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Stock market forecasting in India: A statistical approach

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Abstract
Forecasting is an important task in stock markets, and it has held the attention of academics and practitioners over the last two decades. The extensive research reflects the importance of volatility in investment, security valuation, risk management, and monetary policy decision making. Predicting daily behaviour of stock market is a challenge for investors and corporate stockholders and it can help them to invest with more confident by taking risks and fluctuations into consideration. In this paper, we show the various forecast procedure like Time series Prediction Methods (Random Walk, Regression Method and ARIMA Models) and Machine Learning Method (Artificial Neural Network) to predict the future values. The performance of the models is evaluated by calculating various statistical measures like Mean Error (ME), Mean Absolute Error (MAE), Average Absolute Error (AAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Percentage Square Error (MPSE) and statistical indicators like Autocorrelation, Correlation Coefficient, Mean Absolute Deviation, Squared Correlation, Standard Deviation and compare their values and to compare the results and trends of actual and predicted values of above mentioned indices by Diebold Mariano test, Akaike's minimum final prediction error (FPE), Theil Inequality coefficient, Goodness of fit, t-test, and Mariano's test for significant difference.

Keywords: stock market, forecasting, time series, machine learning method, artificial neural network

1. Introduction

Now-a-days vast amounts of capital are traded through the Stock Markets all around the world. National economies are strongly linked and heavily influenced by the performance of their Stock Markets. The characteristic that all Stock Markets have in common is the uncertainty, which is related with their short and long term future state. This feature is undesirable for the investor but it is also unavoidable whenever the Stock Market is selected as the investment tool. The best that one can do is to try to reduce this uncertainty. Stock Market Prediction (or Forecasting) is one instrument in this process.

The Stock Market prediction task divides researchers and academics into two groups those who believe that we can devise mechanisms to predict the market and those who believe that the market is efficient and whenever new information comes up the market absorbs it by correcting itself, thus there is no space for prediction. Furthermore they believe that the Stock Market follows a Random Walk, which infers that the best prediction you can have about tomorrow's value is today's value.

2. Stock Market

Stock market is a place, whether physical or electronic, where stocks in listed companies are traded. A stock market may be a private company, a non-profit, or a publicly-traded company. A stock market provides a regulated place where brokers and companies may meet to make investments on neutral ground. The stocks are listed and traded on stock exchanges which are entities of a corporation or mutual organization specialized in the business of bringing buyers and sellers of the organizations to a listing of stocks and securities together. Participants in the stock market range from small individual stock investors to large hedge fund traders, who can be based anywhere. Their orders usually end with a professional at a stock exchange, who executes the order.

3. India as an Emerging Market Economy

The performance of India's economy over the last decade has been quite impressive. After a major economic crisis in 1991, the Government of India initiated bold reform measures and consequently the economy started experiencing a rapid economic growth rate and inflow of increasing foreign investment [1]. India was the fourth largest economy in the world after the USA, China and Japan and also the second largest among emerging market economies in terms of gross domestic product (GDP) based on purchasing power parity. Apart from India's success in terms of high growth rates, an important factor necessary for the sustenance of economic growth is high gross domestic savings and consequently high gross domestic capital formation. India is also in a strong position as far as foreign exchange reserve is concerned. Thus, although India continues to maintain strong levels of economic performances, it has a long way to go to achieve significant improvements in terms of such social indicators [2].

India officially liberalized its stock market on November 11, 1992, when it first allowed foreign investors to invest in its stock market [3, 4]. Since the opening up of the Indian equity markets to foreigners, foreign institutional investment (FII) flows have grown substantially. During the same period, foreign direct investment has also increased. Although there is some debate over inherent vulnerabilities with FII flows and their destabilizing effects on equity and foreign exchange markets, it cannot be ignored that India is increasingly becoming an attractive destination to the global investors.

4. Significant Development in the Field of Stock Market Prediction in India

The first study on predictability in the Indian stock market is due to Poshakwale (1996). Based on runs test and tests for serial correlation, he found evidence of violation of weak-form efficiency in Bombay Stock Exchange over the period 1987-1994. In a subsequent study, Gupta and Gupta (1997) re-examined the random walk model in the Indian stock market using data for the period July 1988 to January 1996, and came to the conclusion that the findings were not supportive of the random walk hypothesis. Bhaumik (1997), however, found evidence of market efficiency, although in a very limited framework of analysis. It may be noted that all these studies have mainly used the traditional tests in their efficiency studies and to that extent the scopes of these findings are rather limited. Two other studies on market efficiency in the Indian stock market are due to Basu and Morey (1998) and Kawakatsu and Morey (1999). Although their common objective was to find the effect of economic liberalisation on the efficiency of Indian stock market, their analyses are relevant from the standpoint of market efficiency also. Applying variance ratio test on the monthly all-India share price index data spanning the period July 1987 to October 1996, Basu and Morey found that the aggregate equity prices show signs of being efficient since the mid-1980. Kawakatsu and Morey, on the other hand, found little evidence that liberalisation has changed the behaviour of Indian stock indices. To the best of our knowledge, the most recent work on efficiency/predictability has been done by Poshakwale in 2002, by applying the BDS test (Brock *et al*. 1996) for nonlinearity. Poshakwale (2002) has examined the random walk hypothesis by testing nonlinear dependence using both individual stock prices and equally weighted portfolio of 100 stocks for the period January 1, 1990 to November 30, 1998.

There are also a few studies, although limited in their scopes, focussing on the presence of "seasonal" effects on the Indian stock returns. These studies by Chan *et al*. (1996), Wood and Poshakwale (1997), Choudhury (2000), Bhole and Pattanaik (2002) and Bhattacharya *et al*. (2003) have found evidence of the day-of-the week effect in the returns on Indian stock indices.

5. Objective of the Study

Main objective of the study is to develop models for forecasting the daily, weekly, monthly, quarterly and yearly stock returns of Bombay Stock Exchange and National Stock Exchange. The data is sourced from official website of Bombay Stock Exchange, National Stock Exchange, Reserve Bank of India and Security and Exchange Board of India. In the study Random Walk, Regression Method, Artificial Neural Network and Autoregressive Integrated Moving Average are developed and discussed.

6. Methodology used in Prediction of the Stock Market

Before having any further discussion about the prediction of the market we define the task in a formal way. "Given a sample of N example $\{(x_i, y_i)\ i = 1,2, \ldots .N\}$ where $f(x_i) = y_i$return a function g that approximates f in the sense that the norm of the error vector $E = (e_1, e_2, \ldots ..e_N)$ is minimized. Each $e_i$is defined as $e_i = e(g(x_i), y_i)$ where e is an arbitrary error function".

In other words the definition above shows that to predict the market you should search historic data and find relationships among these data and the value of the market. Then try to exploit these relationships we found in future situations.

Prediction Method

The prediction of the market is without doubt an interesting task. In the literature there are several methods applied to accomplish this task. These methods use various approaches, ranging from highly informal ways (e.g. the study of a chart with the Fluctuation of the market) in more formal ways (e.g. Linear or non-linear regressions). We have categorized these techniques as follows:

- Time Series Prediction Methods;
- Machine Learning Methods.

The criterion to this categorization is the type of tools and the type of data that each method is used to predict the market. What is common to these techniques are that they are used to predict and thus benefit from the market's future behaviour.

6.1. Time Series Prediction Methods

The Time Series Prediction Method analyses historic data and attempts to approximate future values of a time series as a linear combination of these historical data [5]. Various types of time series methods used in stock forecasting are as follows:

6.1.1. Random Walk

The stock market price changes have the same distribution and these are independent of each other. The stock prices are fluctuating and the financial status of a gambler can be modelled as random walk. This will serve as a fundamental model for the recorded of stochastic activity [6]. In stock market theory, stock market efficiency suggest that stock price in corporate all relevant information when the information is readily available and widely disseminated, which implies that there is no systematic way to exploit trading opportunity and acquire excess profits [7]. In other words, stock prices follow a random walk which holds the stock price changes are independent of one another.

Consider $R_t = Log\left(\frac{l_t}{l_{t-1}}\right)$

Where, R_t: Daily stock returns

l_t: Daily closing sensex at time't'

The PP (Phillips-Perron) method estimates the non-argumented DF test equation:

$$\Delta R_t = \alpha R_{t-1} + x_t \delta + \varepsilon_t \ \ and \ \ \alpha = \rho - 1$$

Where, R_t: Monthly compounded rate of return calculated on the basis of monthly stock price indices

x_t: Optional exogenous regressors which may consists of constants, or a constant and trend

ε_t: White noise

$\alpha \ and \ \delta$: Parameters to be estimated

The null and alternative hypothesis of this test is

$$H_0: \alpha = 0 \ and \ H_1: \alpha < 0$$

The null hypothesis that the time series is non-stationary is rejected when test statistic is more negative than the critical value at a given level of significance.

The KPSS (Kwiatkowski, Phillips, Schmidt and Shin) test assumes trend stationary time R_t under the null hypothesis. The KPSS statistic is based on the residual from the OLS regression of R_t on the exogenous variable $x_t: R_t = x_t\delta + u_t$.

The KPSS attempts to test the null hypothesis that the series is stationary against the alternative hypothesis of non-stationary. And this null hypothesis is accepted if the test statistic is less than the critical value; otherwise rejected.

The study regress current stock returns (R_t) on past stock return (R_{t-1}) by formulating the regression model of stock returns with a constant term and a term of past returns so as to examine the mean returning behaviour of stock prices. Such a regression model is: $R_t = \beta_0 + \beta_1 R_{t-1} + \varepsilon_t$. This model will exhibit mean reversion of stock prices if the slope coefficient is negative [8].

6.1.2. Regression Method

In econometrics there are two basic types of time series forecasting: univariate (simple regression) and multivariate (multivariate regression). These types of regression models are the most common tools used in econometrics to predict time series. The way they are applied in practice is that first a set of factors that influence (or more specific is presumed that influence) the series under prediction is formed. These factors are the explanatory variables x_i of the prediction model. Then a mapping between their values x_{it} and the values of the time series y_t(y is the tobe explained variable) is done, so that pairs $\{x_{it}, y_t\}$ are formed. These pairs are used to define the importance of each explanatory variable in the formulation of the explained variable. In other words the linear combination of x_i that approximates in an optimum way y is defined. Univariate models are based on one explanatory variable $(i = 1)$ while multivariate models use more than one variable $(i > 1)$ [9].

Let us suppose that in the bivariate distribution $(x_i, y_i); i = 1,2, \dots \dots n; Y$ is dependent variable and X is independent variable. Let the line of regression of $on\ X\ be\ Y = a + bX$.

According to the principle of least square, the normal equation for a and b are

$$\sum_{i=1}^{n} y_i = na + b\sum_{i=1}^{n} x_i$$

$$\sum_{i=1}^{n} x_i y_i = a\sum_{i=1}^{n} x_i + b\sum_{i=1}^{n} {x_i}^2$$

Solving these above equations, we get

$$a = \bar{y} - b\bar{x}$$

$$b = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sum_{i=1}^{n} {x_i}^2 - (\sum_{i=1}^{n} x_i)^2}$$

Consider the standard linear regression model [10]

$$y = X\beta + Z\gamma + \varepsilon$$

Where $y\ (n \times 1)$ is the vector of observations, $X\ (n \times k)$ and $Z\ (n \times m)$ are matrices of nonrandom regressors, $\varepsilon\ (n \times 1)$ is a random vector of unobservable disturbances, and $\beta\ (k \times 1)$ and $\gamma\ (m \times 1)$ are unknown nonrandom parameter vectors [11]. Assume that, $k \geq 1, m \geq 1, n - k - m \geq 1$, that the design matrix (X: Z) has full column rank k+m, and that the disturbances $\varepsilon_1, \varepsilon_2, \dots \dots \dots \varepsilon_n$ are i.i.d., $N(0, \sigma^2)^2$.

The reason for distinguishing between X and Z is that X contains explanatory variables, while Z contains additional explanatory variables of which are less certain. Now define the matrices

$M = I_n X(X'X)^{-1}X'$ And

$Q = (X'X)^{-1}X'Z(Z'MZ)^{-1/2}$

And the normalized parameter vector $\theta = (Z'MZ)^{1/2}\gamma$, the least-squares estimators of β and γ

Are $b_u = b_r - Q\hat{\theta}$ and $\hat{\gamma} = (Z'MZ)^{-1/2}\hat{\theta}$, where $b_r = (X'X)^{-1}X'y$ and $\hat{\theta} = (Z'MZ)^{-1/2}Z'My$.

The subscripts 'u' and 'r' denote 'unrestricted' and 'restricted' with $\gamma = 0$ respectively. Whereas $\hat{\theta} \sim N(\theta, \sigma^2 I_m)$ and that b_r and $\hat{\theta}$ are independently distributed.

Let S_i be an $m \times r_i$ selection matrix of rank $r_i (0 \leq r_i \leq m)$, so that $S_i{}' = (I_{r_i} : O)$ or a column permutation thereof. The equation $S_i{}'\gamma = 0$ thus selects a subset of the γ's to be equal to zero. The least square estimators of β and γ under the restriction $S_i{}'\gamma = 0$ are given by

$$b_{(i)} = b_r - QW_i\hat{\theta}$$

$$c_{(i)} = (Z'MZ)^{-1/2}W_i\hat{\theta}$$

Where

$$W_i = I_m - (Z'MZ)^{-1/2}S_i\left(S_i{}'(Z'MZ)^{-1}S_i\right)^{-1}S_i{}'(Z'MZ)^{-1/2}$$

is a symmetric idempotent $m \times m$ matrix of rank $m - r_i$. If $r_i = 0$ then $W_i = I_m$. The distribution of $b_{(i)}$ is given by

$$b_{(i)} \sim N\left(\beta + Q(I_m - W_i)\theta, \sigma^2((X'X)^{-1} + QW_iQ')\right)$$

There are 2^m different models to consider, one for each subset of $\gamma_1, \gamma_2, \dots \dots \dots \gamma_m$ set equal to zero. A pretest estimator of β is obtained by first selecting one of these models by using t- or F-test and then estimating β in the selected model.

6.1.3. ARIMA Model

Most of econometric modelling are based on univariate time series methods like auto regressive moving average

(ARMA) as ARMA is a suitable model for the stationary time series data, although most of the software uses least square estimation which requires stationary [12, 13]. To overcome this problem and to allow ARMA model to handle non-stationary data, the Auto-regressive Integrated Moving Average (ARIMA) separate a non-stationary series one or more times until the time series becomes stationary, and then find the fit model. This model is popularized by George Box and Gwilym Jenkins in 1970s [14]. There are a large number of ARIMA models; generally ARIMA (p, q, d) where: P: order of autoregressive part (AR)
d: degree of first differentiation (I) and
q: order of the first moving part (MA).
If there is no differencing been done (d = 0), Then ARMA model can be got from ARIMA model. The general mathematical ARIMA model can be defined as [15]:

$$W_t = \mu + \frac{\beta(v)}{\varepsilon(v)} a_t$$

Where ε: Indexes time
W_t: The response series Y_t, or a difference of response series
μ: The mean term
v: The backshift operator; that is $vX_t = X_{t-1}$
$\varepsilon(v)$: The auto-regressive operator, represented as polynomial in the backshift operator:

$$\varepsilon(v) = 1 - \varepsilon_1(v) - \cdots \ldots\ldots. -\varepsilon_p v^p$$

$\beta(v)$: The moving-average operator, represented as polynomial in the backshift operator:

$$\beta(v) = 1 - \beta_1(v) - \cdots \ldots\ldots. -\beta_p v^p$$

a_t: The independent disturbances, also called the random error.

6.2. Machine Learning Method

Machine learning is a process that begins with the identification of the learning domain and ends with testing and using the results of the learning. It will be useful to start with an overview of how a machine learning system is developed, trained, and tested. The key parts of this process is the "learning domain," the "training set," the "learning system," and "testing" the results of the learning process [16]. All these methods use a set of samples to generate an approximation of the underlying function that generated the data. The aim is to draw conclusions from these samples in such a way that when unseen data are presented to a model it is possible to infer to the explained variable from these data. Two types of analysis are involved in machine learning method. They are:

6.2.1. Fundamental Analysis

Fundamental analysis mainly depends on statistical data of a company. It include audit report, financial status of the company, the quarterly balance sheets, the dividend and policies of companies whole stock are to be observed. It also include sales data, strength and investment of company, plant capacity, the competition, import and export volume, production indexes, price statistics and daily news about the company. Along with these parameter other parameters like book value, price-earnings ratio, earnings, return on investment, inflation, interest rate, net profit margin of a company, etc. are important factor of future business conditions.

6.2.2. Technical Analysis

In stock market analysis there is two approaches. First approach include analysis of graphs, where analyst try to find out certain pattern that are followed by stock, but this approach is very difficult and very complex to be used with Artificial Neural Network (ANN). In second approach analyst make use of quantities parameters like trend indicators, daily ups and downs, highest and lowest value of a day, volume of stock, indices, put/call ratio, etc. Analyst tries to find out some mathematical formula which cam map these input to the desired output. As compared to previous approach this is easy for ANN.

Artificial Neural Network

The artificial neural network is simplified models of the biological neuron system, is a massively parallel distributed processing system made up of highly interconnected neural computing elements that can learn and thereby acquire knowledge and make it available for use [17]. The artificial neural network learns by example. They can therefore be trained with known examples of a problem to acquire knowledge about it. Once appropriately trained, the network can be put to effective use in solving unknown or untrained instances of the problem.

Neuron

A neuron is a processing unit that takes several inputs and gives a distinct output. The Figure – 1, below depicts a single neuron with R inputs $p_1, p_2, \ldots \ldots p_R$, each input is weighted with a value $w_{11}, w_{12}, \ldots . . w_{1R}$ and the output of the neuron an equal to $f(w_{11}p_1 + w_{12}p_2 + \cdots \ldots\ldots + w_{1R}p_R)$.

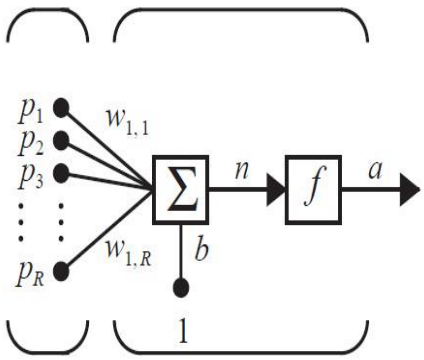

Fig 1: A simple neuron with R-input

Each neuron apart from the number of its input is characterized by thefunction f known as a transfer function. The most commonly used transfer functions are the hard-limit, the pure linear, the sigmoid and the tans sigmoid function Table 1shows. The preferences on these functions derive from their characteristics. Hard-limit maps any value that belongs with $(-\infty, +\infty)$ into two distinct values {0, 1}, thus it is preferred for networks that perform classification tasks (multiplayer perceptron MLP). Sigmoid and tans-sigmoid, known as squashing functions, map any value from $(-,+\infty)$ to the intervals [0, 1] and [1, 1] respectively. Lastly purelinear is used due to its ability to return any real value and is mostly used at the neurons that are related to the output of the network in Table - 1 [18].

Table 1: The most commonly used transfer functions

Hard-limit Trans-sigmoid	Pure-linear	Sigmoid
$f(x) = \{1, x \geq 0\ ; 0, x < 0$ $f(x) = x$	$f(x) = \frac{1}{1+e^{-x}}$	$f(x) = \frac{2}{1+e^{-2x}} - 1$
$f(x) \in \{0,1\}$ $f(x) \in \{-\infty, +\infty\}$	$f(x) \in [0,1]$	$f(x) \in [-1,1]$

Layer

Figure-2 presents the Artificial Neural network is defined as data processing system consisting of many of simple highly interconnected processing elements (artificial neurons) is an architecture inspired by the structure of the cerebral cortex of the brain. Each network has got exactly one input layer, zero or more hidden layers and one output layer. All of them apart from the input layer consist of neuron. The number of inputs to the Artificial Neural Networks equal to the dimension of our input samples Figure-2 shows, while the number of the outputs we want from the Artificial Neural Networks define the number of neurons in the output layer.

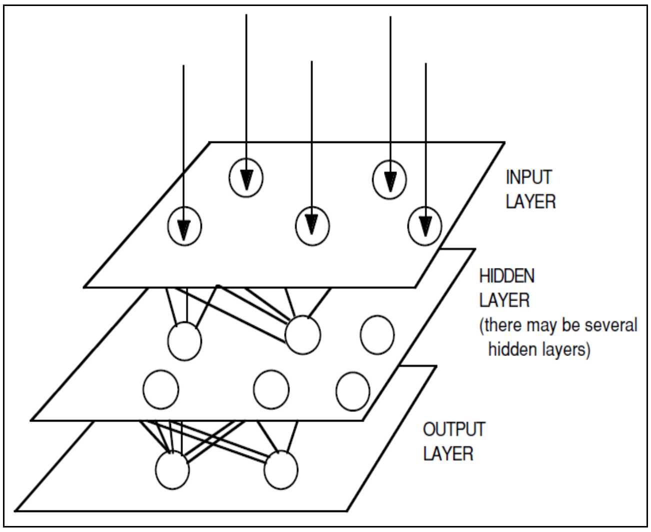

Fig 2: Neural Network Diagram

The mass of hidden layers as well as the mass of neurons in each hidden layer is proportional to the ability of the network to approximate more complicated functions. Of course this does not infer by any means that networks with complicated structures will always perform better. The reason for this is that the more complicated a network is the more sensitive it becomes to noise or else, it is easier to learn apart from the underlying function the noise that exists in the input data. Therefore clearly there is a trade-off between the representational power of a network and the noise it will incorporate.

Weight

The weights used on the connections among different layers have much significance in the working of the Artificial Neural Networks and the characterization of a network. The procedure of adjusting the weights of a Artificial Neural Networks based on a specific dataset is referred as the training of the network on that set (training set). The basic idea behind training is that the network will be adjusted in a way that will be able to learn the patterns that lie in the training set. Using the adjusted network in future situations (unseen data) it will be able based on the patterns that learned to generalize giving us the ability to make inferences. In this case the Artificial Neural Network model on a part of our time series (training set) and we will measure their ability to generalize on the remaining part (test set). The size of the test set is usually selected to be 10% of the available samples [19]. Each sample consists of two parts the input and the target path is called supervised learning. Initially the weights of the network is assigned random values (usually within [–1, 1]). Then the input part of the first sample is presented to the network. The network computes an output based on: the values of its weights, the number of its layers and the type and mass of neurons per layer.

Training Algorithm

The mechanisms of weights update are known as training algorithm. The algorithms described here are related to feed-forward networks. Artificial Neural Networks are characterized as feed-forward network if it is possible to attach successive numbers of the inputs and to all the hidden and output units such that each unit only receives connections from inputs or units having a smaller number [20]. All these algorithms use the gradient of the cost function to determine how to adjust the weights to minimize the cost function. The gradient is determined using a technique called back propagation, which involves performing computations backwards through the network.

Gradient Descent

The weights of a feed forward network are updated using the back propagation gradient descent algorithm. The following description is related to the incremental training mode.

If $\underline{E_N}$ is the value of error function of the sample N and $\vec{w}$ the vector with all the weights of the network then the gradient of E_N w.r.t $\vec{w}$ is

$$\nabla E_N(\vec{w}) = \left[\frac{\partial E_N}{\partial w_{11}}, \frac{\partial E_N}{\partial w_{12}}, \ldots\ldots, \frac{\partial E_N}{\partial w_{mn}}\right]$$

Where w_{ji} is the weight that is related with the neuron j and its input i. When interpreted as a vector in weight space, the gradient specifies the direction that produces the steepest increase in E_N. The negative of this vector therefore gives the direction of the steepest decrease. Based on this concept the updated weights of this network according to

$$\overrightarrow{w'} = \vec{w} + \overrightarrow{Aw}$$
$$\overrightarrow{Aw} = -\varsigma \nabla E_N(\vec{w})$$

Here ς is a positive constants called the learning rate, the greater ς is the greater the change in $\vec{w}$

x_{ji} : i -th input of unit j presuming that each neuron is assigns a number successively.

w_{ji} : weighted associated with the i -th input to neuron j
$net_j = \sum_i w_{ji} x_{ji}$: The weighted sum of inputs of neuron j
$a_j{}'$: The output computed by node j
t_j: The target of output unit j
o' : The sigmoid function
Outputs, the set of nodes in the final layer of the network. Downstream (j), the set of neurons whose immediate input include the output of neuron j.

Parameter Setting
The properties related to a neuron is the transfer function it uses as well as the way it processes its inputs before feeding them to the transfer function. The Artificial Neural Networks we will create use neurons that pre-process the input data as follow, If $x_1, x_2, \ldots\ldots x_N$are the inputs to the neuron and $w_1, w_2, \ldots\ldots w_N$ their weights the value fed to the transfer function would be $\sum_{i=1}^{N} x_i w_i$.
The neurons in the output layer will use the pure linear function while the neurons in the hidden layer the tan-sigmoid function. We select the tans-sigmoid and not the sigmoid since the excess return time series contains values in [–1, 1], thus the representational abilities of a tans-sigmoid function fit in a better way the series we attempt to predict comparable to those of the sigmoid's.

7. Conclusion
Research investigation and their analysis is the part of a wider development of any nation with regard to finance, education, public health, and agriculture, etc. that are indicators of better life of human beings. Any social phenomenon and especially those that can be characterized by numerical facts are the results of one or more causes of action. The concept of models is simplified to describe the complex economic, social, biological etc. processes. In this paper, the performance of the models by calculating various statistical measures like Mean Error (ME), Mean Absolute Error (MAE), Average Absolute Error (AAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Percentage Square Error (MPSE) and statistical indicators like Autocorrelation, correlation Coefficient, Mean Absolute Deviation, Squared Correlation, Standard Deviation and compare their values and to compare the results and trends of actual and predicted values of above mentioned indices by Diebold Mariano test, Akaike's minimum final prediction error (FPE), Theil Inequality coefficient, Goodness of fit, t-test, and Mariano's test for significant difference.

8. References

1. Reserve Bank of India. http://www.rbi.org.in.
2. National Stock Exchange of India, http://www.nseindia.com/content/us/fact2011_sec1.pdf.
3. Bekaert G, Harvey CR. Foreign Speculators and Emerging Equity Markets. Journal of Finance. 2000; 55:565-613.
4. Kim EH, Singal V. Stock Market Openings: Experience of Emerging Economies. Journal of Business. 2000; 73:25-66.
5. Maddala GS. Introduction to Econometrics. 1st Edition, Macmillan Publishing Company, New York, 1992.
6. Wang Yi-Fan, Cheng Shihmin, Hsu Mei-Hua. Incorporating the Markov Chain Concepts into Fuzzy Stochastic Prediction of Stock Indexes. Applied Soft Computing, 2010, 613-617.
7. Fama EF. Efficient Capital Market: A Review of Theory and Empirical work. Journal of Finance. 1970; 25:383-417.
8. Mishra PK, Pradhan BB. Capital Market Efficiency and Financial Innovation – A Prespective Analysis. The Research Network. 2009; 4:1-5.
9. Pesaran HM, Timmermann A. Forecasting Stock Returns: An Examination of Stock Market Trading in the Presence of Transaction Costs. Journal of Forecasting. 1994; 13:335-367.
10. Magnus JR, Durbin J. Estimation of Regression Coefficients of Interest when other Regression Coefficients are of no Interest. Econometrica. 1999; 67:639-643.
11. Abadir KM, Magnus JR. Notation in Econometrics: A Proposal for a Standard. The Econometrics Journal. 2002; 5:76-90.
12. Swider DJ, Weber C. Extended ARMA Models for Estimating Price Developments on day ahead Electricity Markets. Electric Power Systems Research. 2007; 77:583-593.
13. Contreras J, Espinola R, Nogales FR, Conejo AJ. ARIMA Models to Predict next day Electricity Prices. IEEE Transactions on Power Systems. 2005; 18:1014-1020.
14. Box GEP, Jenkins GM. Time Series Analysis: Forecasting and Control. San Francisco, 1970.
15. SAS/ETS® 9.22 User's Guide, SAS Institute Inc, 2010.
16. Michalski RS, Tecuci G. Machine Learning: A Multistrategy Approach. Morgan Kaufmann and Waitham, 1994.
17. Hu MJC. Application of the Adaline System to Weather Forecasting. Master Thesis. Technical Report. Stanford Electronic Laboratories, Stanford, CA, 1964.
18. Demuth H, Beale M. Neural Network Toolbox: For Use with Matlab. 4th Edition. The Math Works Inc. Na-tick, 1997.
19. Mitchell MT. Machine Learning. 1st Edition. The McGraw-Hill Companies, New York, 1997.
20. Bishop MC. Neural Networks for Pattern Recognition. Oxford University Press. New York, 1996.