correctness of the magnitude of the index. Prediction of the direction of the stock market is more important than the value of the index. If the accuracy of the direction of the prediction of the index is high and reliable, the loss in a portfolio returns can be minimized.

In order to test the performance of the direction of the predicted value of the closing of the next day's Nifty Index, Sign Correctness Percentage (SCP) is used. SCP for the sample period under study gives the percentage of correctness in the prediction of the direction of the index. The direction of change is calculated by subtracting today's price from the forecast price and determining the sign (positive or negative) of the result. The percentage of correct direction of change forecasts is corresponding to the percentage of profitable trades enabled by the ANN model.
\[ SCP = 100 \sum_{i=1}^{n} D_i \]

Where \( D_i = 1 \) if \((O_t - P_t)\) \((O_t^- - P_t^-) > 0\) or \( D_i = 0 \), otherwise

In this case, the model with the higher SCP more accurately predicts the markets' movements.

**Empirical Analysis:**
The forecasting tool ANN has been used to forecasts the Nifty Index value. To obtain forecasted value, the daily closing price is used as an input to this model. This model then automatically accustomed with the training datasets and makes forecast, given the current day’s stock prices. ANN models with different network parameters are created, trained and tested for each series is presented in table-1. For the Nifty Index, the study has run neural network simulations for 10 different cases based on data input (different lags) and the activation function (Hyperbolic tangent and Sigmoid). Since the behaviour of stock market is more random, the study has considered 5 day lag data as input for the neural network so that learning can be maximum and higher precision can be achieved.

Table-1 Prediction Performances of ANN model

<table>
<thead>
<tr>
<th>Sl No</th>
<th>Case</th>
<th>Activation Function</th>
<th>MAPE</th>
<th>MAE</th>
<th>NMSE (%)</th>
<th>Sign Correctness Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>SI No</td>
<td>One Day Lag</td>
<td>Hyperbolic Tangent</td>
<td>2.7002</td>
<td>1.315</td>
<td>0.767</td>
<td>71.33</td>
</tr>
<tr>
<td>1</td>
<td>Sigmoid</td>
<td>2.636</td>
<td>1.248</td>
<td>0.338</td>
<td>82.25</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Hyperbolic Tangent</td>
<td>2.836</td>
<td>1.379</td>
<td>2.237</td>
<td>68.03</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Two Day Lag</td>
<td>Sigmoid</td>
<td>2.393</td>
<td>1.181</td>
<td>0.798</td>
<td>74.25</td>
</tr>
<tr>
<td>4</td>
<td>Hyperbolic Tangent</td>
<td>2.414</td>
<td>1.174</td>
<td>1.589</td>
<td>71.90</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Three Day Lag</td>
<td>Sigmoid</td>
<td>2.0001</td>
<td>0.961</td>
<td>0.494</td>
<td>72.72</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
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<td></td>
<td></td>
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</tr>
</tbody>
</table>
The following fig-1 and 2 shows the MAPE, MAE, NMSE and SCP calculated for the forecast of Nifty Index value by using four forecasting techniques.

Figure 1: Prediction Performances of ANN model (Hyperbolic Tangent function)

Figure 2: Prediction Performances of ANN model (Sigmoid function)
It is observed from table-1 that error is minimised at 5-day lag for prediction. For both MAPE and MAE network models, the highest accuracies predictions are obtained with 5 day lag period for the sigmoid activation function are 1.792 and 0.889 respectively. So 5-day lag value shows better predictions for forecasting the next day’s close value of Nifty Index.

The table-1 also exhibits that the minimum value of normalised error is occurring when data for 1 day lag is used along with a sigmoid activation function. Sign correctness percentage (SCP) has been used to correctly predict the direction of movement of Nifty Index. The SCP is maximum for 1 day lag and sigmoid activation function. Thus it is observed that 1 day lag is producing the best predicted result for the Nifty Index over the 7 year data period. This shows that learning for the network is highest under 1 day lag data which is optimum to predict the future values of the Nifty Index price. The analysis indicates that 82 percent data analysis is correctly predicted by the ANN model. So it is recommend for using the sigmoid activation function when predicting the behaviour of a stock market price.

Fig-1 is showing the graphical representation of predicted and actual stock market price of ANN based stock market price prediction where back propagation algorithm is used. The results achieved in both the cases are equally accurate.

**Fig-2 Actual and Predicted Nifty Stock Index values for 2 hidden layers**

**Fig- 3 Actual and Predicted Nifty Stock Index values for 2 hidden layers**
The fig-3 and 4 depicts the prediction of Nifty stock Index value and it is observed that ANN based systems perform quite satisfactory. It is also observed that feed forward network using Back propagation is reasonable for stock market price prediction.

**Conclusion:**

This study has been undertaken with the objective of finding the best model for the prediction of Indian stock market (Nifty Index) price with Artificial Neural Network. The study has used historical prices of the index value for prediction. It is also found from the analysis that the predicted output is very close to the actual data. Among ANN models, SCP performance measures is found to be more appropriate for the prediction. The ANN model accurately predict the direction of movement with prediction rate of 82 percent in the data analysis which is quite good effects. Accurate prediction of stock market price movement is highly significant topic for investors today. It will also help to traders, investors and professionals in their decision making process of buy, sell or hold position. Since stock markets plays an important role in economy, ANN model can help to investors, professional traders to estimate the stock market price and apply the trading strategy that will help them to minimise risk and maximise profit in the stock market. Stock market are highly volatile and are affected by many interrelated economic and political factors across the globe, so the present study will provide some important input to the policy makers to take measures by using ANN model to predict the stock market. One limitations of the study is that we have used 1571 data for training purpose. Hence ANN model can give far better results if more data can be used during training. The second limitation of study is that we have only used the historic prices of the Index values for prediction. Other macro-economic factors and other international stock market data as input variables can also be used as input in order to improve the accuracy of the model

**References:**


Birol Yildiz, Abdullah Yalama, and Metin Coskun (2008), ” Forecasting the Istanbul Stock Exchange National 100 Index Using an Artificial Neural Network” *World Academy of Science, Engineering and Technology*, Vol.46, pp.35-41


M. Majumder and A. Hussian, MD (2010) “Forecasting of Indian Stock Market Index Using 
Artificial Neural Network,” nseindia.com, pp. 1-21

Prediction”, Fifth Conference of the Association of Asian-Pacific Operations Research 
Societies, 5th - 7th July, Singapore


Leandro S. Maciel, RosangelaBallini(2010),”Neural Networks Applied to stock market 
Forecasting: An Empirical Analysis, *Journal of the Brazilian Neural Network Society*, Vol. 8, 
Issue 1, pp. 3-22

dbr.shtr.org, Vol. 7, No. 2, pp. 59-69

Quig Cao, Kary B.Leggio and Marc J.Schniederjans (2005), A comparison between Fama and 
French's model and Artificial Neural Networks in Predicting the Chinese Stock 


S. M. Alhaj Ali, A. A. Abu Hammadb, M. S. Samhouria, and A. Al-Ghandoora(2011) 
“Modeling Stock Market Exchange Prices Using Artificial Neural Network: A Study of 
Amman Stock Exchange”*Jordan Journal of Mechanical and Industrial Engineering*, Volume 
5, No. 5, pp. 439 – 446

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