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Applications of Neuro Deep Learning Models in Predictive Data Analytics for the Movements and Trends of the Indian Stock Market: Financial Data Mining, Nonlinearity, and Quantum Finance

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Abstract

The financial 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 macroeconomic variables, legal frameworks, 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 prices. Achieving accuracy for forecasting the market trend has become difficult due to the prevalence of stochastic behaviour in the stock market and volatility in the stock prices. This paper analyzes the stochastic movement pattern of the highly volatile thirty individual company stocks (in terms of market capitalization) of BSE-Sensex, using the Neuro Deep Learning method, a model of deep learning approach. The findings of the study would help the investors, to make rational and well-informed investment decisions, and to optimize the returns by investing in the most valuable stocks of listed corporate enterprises.

Keywords: *Behavioural Finance, Business Intelligence, Financial Data Mining, Deep Learning, Nonlinearity, Predictive Analytics, Quantum Computing, Quantum Finance, Stochastic Movement, Stock Markets.*
JEL Code: C53, D83, E27, E44, G1.

Introduction

The Efficient Market Hypothesis (EMH) essentially says that all known information about investment securities, such as stocks, is already factored into the prices of those securities. Therefore, assuming this is true; no amount of analysis can give an investor an edge over other investors, collectively known as 'the market'. EMH does not require that investors be rational; it says that individual investors will act randomly, but as a whole, the market is always 'right'. In simple terms, 'efficient' implies 'normal'. For example, an unusual reaction to unusual information is normal. If a crowd suddenly starts running in one direction, it's normal for you to run in that direction, even if there isn't a rational reason. EMH does not say that no investors can outperform the market; it says that there are outliers that can beat the market averages; however, there are also outliers that dramatically lose to the market. The majority is closer to the median. 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 behaviour, in the stock markets **(Fama, Eugene 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, economic conditions, bank rates, 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. Evaluating the prediction of an ensemble typically requires more computation than assessing the prediction of a single

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model. Ensemble methods use multiple learning algorithms to obtain better predictive performance **(Ou, P., & Wang, H., 2009).**

Eric Siegel (2016) emphasized that a little prediction goes a long way. Forecasting the movement of the stock price of a company is a classic problem. Stock market transactions, across the Globe, are voluminous and volatile. Prediction of the 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 only 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, volatility widely persists in the stock prices and index movements. At a particular point in time, there could be trends, cycles, random walks, or a combination of these three cases/events, in respect of stock market movements **(Robert Snigaroff & David Wroblewski, 2011).**

The closing value of the stock index has been used, as important statistical data, to derive useful information about the current and probable future movement pattern of stock markets **(Defu Zhang, et al., 2005).** The supervised learning algorithms perform the task of searching through a hypothesis space to find a suitable hypothesis that will make good predictions with a particular problem.

Ensembles combine multiple hypotheses to form a better hypothesis. An ensemble is usually reserved for methods that generate multiple hypotheses using the same base learning. Ensembles tend to yield better results empirically, when there is significant diversity among the models. One of the variants of the Deep Learning Model, i.e., the Neuro Deep Learning Method, could forecast the future trend of stock prices and it provides stock information signs, for making better investment decisions of buying and selling stocks, by the investors **(Jigar Patel, et al., 2015a).**

Review of Literature

An extensive review of literature in the area of forecasting stock prices has been done to find the research gap and to get an idea of predictive analytics of financial markets.

Nowrouz Kohzadi, et al., (1996) described the methodology, advantages, and demerits of artificial neural networks 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 average, for the neural network approach than for the time series models like Auto-Regressive Integrated Moving Average (ARIMA). **Wang, J. H., & Leu, J. Y., (1996)** forecasted the stock price trend for six weeks, based on the past four years' stock price movements in the Taiwan stock market, by using recurrent neural networks.

Vapnik Vladimir (1998) developed the Support Vector Machine algorithm and applied it in forecasting the financial markets.

Walczak S. (1999) forecasted the fluctuations in financial markets, which varied across the periods, and the rate of financial literacy was considered one of the crucial factors, that influenced the investment decisions of the investors.

Abraham A., et al., (2001) applied a Neuro-fuzzy system for forecasting the stock prices of the next day and the stock index movements of the Nasdaq-100 of the United States of America. It was found that the probabilistic neural network-based investment strategies performed better than the other predictive models.

Kim, K. J. (2003) used twelve technical indicators, to forecasting daily stock price changes in the Korea Composite Stock Price Index.

Simulation results of the Shanghai Composite Index showed that neural networks could be applied to maximize the returns of stock market investment **(Defu Zhang, et al., 2005).**

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Franklin F. 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. **Teo Jasic & Douglas Wood (2006)** calculated the profitability of stock indices, based on daily trades, by applying a neural network for the highly volatile stock index movements of the S&P 500, the DAX, the TOPIX, and the FTSE.

Hassan, M. R., et al., (2007) used a fusion model, combining Hidden Markov Model, Artificial Neural Networks, and Genetic Algorithms, to forecast stochastic financial market behaviour. According to **Yung-Keun Kwon & Byung-Ro Moon (2007),** the prediction of financial objects was a challenging task and the profits for such investments were quite sensitive to transaction costs.

Andre Carvalhal & Beatriz Vazde Melo Mendes (2008) analyzed the forecasting performance of stock returns of emerging market stocks. **Xiaotian Zhu, et al., (2008)** explained the technicalities of forecasting stock index movements, by using different neural networks, and the role and influence of trading volume, under different time horizons of various stock market indices like DJIA and STI.

Ou, P., & Wang, H., (2009) used ten different data mining techniques, to forecast the stock price movements of the Hang Seng index of the Hong Kong stock market. According to **Robin Hanson & Ryan Oprea (2009),** the novelty, complexity, and anonymity influenced the forecasting of the stock markets. Also, **Shinhua Liu (2009)** investigated the forecasting capability of the weekly movement pattern and the returns of Nikkei-225, one of the premier stock indices of Japan.

Melek Acar Boyacioglu & Derya Avci (2010) forecasted the returns on the stock index value of the Istanbul Stock Exchange (ISE), with the help of an Adaptive Network-Based Fuzzy Inference System (ANFIS). The experimental results revealed that the model successfully forecasted the monthly return of the ISE National 100 Index, with an accuracy rate of 98.3%.

Nair, B, B., et al., (2011) forecasted the closing value of the next day for five international stock indices, using an adaptive artificial neural network system.

Chakravarty, S. & Dash, P. K. (2012) found that the volatility persisted in the financial time series, due to both economic and non-economic factors. **Selvan Simon & Arun Raoot (2012)** applied an appropriate number of hidden layers, several neurons in each layer, the size of the training set, initial values for weights, inputs to be included, and activation functions, which are the key issues in designing a network model.

Jigar Patel, et al., (2015$_b$) 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 naive-bayes and the respective values were compared in a group.

Sigo Marxia Oli, et al., (2017) found that the forecasting accuracy was higher in the case of the k-nn algorithm model than that of the logistic regression method.

Marxia Oli Sigo, et al., (2018$_a$) 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.

Marxia Oli Sigo, et al., (2018$_b$) applied Artificial Neural Network, to forecast the stock prices of Reliance Industries Ltd., Tata Consultancy Services Ltd., and HDFC Bank Ltd.,

Marxia Oli Sigo, et al., (2019) applied the machine learning method, to forecast the stock price trends of NSE-Nifty of India, in the pre and post-global crisis (2008) time zones.

So far, 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 the Neuro Deep Learning approach, to forecast the future stock prices of the Indian stock market.

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Statement of the Problem

In general, investors find it difficult to forecast the movements of stock price, since it is highly stochastic and volatile. 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 for investors to buy a stock, at a low market price and sell it at a high market price, 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 investors for investment decisions. Lack of these attributes, among financial investors, would lead to inconsistency and inaccuracy in market forecasting, which would eventually lead to losses in stock market investments **(Melek Acar Boyacioglu & Derya Avci, 2010).** Besides, the financial system develops and suggests some techniques, for the investors, to forecast stock prices. However, there is no proven prediction technique 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 views. To maximize the returns for investments in stocks, the trade-off between risk and return as well as sensitivity to the stock price movements are essential. This study would help a spectrum of investors (retail investors, financial institutions, mutual funds, investment banks, and foreign institutional investors) to make well-informed investment decisions based on scientific thinking and a rational approach **(Amitai Etzioni, 1976).** The absence of prudent forecasting methods, lower level of financial literacy, 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 predict the future direction of the stock price movements of thirty companies indexed in BSE-Sensex, using a Deep Learning Model, the Neuro Deep Learning Method.

Hypotheses of the Study

The following hypotheses were formulated to test and validate the study.

N_H-1: There exists no stochastic trend between the stock prices of thirty companies indexed in BSE-Sensex during the global pre-crisis period.

N_H-2: There exists no variation between actual and predicted stock price values of thirty companies indexed in BSE-Sensex during the global pre-crisis period.

N_H-3: There exists no stochastic trend between the stock prices of thirty companies indexed in BSE-Sensex during the global post-crisis period.

N_H-4: There exists no variation between actual and predicted stock price values of thirty companies indexed in BSE-Sensex during the global post-crisis period.

N_H-5: An investor couldn't outperform the market, since all the available information is already reflected in the market prices.

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Research Methodology

Sampling Design of the Study

The sample consisted of the stock prices of thirty companies of BSE-Sensex, based on the top value in its free-float market capitalization as of 1st 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.bseindia.com)**. Hence, stock-exchange-listed stocks of those thirty companies were taken as the sample units for this study.

Sources of Data

The secondary data of the four variants of daily prices (opening price, high price, low price, and closing price) of thirty companies of BSE-Sensex were collected from the websites of Bombay Stock Exchange Limited.

Study Period

A period of twenty years (from 1st January 1999 to 31st December 2018) was considered for the study.

Statistical Tools Used

To forecast the stock price trends of thirty companies of BSE-Sensex, the statistical tools, SPSS (version 20.0) and Neural Works Predict (version 3.24), were used in this study.

Forecasting The Future Trends of Stock Prices in India

The analysis of stock price prediction of thirty companies indexed in BSE-Sensex is presented as follows:

Prediction Performance of BSE-Sensex Companies using the Neuro Deep Learning Method during the pre-crisis period from 1999 to 2008

Prediction Performance of BSE-Sensex Companies using the Neuro Deep Learning Method during the post-crisis period from 2009 to 2018

Prediction Performance of Bse-Sensex Indexed Companies Using Ensemble Machine Learning Method During the Pre-Crisis Period From 1999 To 2008

Table 1 illustrates the holistic view of the stock price trends of thirty companies included in BSE-Sensex, during the global pre-crisis period from 1999 to 2008.

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Table 1. Prediction Performance of BSE-Sensex Companies During 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	Asian Paints	Actual	0.9471	0.9951	9.8523	39.1059	12.6241	3765.26
		Predicted	0.9977	0.9955	10.1837	38.0234	**12.6870**	3524.01
2	Axis Bank	Actual	0.9970	0.9954	9.8649	38.9736	9.8920	1384.68
		Predicted	0.9976	0.9951	8.1857	**42.4135**	10.6871	1537.20
3	Bajaj Auto	Actual	0.9977	0.9925	**10.1957**	42.0135	12.4771	2912.50
		Predicted	0.9975	0.9931	9.8523	37.1059	12.6214	2598.01
4	Bajaj Fin	Actual	0.9971	0.9950	9.8521	39.1050	12.6240	1354.02
		Predicted	0.9930	0.9752	9.8524	38.7452	12.6200	1098.30
5	Bharti Air	Actual	0.9673	0.9949	**8.1857**	35.7059	10.5120	842.32
		Predicted	0.9972	0.9951	9.8525	36.5059	12.6241	851.04
6	Coal India	Actual	-------	-------	-------	-------	-------	-------
		Predicted	-------	-------	-------	-------	-------	-------
7	HCL Tech	Actual	0.8979	0.9951	8.1972	40.4135	12.1217	1019.56
		Predicted	0.9933	0.9925	8.1523	39.1259	12.5241	1100.75
8	HDFC	Actual	0.9975	0.9951	9.8523	39.1059	12.6241	2772.51
		Predicted	0.9907	0.9955	**10.8517**	42.0235	12.6810	2969.09
9	HDFC Bank	Actual	**0.9979**	0.9954	9.8649	38.9761	11.8912	2023.06
		Predicted	0.9932	0.9951	9.8523	39.1059	12.6241	2027.01
10	Hero M	Actual	0.9577	0.9935	9.1874	42.0135	12.6871	3283.35
		Predicted	0.9941	0.9924	9.5649	38.9762	**8.8901**	3021.96
11	HUL	Actual	0.9972	0.9911	9.8523	39.3269	12.6241	2297.82
		Predicted	0.9904	**0.8954**	9.3649	38.9739	11.8763	2053.29
12	ICICI Bk	Actual	0.9907	0.9955	10.2433	42.0935	12.6810	1191.25
		Predicted	0.9972	0.9954	9.8649	38.9761	11.8912	1009.21
13	IndusInd	Actual	**0.8977**	0.9950	8.1872	41.4135	12.3217	1219.56
		Predicted	0.9932	0.9927	**8.0523**	39.1059	12.6241	1100.75
14	Infosys	Actual	0.9904	0.9754	9.8649	38.9739	11.8763	**7419.25**
		Predicted	0.9941	0.9956	9.9649	38.9762	8.8901	**7516.65**
15	ITC	Actual	0.9932	0.9951	9.8523	39.1059	12.6241	1121.07
		Predicted	0.9904	0.9254	9.8621	38.9739	11.8163	1105.87
S. No	**Company Name**	**Trend**	**R**	**Net-R**	**Average Absolute Error**	**Maximum Absolute Error**	**Root Mean Square Error**	**Confidence Interval (95%)**
16	Kotak M Bank	Actual	0.9927	0.9955	10.1176	39.4176	12.2571	1047.41
		Predicted	0.9673	0.9951	9.8523	39.0159	10.6240	998.26
17	L & T	Actual	0.9941	0.9954	9.8649	38.9762	**8.7511**	2590.69
		Predicted	0.9904	0.9961	9.8649	38.9739	11.8763	2780.31
18	M & M	Actual	0.9972	0.9951	9.8523	39.1059	12.6241	1354.00
		Predicted	0.9932	0.9751	9.8523	38.7459	12.6201	1098.32
19	Maruti	Actual	0.9972	0.9954	9.8649	38.9761	11.8912	6205.32
		Predicted	0.9973	**0.9997**	9.8649	39.4761	11.8912	6501.98

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20	NTPC	Actual	0.9977	0.9925	9.1837	42.4135	12.2211	212.52
		Predicted	0.9924	0.9850	9.7649	38.9736	11.8912	**205.14**
21	ONGC	Actual	0.9972	0.9954	9.5649	38.9761	11.8928	1213.00
		Predicted	0.9932	0.9951	9.2523	39.2456	12.6201	1198.41
22	Powergrid	Actual	0.9951	0.9951	9.8523	37.1059	12.0215	**206.18**
		Predicted	**0.8814**	0.9216	9.7546	39.2154	12.6241	201.15
23	RIL	Actual	0.9971	**0.9957**	9.7723	**49.1057**	**12.9871**	4020.71
		Predicted	0.9968	0.9941	10.0716	47.9473	11.1759	3823.21
24	SBI	Actual	0.9972	0.9951	9.8523	39.1059	12.6215	2560.43
		Predicted	0.9924	0.9805	9.8649	38.9736	11.8912	2431.01
25	Sun Pharma	Actual	0.9971	0.9924	9.0649	38.9761	11.8912	1553.26
		Predicted	0.9972	0.9651	9.8523	39.1059	12.6241	1452.98
26	Tata Motor	Actual	0.9970	**0.8907**	9.8649	**37.0215**	11.8912	961.91
		Predicted	0.9951	0.8151	9.8523	36.1059	12.6241	876.23
27	Tata Steel	Actual	0.9977	0.9955	10.1851	42.4135	12.2671	687.84
		Predicted	0.9924	0.9250	9.8649	38.9736	11.8912	599.37
28	TCS	Actual	0.9970	0.9821	9.8169	48.1047	11.6872	3750.90
		Predicted	**0.9971**	0.9955	10.1857	41.4135	10.3571	3815.40
29	Vedanta	Actual	0.9972	0.9954	9.8649	38.9761	11.8912	1897.97
		Predicted	0.9955	0.8951	9.8523	39.1059	12.6241	1478.77
30	Yes Bank	Actual	0.9924	0.9750	9.8649	38.9736	11.8912	1405.58
		Predicted	0.9951	0.9651	9.8523	**35.1059**	12.6241	1209.76

Source: Data collected from www.bseindia.com, computed using Neural Works Predict (v 3.24)

Note: ----- (Data is not available for Coal India Limited)

According to **Table 1,** the R-value (Actual) was recorded for IndusInd Bank Limited at 0.8977 (Minimum), followed by HDFC Bank Limited at 0.9979 (Maximum) while, the Predicted R-values ranged from 0.8814 (Minimum for Power Grid Corporation of India Limited) to 0.9971 (Maximum for Tata Consultancy Services Limited), among the BSE-Sensex companies during the global pre-crisis period from 1999 to 2008.

The computed **Net-R values** (Actual) varied between 0.8907 (the Minimum for Tata Motors Limited), and 0.9957 (the Maximum for Reliance Industries Limited), whereas, the Predicted Net-R values fluctuated between 0.8954 (the Minimum for Hindustan Unilever Limited) and 0.9997 (the Maximum for Maruti Suzuki India Limited), in respect of BSE-Sensex companies during the pre-crisis period.

The **Average Absolute Error (AAE)** indicates the average absolute difference between the values of stock prices of listed companies. It is evinced that the Actual Average Absolute Error (AAE) values ranged between 8.1857 (the Minimum for Bharti Airtel Limited) and 10.1957 (Maximum for Bajaj Auto Limited) whereas, the Predicted AAE values differed between 8.0523 (the Minimum for Indusind Bank Limited) and 10.8517 (Maximum for HDFC Limited), among the Sensex companies during the pre-crisis period.

Maximum Absolute Error refers to the maximum absolute difference between the daily prices of the stocks **(Jigar Patel, et al., 2015a). Table 1** shows that Actual Maximum Absolute Error values were recorded at 37.0215 (Minimum for Tata Motors Limited) and it was 49.1057 (Maximum for Reliance Industries Limited) while, the Predicted values differed between 35.1059 (Zee) and 42.4135 (Axis Bank Limited) among Sensex companies during the pre-crisis period from 1999 to 2008.

Root Mean Square Error (RMSE) revealed the mean difference between two days' stock price values**.** The lowest actual value of Root Mean Square Error (RMSE) was recorded at 8.7511 (L&T Limited), and the highest value was recorded at 12.9871(Reliance Industries Limited) while the Predicted RMSE values

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were extended between 8.8901 (Minimum value for Hero MotoCorp Limited) and 12.6870 (Maximum for Asian Paints Limited), among the Sensex companies during the pre-crisis period from 1999 to 2008.

According to **Table 1, at 95% confidence intervals,** the actual stock price trend value, for Powergrid Limited, was recorded at 206.18 (Minimum) and for Infosys, the value was 7419.25 (Maximum) whereas the Predicted values were stretched between 205.14 (Minimum for NTPC Limited) and 7516.65 (Maximum for Infosys Limited), among Sensex companies.

The analysis of this study found the stochastic nature of price movements **(Sureshkumar, K.K & Elango, N.M., (2012).** i.e., there was an increase and decrease in the stock price in the case of BSE-Sensex companies in a wide manner, during the pre-crisis period from 1999 to 2008.

However, the stock price trends of the thirty 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 other words, the actual stock price values of these thirty sample stocks (i.e., BSE-Sensex) experienced wide variations, with the predicted values of stock prices of respective company stocks **(Chakravarty, S. & Dash, P. K. (2012)**.

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 pre-crisis period from 1999 to 2008. The accuracy was measured at 95% confidence intervals.

Graph 1 and Figure 1 evidenced actual and predicted values of daily stock price trends of all the thirty Sensex stocks, during the pre-crisis period from 1999 to 2008, which supported the values depicted in **Table 1** i.e., the Prediction Performance for BSE-Sensex Companies during the pre-crisis period from 1999 to 2008.

This study confirmed the findings of **Melek Acar Boyacioglu & Derya Avci (2010),** who found that the stock market investment strategies differed from investor to investor, based on their interest, investor's psychology, investment value, and expected returns.

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 BSE-Sensex-indexed thirty companies had recorded a stochastic nature in price trends. Besides, price variations were found between the actual and predicted values of all the thirty sample stocks of BSE-Sensex (**Xiaotian Zhu, et al., 2008).**

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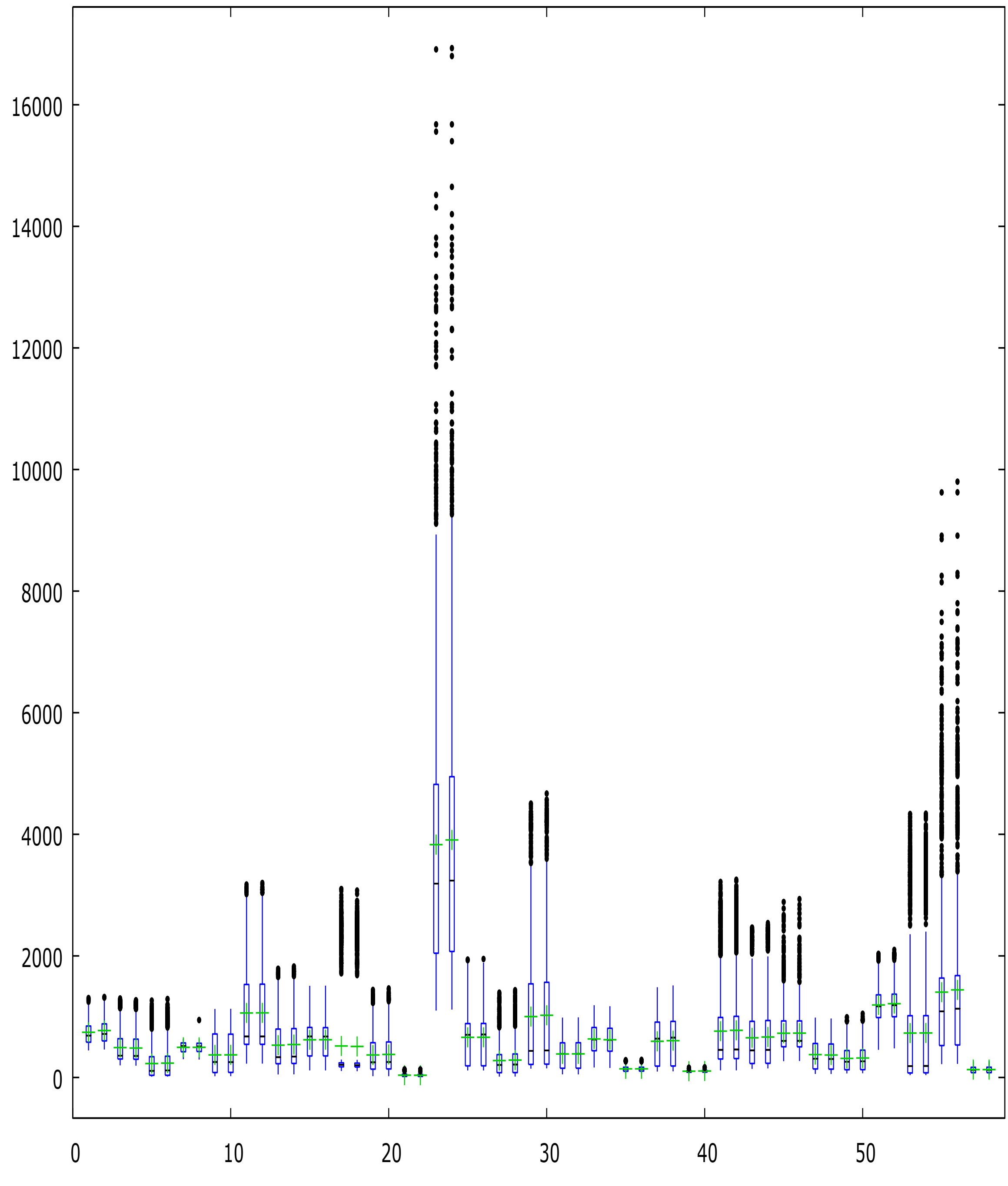
Graph 1. Prediction Performance of Stock Price Trends for BSE-Sensex Stocks

During the Pre-Crisis Period From 1999 To 2008



Source: Data collected from www.bseindia.com, and computed using Neural Works Predict (v3.24)

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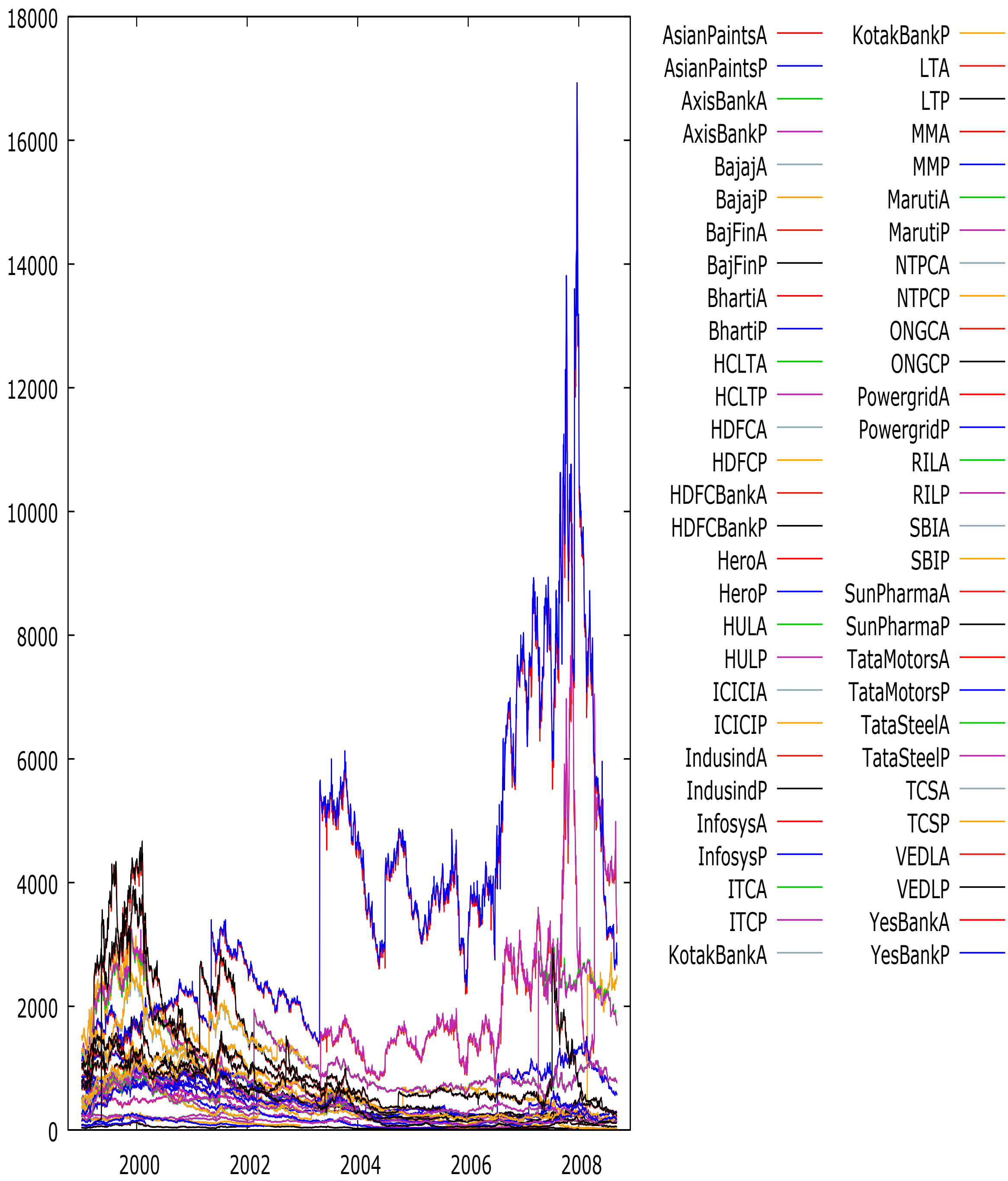
Figure 1. Prediction Performance Trend For BSE-Sensex Stocks During the Pre-Crisis Period From 1999 To 2008



Source: Data collected from www.bseindia.com, and computed using Neural Works Predict (v 3.24)

Based on the observations and analytics of statistical data, the null hypothesis **N_H-1 (There exists no stochastic trend between the stock prices of thirty companies indexed in BSE-Sensex during the**

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global pre-crisis period) was not accepted. Similarly, **N_H-2 (There exists no variation between actual and predicted stock price values of thirty companies indexed in BSE-Sensex during the global pre-crisis period)** was not accepted, in the study. It is suggested that investors may take note of the above information while making investment decisions.

Prediction Performance Of BSE-Sensex 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 BSE-Sensex thirty companies during the post-crisis period from 2009 to 2018.

According to **Table 2,** the **R-value** (Actual) was recorded, for ICICI Bank Limited, at 0.8809 (Minimum), followed by HDFC Limited at 0.9981 (Maximum) while the Predicted R-values ranged from 0.8714 (Minimum) for Power Grid Corporation of India Limited to 0.9972 (Maximum) for Tata Consultancy Services Limited, among the Sensex companies during the post-crisis period from 2009 to 2018.

The **Net-R values** (Actual) varied between 0.8906 (the Minimum for Tata Motors Limited), and 0.9955 (the Maximum for Reliance Industries Limited) whereas, the Predicted Net-R values were stretched between 0.8951 (the Minimum for Hindustan Unilever Limited) and 0.9993 (the Maximum for Maruti Suzuki India Limited), in respect of Sensex companies, during the post-crisis period from 2009 to 2018.

The analysis of **Average Absolute Error (AAE)** brought out the fact that there was an average absolute difference between the values of price trends. The minimum value of Actual Average Absolute Error (AAE) was recorded at 8.1854 (Coal India Limited) while, the maximum value was recorded at 10.1957 (Bajaj Auto Limited) whereas, the minimum value of Predicted AAE differed between 8.0521 (IndusInd Bank Limited) and 10.8517 (HDFC Limited), among Sensex companies, during the post-crisis period from 2009 to 2018.

Table 2. Prediction Performance Of BSE-Sensex 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	Asian Paints	Actual	0.9471	0.9951	9.8523	39.1059	12.6241	3765.26
		Predicted	0.9977	0.9955	10.1837	**42.4135**	**12.6870**	3524.01
2	Axis Bank	Actual	0.9970	0.9954	9.8649	38.9736	9.8920	1384.68
		Predicted	0.9976	0.9951	8.1857	38.0234	10.6871	1537.20
3	Bajaj Auto	Actual	0.9977	0.9925	**10.1957**	42.0135	12.4771	2912.50
		Predicted	0.9975	0.9931	9.8523	37.1059	12.6214	2598.01
4	Bajaj Fin	Actual	0.9870	0.9154	9.8749	38.9136	10.8120	984.68
		Predicted	0.9856	0.9351	8.1257	38.1234	10.6271	937.20
5	Bharti Airtel	Actual	0.9673	0.9949	9.8523	35.7059	10.5120	842.32
		Predicted	0.9972	0.9951	9.8525	36.5059	12.6241	851.04
6	Coal India	Actual	0.9976	0.9955	**8.1854**	42.4135	10.6571	393.70
		Predicted	0.9904	0.9954	9.7649	38.9739	11.8763	398.25
7	HCL Tech	Actual	0.9851	0.9151	9.8123	35.1059	11.0215	326.18
		Predicted	0.9114	0.9016	9.7246	38.2154	11.6241	311.15
8	HDFC	Actual	**0.9981**	0.9951	9.8523	39.1059	12.6241	2772.51
		Predicted	0.9907	0.9955	**10.8517**	42.0235	12.6810	2969.09
9	HDFC Bank	Actual	0.9979	0.9954	9.8649	38.9761	11.8912	2023.06
		Predicted	0.9932	0.9951	9.8523	39.1059	12.6241	2027.01
10	HeroMoto	Actual	0.9577	0.9935	9.1874	42.0135	12.6871	3283.35
		Predicted	0.9941	0.9924	9.5649	38.9762	**8.8901**	3021.96
11	Hindustan Unilever	Actual	0.9972	0.9911	9.8523	39.3269	12.6241	2297.82
		Predicted	0.9904	**0.8951**	9.3649	38.9739	11.8763	2053.29

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12	ICICI Bank	Actual	**0.8809**	0.9955	10.2433	42.0935	12.6810	1191.25
		Predicted	0.9972	0.9954	9.8649	38.9761	11.8912	1009.21
13	IndusInd Bank	Actual	0.8977	0.9950	8.1872	41.4135	12.3217	1219.56
		Predicted	0.9932	0.9927	**8.0521**	39.1059	12.6241	1100.75
14	Infosys	Actual	0.9904	0.9754	9.8649	38.9739	11.8763	**7419.25**
		Predicted	0.9941	0.9956	9.9649	38.9762	8.8901	**7516.65**
15	ITC	Actual	0.9932	0.9951	9.8523	39.1059	12.6241	1121.07
		Predicted	0.9904	0.9254	9.8621	38.9739	11.8163	1105.87
S. No	**Company Name**	**Trend**	**R**	**Net-R**	**Average Absolute Error**	**Maximum Absolute Error**	**Root Mean Square Error**	**Confidence Interval (95%)**
16	Kotak M Bank	Actual	0.9927	0.9955	10.1176	39.4176	12.2571	1047.41
		Predicted	0.9673	0.9951	9.8523	39.0159	10.6240	998.26
17	L & T	Actual	0.9941	0.9954	9.8649	38.9762	**8.7511**	2590.69
		Predicted	0.9904	0.9961	9.8649	38.9739	11.8763	2780.31
18	M & M	Actual	0.9972	0.9951	9.8523	39.1059	12.6241	1354.00
		Predicted	0.9932	0.9751	9.8523	38.7459	12.6201	1098.32
19	Maruti Suzuki	Actual	0.9972	0.9954	9.8649	38.9761	11.8912	6205.32
		Predicted	0.9973	**0.9993**	9.8649	39.4761	11.8912	6501.98
20	NTPC	Actual	0.9977	0.9925	9.1837	42.4135	12.2211	212.52
		Predicted	0.9924	0.9850	9.7649	38.9736	11.8912	**205.14**
21	ONGC	Actual	0.9972	0.9954	9.5649	38.9761	11.8928	1213.00
		Predicted	0.9932	0.9951	9.2523	39.2456	12.6201	1198.41
22	Powergrid	Actual	0.9951	0.9951	9.8523	37.1059	12.0215	**206.18**
		Predicted	**0.8714**	0.9216	9.7546	39.2154	12.6241	201.15
23	RIL	Actual	0.9971	**0.9955**	9.7723	**49.1057**	**12.9871**	4020.71
		Predicted	0.9968	0.9941	10.0716	47.9473	11.1759	3823.21
24	SBI	Actual	0.9972	0.9951	9.8523	39.1059	12.6215	2560.43
		Predicted	0.9924	0.9805	9.8649	38.9736	11.8912	2431.01
25	Sun Pharma	Actual	0.9971	0.9924	9.0649	38.9761	11.8912	1553.26
		Predicted	0.9972	0.9651	9.8523	39.1059	12.6241	1452.98
26	Tata Motor	Actual	0.9970	**0.8906**	9.8649	**37.0210**	11.8912	961.91
		Predicted	0.9951	0.8151	9.8523	36.1059	12.6241	876.23
27	Tata Steel	Actual	0.9977	0.9955	10.1851	42.4135	12.2671	687.84
		Predicted	0.9924	0.9250	9.8649	38.9736	11.8912	599.37
28	TCS	Actual	0.9970	0.9821	9.8169	48.1047	11.6872	3750.90
		Predicted	**0.9972**	0.9955	10.1857	41.4135	10.3571	3815.40
29	Vedanta	Actual	0.9972	0.9954	9.8649	38.9761	11.8912	1897.97
		Predicted	0.9955	0.8951	9.8523	39.1059	12.6241	1478.77
30	Yes Bank	Actual	0.9924	0.9750	9.8649	38.9736	11.8912	1405.58
		Predicted	0.9951	0.9651	9.8523	**35.1059**	12.6241	1209.76

Source: Data retrieved from www.bseindia.com, and computed using Neural Works Predict (version3.24)

Maximum Absolute Error refers to the maximum absolute difference between the daily prices of the stock **(Jigar Patel, et al., 2015a). Table 2** shows that Actual Maximum Absolute Error values varied between 37.0210 (Minimum for Tata Motors Limited) and 49.1057 (Maximum for Reliance Industries Limited) while, the Predicted values fluctuated between 35.1059 (Yes Bank Limited) and 42.4135 (Asian Paints Limited), among the Sensex companies, during the post-crisis period from 2009 to 2018.

Root Mean Square Error (RMSE) is the mean difference between the stock price values of any two consecutive days of stock market trading**.** The minimum value of Root Mean Square Error (RMSE) was registered at 8.7511 (Larsen & Toubro Limited), and the maximum value was recorded at 12.9871 (Reliance Industries Limited) while the Predicted values of RMSE were extended between 8.8901 (Minimum value for Hero MotoCorp Limited) and 12.6870 (Maximum for Asian Paints Limited) among Sensex companies, during the post-crisis period from 2009 to 2018.

It is noted from **Table 2** that **at 95% confidence intervals,** the actual stock price trend value for Power Grid Corporation of India Limited was recorded at 206.18 (Minimum) and for Infosys Limited, the value was 7419.25 (Maximum) whereas, the Predicted values were differed between 205.14 (Minimum for NTPC Limited) and 7516.65 (Maximum for Infosys Limited), among Sensex companies, during the post-crisis period from 2009 to 2018.

The analysis of this study found the stochastic nature of price movements i.e., there was an increase and decrease in the stock price in the case of BSE-Sensex companies in a wide manner, during the study period from 1999 to 2018. Besides, the stock price trends of the thirty 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 analysis showed that the actual stock price trends of these thirty sample stocks (i.e., BSE-Sensex) experienced wide variations, from the predicted values of stock prices of respective company stocks, during the global post-crisis period from 2009 to 2018.

It is clear 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 global post-crisis period from 2009 to 2018. It is to be noted that Accuracy was measured at 95% confidence intervals.

Graph 2 and Figure 2 evidenced the actual and predicted values of daily stock price trends of all the thirty Sensex stocks, during the global post-crisis period from 2009 to 2018, which supported the values depicted in **Table 2** i.e., the Prediction Performance for BSE-Sensex Companies during the post-crisis period from 2009 to 2018.

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 make intelligent investment decisions, to earn capital appreciation, in addition to dividends **(Sigo Marxia Oli & Murugesan Selvam, (2020, 2015), Marxia Oli Sigo, et al., (2018c))** from their stock market investments.

The findings of this study confirmed the findings of **Melek Acar Boyacioglu & Derya Avci (2010),** who found that the stock market investment strategies differed from investor to investor, based on their interest, investor's psychology, investment value, and expected returns. The information on 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.

In light of this study, it is found that the Neuro Deep Learning method 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

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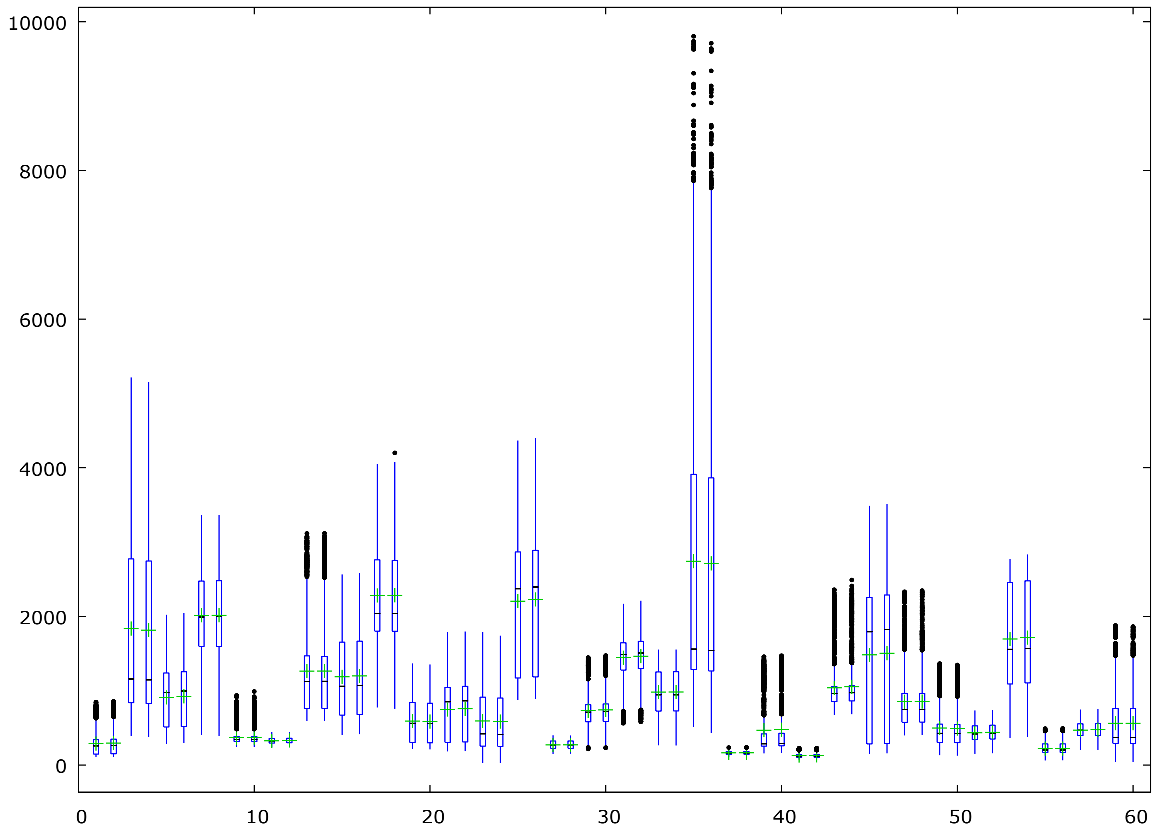
wealth **(Eric Siegel, 2016).** It is interesting to note from the analysis of **Table 2, Graph 2, and Figure 2** that the stock prices were volatile, during the post-crisis period from 2009 to 2018.

The stock prices of BSE-Sensex-indexed thirty companies had recorded a stochastic nature in price trends. Besides, the price variations were notified between the actual and predicted values of all the thirty sample stocks of BSE-Sensex (**Xiaotian Zhu, et al., 2008).**

Graph 2. Prediction Performance of Stock Price Trends For BSE-Sensex Stocks During the Post-Crisis Period From 2009 To 2018



Source: Data collected from www.bseindia.com, and computed using Neural Works Predict (v 3.24).

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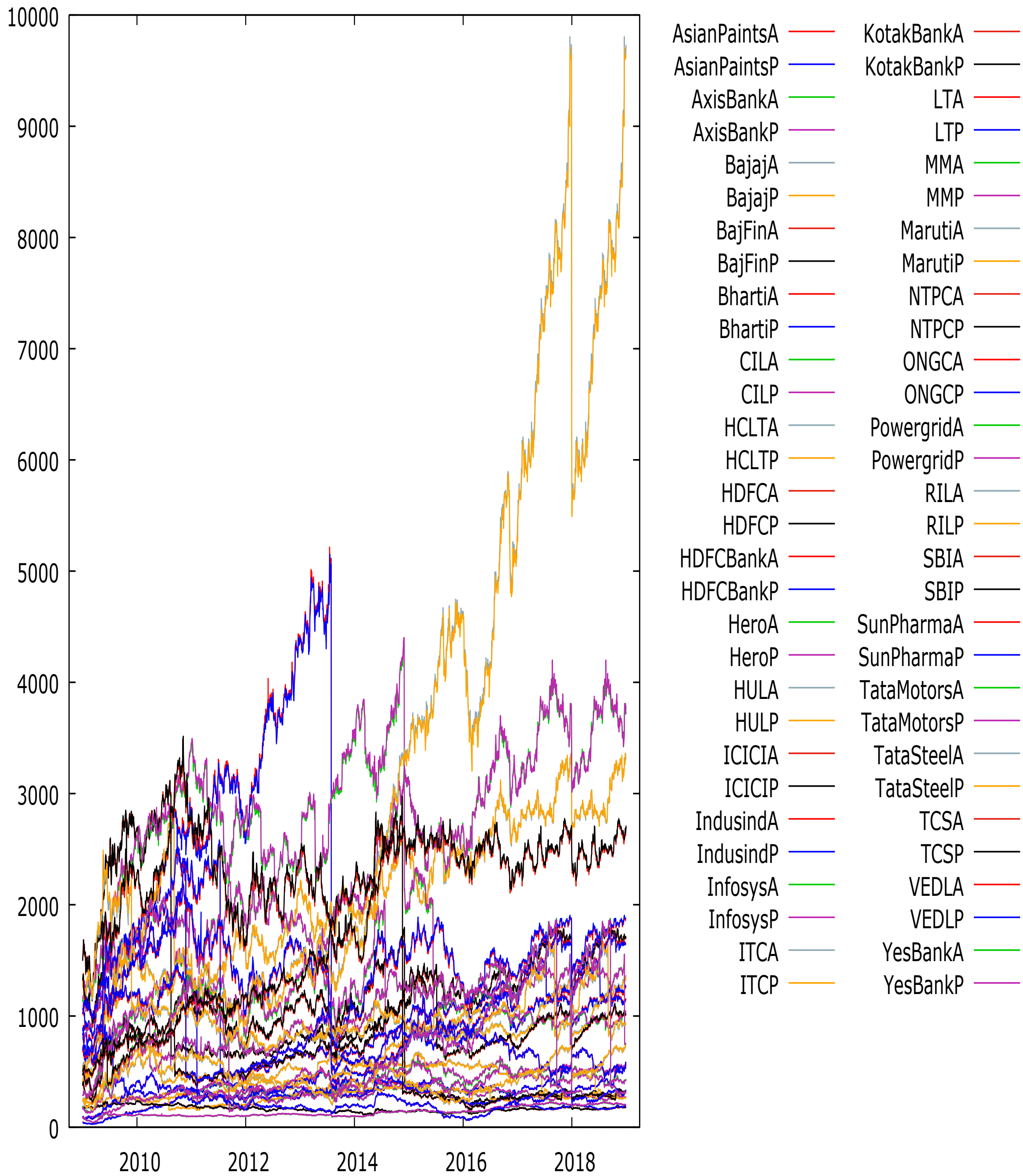
Figure 2. Prediction Performance Trend For BSE-Sensex Stocks During the Post-Crisis Period From 2009 To 2018



Source: Data collected from www.bseindia.com, and computed using Neural Works Predict (v 3.24)

Based on the observations and analytics of statistical data, the null hypothesis, **N_H-3 (There exists no stochastic trend between the stock prices of thirty companies indexed in BSE-Sensex during the global post-crisis period)** was not accepted. Similarly, the null hypothesis, **N_H-4 (There exists no variation between actual and predicted stock price values of thirty companies indexed in BSE-Sensex during the global post-crisis period)** was not accepted, in the study. Investors may observe these developments and the information given above while, making investment decisions.

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Also based on the statistical data results derived from the quantitative big data analytics, the null hypothesis, **N_H-5 (An investor couldn't outperform the market, since all the available information is already reflected in the market prices)** was accepted in the study.

Findings of the Study

The market value of each company stock changes per millisecond based on the demand and supply forces, namely, the buyers and sellers of stocks. The stock prices of the BSE-Sensex indexed thirty stocks had ranged between Rs. 41.45 and Rs.9804.50 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 microeconomic factors. In addition to some microeconomic factors (bearish and bullish trends), the investors' sentiments in the stock market were directly related to the stock performance **(Marxia Oli Sigo, et al., 2018b).**

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 used to derive valuable inferences and investment decisions **(Shuai Wanga & Wei Shangb, 2014).**

The above analysis of 5, 97, 960 observations of stock price data relating to BSE-Sensex-indexed thirty 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 **(Marxia Oli. Sigo, et al., 2018b).**

The Neuro Deep 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 linear and non-linear data, in the predictive analytics of market trends. Though, it is not comparable with the power of the human brain, still, construed as the basic building block of Artificial Intelligence **(Phil Simon, 2013).**

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). Investments in blue chip stocks would make the investors get more benefits 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 the Neuro Deep 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. The experience gained by the investors, using neural network approaches, would help the investors in making wiser decisions and optimizing stock returns.

Conclusion

This study analyzed the stock price trends and predicted the values of thirty top market capitalization stocks, of BSE-Sensex, which are listed in the Bombay Stock Exchange in India. Forecasting stock market movements becomes difficult, due to the uncertainties involved, with future stock prices **(Hassan, M. R., et al., 2007).** The prediction of the stock price trend is euphoric and positive even for the future period. 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 Neuro Deep 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.

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Limitations of the Study

The study only considered the thirty stocks of BSE-Sensex. The study period is only 20 years starting in 1999 and ending in 2018. The researchers faced issues with applying complex statistical tools and the unavailability of certain kinds of data.

Scope For Future Research

Attempts should be made to forecast the corporate stocks listed in the NSE of India and other regional stock exchanges of India using other Deep Learning Methods. Efforts should be taken to study the movements of the stock markets of developed economies like the United States of America, England, and Japan **(Teo Jasic & Douglas Wood, 2006).** A comparative analysis of global stock indices should be made by applying different Machine Learning and Neural Network Approaches.

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