BIG DATA ANALYTICS-APPLICATION OF ARTIFICIAL NEURAL NETWORK IN FORECASTING STOCK PRICE TRENDS IN INDIA

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ABSTRACT

The world has become data driven, which highly accentuated the utilization of information technology. The movements of stock markets are influenced, by both the micro as well as macro economic variables including the 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 and stock indices, based on historical past prices. The accuracy, in forecasting the market trend, has become difficult due to the prevalence of stochastic behaviour and volatility in the stock prices and index movements. This paper analyses the non-linear movement pattern of the most volatile, top three stocks in terms of market capitalization, listed in the Bombay Stock Exchange (BSE) in India, namely Reliance Industries Limited (RIL), Tata Consultancy Services (TCS) Limited and HDFC Bank Limited, using the Artificial Neural Network (ANN) for the study period from 2008 to 2017. The findings of the study would help the investors, to make rational, well informed investment decisions, to optimize the stock returns by investing in the most valuable stocks.

Keywords: Artificial Neural Network, Behavioural Finance, Big Data, Machine Learning, Predictive Analytics, Stochastic**,** Stock Markets and Volatility.

JEL Code: C45, C53, E27, E44, G1

INTRODUCTION

Big Data becomes the buzzword in the field of technology for some time now (Tayal et al., 2018). Siegel (2016) emphasized that a little prediction goes a long way. Forecasting the movement of stock price of a company and stock index is a classic problem, to all those who are connected to the stock markets. The Efficient Market Hypothesis (EMH) clearly asserts that it is not possible to exactly forecast the stock prices of companies, due to the existence of random walk behaviour, in the stock markets (Fama, 1970). The movements of stock prices and stock indices are influenced by many macro-economic variables, such as political events, business policies of the corporate enterprises, general economic conditions, commodity price index, 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). Neural networks are a class of generalized, non-linear and non-parametric models, developed from the studies of human brain. It is one of the data mining tools, which performs better than the conventional statistical tools of financial forecasting. The construction of an intelligent data mining system, mainly involves a selection of better forecasting models and trading strategies. The feed-forward networks are the most widely used architecture since such networks offer good generalization abilities, for forecasting the future movements (Ou and Wang, 2009). The stock market transactions, across the globe, are voluminous and volatile. Prediction of stock price movements, being big data, is increasingly difficult due to the prevalence of an element of uncertainties involved with the probable future outcomes (Siegel, 2016). To get accurate response, we use big data analytic concept (Mishra et al., 2018). If and only 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. Big data tools are used to process unstructured data sets to get the meaningful visualizations (Sankaranarayanan and Thind, 2017). Every industry and business is digitizing their data ushering in the dawn of an era of big data in India (Panicker and Srivastava, 2017). Big Data processes huge volumes of transactional information in real time (Gupta and Tripathi, 2016). 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 and 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). Based on the neural network forecasting model, an intelligent mining system has been developed. Artificial Neural Network (ANN) approach could forecast the future trend of stock market and it provides stock information signs, for taking better investment decision of buying and selling of stocks, by the investors (Patel et al., 2015). High frequency data has great potential for new insights (Balaji, 2017). ANN, one of the applications of neural network (machine learning) method, is used in this study, to analyze current price trends and probable future prices of company stocks (Maas, 2017).

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. Etzioni (1976) forecasted the movements of stock indices and individual stock prices and explained the difficulties in making specific forecasting of financial markets. It was emphasized that buying a stock, exactly when the price was at the lowest ebb and making a sale when the market price of the share was at the highest ebb, would help the investors to make more profitable choices. A study undertaken by 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 (ARIMA). Wang and Leu (1996) forecasted stock price trend for six weeks, based on past four years stock price movements of Taiwan stock market, by using recurrent neural network. Vladimir (1998) has developed Support Vector Machine (SVM) algorithm and applied the same in forecasting the financial markets. Walczak (1999) forecasted the fluctuations in financial markets, vary across the time periods and the rate of financial literacy was considered as one of the crucial factors, which influence the investment decisions of the investors. Abraham et al. (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 and stock index values of Korea Composite Stock Price Index (KOSPI). 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). Besides, Huang et al. (2005) investigated 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 (U.S.A), the DAX (Germany), the TOPIX (Japan) and the FTSE (U.K). According to Hassan et al., (2007), a fusion model, by combining Hidden Markov Model, Artificial Neural Network and Genetic Algorithms, was used to forecast the stochastic financial market behaviour. Kwon and Moon (2007) observed that the prediction of financial objects, a challenging task and the profits, were quite sensitive to transaction costs. Carvalhal and 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 Dow Jones Industrial Average (DJIA) and Strait Times Index (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%. 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 Artificial Neural Network to forecast the stock price movements. The selection of 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, are the key issues in designing a network model. Sureshkumar and Elango (2012) applied artificial neural network, to predict the stock prices, and the accuracy rate was 20% of the output. Patel et al. (2015) predicted the movements of BSE-Sensex, 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. Marxia Oli. Sigo et al. (2018) applied the technical indicators and forecasted the stock index trends of BSE-Sensex and NSE-Nifty of India, in pre and post-global crisis (2008) time zones. Based on the above reviews, the researchers of this study have applied Artificial Neural Network in this study, to forecast the highly volatile stocks, Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited, listed in BSE of India (Wu & Lee, 2015).

STATEMENT OF THE PROBLEM

Forecasting the movements of financial market is one of the classic issues for the market participants i.e., the investors and other stakeholders. Generally, 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 lose their fortunes or miss the earning opportunities. Hence the forecasting of stock indices is a herculean task, in highly growing economies like India, since only a few research studies exist. It is important that market intelligence and financial literacy are the two essential inputs to be considered, by the investors, for investment decision making. Lack of these attributes, among the financial investors, would lead to inconsistency and inaccuracy of market forecasting, which would eventually lead to the loss of their stock market investments (Boyacioglu and Avci, 2010). Besides, the financial system develops and suggests some proven techniques, for the investors, to forecast the price. But, there is no proven technique, available for the investors. The absence of proven forecasting techniques, to exactly forecast the probable futuristic price movements of stock price, increases the magnitude and severity of this issue (Lopez et al., 2014).

NEED OF THE STUDY

Different kinds of uncertainties exist, in forecasting the stock market trends, especially stock price movements. It is highly imperative to ensure a high degree of predictive ability and accuracy, for both short term and long term view. To maximize the returns for the investments in stocks, trade-off between risk and return as well as the sensitivity to the stock price movements, is essential. This study would help a spectrum of investors (including the retail investors, financial institutions, mutual funds, investment banks and the foreign institutional investors), to take timely and well-informed investment decisions, based on scientific thinking and rational approach (Etzioni, 1976). The absence of prudent forecasting methods, lower level of financial literacy and alternate investment options, reiterate the need for this kind of study, for the present context, in India.

OBJECTIVE

The objective of this study is to find out the existing trend and to forecast the future direction of the stock price movements of Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited, using artificial neural network.

HYPOTHESES

H1: *There is no stochastic movement between the stock prices of Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited during the study period.*

H2: *There exists no price trend variation between the stock prices of Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited during the study period*.

H3: *There exists no variation between actual and predicted stock prices of Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited during the study period.*

RESEARCH METHODOLOGY

Sampling Design of the Study

The stock of three top companies, namely Reliance Industries Limited (Rs. 5,91,580 crores), Tata Consultancy Services Limited (Rs. 5,60,072 crores) and HDFC Bank Limite (Rs. 4,88,604 crores) were selected, based on the top value in its free-float market capitalization, as on 15-02-2017. Hence, these three companies stocks were taken, as sample units, for this study.

Sources of Data

The secondary data of the four types of daily prices (opening price, high price, low price, and closing price) of sample companies, Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited, were collected from the websites of Bombay Stock Exchange Limited and the sample firms.

Study Period

A period of ten years (from 01st January 2008 to 31st December 2017) was considered for the study.

Statistical Tools Used

In order to forecast the stock price trends of Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited, the statistical tools, SPSS (version 20.0) and Neural Works Predict (version. 3.24), were used in the study.

DESCRIPTIVE ANALYTICS OF RIL, TCS AND HDFC BANK

Table 1 depicts the descriptive statistics of the stock prices of Reliance Industries Limited, Tata Consultancy Services and HDFC Bank, for the time period 2008-2017. The equity shares of these three companies are listed in Bombay Stock Exchange (S&P BSE Sensex). These three stocks are the prime movers in the Indian stock market and they have top market capitalization values. Volatility generally persists in stock prices of the listed companies in India.

One of the measures of central tendency, namely the average mean value for TCS was maximum at Rs. 2570.51, followed by HDFC Bank at Rs. 1910.45, but for RIL, the value was minimum at Rs. 1883.92, during the study period. Another measure of central tendency, considered for this study, was the Median and the average median value was at Rs. 1722.45, followed by RIL, and was at minimum of Rs. 1579.26 during the period 2008-2017.

The analysis of average value of Minimum shows that RIL was at Rs. 1081.98, TCS was at Rs. 583.38 and HDFC Bank was at Rs. 650.44, whereas the average value of Maximum, for RIL was at Rs. 5127.84, followed by TCS, with the value of Rs. 4449.80 and HDFC Bank with the value of Rs. 4105.42, during the study period. The average value of Standard Deviation, for RIL was at 754.943, followed by HDFC Bank (869.288) and TCS (1214.01), during the period.

The two major measures of dispersion, in the descriptive statistics, are Skewness and Kurtosis. It was found that the Skewness value (average) for RIL was at 2.97564, followed by HDFC Bank (0.98025) and TCS (0.10447). Kurtosis value (average) for RIL was at 4.15644, followed by HDFC Bank (-0.92863) and TCS (-2.54764), during the study period.

The total value at 95% level, for TCS was at 10477.5, followed by HDFC Bank (9143.02) and RIL (9018.59). The total value of Inter-quartile range, for HDFC Bank was at 3537.37, TCS was at 6042.58 and RIL was at 958.18. The average value of the HDFC Bank was at 1414.95, TCS was at 2417.03 and RIL was at 383.272, during the period of 2008 to 2017.

The analysis clearly indicates that the stock prices of all the three sample stocks (RIL, TCS and HDFC Bank), varied widely, in tune with price variants, namely opening price, high price, low price and closing price during intra-day transactions, during the study period, on all parameters of descriptive statistics, used in this study. Hence the hypothesis *H1* (There is no stochastic movement between the stock prices of Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited during the study period), is not accepted.

The stock market data are a kind of big data. For each trading day, four strata values were considered. The total observations, used in the study, were 29718 for the 2476 trading days (9904 observations for each stock), which is voluminous in nature and they require machines and human intelligence to process and to draw meaningful inferences (Kohzadi et al., 1996).

Table 1
DESCRIPTIVE ANALYTICS FOR RIL, TCS AND HDFC BANK STOCK PRICES DURING THE PERIOD FROM 2008 TO 2017

Factor	Company	Opening Price	High Price	Low Price	Closing Price	Total	Average
Mean (Rs.)	RIL	1146.68	1163.10	1129.42	1145.61	4584.81	1833.92
	TCS	1606.80	1625.40	1587.75	1606.32	6426.27	2570.51
	HDFC Bank	1194.87	1208.41	1178.78	1194.06	4776.12	1910.45
Median (Rs.)	RIL	988.00	996.60	977.15	986.40	3948.15	1579.26
	TCS	1336.03	1348.67	1323.12	1336.05	5343.87	2137.55
	HDFC Bank	1078.00	1090.00	1062.10	1076.03	4306.13	1722.45
Minimum (Rs.)	RIL	675.00	682.75	671.00	676.20	2704.95	1081.98
	TCS	360.000	377.000	355.250	366.200	1458.45	583.38
	HDFC Bank	405.900	413.700	400.450	406.050	1626.1	650.44
Maximum (Rs.)	RIL	3216.00	3252.10	3135.20	3216.30	12819.6	5127.84
	TCS	2775.00	2834.00	2739.80	2775.70	11124.5	4449.8
	HDFC Bank	2564.00	2582.50	2552.35	2564.95	10263.8	4105.52
Std. dev.	RIL	471.998	483.841	459.683	471.835	1887.36	754.943
	TCS	759.369	763.182	754.135	758.349	3035.04	1214.01
	HDFC Bank	543.309	548.913	537.509	543.490	2173.22	869.288
Skewness	RIL	1.8618	1.8582	1.8608	1.8583	7.4391	2.97564
	TCS	0.0650885	0.0669944	0.0638776	0.0652188	0.26118	0.10447
	HDFC Bank	0.611918	0.606260	0.619980	0.612466	2.45062	0.98025
Kurtosis	RIL	2.6065	2.5705	2.6256	2.5885	10.3911	4.15644
	TCS	-1.59124	-1.59446	-1.58997	-1.59342	-6.3691	-2.54764
	HDFC Bank	-0.579665	-0.586630	-0.573415	-0.581858	-2.3216	-0.92863
95% perc.	RIL	2260	2300.15	2207.20	2251.24	9018.59	3607.44
	TCS	2620.00	2644.87	2594.81	2617.78	10477.5	4190.98
	HDFC Bank	2292.15	2314.32	2253.34	2283.21	9143.02	3657.21
IQ range	RIL	238.25	248.49	233.34	238.10	958.18	383.272
	TCS	1506.62	1512.41	1511.34	1512.21	6042.58	2417.03
	HDFC Bank	885.000	903.212	869.075	880.087	3537.37	1414.95

Source: Data retrieved from www.bseindia.com, using SPSS (version 20.0)

STOCK PRICE TRENDS OF RIL, TCS AND HDFC BANK DURING 2008-2017

The holistic view of the stock price trends of Reliance Industries Limited, Tata Consultancy Services and HDFC Bank, is illustrated in Table 2. The total number of trading days considered, in this study, was 2476 days. The four strata values (opening price, high price, low price and closing price), on every trading day, envisaged the stochastic behaviour of stock markets trends. The trends were calculated, from 1st January 2008 to 31st December 2017.

According to Table 2, the R-value was recorded, at maximum, for Reliance Industries Limited (0.9977), followed by HDFC Bank (0.9974) and Tata Consultancy Services (0.9972), whereas the Net-R value computed was ranging between 0.9955 to 0.9951 (RIL: 0.9955; HDFC Bank: 0.9954 and TCS: 0.9951), during the study period.

The Average Absolute Error (AAE) denotes the average absolute difference between the values of price (four strata values) trends. The average absolute error was recorded at 10.1857 (maximum) for RIL while it was recorded at 9.8523 (minimum) for TCS and at 9.8649 for HDFC Bank. Similarly, the Maximum Absolute Error (MAE) refers to the maximum absolute difference between the daily prices (four strata values) of the stock. Such values were recorded at 42.4135 (maximum) for RIL, 39.1059 for TCS and at 38.9736 (minimum) for HDFC Bank.

The Root Mean Square Error (RMSE) emphasizes the mean difference between two days stock price values. The values of RMSE were recorded at 12.6871 (maximum), for RIL, at 12.6241, for TCS and at 11.8912 (minimum) for HDFC Bank. At the 95% confidence intervals, the stock price trend value, for RIL, was recorded as 24.8154 (maximum) whereas it was recorded at 24.7182, for TCS and at 22.4873 (minimum), for HDFC Bank, during the study period. The stochastic nature of price movements i.e., price increase and decrease in a wide manner, were evidenced from the market statistics of RIL, TCS and HDFC Bank.

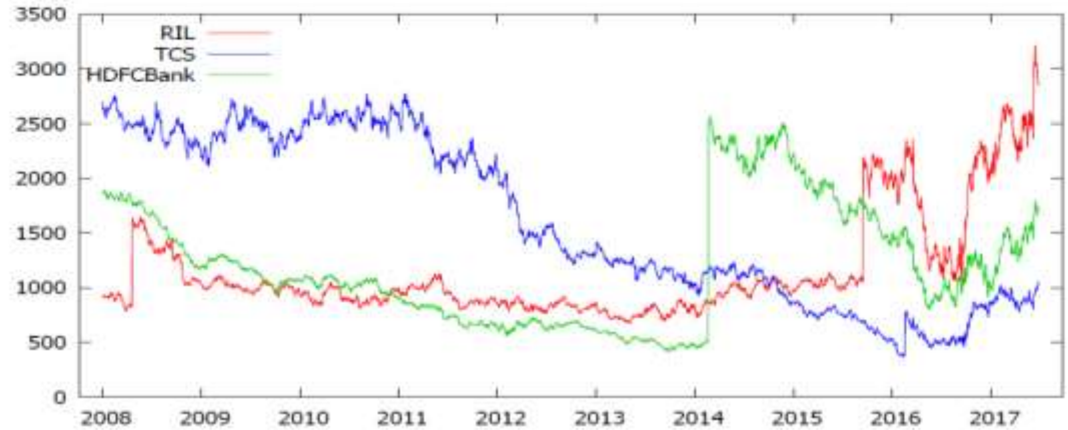
TABLE 2
STOCK PRICE TRENDS FOR RIL, TCS AND HDFC BANK DURING THE PERIOD 2008 TO 2017

Name of the Company	R	Net-R	Average Absolute Error	Maximum Absolute Error	Root Mean Square Error	Confidence Interval (95%)	Trading Days
RIL	0.9977	0.9955	10.1857	42.4135	12.6871	24.8154	2476
TCS	0.9972	0.9951	9.8523	39.1059	12.6241	24.7182	2476
HDFC Bank	0.9974	0.9954	9.8649	38.9736	11.8912	22.4873	2476

Source: Data retrieved from www.bseindia.com, using SPSS (version 20.0)

Figure 1 evidences the daily stock price trends, in terms of four strata values of RIL, TCS and HDFC Bank, during the period and the trend also supports the statistical values, depicted in Table 2. Hence the hypothesis *H2* (There exist no variations in the price trends among the stock prices of Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited), is not accepted, in the study.

The stock prices normally tend to vary, due to buying and selling of stocks and a host of macro as well as micro economic variables. ANN is a class of generalized, non-linear and non-parametric model, which is used to derive inferences in the analysis of big data domains like stock market analytics. The stock price trends of RIL, TCS and HDFC Bank 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. Neural networks would be helpful for the investors, to arrive at right price discovery of the stocks, in both the short term point of view and the long term perspective, so as to make investment strategies accordingly, to maximize the returns (Boyacioglu and Avci, 2010).



Source: Data using SPSS (version 20.0)

FIGURE 1
STOCK PRICE TRENDS FOR RIL, TCS AND HDFC BANK DURING 2008-2017

PREDICTION PERFORMANCE OF RIL, TCS AND HDFC BANK

The main objective of this study was to predict the stock prices of Reliance Industries Limited, Tata Consultancy Services and HDFC Bank, using the past prices/historical values of the company stock. In this study, Neural Works Predict (version 3.24) package was used to predict the future stock prices. The performance of the neural network largely depends on the architecture of the neural network. The critical issues of neural network modeling include selection of input variables, data pre-processing technique, network architecture design and performance measuring statistics, in designing the right predictive models.

Table 3 exemplifies the results of prediction performance statistics, for three sample stocks, namely Reliance Industries Limited (RIL), Tata Consultancy Services (TCS) and HDFC Bank, during the study period from 2008 to 2017. The total number of trading days considered in this study was 2476 days. The four variants of statistics of stock values (opening value, high value, low value and closing value) were considered. Both the actual values recorded and the predicted values calculated, were compared, to analyze the prediction performance. The R-value for RIL was 0.9971 (actual) and 0.9968 (predicted) whereas the values for TCS were 0.9971 (actual) and 0.9971 (predicted) and the values for HDFC Bank were at 0.9965 (actual) and 0.9963 (predicted). Similarly, the Net-R values, computed for RIL, were 0.9952 (actual) and 0.9961 (predicted) whereas the values, for TCS, were 0.9950 (actual) and 0.9955 (predicted) and the values for HDFC Bank were 0.9953 (actual) and 0.9949 (predicted).

The Average Absolute Error (AAE) denotes the average absolute difference between predicted output values and target output values. The values of AAE were recorded as 9.8723 (actual) and 10.8716 (predicted) for Reliance Industries Limited, whereas the AAE values were at 9.8169 (actual) and 10.1857 (predicted) for Tata Consultancy Services and the values were 9.8169 (actual) and 8.1857 (predicted) for HDFC Bank. This shows that the variations persisted between actual and predicted values of stock prices of sample firms. The Maximum Absolute Error (MAE) is the maximum absolute difference, between a predicted output value and a target output value. Such values were 49.1059 (actual) and 47.9437 (predicted) for RIL whereas the values of MAE were 48.1047 (actual) and 41.4135 (predicted), for TCS and the values were

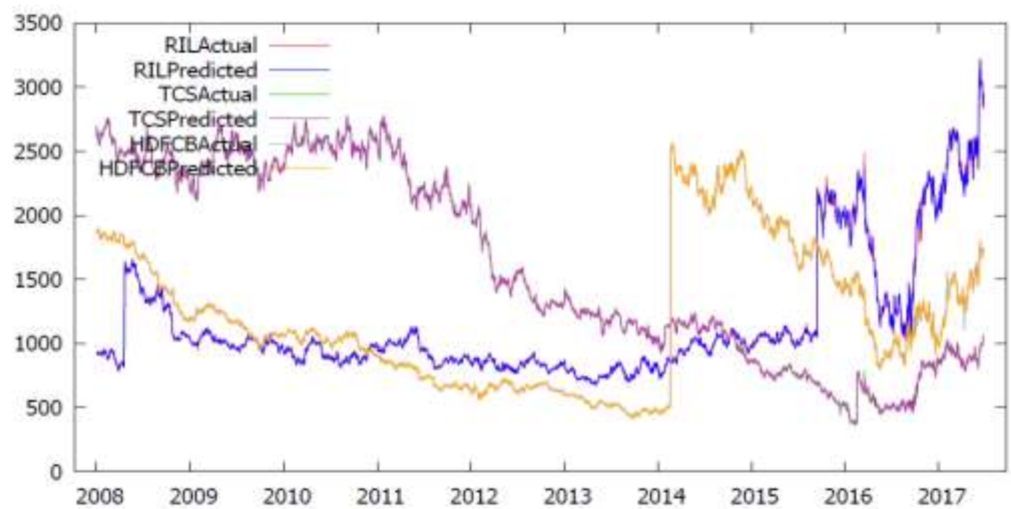
43.1047 (actual) and 37.4135 (predicted), for HDFC Bank. The values of Root Mean Square Error (RMSE) were 12.6841 (actual) and 11.1759 (predicted), for RIL, whereas the values were at 11.6872 (actual) and 10.3571 (predicted), for TCS and the values of RMSE were at 10.6872 (actual) and 9.6571 (predicted) for HDFC Bank. The accuracy is measured in terms of either significance level or confidence intervals. At 95% confidence intervals, the model predictions were within the range, around the target values. The values of accuracy were 24.7182 (actual) and 23.8237 (predicted), for RIL, the values were at 22.8154 (actual) and 22.8154 (predicted), for TCS and 21.7509 (actual) and 20.8154 (predicted), for HDFC Bank.

The close correlation between the market value predicted, using the neural network and the actual value, suggests that such networks are powerful tools in stock price prediction and helps the investors to take intelligent investment decisions, to earn capital appreciation, in addition to dividends (Sigo and Selvam, 2015) for their stock market investments. The real output was compared with predicted values.

Table 3
PREDICTION PERFORMANCE FOR RIL, TCS AND HDFC BANK STOCK PRICES DURING THE PERIOD 2008 TO 2017

Name of the Company	Trend	R	Net-R	Average Absolute Error	Maximum Absolute Error	Root Mean Square Error	Confidence Interval (95%)
RIL	Actual	0.9971	0.9952	9.8723	49.1059	12.6841	24.7182
	Predicted	0.9968	0.9961	10.8716	47.9473	11.1759	23.8237
TCS	Actual	0.9970	0.9950	9.8169	48.1047	11.6872	23.7509
	Predicted	0.9971	0.9955	10.1857	41.4135	10.3571	22.8154
HDFC Bank	Actual	0.9965	0.9953	9.8169	43.1047	10.6872	21.7509
	Predicted	0.9963	0.9949	8.1857	37.4135	9.6571	20.8154

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



Source: Data using NeuralWorks Predict (version 3.24)

FIGURE 2
PREDICTION PERFORMANCE OF STOCK PRICE TRENDS FOR RIL, TCS AND HDFC BANK DURING 2008-2017

Figure 2 evidences the actual and predicted values of daily stock price trends of RIL, TCS and HDFC Bank, during the period from 2008 to 2017 and it also supports the values depicted in Table 3. Hence the hypothesis *H3* (There exist no price variation between actual and predicted stock prices of Reliance Industries Limited, Tata Consultancy Services Limited and HDFC Bank Limited during the study period), is rejected, in the study.

The information of historical 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 help the investors in this aspect. Artificial Neural Network, being one of the neural network methods, is a non-linear and non-parametric model, used to derive inferences, in big data domains like stock market analytics.

The analysis of Tables 1-3 and Figures 1 & 2, there was volatility and stock prices of Reliance Industries Limited (RIL), Tata Consultancy Services (TCS) and HDFC Bank recorded stochastic nature in price trends, as well as the price variations between the actual and predicted values of all these three sample stocks, during the study period (Zhu, 2008).

DISCUSSIONS AND FUTURE RESEARCH ORIENTATIONS

The market value of every stock is changing every bit of a second, based on the demand and supply forces, namely the buyers and sellers of stocks. The stock prices of the three sample stocks ranged between Rs. 355.25 to Rs. 3252.10 (for RIL: Rs. 671.00 to Rs. 3252.10, for TCS: Rs. 355.25 to Rs. 2834.00 and HDFC Bank: Rs. 400.45 to Rs. 2582.50), during the study period (Table 1). This phenomenon happens due to various macro and micro economic factors. There are micro economic factors i.e., bearish and bullish trends and the investors' sentiments in the stock market, which are directly related to the stock performance and some other factors, which may be of macroeconomic in nature, which do not directly impact the price movement of the specific stock. In this study, the stock prices were forecasted, using artificial neural network, since the stock price data of the three sample stocks (RIL, TCS and HDFC Bank) was volatile and voluminous, i.e., big data. The stock price data were collected and processed, to find out the current price trends and the future price trend of these three stocks were predicted by applying the Neural Works Predict (version 3.24). This machine learning model was found better than the time series models, in processing the volatile stock information and big data and to give valuable inferences (Wanga and Shangb, 2014).

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 like RIL, TCS and HDFC bank would make the investors to get more benefit, if they could invest rationally in those stocks, since these stocks are the top three market capitalization stocks and the market leaders in the respective sectors of business. The applications and the use of machine learning oriented artificial neural networks would probably enhance the predictive accuracy of stock price prediction. The fusion of two or more neural networks could be applied, to increase the predictive accuracy of stock prices and stock market trends (Snigaroff and Wroblewski, 2011). The experience gained by the investors, using neural network approaches, would help the investors, in rationalizing the decisions and optimizing the stock returns.

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

CONCLUSION

This study analyzed the stock price trends and predicted values of three top market capitalization stocks, namely RIL, TCS and HDFC Bank, 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 et al., 2007). The investment behaviour 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 machine learning method like the artificial neural network, the forecasting would become more accurate and the investors could ensure earning capital appreciation, for their stock investments, which would ensure maximization of wealth in the long run.

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