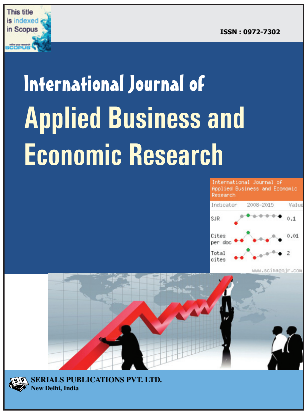


International Journal of Applied Business and Economic Research

ISSN : 0972-7302

available at http: www.serialsjournals.com

Volume 15 • Number 23 (Part 2) • 2017

Role of Technical Indicators in Predicting Stock Indices: Evidence from India

Priya Angle[1], Tarun Mayakuntla[2], Sravani Naguri[3], Vaddi Priyanka[4], Ankit Sharma[5] and K.T. Vigneswara Rao[6]

[1]*Prof. Associate Professor, IFIM Bangalore*

[2-4]*PGDM Student, IFIM Bangalore*

[5]*Corresponding author, Research Mentor, Accendere Knowledge Management Services Pvt. Ltd, 144/15, Kailash Colony, Anna Nagar West, Chennai – 600101, Tamil Nadu. Email: ankit.sharma@accendere.co.in*

[6]*Accendere Knowledge Management Services Pvt. Ltd.*

ABSTRACT

This paper analyse the importance of technical indicators in predicting sectoral stock indices using the Multi Layer Perceptron Artificial Neural Network (MLP-ANN). We analysed data on nine Nifty sectoral indices spanning form January 2012 to December 2016 using nine commonly used technical indicators. The result shows that only four technical indicators are important in predicting the sectoral indices. The results will help the finance modellers in developing better prediction models.

JEL Classification: G100, G240, C205.

Keywords: Stock market, Technical Indicators, ANN.

1. INTRODUCTION

The stock index is time variant and moves in a non-linear pattern. So, predicting future Stock price is highly challenging. Predicting Stock price is the major challenge for investors, brokers, and researchers. People spend a lot of money and efforts for predicting stock, but still, there is difficulty in figuring out the stock movements. A successful prediction of the stock indicates the future value of stock price, which may yield huge profits.

Researchers have used various data mining techniques especially neural networks in predicting stock prices. According to most of the results, Artificial Neural Networks have the highest hit rate of success in prediction. This predictive ability may be due to the reason that Artificial Neural Networks are designed on functions of biological neural networks (called as non-linear statistical data modeling tool) which learns the complex relation between inputs and outputs by observing the data sets.

In this paper, we use the predictive ability of neural networks to find which technical indicator is best in predicting the sectoral indices in India. We used nine technical indicators as inputs to predict the sectoral stock indices using Multi-Layer Perceptron Artificial Neural Network. This paper is first to understand the importance of individual technical indicator in predicting stock indices. Previous researchers have used a bunch of technical indicators in predicting the stock prices and stock indices. The outcome of this research will help in selecting the technical indicators which are most helpful in predicting the stock indices and making better predictive models.

The remainder of this paper is organized as follows: next section presents the relevant literature, then a brief description about Prediction Technologies and Artificial Neural Network, continued by Data and Methodology followed by results, and conclusions.

2. LITERATURE REVIEW

The Statistical model assumes the time series to be stationary and linear, thus resulting in statistical errors. Artificial Neural Network (ANN) and Support Vector Regression (SVR) can model non-linear data quite efficiently but, they are sensitive to parameter selection (Jothimani *et. al.*, 2015). In this section we present the relevant literature related to the use of neural networks and other predictive analytic techniques used in the prediction of stock prices and stock indices.

Financial tasks are highly complicated. They are often dynamic, nonlinear, stochastic, and flexible structured, time-varying, which are affected by many economic, political factors. Subha (2012) studied the behavior of the market and the predictability of stock market return by using k-NN on the stock index values of SENSEX and NIFTY. The results showed that the k-NN classifier overtakes the traditional logistic regression method in all the model evaluation parameters such as kappa statistics, precision, % error, TPF, TNR, F-measure.

Scholars have studied stock prediction by focusing on various microeconomic indicators, such as CPI and GDP, to train the prediction model. Wang (2014) used Principle Component Analysis - Support Vector Machine (PCA-SVM) integrated model to forecast the stock market indices and the individual stock prices. The results showed high hit ratio for forecasting movement direction for Korean Composite Stock Price Index and Hang Seng Index.

Kara *et. al.,* (2011) used Ten technical indicators to predict the direction of daily movement of Istanbul Stock Exchange (ISE) National 100 Index. They compared two classification techniques, artificial neural networks (ANN) and support vector machines (SVM). The results revealed that average performance of ANN model was significantly better than that of SVM model. Ticknor (2013) used daily stock prices and technical indicators in a Bayesian regularized artificial neural network to forecast closing price of individual stocks. The predictive ability of this novel technique is comparable to advanced hybrid artificial neural networks and allows the traders to make profitable investment strategies.

3. DATA AND METHODOLOGY

We studied nine technical indicators on nine Nifty sectoral indices from 6 February 2012 to 30 December 2016 using Multi Layer Perceptron Artificial Neural Network (MLP-ANN) to understand the role of various technical indicators in predicting the stock indices. The Nifty sectoral indices include Nifty Auto, Nifty Bank, Nifty Financial Services, Nifty FMCG, Nifty Media, Nifty Metal, Nifty Pharma, Nifty PSU Bank, and Nifty Realty. The nine technical indicators used in the present study are 10 day Moving Average, Weighted 10 day Moving Average, Momentum, 10-day Williams %R, Stochastic %K. Stochastic %D, 10 day Relative Strength Index, Moving Average Convergence Divergence (MACD), and Accumulation Distribution Line (ADL) [Appendix 1 provides the formulas for all the technical indicators].

We used closing price of the stock index as the input value and all the technical indicators as covariates to find the relative importance of the independent variables in predicting the closing prices. As indicated in many studies, we have not used open, high, low and shares traded as the input variables because the objective is not to find the best input variables that can predict stock indices but to find out the relative importance of various technical indicators in predicting stock indices. Therefore, our input variables are strictly the technical indicators.

4. RESULTS AND DISCUSSION

We have analyzed sectoral indices from 2 January 2012 to 30 Dec 2016. The data points for the input variable and technical indicators should be same in number for better prediction. The calculation of MACD requires 26 days closing values, therefore, the data used for prediction in the artificial neural network spans from 6 February 2012 to 30 December 2016. The figure 1 shows various sectoral indices. For ease of comparison all the indices are assumed to start from 100 on 2 January 2012.

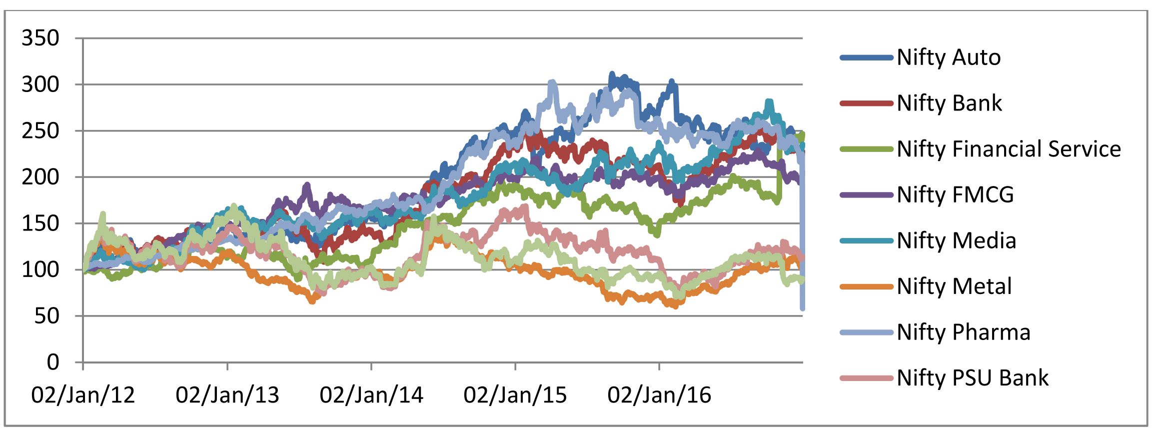


Figure 1: Graphical representation of Nifty sectoral indices

The Figure 1 shows that till July 2014 all the sectoral indices move in the similar fashion. After July 2014, Nifty Metal, Nifty Realty and Nifty PSU Bank did not perform well whereas Nifty Auto and Nifty Pharma were the best performers. Table 1 provides the descriptive analysis of the closing prices of the sectoral indices.

Table 1 shows that the maximum returns are given by Nifty Financial services followed by Nifty Auto, Nifty Bank and Nifty Media. The highest amount of variability is seen in the returns of Nifty Pharma followed by Nifty Realty and Nifty PSU Bank. It is seen that there is no direct relationship between the variability of the index and the returns provided. Negative skewness is observed in Nifty Pharma followed by Nifty Auto, Nifty Realty, Nifty FMCG, and Nifty Media. Positive skewness is observed in Nifty Financial Services followed by Nifty PSU Bank, Nifty Bank, and Nifty Metal. Kurtosis of very high order is observed in Nifty Pharma followed by Nifty Financial Services and Nifty Auto. Nifty Bank, Nifty FMCG, Nifty Media, Nifty Metal and Nifty PSU Banks seems to be normally distributed.

Table 1
Descriptive statistics of returns of the various sectoral indices

	Nifty Auto	*Nifty Bank*	*Nifty Financial Service*	*Nifty FMCG*	*Nifty Media*	*Nifty Metal*	*Nifty Pharma*	*Nifty PSU Bank*	*Nifty Realty*
Mean	0.0008	0.0008	0.0009	0.0006	0.0008	0.0002	0.0001	0.0003	0.0002
Median	0.0013	0.0006	0.0004	0.0012	0.0009	0.0003	0.0011	0.0002	0.0007
Maximum	–0.1562	–0.0690	–0.0655	–0.0465	–0.0805	–0.0705	–0.7416	–0.0935	–0.1160
Minimum	0.0598	0.0946	0.3392	0.0538	0.0532	0.0984	0.0511	0.0990	0.0843
Standard Deviation	0.0132	0.0149	0.0166	0.0109	0.0142	0.0168	0.0237	0.0207	0.0223
Skewness	–2.0629	0.1767	6.8241	–0.2219	–0.1653	0.1330	–24.8466	0.2827	-0.2717
Kurtosis	22.2717	2.6844	138.9982	2.3381	1.3422	1.8288	776.3062	2.0070	1.9962

The input closing value of index is partitioned into three parts viz. Training (60 percent), Testing (20 percent), and Holdout (20 percent). Table 2 provides the details about the number of neurons in the hidden layer and the predictive ability of the model is shown in the form of sum of squares error.

Table 2
Predictive ability of artificial neural network

	Nifty Auto	*Nifty Bank*	*Nifty Financial Service*	*Nifty FMCG*	*Nifty Media*	*Nifty Metal*	*Nifty Pharma*	*Nifty PSU Bank*	*Nifty Realty*
Training SSE	0.364	0.34	0.475	0.359	0.314	0.444	0.421	0.722	0.701
Testing SSE	0.104	0.111	0.238	0.126	0.116	0.159	0.176	0.219	0.249
Neurons in Hidden Layer	7	6	6	6	6	5	5	7	7

SSE-Sum of Squares Error

Table 2 shows that the minimum prediction error in the testing data is observed in Nifty Auto followed by Nifty Bank, Nifty Media, Nifty FMCG, Nifty Metal, and Nifty Pharma. The highest prediction error is observed in Nifty Realty followed by Nifty Financial Services, and Nifty PSU Bank. All the artificial neural networks consist of one hidden layer with five to seven neurons.

Figure 2 shows the predicted by observed charts for the various sectoral indices. It can be seen that in all the cases resulted in linear fashion with an increasing trend. This shows that as the input value of the indices increased with time the predicted value of the model too increased in the same fashion. This shows how well the neural networks can predict the sectoral indices.

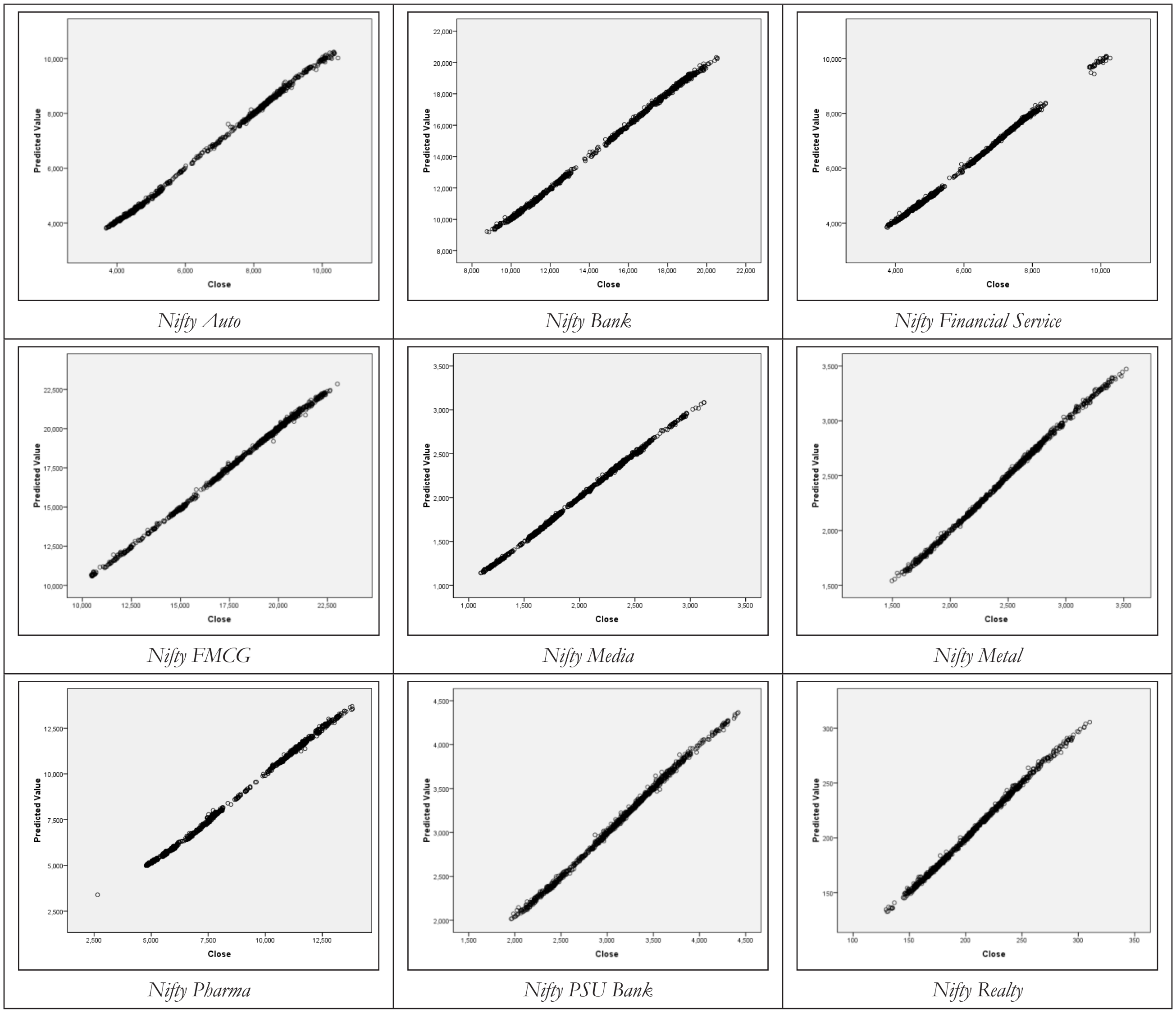
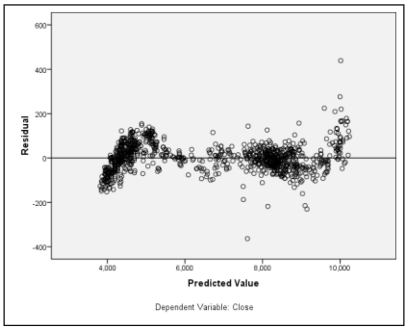


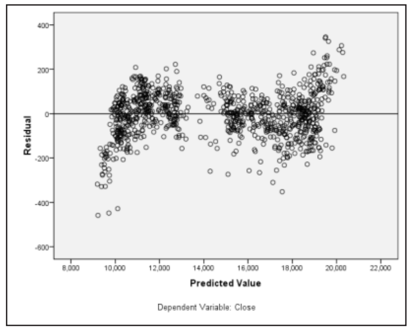
Figure 2: Predicted by observed chart for various sectoral indices

Figure 3 shows the residual by predicted chart for the various sectoral indices. This graph plots the residual values produced by the artificial neural network model with respect to the predicted value. As evident from the Figure 3, the residual values lieabove and below the mean line indicating both the positive as well as negative residual values produced by the model. Residuals are clustered into two groups for Nifty Auto, Nifty Bank, Nifty Financial Services, and Nifty Pharma. The residuals are scattered for Nifty FMCG, Nifty Media, Nifty Meta, Nifty PSU Bank, and Nifty Realty.

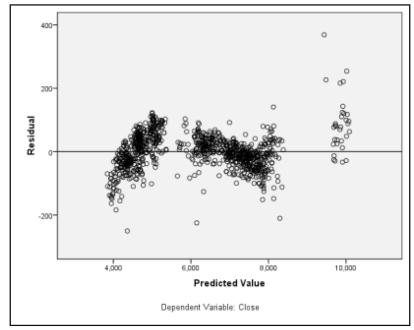
Table 3 provides the details about the Normalized importance of independent variables in predicting the neural network. In this analysis nine technical indicators are used as input variables namely 10 day Moving Average, Weighted 10 day Moving Average, Momentum, 10-day Williams %R, Stochastic %K. Stochastic %D, 10 day Relative Strength Index, Moving Average Convergence Divergence (MACD), and Accumulation Distribution Line (ADL). Figure 4 shows the Normalized importance of independent variables in the graphically. The results show that out of nine technical indicators used as input variable for the neural network Moving Average Convergence Divergence (MACD) was the most important technical indicator followed by Weighted 10 day Moving Average, Stochastic %K, 10-day Williams %R, and Momentum. 10 day Moving Average, Accumulation Distribution Line, 10 day Relative Strength Index and Stochastic % D were shown to have minimum contribution in predicting the closing prices of the stock indices.



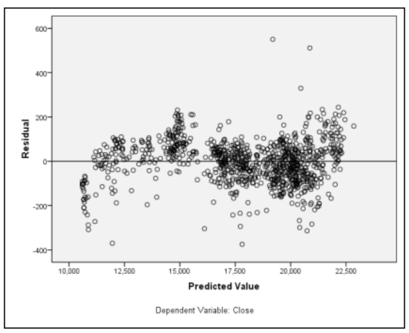
Nifty Auto



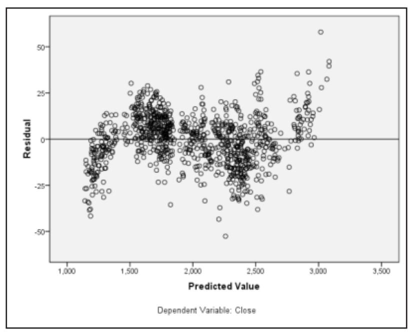
Nifty Bank



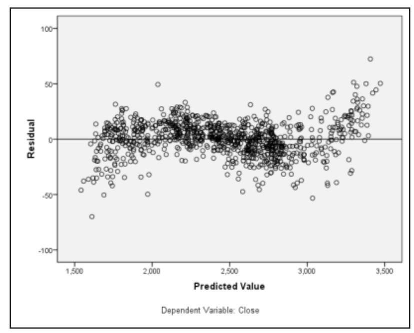
Nifty Financial Service



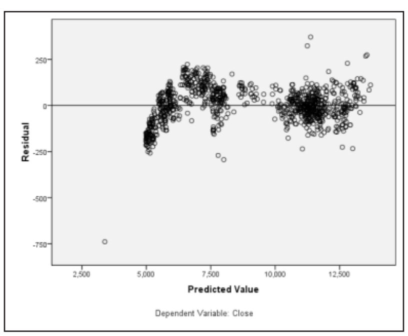
Nifty FMCG



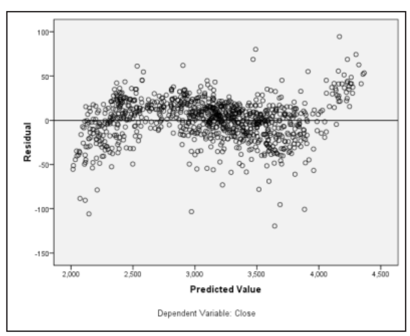
Nifty Media



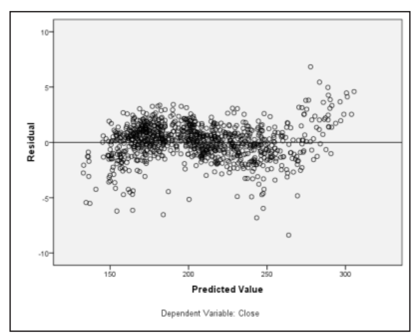
Nifty Metal



Nifty Pharma



Nifty PSU Bank



Nifty Realty

Figure 3: Residual by predicted chart for the various sectoral indices

A: 10 day Moving Average, B: Weighted 10 day Moving Average, C: Momentum, D: 10-day Williams %R, E: Stochastic %K, F: Stochastic %D, G: 10 day Relative Strength Index, H: Moving Average Convergence Divergence (MACD), I: Accumulation Distribution Line (ADL)

Table 3
Normalized importance of independent variables

	Nifty Auto	*Nifty Bank*	*Nifty Financial Service*	*Nifty FMCG*	*Nifty Media*	*Nifty Metal*	*Nifty Pharma*	*Nifty PSU Bank*	*Nifty Realty*	*Average*	*Overall Rank*
A	24%	15%	19%	9%	28%	17%	12%	22%	21%	19%	6
B	60%	85%	63%	57%	100%	62%	100%	75%	78%	75%	2
C	15%	8%	52%	16%	12%	13%	23%	20%	16%	20%	5
D	31%	57%	14%	13%	71%	15%	71%	11%	14%	33%	4
E	36%	63%	20%	18%	76%	24%	70%	24%	25%	39%	3
F	5%	4%	4%	5%	4%	5%	5%	4%	6%	5%	9
G	4%	6%	6%	3%	6%	2%	7%	4%	6%	5%	8
H	100%	100%	100%	100%	82%	100%	86%	100%	100%	97%	1
I	8%	5%	9%	10%	4%	5%	9%	2%	2%	6%	7

Nifty Auto | *Nifty Bank* | *Nifty Financial Service*

Nifty FMCG | *Nifty Media* | *Nifty Metal*

Nifty Pharma | *Nifty PSU Bank* | *Nifty Realty*

Figure 4: Graphical representation of Normalized importance of various technical indicators.

5. CONCLUSION

Technical indicators has been used in many studies to predict the stock indices (Armano et. al., 2004; Atsalakis and Valavanis,2006; Baba and Kozaki, 1992; Bautista, 2001; Dong and Zhou, 2002; Dong et. al., 2003; Dourra and Siy, 2002; Grudnitski and Osburn, 1993; Jaruszewicz and Mandziuk, 2004; Kanas and Yannopoulos, 2001, Kim and Han, 1998; Kuo, 1998; Leigh et. al., 2002; Lendasse et. al., 2000; Mizuno et. al., 1998; Motiwalla and Wahab, 2000; Refenes et. al., 1993; Steiner and Wittkemper, 1997; Tsaih et. al., 1998; Wong et. al., 1992). The present study used thenine technical indicators (10 day Moving Average, Weighted 10 day Moving Average, Momentum, 10-day Williams %R, Stochastic %K. Stochastic %D, 10 day Relative Strength Index, Moving Average Convergence Divergence (MACD), and Accumulation Distribution Line (ADL)) in a MLP-ANN framework to predict the Indian Nifty sectoral indices. The results show that Moving Average Convergence Divergence contributes the most in predicting the Nifty Sectoral indices followed by Weighted 10 day Moving Average, Stochastic %K, and 10-day Williams %R.

Acknowledgement

Authors wish to acknowledge with gratitude to Dr. Ankit Sharma, Research Mentor, Accendere Knowledge Management Services (P) Ltd., for his valuable comments and suggestions in preparation of the manuscript.

References

Armano, G., Marchesi, M., & Murru, A. (2005). A Hybrid Genetic-Neural Architecture For Stock Indexes Forecasting. *Information Sciences*, *170*(1), 3-33.

Atsalakis, G. S., & Valavanis, K. P. (2009). Surveying Stock Market Forecasting Techniques–Part II: Soft Computing Methods. *Expert Systems With Applications*, *36*(3), 5932-5941.

Atsalakis, G., & Valavanis, K. (2006). *Neuro-Fuzzy And Technical Analysis For Stock Prediction*. Working Paper, Technical University of CRETE.

Baba, N., & Kozaki, M. (1992, June). An Intelligent Forecasting System of Stock Price Using Neural Networks. In *Neural Networks, 1992. IJCNN., International Joint Conference On Neural Networks*, 371-377.

Bautista, C. C. (2001). Predicting The Philippine Stock Price Index Using Artificial Neural Networks. *UPCBA Discussion*, *107*.

Dong, M., & Zhou, X. S. (2002). Exploring The Fuzzy Nature Of Technical Patterns Of US Stock Market. *Proceedings Of Fuzzy System And Knowledge Discovery*, *1*, 324-328.

Dourra, H., & Siy, P. (2002). Investment Using Technical Analysis and Fuzzy Logic. *Fuzzy Sets And Systems*, *127*(2), 221-240.

Grudnitski, G., & Osburn, L. (1993). Forecasting S&P and Gold Futures Prices: An Application Of Neural Networks. *Journal of Futures Markets*, *13*(6), 631-643.

Jaruszewicz, M., & Mańdziuk, J. (2004). One Day Prediction of NIKKEI Index Considering Information From Other Stock Markets. *Artificial Intelligence And Soft Computing-ICAISC 2004*, 1130-1135.

Jothimani, D., Shankar, R., Yadav, S.S., (2015) Discrete Wavelet Transform-Based Prediction Of Stock Index: A Study On National Stock Exchange Fifty Index, *Journal of Financial Management And Analysis*, *28*(2), 35-49.

Kanas, A., & Yannopoulos, A. (2001). Comparing Linear And Nonlinear Forecasts For Stock Returns. *International Review of Economics & Finance*, *10*(4), 383-398.

Kara, Y., Boyacioglu, M. A., & Baykan, Ö. K. (2011). Predicting Direction Of Stock Price Index Movement Using Artificial Neural Networks And Support Vector Machines: The Sample Of The Istanbul Stock Exchange. *Expert Systems With Applications*, *38*(5), 5311-5319.

Kim, K. J., Han, I., & Chandler, J. S. (1998). Extracting Trading Rules from The Multiple Classifiers And Technical Indicators In Stock Market. In *Proceedings Of KMIS'98 International Conference*.

Kuo, R. J. (1998). A Decision Support System For The Stock Market Through Integration Of Fuzzy Neural Networks And Fuzzy Delphi. *Applied Artificial Intelligence*, *12*(6), 501-520.

Leigh, W., Paz, M., & Purvis, R. (2002). An Analysis Of A Hybrid Neural Network And Pattern Recognition Technique For Predicting Short-Term Increases In The NYSE Composite Index. *Omega*, *30*(2), 69-76.

Lendasse, A., De Bodt, E., Wertz, V., & Verleysen, M. (2000). Non-Linear Financial Time Series Forecasting-Application to The Belgium 20 Stock Market Index. *European Journal Of Economic And Social Systems*, *14*(1), 81-91.

Mizuno, H., Kosaka, M., Yajima, H., & Komoda, N. (1998). Application Of Neural Network To Technical Analysis Of Stock Market Prediction. *Studies In InformaticAnd Control*, *7*(3), 111-120.

Motiwalla, L., & Wahab, M. (2000). Predictable Variation and Profitable Trading Of US Equities: A Trading Simulation Using Neural Networks. *Computers & Operations Research*, *27*(11), 1111-1129.

Refenes, A. N., Azema-Barac, M., & Zapranis, A. D. (1993). Stock Ranking: Neural Networks Vs Multiple Linear Regression. In *IEEE International Conference on Neural Networks,* 1419-1426.

Steiner, M., & Wittkemper, H. G. (1997). Portfolio Optimization with a Neural Network Implementation Of The Coherent Market Hypothesis. *European Journal of Operational Research*, *100*(1), 27-40.

Subha, M. V., & Nambi, S. T. (2012). Classification of Stock Index Movement Using K-Nearest Neighbours (K-NN) Algorithm. *Wseas Transactions on Information Science And Applications*, *9*, 261-270.

Ticknor, J. L. (2013). A Bayesian Regularized Artificial Neural Network For Stock Market Forecasting. *Expert Systems with Applications*, *40*(14), 5501-5506.

Tsaih, R., Hsu, Y., & Lai, C. C. (1998). Forecasting S&P 500 Stock Index Futures with A Hybrid AI System. *Decision Support Systems*, *23*(2), 161-174.

Wang, Y. (2014). Stock Price Direction Prediction by Directly Using Prices Data: An Empirical Study on The KOSPI And HSI. *International Journal of Business Intelligence and Data Mining*, *9*(2), 145-160.

Wong, F. S., Wang, P. Z., Goh, T. H., & Quek, B. K. (1992). Fuzzy Neural Systems for Stock Selection. *Financial Analysts Journal*, 47-74.

Appendix 1
Formulas of technical indicators

Technical Indicator	*Formulas*
10 day Moving Average	$(C_t + C_{t-1} + \cdots + C_{t-10})/10$
Weighted 10 day Moving Average	$((n) \times C_t + (n-1) \times C_{t-1} + \cdots + C_{10})/(n + (n-1) + \cdots + 1)$
Momentum	$C_t - C_{t-1}$
10-day Williams %R	$(H_n - C_t)/(H_n - L_n) \times 100$
Stochastic %K	$(C_t - L_n)/(H_n - L_n) \times 100$
Stochastic %D	$\sum_{i=0}^{n-1} \frac{\%K_{t-1}}{n}$

Technical Indicator	*Formulas*
10 day Relative Strength Index	$100 - 100 \Big/ \left(1 + \dfrac{\sum_{i=0}^{n-1} \mathrm{U}p_{t-i}}{n} \Big/ \dfrac{\sum_{i=0}^{n-1} \mathrm{D}w_{t-i}}{n} \right)$
Moving Average Convergence Divergence (MACD)	(12-day EMA - 26-day EMA)
Accumulation Distribution Line (ADL)	$\dfrac{(\mathrm{C}_t - \mathrm{L}_t) - (\mathrm{H}_t - \mathrm{C}_t)}{(\mathrm{H}_t - \mathrm{L}_t)} \times$ Period Volume

C_t is the closing price and L_t is the lowest price of the Sectoral indices at time t. L_n is the lowest low price of the Sectoral indices in the last n days, H_t is the highest price of the Sectoral indices at time t, H_n is the highest high price of the Sectoral indices in the last n days. Up_t is the upward price change of the Sectoral indices at time t and Dw_t is the downward price change of the Sectoral indices at time t.