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Application of Ensemble Machine Learning in the Predictive Data Analytics of Indian Stock Market

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Abstract

The world of today is high frequency data driven and characterized by the application and use of information technology for better business development and decision making. The price movements of stock markets are mainly influenced by micro and macro economic variables, legal framework and taxation policies of the respective economies. The crux of the issue lies in exactly forecasting the future stock price movements of individual firms, based on historical or past prices. Achieving the accuracy for forecasting the market trend has become difficult due to the prevalence of stochastic behavior in the stock market and volatility in the stock prices. This paper analyses the stochasticity of movement pattern of the most volatile, fifty company stocks (in terms of market capitalization) of NSE-Nifty, using ensemble machine learning method. The findings of the study would help the investors, to make rational and well informed investment decisions, to optimize the stock returns by investing in the most valuable stocks.

Keywords

Behavioral finance; Business intelligence; Data science; Ensemble machine learning; Predictive analytics; Stochastic movement of stock markets

Introduction

The efficient market hypothesis denotes that it is not possible to exactly predict the stock prices of companies, due to the existence of random walk behavior, in the stock markets (Fama, 1970). Movements of stock prices and stock indices are mainly influenced by many macro-economic variables, such as political events, business policies of the corporate enterprises, general economic conditions, bank rate and loan rates and changes in foreign exchange rates, investors' expectations, investors' choices, investors' perception and the human psychology of stock market investors (Miao et al., 2007).

Supervised Learning Algorithms perform the task of searching through a hypothesis. To evaluate the prediction of an ensemble typically requires more computation than evaluating the prediction of a single model. Ensemble methods use multiple learning algorithms to obtain better predictive performance. Eric Siegel (2016) emphasized that a little prediction goes a long way. Forecasting the movement of stock price of a company is a classic problem. Stock market transactions, across the Globe, are voluminous and volatile. Prediction of stock price movements, in the long run, is increasingly difficult due to the prevalence of an element of uncertainties involved with the probable future outcomes.

If the information obtained relating to the stock prices is pre-processed efficiently, the forecasting would become more accurate and reliable. Since the stock price movement is stochastic, non-stationary and non-linear in nature, the volatility widely persists in the stock prices and index movements. At a particular point of time, there could be trends, cycles and random walk or a combination of these three cases/events, in respect of stock market movements (Snigaroff & Wroblewski, 2011). The closing value of the stock index has been used, as one of the important statistical data, to derive useful information about the current and probable future movement pattern of stock markets (Zhang, et al., 2005). One of the variants of Deep Learning Model, i.e., Ensemble Machine Learning Method, could forecast the future trend of stock prices and it provides stock information signs, for taking better investment decision of buying and selling of stocks, by the investors (Patel, et al., 2015_a, 2015_b). Hence Ensemble Machine Learning Approach was applied in this study, to forecast the fifty future prices of company stocks.

Review of Literature

An extensive review of literature, in the area of forecasting of stock prices, has been done to find the research gap and to get an idea of predictive analytics of financial markets. Wang and Leu (1996) predicted stock price trend for six weeks, based on past four years stock price movements of Taiwan stock market, by using recurrent neural network. Kohzadi et al. (1996) described the methodology, advantages and demerits of artificial neural network and used time series models to forecast the highly volatile commodity markets. The mean squared error, absolute error, and mean absolute percentage error were all lower, on an average, for the neural network approach than for the time series models like Auto Regressive Integrated Moving Average. Vapnik (1998) developed the Support Vector Machine algorithm and applied the same in forecasting the financial markets. Walczak (1999) forecasted the fluctuations in financial markets, which varied across the time periods and the rate of financial literacy was considered as one of the crucial factors, which influenced the investment decisions of the investors.

Abraham, Nath and Mahanti (2001) applied neuro-fuzzy system for forecasting the stock prices of next day and the stock index movements of Nasdaq-100 of United States of America. It was found that the probabilistic neural network based investment strategies performed better than the other predictive models. Kim (2003) used twelve technical indicators, to make forecasting of daily stock price changes of Korea Composite Stock Price Index. Simulation results of Shanghai Composite Index showed that neural networks could be applied to maximize the returns of stock market investment (Zhang, et al., 2005). Also, an investigation was made to find out the forecasting capability of the weekly movement pattern of Nikkei-225, one of the premier stock indices of Japan. Kuo (2006) classified the networks into linear, passive, reciprocal, causal and time invariant and each one of the network approaches has different characteristic properties accordingly. Jasic and Wood (2006) calculated the profitability of stock indices, based on daily trades, by applying neural network for the highly volatile stock index movements of S&P 500, the DAX, the TOPIX and the FTSE.

Hassan, Nath and Kirley (2007) used a fusion model, by combining Hidden Markov Model, Artificial Neural Network and Genetic Algorithms, to forecast the stochastic financial market behavior. According to Kwon and Moon (2007), the prediction of financial objects, was a challenging task and the profits for such investments, were quite sensitive to transaction costs. Carvalhal and de Melo Mendes (2008) analyzed the forecasting performance of stock returns of emerging market stocks. Zhu et al. (2008) explained the technicalities of forecasting the stock index movements, by using different neural networks, the role and influence of trading volume, under different time horizons of various stock market indices like DJIA and STI. Ou and Wang (2009) used ten different data mining techniques, in order to forecast the stock price movements of Hang Seng index of Hong Kong stock market.

According to Hanson and Oprea (2009), the novelty, complexity and anonymity influenced the forecasting of the stock markets. Boyacioglu and Avci (2010) forecasted the returns on stock index value of the Istanbul Stock Exchange (ISE), with the help of Adaptive Network-Based Fuzzy Inference System (ANFIS). The experimental results revealed that the model successfully forecasted the monthly return of ISE National 100 Index, with an accuracy rate of 98.3 percent.

Nair et al. (2011) forecasted the closing value of next day for five international stock indices, using an adaptive artificial neural network system. Chakravarty and Dash (2012) found that the volatility persisted in the financial time series, due to both economic and non-economic factors. Simon and Raoot (2012) applied appropriate number of hidden layers, number of neurons in each layer, size of the training set, initial values for weights, inputs to be included, activation function, which are the key issues in designing a network model. Patel et al., (2015a) predicted the movements of NSE-Nifty, NSE-Nifty, Reliance Industries and Infosys Limited, using four predictive models, namely artificial neural network, support vector machine, random forest and naïve-bayes and the respective values were compared in a group. Sigo et al. (2017) found that the forecasting accuracy was higher in the case of k-nn algorithm model than that of logistic regression method. Sigo et al. (2018_b) applied the technical indicators and forecasted the stock index trends of NSE-Nifty and NSE-Nifty of India, in pre and post-global crisis (2008) time zones. Sigo et al. (2018_c) applied Artificial Neural Network, to forecast the stock prices of Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited.

A few research studies do exist relating to the prediction of Indian stock markets using machine learning methods. Based on the above reviews, the researcher applied one of the deep learning methods, namely ensemble machine learning approach, to forecast the future stock prices of Indian stock market.

Statement of the Problem

In general, the investors find it difficult to forecast the movements of stock price, since it is highly stochastic and volatile in nature. If an investor closely observes and analyzes the stock price movements, rationally and consistently, such investors could have earned more returns by way of capital appreciation. It is normal that the investors buy a stock, at a low market price and sell it at high market prices, thereby earning the returns hugely in the stock market. Only such intelligent investors would become wealthy. On the flip side, the investors, who do not practice it, would probably miss their fortunes. Hence the forecasting of stock prices is a herculean task, in highly growing economies like India, since only a few research studies exist. Market intelligence and financial literacy are the two essential inputs to be considered, by the investors for investment decisions. Lack of these attributes, among the financial investors, would lead to inconsistency and inaccuracy in market forecasting, which would eventually lead to losses in stock market investments (Seigel, 2016). The financial system develops and suggests some techniques, for the investors, to forecast the stock prices. But, there is no proven prediction technique is available for the investors, which increases the magnitude and severity of this issue. Hence this study was undertaken.

Need of the Study

The uncertainties did exist in predicting the stock market trends, especially stock price movements. It is imperative to ensure a high degree of predictive ability and accuracy, for both short term and long term view. To maximize the returns for investments in stocks, trade-off between risk and return as well as sensitivity to the stock price movements, is essential. This study would help a spectrum of investors (retail investors, financial institutions, mutual funds, investment banks and the foreign institutional investors) to take well-informed investment decisions, based on scientific thinking and rational approach (Etzioni, 1976; Sigo et al., $2018_{a,}$ $2018_{b,}$ 2018_{c}; Kathiravan et al., 2018, 2019_{a}, 2019_{b}; Sankarkumar, 2017). Absence of prudent forecasting methods, lower level of financial literacy (Sigo et al., 2018_{a}) and availability of alternate investment avenues reiterated the need for the study of this kind, in the present context, in India.

Objective of the Study

The objective of this study is to forecast the future direction of the stock price movements of fifty companies indexed in NSE-Nifty, using Ensemble Machine Learning Method.

Hypotheses of the Study

NH-1: There exists no stochastic trend between the stock prices of fifty companies indexed in NSE-Nifty during the global pre-crisis period.

NH-2: There exists no variation between actual and predicted stock price values of fifty companies indexed in NSE-Nifty during the global pre-crisis period.

NH-3: There exists no stochastic trend between the stock prices of fifty companies indexed in NSE-Nifty during the global post-crisis period.

NH-4: There exists no variation between actual and predicted stock price values of fifty companies indexed in NSE-Nifty during the global post-crisis period.

Materials and Methods

7.1. Sampling Design of the Study

The sample consisted, the stock prices of fifty companies of NSE-Nifty, based on the top value in its free-float market capitalization, as on 01^{st} January 2019. Those 30 sample companies are Asian Paints Limited, Axis Bank Limited, Bajaj Auto Limited, Bajaj Finance Limited, Bharti

Airtel Limited, Coal India Limited, HCL Technologies Limited, HDFC Limited, HDFC Bank Limited, Hero MotoCorp Limited, Hindustan Unilever Limited, ICICI Bank Limited, Indusind Bank Limited, Infosys Limited, ITC Limited, Kotak Mahindra Bank Limited, Larsen & Toubro Limited, Mahindra & Mahindra Limited, Maruti Suzuki India Limited, NTPC Limited, Oil & Natural Gas Corporation Limited, Powergrid Corporation of India Limited, Reliance Industries Limited, State Bank of India, Sun Pharmaceutical Industries Limited, Tata Motors Limited, Tata Steel Limited, Tata Consultancy Services Limited, Vedanta Limited, and Yes Bank Limited (www.nseindia.com). Hence the stocks of those fifty companies were taken, as sample units, for this study.

7.2. Sources of Data

The secondary data of the four types of daily prices (opening price, high price, low price, and closing price) of fifty companies of NSE-Nifty were collected from the websites of National Stock Exchange of India Limited.

7.3. Study Period

A period of twenty years (from 01st January 1999 to 31st December 2018) was considered for the study.

7.4. Statistical Tools Used

To forecast the stock price trends of fifty companies of NSE-Nifty, the statistical tools, SPSS (version 20.0) and Neural Works Predict (version 3.24), were used in the study.

8. Forecasting the Future Trends of Stock Prices in India

The analysis of stock prices prediction of fifty companies indexed in NSE-Nifty, are presented as follows:

a) Prediction Performance of NSE-Nifty Companies using Ensemble Machine Learning Method during the pre-crisis period from 1999 to 2008
b) Prediction Performance of NSE-Nifty Companies using Ensemble Machine Learning Method during the post-crisis period from 2009 to 2018.

8. a) Prediction Performance of NSE-Nifty Indexed Companies using Ensemble Machine Learning Method during the pre-crisis period from 1999 to 2008

The holistic view of the stock price trends for fifty companies included in NSE-Nifty, during the pre-crisis period from 2009 to 2018 is presented in Table 1.

It is evident that the R-value (Actual) was recorded for Bharat Petroleum Corporation Limited at 0.7673 (Minimum), followed by Bajaj Auto Limited at 0.9977(Maximum) while the Predicted R-values ranged between 0.7504 (Eicher Motors Limited) and 0.9975 (Asian Paints Limited), among Nifty companies, during the pre-crisis period from 2009 to 2018.

The Net-R values (Actual) ranged between 0.7955 (the Minimum for Eicher Motors Limited), and 0.9954 (the Maximum for Bajaj Finance Limited), whereas the Predicted Net-R values ranged between 0.7154 (the Minimum for Eicher Motors Limited), and 0.9735 (the Maximum for Axis Bank Limited), in respect of Nifty companies, during the pre-crisis period from 2009 to 2018.

It is found that the minimum value of actual Average Absolute Error (AAE) was recorded at 7.9356 (HCL Technologies Limited) while the maximum value recorded at 10.4257 (ICICI Bank Limited) whereas the minimum value of Predicted AAE was recorded at 7.9102 (GAIL (India) Limited) while the maximum value was recorded at 10.8716 (Reliance Industries Limited), among Nifty companies, during the pre-crisis period from 2009 to 2018.

Table 1 shows that the minimum value of actual Maximum Absolute Error was recorded at 19.9736 (Minimum for UPL Limited) and the maximum value was recorded at 49.1059 (Reliance Industries Limited) while the Predicted values ranged between 17.1059 (Minimum value for UPL Limited) and 47.9473 (Maximum for Reliance Industries Limited), among Nifty companies during the pre-crisis period from 2009 to 2018.

It is clear from the Table that the Actual values of Root Mean Square Error (RMSE) was ranged between 8.6871 (Minimum for Hindalco Industries Limited), and 12.7052(Maximum for Bajaj Auto Limited) while the Predicted RMSE ranged between 8.2340 (Minimum value for Hindalco Industries Limited) and 12.6872 (Maximum for Asian Paints Limited), among Nifty companies, during the pre-crisis period from 2009 to 2018.

It is noted from Table 1 that at 95 percent confidence intervals, the actual stock price trend value, for Indian Oil Corporation Limited, was recorded at 151.08 (Minimum) and for Maruti Suzuki India Limited, the value was 6205.32 (Maximum) whereas the Predicted values ranged between 160.75 (Minimum for Indian Oil Corporation Limited) and 6501.98 (Maximum for Maruti Suzuki India Limited), among Nifty companies, during the pre-crisis period.

Table 1 displays the results of prediction performance statistics, for fifty sample stocks of NSE, during the pre-crisis period from 2009 to 2018. Both the actual values and the predicted values were compared to analyze the prediction performance in the study. The real output was compared with predicted values.

The close correlation between the predicted market value, using the neural network and the actual value, indicated that such networks were powerful tools in stock price prediction and helped the investors to take intelligent investment decisions, to earn capital appreciation, in addition to dividends from their stock market investments (Sigo & Selvam, 2015).

The study also found the stochastic nature of price movements i.e., there was an increase and decrease of stock price of NSE-Nifty companies, in a wide manner, during the study period from 1999 to 2018. It is understood from Table 1 that the actual and predicted R-values, Net-R values, Average Absolute Error (AAE), Maximum Absolute Error, and Root Mean Square Error (RMSE) varied widely during the study period. It is to be noted that Accuracy was measured at 95 percent confidence intervals. The analysis of Table 1 reveals that the actual stock price trends of these fifty sample stocks (i.e., NSE-Nifty) experienced deviations from the predicted values.

Graph 1 and Figure 1 show the actual and predicted values of daily stock price trends of all the fifty stocks of Nifty during the period from 1999 to 2018 and it confirmed the findings of Table 1, i.e., the Prediction Performance for NSE-Nifty Companies, during the pre-crisis period.

It is found from the analysis of Table 1 that the stock price trends of the fifty sample stocks varied widely during the intra-day transactions, since the volume of transactions and the price quotes for buying and selling were different for each of the stocks.

In the light of the study, it is suggested that Neural Networks would be helpful for the investors, to find price discovery of the stocks, in both the short term perspective and the long term point of view, so as to evolve strategies accordingly and maximize the returns on the stock market investment. This study confirmed the findings of Boyacioglu and Avci (2010), who found that the stock market investment strategies differed from investor to investor, based on their interest, investor psychology, investment value and expected returns.

It is to be noted that, the stock markets have been considered as one of the avenues for wealth maximization all over the world, and it caters to the financial needs of different kinds of investors. Artificial Neural Network (ANN), being one of the neural network methods and also a non-linear and non-parametric model, it is used to derive inferences, in the analysis of big data domains like stock market analytics (Sureshkumar & Elango, 2012).

It is interesting to note from the analysis of Table 1, Graph 1 and Figure 1 that there was volatility, in the stock prices, during the pre-crisis period from 1999 to 2008. The stock prices of NSE-Nifty indexed fifty companies and NSE-Nifty indexed fifty companies had recorded stochastic nature in price trends.

Besides, the price variations were found between the actual and predicted values of all the fifty sample stocks of NSE-Nifty, and all the fifty stocks of NSE-Nifty (Zhu, et al., 2008). Hence the null hypotheses, NH-1 (*There exists no stochastic trend between the stock prices of fifty companies indexed in NSE-Nifty during the global pre-crisis period*) and NH-2 (*There exists no variation between actual and predicted stock price values of fifty companies indexed in NSE-Nifty during the global pre-crisis period*) were not accepted in the study. Investors should take note of it while making investment decisions.

Table 1. Prediction Performance of NSE-Nifty Companies for the pre-crisis period from 1999 to 2008

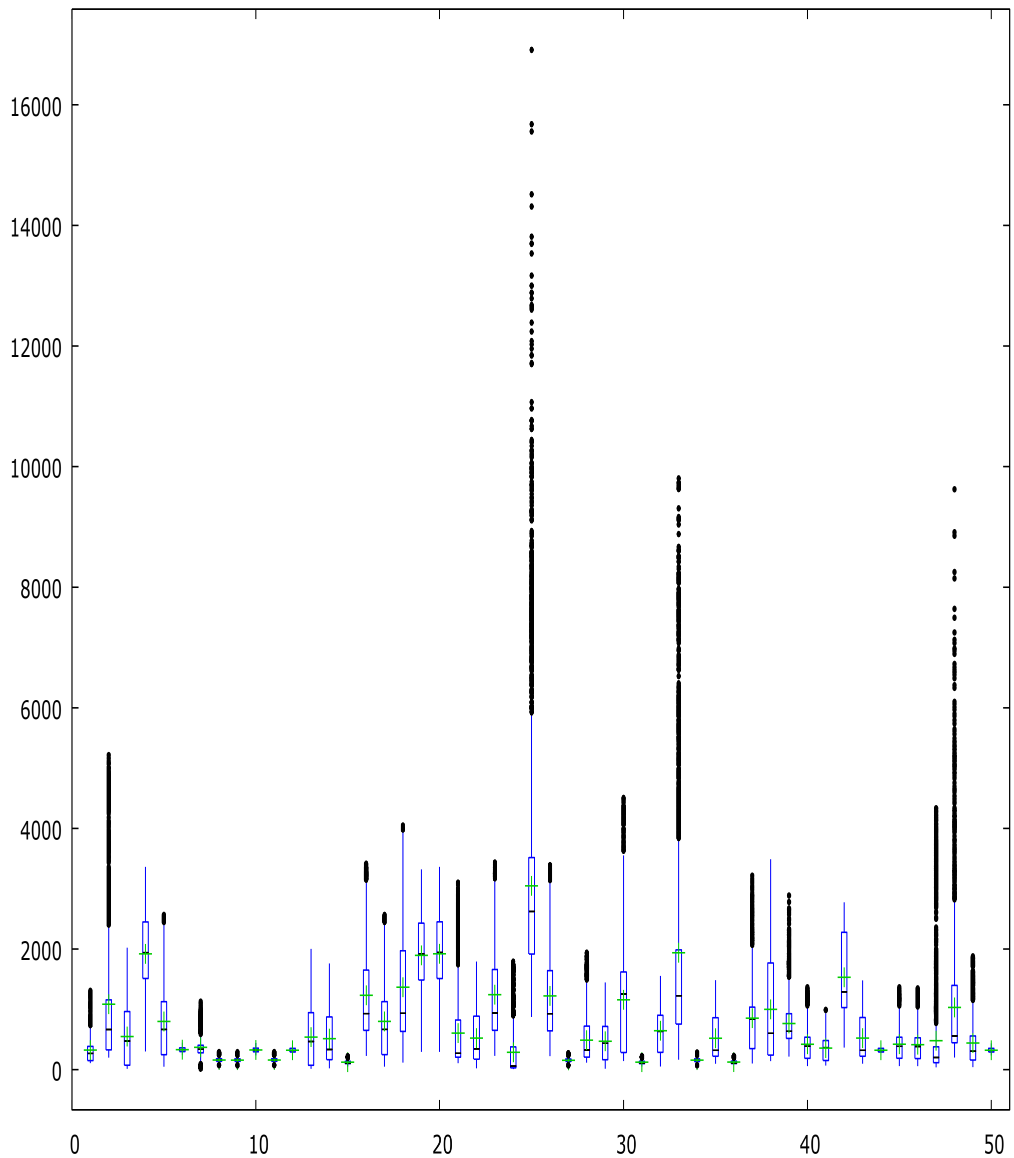
S. No.	Company Name	Trend	R	Net-R	Average Absolute Error	Maximum Absolute Error	Root Mean Square Error	Confidence Interval (95%)
1	Adani Ports	Actual	0.9972	0.9954	9.8649	38.9761	11.8912	754.83
		Predicted	0.9907	0.9255	10.2357	42.4135	12.6810	722.08
2	Asian Paints	Actual	0.9471	0.9951	9.8523	39.1059	12.6241	3765.26
		Predicted	**0.9975**	0.9155	10.1857	42.4135	**12.6872**	3824.01
3	Axis Bank	Actual	0.9970	0.9954	9.8649	38.9736	9.8920	1384.68
		Predicted	0.9976	**0.9735**	8.1857	42.4135	10.6871	1537.20
4	Bajaj Auto	Actual	**0.9977**	0.9956	10.3747	41.0335	**12.7052**	2912.50
		Predicted	0.9974	0.9951	9.8523	39.1059	12.6241	2598.01
5	Bajaj Finance	Actual	0.8577	**0.9954**	8.5816	34.4135	11.6871	1412.70
		Predicted	0.8975	0.9951	8.4523	32.1059	11.6241	1340.15
6	Bajaj Finserve	Actual	0.8927	0.8915	9.1857	27.4135	11.4366	1912.50
		Predicted	0.8901	0.8510	8.8523	26.1059	11.0238	1598.01
7	BPCL	Actual	**0.7673**	0.8951	8.7968	31.7059	9.6240	442.32
		Predicted	0.7972	0.7507	8.2523	30.3104	9.0341	391.45
8	Bharti Airtel	Actual	0.9673	0.9951	9.8523	39.1059	10.6240	842.32
		Predicted	0.9972	0.9951	9.8523	39.1059	12.6241	851.04
9	Bharti Infratel	Actual	0.8977	0.8955	8.1872	21.4135	10.6871	284.17
		Predicted	0.8932	0.8951	8.0523	19.2416	9.1426	280.56
10	Cipla	Actual	0.9673	0.8951	9.8523	29.1059	10.6240	512.42
		Predicted	0.9972	0.8812	9.5123	27.0497	9.5018	471.84
11	Coal India	Actual	-------	-------	-------	-------	-------	-------
		Predicted	-------	-------	-------	-------	-------	-------
12	DRL	Actual	0.8976	0.8955	8.1356	37.8512	10.6871	1939.40
		Predicted	0.8904	0.8932	8.0692	36.9739	10.5763	1798.15
13	Eicher Motors	Actual	0.7976	**0.7955**	8.1857	40.2035	9.8671	4393.70
		Predicted	**0.7504**	**0.7154**	7.8649	36.5643	9.2050	4098.25
14	GAIL	Actual	0.8976	0.8155	8.0857	32.0213	9.6871	323.18
		Predicted	0.8904	0.7941	**7. 9102**	31.9739	8.8763	308.25
15	Grasim	Actual	0.9176	0.8255	8.1857	30.4135	10.9125	1073.70
		Predicted	0.8904	0.7954	8.0649	29.9739	10.8763	896.72
16	HCL Tech	Actual	0.9012	0.8832	**7.9356**	41.3541	11.6871	1033.70
		Predicted	0.8924	0.8756	7.8649	39.0739	10.8763	998.51
17	HDFC Bank	Actual	0.9972	0.9954	9.8649	38.9761	11.8912	2023.06
		Predicted	0.9932	0.9951	9.8523	39.1059	12.6241	2027.01
18	Hero Motocorp	Actual	0.9577	0.9955	9.1874	42.5825	12.6871	3283.35
		Predicted	0.9941	0.9954	9.8649	38.9762	11.8901	3021.96
19	Hindalco	Actual	0.8577	0.8955	8.1874	21.2635	**8.6871**	283.35
		Predicted	0.8941	0.8754	8.0649	19.9762	**8.2340**	221.96
20	HPCL	Actual	0.9677	0.9155	9.0474	26.4067	9.6871	257.71
		Predicted	0.9641	0.9054	9.0649	25.4132	9.0901	235.43
21	Hindustan Unilever	Actual	0.9972	0.9951	9.8523	39.1059	12.6241	2297.82
		Predicted	0.9904	0.9954	9.8649	38.9739	11.8763	2053.29
22	HDFC	Actual	0.9975	0.9951	9.8523	39.1059	12.6241	2772.51

		Predicted	0.9907	0.9955	10.1857	42.4135	12.6810	2569.09
23	ITC	Actual	0.9932	0.9951	9.8523	39.1059	12.2410	1121.07
		Predicted	0.9904	0.9954	9.8649	38.9739	11.8763	1105.87
24	ICICI Bank	Actual	0.9907	0.9955	**10.4257**	42.4135	12.6810	1191.25
		Predicted	0.9970	0.9954	9.8649	38.9761	11.8912	1009.21
25	Indiabulls	Actual	0.9827	0.9371	9.8857	23.0973	12.6810	1251.25
		Predicted	0.9102	0.9154	9.3649	21.1615	11.8912	1149.68
26	IOC	Actual	0.8977	0.8955	8.5872	20.2873	10.1621	**151.08**
		Predicted	0.8932	0.9895	8.8523	19.0159	9.6245	**160.75**
27	Indusind Bank	Actual	0.9977	0.9955	8.1872	42.4452	12.6871	1219.56
		Predicted	0.9932	0.9951	9.8523	39.1059	12.6241	1100.75
28	Infosys	Actual	0.9904	0.9954	9.8649	38.9739	11.8763	2419.25
		Predicted	0.9941	0.9954	9.8649	38.9762	11.8901	2516.65
29	JSW Steel	Actual	0.8577	0.8155	8.8122	21.8173	11.1621	161.80
		Predicted	0.8232	0.8095	8.8023	20.0152	10.6245	163.75
30	Kotak M Bank	Actual	0.9927	0.9955	10.0857	42.4035	12.6871	1047.41
		Predicted	0.9673	0.9951	9.8523	39.1059	10.6240	998.26
31	L & T	Actual	0.9941	0.9954	9.8649	38.9762	8.8901	2590.69
		Predicted	0.9904	0.9954	9.8649	38.9739	11.8763	2780.31
32	M & M	Actual	0.9972	0.9951	9.8523	39.1059	12.3241	1354.00
		Predicted	0.9932	0.9951	9.8523	39.1059	12.6201	1098.32
33	Maruti	Actual	0.9942	0.9954	9.8649	38.9761	11.8912	**6205.32**
		Predicted	0.9970	0.9907	9.8649	38.9761	11.8912	**6501.98**
34	NTPC	Actual	0.9977	0.9925	9.1837	42.4135	12.6871	212.52
		Predicted	0.9924	0.9950	9.8649	38.9736	11.8912	205.14
35	ONGC	Actual	0.9972	0.9954	9.8649	38.9761	11.8928	1213.00
		Predicted	0.9932	0.9951	9.8523	39.1059	12.6201	1198.41
36	Powergrid	Actual	0.9951	0.9951	9.8523	39.1059	12.6241	2206.18
		Predicted	0.9924	0.9950	9.8649	38.9736	11.8912	2274.15
37	RIL	Actual	0.9971	0.9952	9.8723	**49.1059**	12.6841	1020.71
		Predicted	0.9968	0.9961	**10.8716**	**47.9473**	11.1759	1223.21
38	SBI	Actual	0.9972	0.9951	9.8523	39.1059	12.6215	2560.43
		Predicted	0.9924	0.9950	9.8649	38.9736	11.8912	2431.01
39	Sun Pharma	Actual	0.9971	0.9924	9.8649	38.9761	11.8912	1553.26
		Predicted	0.9972	0.9951	9.8523	39.1059	12.6241	1452.98
40	TCS	Actual	0.9970	0.9950	9.8169	48.1047	11.6872	3750.90
		Predicted	0.9971	0.9955	10.1857	41.4135	10.3571	2815.40
41	Tata Motors	Actual	0.9970	0.9907	9.8649	38.9761	11.8912	961.91
		Predicted	0.9951	0.9951	9.8523	39.1059	12.6241	876.23
42	Tata Steel	Actual	0.9977	0.9955	10.1851	42.4135	12.6871	687.84
		Predicted	0.9924	0.9950	9.8649	38.9736	11.8912	599.37
43	Tech Mahindra	Actual	0.8970	0.8950	8.3169	28.1047	10.3210	700.90
		Predicted	0.8971	0.8955	8.1857	25.4135	9.2571	681.40
44	Titan	Actual	0.8972	0.8954	8.3649	28.9761	11.8912	897.97
		Predicted	0.8955	0.8951	8.8523	29.1059	12.6241	928.77
45	UPL	Actual	0.7924	0.7950	7.8649	**19.9736**	10.8912	620.58
		Predicted	0.7951	0.7223	7.2523	**17.1059**	9.6241	507.76
46	Ultratech	Actual	0.9977	0.9921	9.8857	42.4135	12.6115	4221.20
		Predicted	0.9915	0.9951	10.8523	39.1059	12.6971	4516.95
47	VEDL	Actual	0.9972	0.9954	9.8649	38.9761	11.8912	1897.97
		Predicted	0.9955	0.9951	9.8523	39.1059	12.6211	1478.77

48	Wipro	Actual	0.9977	0.9921	10.1857	42.4135	12.6815	3221.20
		Predicted	0.9915	0.9951	9.8523	39.1059	12.6271	3516.95
49	Yes Bank	Actual	0.9924	0.9950	9.8649	38.9736	11.8912	1405.58
		Predicted	0.9951	0.9951	9.8523	39.1059	12.6241	1209.76
50	Zee	Actual	0.8970	0.8950	8.9169	38.1047	11.5872	450.90
		Predicted	0.8397	0.8425	8.7857	31.4135	10.9571	415.40

Source: Data retrieved from www.nseindia.com, computed using Neural Works Predict (version 3.24)

Note: (Data is not available)



Graph 1. Prediction of Performance of Stock Price Trends for NSE-Nifty Stocks during the pre-crisis period from 1999 to 2008

Source: Data retrieved from www.nseindia.com, computed using Neural Works Predict (version 3.24).

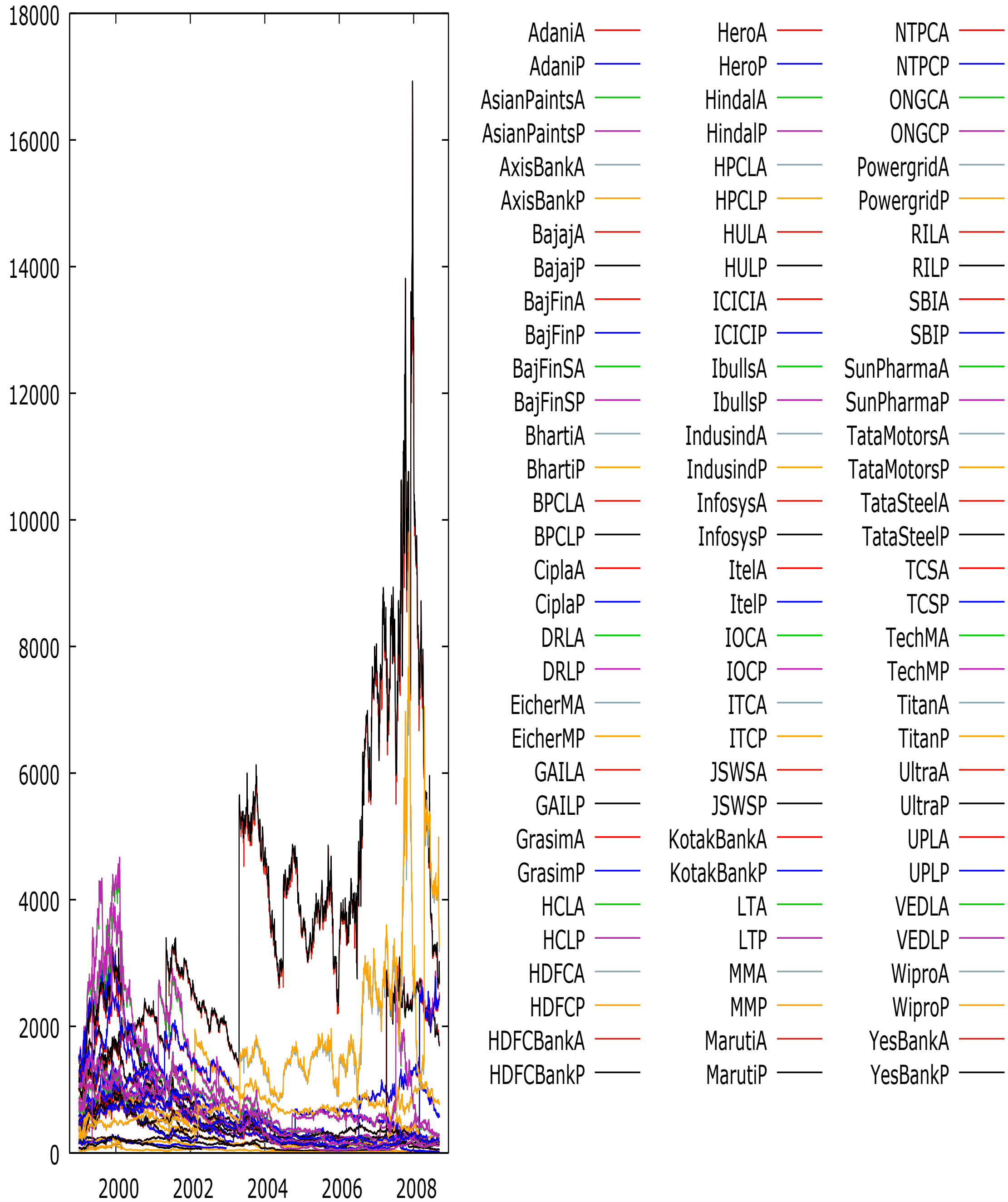


Figure 1. Prediction of Performance Trend for NSE-Nifty Stocks during the pre-crisis period from 1999 to 2008

Source: Data retrieved from www.nseindia.com, and computed using Neural Works Predict (version 3.24).

8.b) Prediction Performance of NSE-Nifty Companies using Ensemble Machine Learning Method during the post-crisis period from 2009 to 2018

Table 2 demonstrates the holistic view of the stock price trends of NSE-Nifty fifty companies, during the post-crisis period from 2009 to 2018. It is clearly evident that the R-value (Actual) was recorded, for Bharat Petroleum Corporation Limited, at 0.7671 (Minimum), followed by Bajaj Auto Limited at 0.9976 (Maximum) while the Predicted R-values ranged between 0.7502 (Eicher Motors Limited) and 0.9975 (Asian Paints Limited), among Nifty companies, during the post-crisis period from 2009 to 2018.

The Net-R values (Actual) computed ranged between 0.7955 (the Minimum for Eicher Motors Limited), and 0.9954 (the Maximum for Bajaj Finance Limited), whereas the Predicted Net-R values ranged between 0.7154 (the Minimum for Hindustan Unilever Limited), and 0.9731 (the Maximum for Axis Bank Limited), in respect of Nifty companies, during the post-crisis period from 2009 to 2018.

It is found that the minimum value of Actual Average Absolute Error (AAE) was recorded at 7.9356 (HCL Technologies Limited) while the maximum value was recorded at 10.4257 (ICICI Bank Limited) whereas the minimum value of Predicted AAE was recorded at 7.9102 (GAIL (India) Limited while its maximum was recorded at 10.8716 (Reliance Industries Limited), among Nifty companies, during the post-crisis period from 2009 to 2018.

Table 2 shows that the minimum value of Actual Maximum Absolute Error was recorded at 19.9736 (UPL Limited) and its maximum was 49.1059 (Reliance Industries Limited) while the Predicted values ranged between 17.1059 (Minimum value for UPL Limited) and 47.9473 (Maximum for Reliance Industries Limited), among Nifty companies, during the post-crisis period from 2009 to 2018.

It is clear from the Table that the minimum of Actual value of Root Mean Square Error (RMSE) was recorded at 8.6871 (Hindalco Industries Limited), and its maximum was at 12.7052 (Bajaj Auto Limited) while the Predicted RMSE ranged between 8.2340 (Minimum value for Hindalco Industries Limited) and 12.6870 (Maximum for Asian Paints Limited), among Nifty companies, during the post-crisis period from 2009 to 2018.

It is noted from the Table 2 that at 95 percent confidence intervals, the actual stock price trend value, for IOC Limited, was recorded at 151.08 (Minimum) and for Maruti Suzuki India Limited, the value was at 6205.32 (Maximum) whereas the minimum Predicted value was at 159.72 (IOC Limited) and its maximum was at 6501.98 (Maruti Suzuki India Limited), among Nifty companies, during the post-crisis period from 2009 to 2018.

Table 2 displays the results of prediction performance statistics, for fifty sample stocks, during the post-crisis period from 2009 to 2018. Both the actual values and the predicted values were compared to analyze the prediction performance in the study. The real output was compared with predicted values.

The study also found the stochastic nature of price movements i.e., there was an increase and decrease of stock price of NSE-Nifty companies, in a wide manner, during the post-crisis period from 2009 to 2018.

It is understood from Table 2 that the actual and predicted R-values, Net-R values, Average Absolute Error (AAE), Maximum Absolute Error, and Root Mean Square Error (RMSE) varied widely during the post-crisis period from 2009 to 2018. It is to be noted that Accuracy was measured at 95 percent confidence intervals. The analysis of Table 2 reveals that the actual stock price trends of these fifty stocks (i.e., NSE-Nifty) reported deviations from predicted values.

Graph 2 and Figure 2 show the actual and predicted values of daily stock price trends of all the fifty stocks of Nifty, during the period from 1999 to 2018 and it confirmed the findings of Table 2 i.e., the Prediction Performance for NSE-Nifty listed Companies during the post-crisis period from 2009 to 2018. It is found from the analysis of Table 2 that the stock price trends of the fifty sample stocks varied widely, during the intra-day transactions, since the volume of transactions and the price quotes for buying and selling, were different for each of the stocks.

The close correlation between the predicted market value, using the neural network and the actual value, indicated that such networks were powerful tools in stock price prediction and helped the investors to take intelligent investment decisions, to earn capital appreciation, in addition to dividends from their stock market investments (Sigo & Selvam, 2015).

This study concurred with the findings of Boyacioglu and Avci (2010), who found that the stock market investment strategies differed from investor to investor, based on their interest, investor psychology, investment value and expected returns. The information of historical or past prices would be helpful for the investors to forecast the possible future prices of individual stocks. The fundamental and technical analysis of a stock would also help the investors to make investments both in the short term and the long term perspective.

Neural networks would be helpful for all types of investors, to predict the prices of the respective stocks for the future period (for both short term and long term) and for devising appropriate investment strategies accordingly to maximize the stock returns and wealth (Eric Siegel, 2016). It is interesting to note, from the analysis of Table 2, Graph 2 and Figure 2 that there was volatility in the stock prices, during the post-crisis period from 2009 to 2018.

The stock prices of NSE-Nifty indexed fifty companies and NSE-Nifty indexed fifty companies had recorded stochastic nature in price trends. Price variations were found between actual and predicted values of all the fifty sample stocks of NSE-Nifty, and all the fifty stocks of NSE-Nifty (Zhu, et al., 2008). Hence the null hypotheses, NH-3 (*There exists no stochastic trend between the stock prices of fifty companies indexed in NSE-Nifty during the global post-crisis period*) and NH-4 (*There exists no variation between actual and predicted stock price values of fifty companies indexed in NSE-Nifty during the global post-crisis period*) were not accepted in the study. Investors should observe these developments, while making investment decisions.

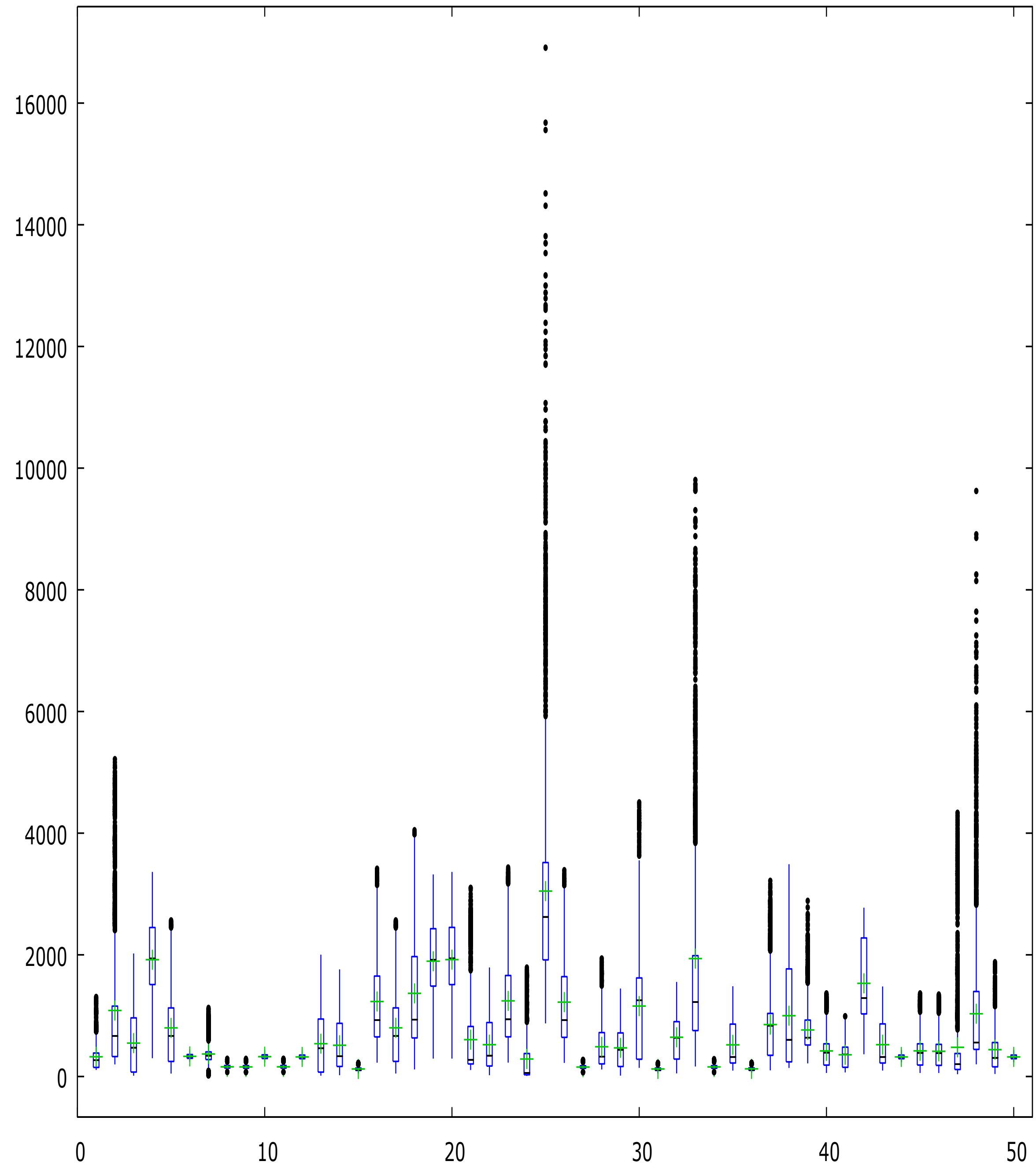
Table 2. Prediction Performance of NSE-Nifty Companies during the post-crisis period from 2009 to 2018

S. No.	Company Name	Trend	R	Net-R	Average Absolute Error	Maximum Absolute Error	Root Mean Square Error	Confidence Interval (95%)
1	Adani Ports	Actual	0.9972	0.9954	9.8649	38.9761	11.8912	754.83
		Predicted	0.9907	0.9255	10.2357	42.4135	12.6810	722.08
2	Asian Paints	Actual	0.9471	0.9951	9.8523	39.1059	12.6241	3765.26
		Predicted	**0.9975**	0.9155	10.1857	42.4135	**12.6870**	3824.01
3	Axis Bank	Actual	0.9970	0.9954	9.8649	38.9736	9.8920	1384.68
		Predicted	0.9976	**0.9731**	8.1857	42.4135	10.6871	1537.20
4	Bajaj Auto	Actual	**0.9976**	0.9956	10.3747	41.0335	**12.7052**	2912.50
		Predicted	0.9974	0.9951	9.8523	39.1059	12.6241	2598.01
5	Bajaj Finance	Actual	0.8577	**0.9954**	8.5816	34.4135	11.6871	1412.70
		Predicted	0.8975	0.9951	8.4523	32.1059	11.6241	1340.15
6	Bajaj Finserve	Actual	0.8927	0.8915	9.1857	27.4135	11.4366	1912.50
		Predicted	0.8901	0.8510	8.8523	26.1059	11.0238	1598.01
7	BPCL	Actual	**0.7671**	0.8951	8.7968	31.7059	9.6240	442.32
		Predicted	0.7972	0.7507	8.2523	30.3104	9.0341	391.45
8	Bharti Airtel	Actual	0.9673	0.9951	9.8523	39.1059	10.6240	842.32
		Predicted	0.9972	0.9951	9.8523	39.1059	12.6241	851.04
9	Bharti Infratel	Actual	0.8977	0.8955	8.1872	21.4135	10.6871	284.17
		Predicted	0.8932	0.8951	8.0523	19.2416	9.1426	280.56
10	Cipla	Actual	0.9673	0.8951	9.8523	29.1059	10.6240	512.42
		Predicted	0.9972	0.8812	9.5123	27.0497	9.5018	471.84
11	Coal India	Actual	0.9976	0.9955	8.1857	42.4135	10.6871	393.70
		Predicted	0.9904	0.9954	9.8649	38.9739	11.8763	398.25
12	DRL	Actual	0.8976	0.8955	8.1356	37.8512	10.6871	1939.40
		Predicted	0.8904	0.8932	8.0692	36.9739	10.5763	1798.15
13	Eicher Motors	Actual	0.7976	**0.7955**	8.1857	40.2035	9.8671	4393.70
		Predicted	**0.7502**	**0.7154**	7.8649	36.5643	9.2050	4098.25
14	GAIL	Actual	0.8976	0.8155	8.0857	32.0213	9.6871	323.18
		Predicted	0.8904	0.7941	**7. 9102**	31.9739	8.8763	308.25
15	Grasim	Actual	0.9176	0.8255	8.1857	30.4135	10.9125	1073.70
		Predicted	0.8904	0.7954	8.0649	29.9739	10.8763	896.72
16	HCL Tech	Actual	0.9012	0.8832	**7.9356**	41.3541	11.6871	1033.70
		Predicted	0.8924	0.8756	7.8649	39.0739	10.8763	998.51
17	HDFC Bank	Actual	0.9972	0.9954	9.8649	38.9761	11.8912	2023.06
		Predicted	0.9932	0.9951	9.8523	39.1059	12.6241	2027.01
18	Hero Motocorp	Actual	0.9577	0.9955	9.1874	42.5825	12.6871	3283.35
		Predicted	0.9941	0.9954	9.8649	38.9762	11.8901	3021.96
19	Hindalco	Actual	0.8577	0.8955	8.1874	21.2635	**8.6871**	283.35
		Predicted	0.8941	0.8754	8.0649	19.9762	**8.2340**	221.96
20	HPCL	Actual	0.9677	0.9155	9.0474	26.4067	9.6871	257.71
		Predicted	0.9641	0.9054	9.0649	25.4132	9.0901	235.43
21	Hindustan Unilever	Actual	0.9972	0.9951	9.8523	39.1059	12.6241	2297.82
		Predicted	0.9904	0.9954	9.8649	38.9739	11.8763	2053.29
22	HDFC	Actual	0.9975	0.9951	9.8523	39.1059	12.6241	2772.51

		Predicted	0.9907	0.9955	10.1857	42.4135	12.6810	2569.09
23	ITC	Actual	0.9932	0.9951	9.8523	39.1059	12.2410	1121.07
		Predicted	0.9904	0.9954	9.8649	38.9739	11.8763	1105.87
24	ICICI Bank	Actual	0.9907	0.9955	**10.4257**	42.4135	12.6810	1191.25
		Predicted	0.9970	0.9954	9.8649	38.9761	11.8912	1009.21
25	Indiabulls	Actual	0.9827	0.9371	9.8857	23.0973	12.6810	1251.25
		Predicted	0.9102	0.9154	9.3649	21.1615	11.8912	1149.68
26	IOC	Actual	0.8977	0.8955	8.5872	20.2873	10.1621	**151.08**
		Predicted	0.8932	0.9895	8.8523	19.0159	9.6245	**159.72**
27	Indusind Bank	Actual	0.9977	0.9955	8.1872	42.4452	12.6871	1219.56
		Predicted	0.9932	0.9951	9.8523	39.1059	12.6241	1100.75
28	Infosys	Actual	0.9904	0.9954	9.8649	38.9739	11.8763	2419.25
		Predicted	0.9941	0.9954	9.8649	38.9762	11.8901	2516.65
29	JSW Steel	Actual	0.8972	0.8952	8.9170	38.1048	11.5873	250.92
		Predicted	0.8497	0.8427	8.7859	31.4137	10.9570	215.45
30	Kotak M Bank	Actual	0.9927	0.9955	10.0857	42.4035	12.6871	1047.41
		Predicted	0.9673	0.9951	9.8523	39.1059	10.6240	998.26
31	L & T	Actual	0.9941	0.9954	9.8649	38.9762	8.8901	2590.69
		Predicted	0.9904	0.9954	9.8649	38.9739	11.8763	2780.31
32	M & M	Actual	0.9972	0.9951	9.8523	39.1059	12.3241	1354.00
		Predicted	0.9932	0.9951	9.8523	39.1059	12.6201	1098.32
33	Maruti	Actual	0.9942	0.9954	9.8649	38.9761	11.8912	**6205.32**
		Predicted	0.9970	0.9907	9.8649	38.9761	11.8912	**6501.98**
34	NTPC	Actual	0.9977	0.9925	9.1837	42.4135	12.6871	212.52
		Predicted	0.9924	0.9950	9.8649	38.9736	11.8912	205.14
35	ONGC	Actual	0.9972	0.9954	9.8649	38.9761	11.8928	1213.00
		Predicted	0.9932	0.9951	9.8523	39.1059	12.6201	1198.41
36	Powergrid	Actual	0.9951	0.9951	9.8523	39.1059	12.6241	2206.18
		Predicted	0.9924	0.9950	9.8649	38.9736	11.8912	2274.15
37	RIL	Actual	0.9971	0.9952	9.8723	**49.1059**	12.6841	1020.71
		Predicted	0.9968	0.9961	**10.8716**	**47.9473**	11.1759	1223.21
38	SBI	Actual	0.9972	0.9951	9.8523	39.1059	12.6215	2560.43
		Predicted	0.9924	0.9950	9.8649	38.9736	11.8912	2431.01
39	Sun Pharma	Actual	0.9971	0.9924	9.8649	38.9761	11.8912	1553.26
		Predicted	0.9972	0.9951	9.8523	39.1059	12.6241	1452.98
40	TCS	Actual	0.9970	0.9950	9.8169	48.1047	11.6872	3750.90
		Predicted	0.9971	0.9955	10.1857	41.4135	10.3571	2815.40
41	Tata Motors	Actual	0.9970	0.9907	9.8649	38.9761	11.8912	961.91
		Predicted	0.9951	0.9951	9.8523	39.1059	12.6241	876.23
42	Tata Steel	Actual	0.9977	0.9955	10.1851	42.4135	12.6871	687.84
		Predicted	0.9924	0.9950	9.8649	38.9736	11.8912	599.37
43	Tech Mahindra	Actual	0.8970	0.8950	8.3169	28.1047	10.3210	700.90
		Predicted	0.8971	0.8955	8.1857	25.4135	9.2571	681.40
44	Titan	Actual	0.8972	0.8954	8.3649	28.9761	11.8912	897.97
		Predicted	0.8955	0.8951	8.8523	29.1059	12.6241	928.77
45	UPL	Actual	0.7924	0.7950	7.8649	**19.9736**	10.8912	620.58
		Predicted	0.7951	0.7223	7.2523	**17.1059**	9.6241	507.76
46	Ultratech	Actual	0.9977	0.9921	9.8857	42.4135	12.6115	4221.20
		Predicted	0.9915	0.9951	10.8523	39.1059	12.6971	4516.95
47	VEDL	Actual	0.9972	0.9954	9.8649	38.9761	11.8912	1897.97
		Predicted	0.9955	0.9951	9.8523	39.1059	12.6211	1478.77

48	Wipro	Actual	0.9977	0.9921	10.1857	42.4135	12.6815	3221.20
		Predicted	0.9915	0.9951	9.8523	39.1059	12.6271	3516.95
49	Yes Bank	Actual	0.9924	0.9950	9.8649	38.9736	11.8912	1405.58
		Predicted	0.9951	0.9951	9.8523	39.1059	12.6241	1209.76
50	Zee	Actual	0.8970	0.8950	8.9169	38.1047	11.5872	450.90
		Predicted	0.8397	0.8425	8.7857	31.4135	10.9571	415.40

Source: Data retrieved from www.nseindia.com, and computed using Neural Works Predict (version 3.24



Graph 2. Prediction of Performance of Stock Price Trends for NSE-Nifty Stocks during the post-crisis period from 2009 to 2018

Source: Data retrieved from www.nseindia.com, computed using Neural Works Predict (version 3.24).

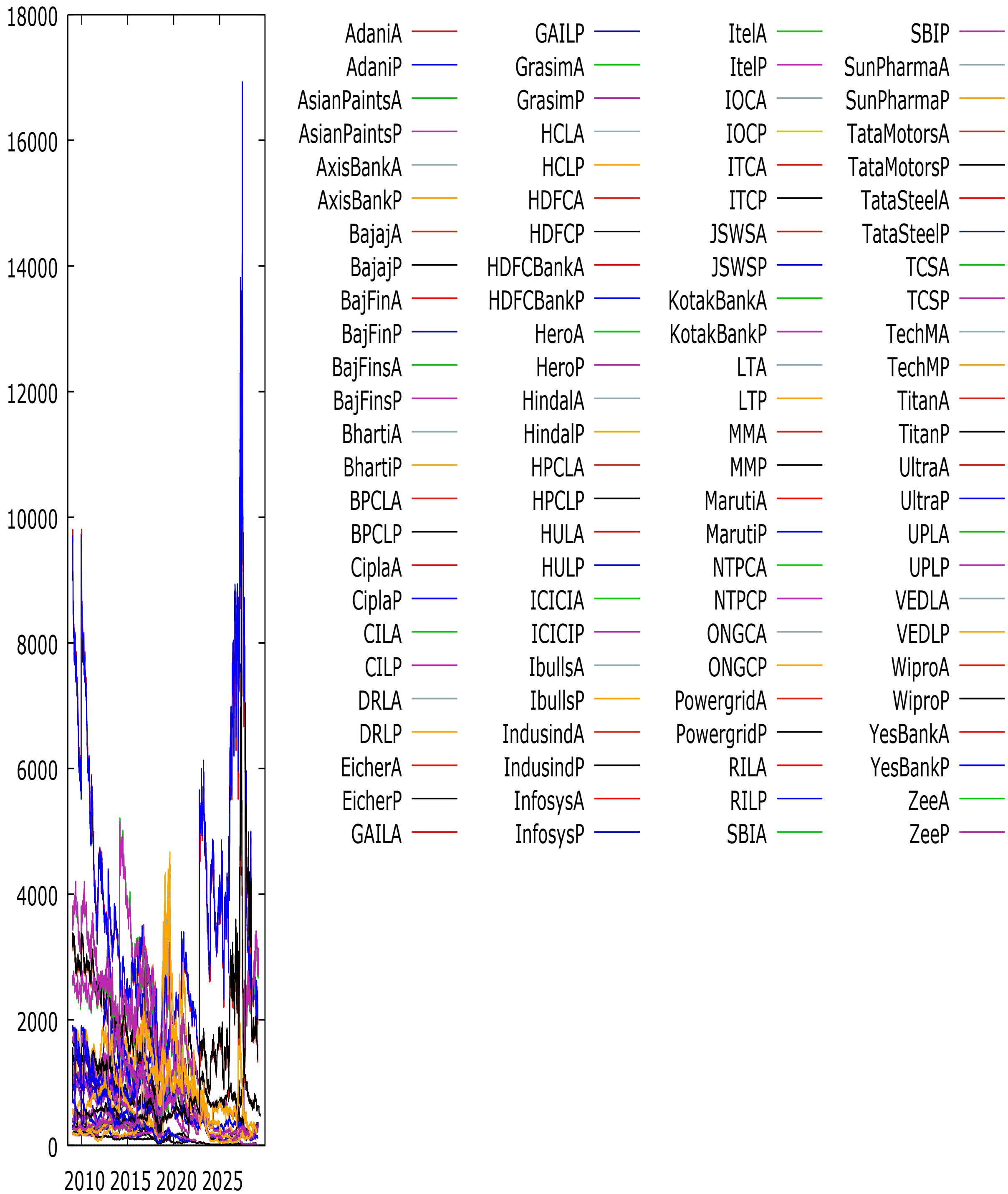


Figure 2. Prediction of Performance Trend for NSE-Nifty Stocks during the post-crisis period from 2009 to 2018

Source: Data retrieved from www.nseindia.com, and computed using Neural Works Predict (version 3.24).

Findings of the Study

The market value of each company stock is changing per millisecond, based on the demand and supply forces, namely, the buyers and sellers of stocks. The stock prices of the NSE-Nifty indexed fifty stocks had ranged between Rs. 9.20 and Rs.9812.70, during the study period of twenty years from 1999 to 2018, i.e., the two spells of both the pre and post crisis period of the Global financial crisis 2008. This phenomenon happened due to the influence of various macro and micro economic factors. In addition to some micro economic factors (bearish and bullish trends), the investors' sentiments in the stock market were also directly related to the stock performance (Sigo et al., 2018_c).

In this study, the stock prices were forecasted by using artificial neural network, and it was found that the stock price data of the fifty sample stocks were volatile and voluminous, i.e., the nature of Big Data (Siegel, 2016).

It was found that the machine learning model was found to be better than the time series models, in processing the high frequency stock market data and stock price information, which was a kind of big data and used to derive valuable inferences and investment decisions (Wang & Shang, 2014).

The applications and the use of machine learning oriented artificial neural networks would probably enhance the predictive accuracy of stock price movement prediction. The fusion of two or more neural networks could be applied, to increase the predictive accuracy value of stock prices and stock market trends. The experience gained by the investors, using neural network approaches, would help the investors in taking wiser decisions and optimizing the stock returns.

From the above analysis of 10,35,640 observations of stock price data relating to NSE-Nifty indexed fifty companies facilitated the more accurate prediction of price discovery, in the realm of technology driven markets and decision science. The ANN approach sharpens the market intelligence of an investor to make intelligent investment decisions (Sigo et al., 2018_c).

Ensemble Machine Learning Method is designed as a mathematical model to enhance the existing data analysis technologies. It is one of the sophisticated data mining tools, used to perform better for both the linear and non-linear data, in the predictive analytics of market trends Although, it is not comparable with the power of the human brain, still it is construed as the basic building block of the Artificial intelligence (Simon & Raoot, 2012).

Suggestions

Stock markets are mostly dynamic in nature. A high degree of financial literacy, alertness, and rationality is required, for investors, before taking any investment decisions (i.e., buy, sell and hold). The investments in blue chip stocks would make the investors to get more benefit, if they could invest rationally in those stocks, since these stocks are the top market capitalization stocks and the market leaders in the respective industrial and business sectors of business. The applications and the use of Ensemble Machine Learning Method would probably enhance the predictive accuracy of stock price movement prediction. The fusion of two or more neural networks could be applied, to increase the predictive accuracy value of stock prices and stock market trends (Snigaroff & Wroblewski, 2011). The experience gained by the investors, using neural network approaches, would help the investors in taking wiser decisions and optimizing the stock returns.

Conclusion

This study analyzed the stock price trends and predicted the values of fifty top market capitalization stocks, of NSE-Nifty, which are listed in the Bombay Stock Exchange in India. Forecasting of stock market movements become difficult, due to the uncertainties involved, with the future stock prices (Hassan, Nath and Kirley, 2007). The prediction of the stock price trend is euphoric and positive even for the future time period. The investment behavior also varied for different kinds of investors (traders, arbitrageurs and investors). If and only if the information obtained, relating to the stock prices, were pre-processed efficiently, using the ensemble machine learning method, the forecasting would become more accurate and the investors could earn capital appreciation, for their stock investments, and maximization of wealth in the long run.

Limitations of The Study

The study only considered the fifty stocks of to NSE-Nifty. The period of the study was only 20 years starting from 1999 to 2018. The typical issues were also faced by the researchers in using the statistical tools and unavailability of certain kind of data.

Scope for Future Research

Attempts could be made, to forecast stocks listed in BSE and other regional stock exchanges of India using other Machine Learning Methods. Efforts could be made, to study the movements of the stock markets of developed economies like U.S.A, U.K and Japan (Jasic and Wood, 2006). A comparative analytics of global stock indices could be made, by applying different Machine Learning Approaches.

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