Forecasting of Service Sectors in Indian Markets Using Machine Intelligence

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August 25, 2022

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Preprint · July 2019

DOI: 10.13140/RG.2.2.24411.85281

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Abstract. The study examines stock index closing from myriad set of technical and fundamental analysis variables extracted from real market data to assist forecast of market closing. For this, major service sector indices of Bombay stock exchange (BSE) and National stock exchange (NSE) with historical data from 2004-2016 were taken from banking industry. The predictive performance for index closing phenomena using automatic linear modeling, time-series based econometric forecasting, vector auto regression and artificial neural network based models were compared. Results indicate that BSE had higher forecast accuracy with autoregressive models and was affected more by market volatility. On the other hand, NSE was impacted by quarterly performance that can be modeled using neural networks. These variant effects were contrasted with latest state-of-art research to identify the challenges of developing advanced intelligent market forecast systems.

Keywords: Stock index forecasting, Hybrid models

1 Introduction

The stock market fluctuations with its factors have been studied globally and documented widely in scientific literature. Many methods and complex models were proposed over the years [Atsalakis and Valavanis, 2009, Guresen, Kayakutlu and Daim, 2011, Rather, Sastry and Agarwal, 2017, Tkáč and Verner, 2016]. In India, the capital markets contribute more than half of Gross Domestic Product (GDP) from services sector despite the overall high volatility. Nevertheless, lot of earlier work has failed to focus on market prediction with respect to index forecast or in addressing the challenges related to specific sectors [Dutta, Jha, Laha and Mohan, 2006]. Interestingly, a recent study opines; "*the phenomena that people seek to comprehend, like neural networks or the dynamics of the stock market, comprise of a vast myriad of interacting components, whose internal details are too complex or inaccessible to model their behavior from first principles*" [Palsson et al., 2017]. Hence, the proposed study attempts to approach the problem of stock market index prediction specific for two major services sector stock exchange indices from banking industry due to its economic impact [Cooper et al. 2003]. The methodological approach intends perform a comparative investigation of statistical estimation and artificial neural network models. The originality of work arises from lack of empirical studies on stock market index closing in Indian context using both fundamental and technical variable categories [Kumar, Agrawal and Joshi 2004, Panda and Narasimhan, 2006, Rihani and Garg, 2006]. Fundamental analysis relies upon the evaluation of economic and financial statistics in an effort to determine the "*intrinsic value*" of a corporate security. Technical analysis is used for investment timing that focuses its attention on the market itself rather than the companies or the economy. Its object is forecasting of market trends and security prices using mainly past price and volume measurements [Felsen 1975]. The prediction models that simultaneously include datasets pertaining to both these categories of variables are termed hybrid models [Abraham, Nath and Mahanti, 2001] [Armano, Marchesi, and Murru, 2005] [Ince and Trafalis, 2017] [Paluch and Jackowska-Strumiłło, 2018] [Wang, Wang, Zhang and Guo, 2012a] [Wang, 2009]. The remaining part of paper is organized as follows: Section 2; a background of earlier studies and theory, Section 3; a framework of current study, Section 4; describes the data and methods, Section 5; empirical results and discussions, Section 6; conclusions, Section 7; limitations and future work.

2 Background and Related Work

An extensive but not comprehensive systematic literature survey was carried out on the topic. The researchers have used both Scopus and Web of Science database to extract the research articles published during 1956-2019. Additionally IEEEXplore and ACM Digital Library coupled with Google Patents database enabled to unearth the impactful research in the form of patents, books etc. However, after initial screening based on recency, impact factor and citations, 101 articles were finally chosen. However only 27 articles were studies relevant in the Indian context. The above metrics indicated dearth of adequate research and empirical analysis for gaps found in body of knowledge.

The data from 16 financial services that made 7500 recommendations of individual common stocks for investment during period from January 1, 1928 to July 1, 1932 compiled an average record that was worse than that of average common stock by 1.43% annually. Statistical tests of best individual records failed to demonstrate that they exhibited skill, and show they are were probably were results of chance. Also 24 financial publications engaged in forecasting stock market during the 4 years during January 1, 1928 to June 1, 1932, failed as a group by 4 percent per annum to achieve a result as good as the average of all purely random performances [Cowles 1933].

In a first, a research study mentioned the benefits of using computer in stock market analysis from technical analysis perspective. The system was developed as part of contract for New York stock brokerage firm. Researcher explained the categories of task needed to be done by analyst; segregating technical and fundamental indicator variables and complexities involved in computation steps. The future challenges were discussed such as type of analysis required on past history to determine validity, checking of other current theories of market analysis, and the computation of all-market weighted averages [Hansen 1956].

A pioneering study used simulation techniques that experimented an operational scenario of the stock market. They identified key features of market fluctuations assuming the random walk hypothesis as the underlying theoretical basis. In their model, historical datasets from both fundamental and technical factors of 3 months and 3 weeks respectively were used to predict the closing price of next month and week. They demonstrated that both the price and the volume variables are joint products of a single market mechanism as well as contributed to reasons of bullish psychology among the traders [Ying, Bromberg and Solomon, 1971].

By using a decision model one study elaborated on five theories intended for investment analysis and devised a learning process that can be applied to stock selection and market forecasting tasks. On basis of experimental techniques using New York composite index data-sets from 1970, they supported earlier finding and concludes that investment analysis requires processing of complex information patterns and that the investment policy must reflect number of fundamental, psychological, technical, and other factors [Felsen 1975],.

A study designed framework for Decision support system (DSS) for market analyst. A rule-induction by algorithm approach to analyzing the stock market prediction decision was provided. They focused on categorical and quantitative measures to derive predictions. The system outperformed expert analyst and study pointed constraints of decision environment involved in stock market [Braun and Chandler, 1987].

Using sample data by taking one day rate of return '*r*' to holding IBM common stock on any day'*t*'. With 5000 days of returns data, a sample of 1000 days for training purposes taken with samples of 500 days before and after training period. The trading day's data was 1974-1978. Linear auto-regressive model, ordinary least squares (OLS) and out-of-sample based forecast experiments were carried out. Conclusions drawn was that evidence against efficient markets theory was hard; and model over fitted the asset prices on small observations. Suggestion was to allow more inputs in model such as volume, stock prices and volume, leading indicators, macro-economic data, etc. [White 1988].

A high speed learning algorithm on novel prediction model was developed and tested it on Tokyo stock exchange index datasets having technical and economic indexes. For model, weekly data from January 1985 to September 1989 were used. They got better performance in terms of correlation coefficient of prediction output with actual market data. Further this model using cluster analysis method had produced better accurate buy-sell decision signals and thereby generate profits. A comparative analysis showed that the model out performed multiple regression analysis and suggests significance of using moving simulation for such models to adapt to new data [Kimoto 1990].

One study used the real-world data from Wall Street Journal's Dow Jones Index covering two discrete periods from January 1988 to December 1992. Two neural network models, radial basis function and back-propagation model were used to perform internal representation of these indices and predict the future value. Both models produce very good prediction rate up to 90%. However, from the results, they concluded that radial basis function model had more promising than back propagation model in stock market index prediction since radial basis function gave better prediction, required less time to train and also does not need a very low level of mean-squared-error to produce good prediction [Komo, Chang and Ko, 1994].

By performing study on 9 years of data concerning 35 large capitalization companies of the Toronto Stock Exchange (TSE) from universe of 36 assets, including 35 risky assets and one risk-free asset. The risky assets were 35 Canadian large-capitalization stocks. The risk-free asset is represented by 90-days Canadian treasury bills. The data is monthly and spans 8 years, from February 1986 to January 1994 (96 months). Better results were obtained when some of the parameters of the stock models are free (not shared). They opine that partially sharing the parameters is even preferable, since it does not yield a deterioration in performance, and has more consistent results. Also very large returns can be obtained at risks comparable to the market using a combination of partial parameter sharing and training with respect to a financial training criterion, with a small number of explanatory input features that include technical, micro-economic and macroeconomic information [Ghosn and Bengio, 1997].

Based on smoothing techniques such as nonparametric kernel regression, study approach incorporates the essence of technical analysis: to identify regularities in the time series of prices by extracting nonlinear patterns from noisy data. Daily returns of individual NYSE/AMEX and NASDAQ stocks from 1962 to 1996 was used with bootstrapping and Monte Carlo simulation procedures. They concluded that empirically show of raise in the possibility that technical analysis can add value to the investment process [Lo, Mamaysky and Wang, 2000].

Abraham, Nath and Mahanti, 2001 in empirical study, implemented a hybrid intelligent system which based on an artificial neural network trained using scaled conjugate algorithm and a neuro-fuzzy system. Study achieved 100% performance of price prediction for 6 companies using 24 months of historical data of NASDAQ-100 index.

A similar study used flexible neural tree (FNT) and analyzed 7-year Nasdaq-100 main index and 4-year NIFTY index data values. They found that in terms of RMSE (Root mean square error), the local weighted polynomial regression marginally performed better. Nevertheless, study also suggested that opening, closing and maximum values enhances predictability especially using ensemble method [Chen, Yang and Abraham, 2007].

A patent "*Method and system for artificial neural networks to predict price movements in the financial markets*" devises an automated artificial neural networks to predict market performance and direction movements of the US. Treasury market, mortgage option-adjusted spreads (OAS), interest rate swap spreads, and US. Dollar/Mexican Peso exchange rate. Here on the historical data a back propagation or gradient descent method is implemented also which is step-wise reductions in model errors by feedback adjustments (trainings) on each of the weights in the model [Benzschawel, Dzeng and Berman, 2009].

In a detailed review study, says neural network models are preferable when the relationship between the variables is not known or is complex and hence it is difficult to handle statistically. One of drawback of neural networks are lack of interpretability of the weights obtained during the model building process. In this respect, statistical model clearly stands out as it allows interpretation of coefficients of the individual variables. Also opines that combine the features of both the techniques can enhance overall prediction/classification performance [Paliwal and Kumar, 2009].

A high impact research used sample of 10 years of data of total two stock price indices (CNX Nifty, S&P BSE Sensex) and two stocks (Reliance Industries, Infosys Ltd.) from Jan 2003 to Dec 2012. The performance of ANN, SVM (Support Vector Machines), random forest and naive-Bayes was used and got improved significantly when they were learnt through trend deterministic data. ANN was slightly less accurate in terms of prediction accuracy compare to other three models [Patel, Shah, Thakkar and Kotecha, 2015a, 2015b].

Another related study used only 7 to 14 financial numerical inputs integrating deep neural networks and econometric models such as LSTM (Long short term memory) and GARCH (Generalized autoregressive conditional heteroscedasticity). Their study predicted volatility by adding the parameters of financial time-series models as input for the neural network. However, researchers opined that adding non-quantifiable data could improve predictions using the new multi- modal hybrid model [Weng et al. 2018].

Recent study conceptualized stock index prediction as classification problem. Here a TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)-based MCDM (Multi-Criteria Decision Making) framework is used to evaluate the performance of different classifiers considering four criteria such as accuracy, F-measures, precision, and recall for prediction of future stock index price movements. An experimental study of 11 classifiers and four criteria conducted over two benchmark stock indices such as BSE SENSEX and S&P500 revealed that ranking a classifier using single performance criteria may lead to unreliable conclusions [Dash et al. 2019].

A study focused on energy sector in NIFTY closing price and suggests that Box–Jenkins method offers an excellent technique for forecasting the importance of any variables. The chosen sector's data of Nifty is found to be non-stationary, but the first-order differentiating of all sectors is stationarity. The monitoring of BIC values for tentative ARIMA models, with R-squared values and MAPE (Mean average percentage errors) are helpful in prediction of sector specific indices [Ashik and Kannan, 2019].

A research concluded that behavior and trends of the stock, closure of the next day is function, the five-day annotations successfully obtains results. ANN can improve learning algorithm and association weights. Suggest that combining of genetic algorithm with ANN can overcome the limitations [Nadh and Prasad, 2019].

From review of literature, evident is the fact that very few negligible studies had focused on the stock market prediction especially for index closing. There have been similar studies on same area in countries such as Brazil, China, Croatia, Istanbul, Kuwait, Qatar, Warsaw, USA [Weng et al. 2018][Chen and Hao, 2017] [Fadlalla and Amani, 2014] [Kara, Boyacioglu and Baykan, 2011] [Paluch and Jackowska-Strumiłło, 2018] [Svalina, Galzina, Lujic and ŠImunovic, 2013]. However recently Indian studies have also started to address specific stock prediction problems on indices/ sectors using mixed methodologies [Nayak and Misra, 2018] [Kaur, Dhar, and Guha, 2016].

Following research questions were addressed: What are the major factors affect the stock index close in India? Which statistical model is efficient in forecasting the stock index closing of service sectors such as banking? How can artificial neural network model based prediction be designed with better performance comparing statistical models?

The following are variables with operational definitions to build a predictive model.

1) Price-to-Earnings (P/E) ratio: - An estimate of current price of a company share with respect to its per-share earnings. P/E = Market value per share/ Earnings per share (EPS). Where, Market value per share is the market price. EPS ratio is defined as EPS = Net Income Dividends on Stocks / Average Outstanding Shares [Zorn et al., 2009].

2) Price-to-book (P/B) ratio: Used to compare a stock's market value to its book value. It is calculated by dividing current closing price of stock by the latest quarter's book value per share. Calculated as: P/B Ratio = Market Price per Share / Book Value per Share. Where, Book Value/Share = (Total Assets – Total Liabilities) / Number of shares outstanding [Wu and Hu, 2012].

3) Dividend yield: - A financial ratio that does indicates how much a company pays out in dividends each year relative to its share price. Dividend yield (D.Y) is represented as a percentage and can be calculated by dividing the dollar/rupee value of dividends paid in a given year per share of stock held by the dollar/rupee value of one share of stock. The D.Y = Annual Dividends per share/Price per share [Benzschawel et al., 2009] [Wu et al., 2012].

4) Beta (β):- Beta is a measure of the volatility/ risk, of security or a portfolio in comparison to whole market. A beta value, $\beta = 1$ indicates that security's price moves with the market. A value lesser ($\beta < 1$) means security is less volatile than market, ($\beta > 1$) shows security's price is more volatile than market. It's computed by covariance of stock asset with returns of benchmark divided by variance of benchmark returns [Oh et al. 2006] [Samaras et al., 2008].

5) High index: - The highest value for prices in a specific index as computed in high frequency level, day, month or yearly basis [Balasubramanian et al., 2015].

6) Close index: - Price of the last transaction of stock exchange on given trading session [Jadhav et al., 2018].

Variables 5 and 6 are technical indicators that are used to construct other measures such as MACD (Moving Average Convergence/Divergence), Oscillation etc. [Lahmiri 2018].

3 Conceptual Framework

The Figure 1 below depicts the conceptual framework of research. The dependent variable is stock market index close. The independent variables are High index, P/E ratio, P/B ratio, Dividend Yield and Beta.

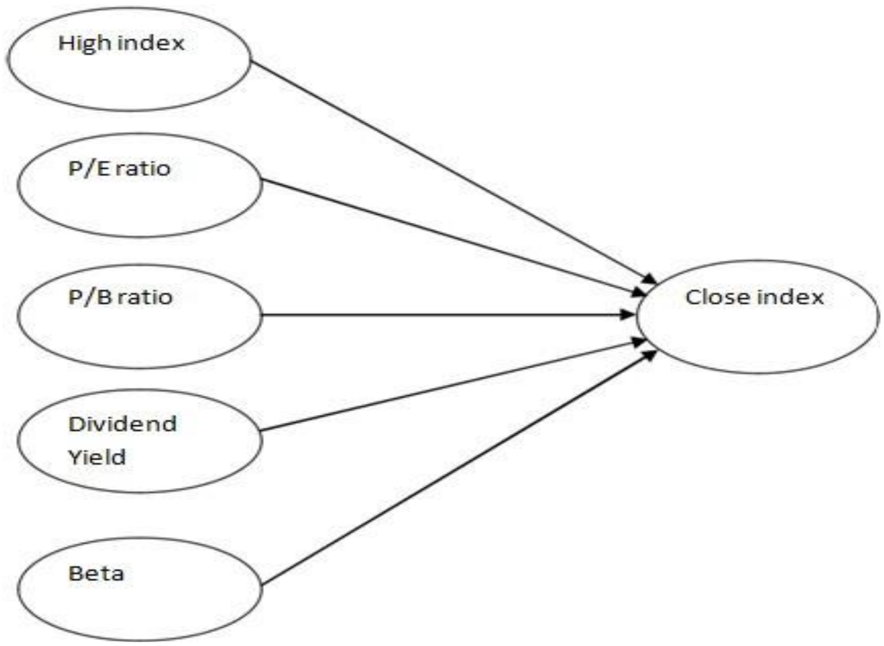

Figure 1: A conceptual framework of the study

4 Data and Methodology

An inductive approach was adopted with scientific method of inquiry. Simulation tools and multiple modeling techniques were tested to verify theories in literature.

4.1. **Data-sets and Sampling**: The secondary data for study was retrieved from official BSE and NSE websites sources. The Excel files were tabulated and IBM SPSS version 21 and Gretl (GNU regression time series library) software was used for analysis and simulation. The yearly data of BSE Bankex index from 2004- 2017 (13 years) and NSE NIFTY Bank index from 2005-2016 (11 years) had 126 and 96 historical data points respectively. Index data was preprocessed and sample was fixed as per data availability of both exchanges. The sampling event window covers period of index history and yearly frequency is used. High frequency (microsecond) tick data can be used using big computing framework as studied by Kenett et al. 2013.

5 Results and Discussions

The Table 1 in appendix shows results from simulation output validated on datasets. Also Figure 4, Table 2 and Figure 5 shows the BSE index data, summary statistics and cross correlations respectively. Similarly Figure 6, Table 3 and Figure 7 shows the NSE index data, summary statistics and cross correlations. Prediction performance measured with Sum of squares error (SSE), Relative error, Prediction accuracy (%), and Model fit of *R*-squared (R^2).

5.1. **Statistical Methods**: Normality check of datasets using Shapiro-Wilks tests confirmed that observations in both indices datasets were not normal. ($W = 0.94639$, with p-value 0.506183) for BSE and ($W = 0.929063$, with p-value 0.370283) for NSE. Hence any prediction techniques with reasonable accuracy are of limited scope. ALM (Automatic Linear modeling) overcomes shortcomings of regression analysis such as outlier detection, model ensembles, and optimality of variable selections. The AIC (Akaike information criterion) with forward step wise method was run getting lower value in NSE index data, but accuracy reduces over 8% comparing to BSE index having 91.5% (Table 1). Assuming normal distributed errors, Ordinary Least Squares (OLS) model had technical indicators with $N = 151$ (Figure 12). Here the P/B and P/E ratio was most significant with adjusted R^2= .785.

5.2. **Time-Series Prediction**: The variable importance analysis option of SPSS describes in normalized percentage the particular factors impact in the dependent variable (index close). Autoregressive Integrated Moving Average (ARIMA) is for short-term forecasts assuming linear dependence on variable lags and that dataset is of a non-stationary nature. ACF (Autocorrelation Function) and PCF (Partial autocorrelation function) tests were done on both datasets to check lags. For BSE Bankex index, ARIMA (0,0,0) model without lagged values, had a Stationary R^2= 0.976 (Figure 10 & 11). The ARIMA model in NSE index detected 1 outlier and had lesser model fit.

5.3. **Artificial Neural Networks**: An artificial neural network (ANN) is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge. Many neural network architectures exist in literature and applications. The Multi-Layer perceptron (MLP) with back propagation algorithm outperforms other models for NSE index forecasting with sum of squares error (SSE) = 0.002 and relative error value 0.000 proves strong applicability. The model also identifies P/B ratio as most important with least importance of the Beta (Table 1), and complies with finding of Wu and Hu, 2012. The experiment used hyperbolic tangent activation function with {51-4-1} architecture (Figure 9). Radial basis function (RBF) computes Euclidean distance for approximation function of target. Such models may be improved with learning algorithm but is outside scope of study.

5.4. **Vector Auto regression (VAR)**: Vector auto regression is powerful method for stochastic process modeling wherein the model captures the linear interdependence among multiple time-series evolving from K variables over any sample period (t= 1,2…. T) [Bahrammirzaee 2010]. Here it vectorizes input data-set such that variables are collected in a $k \times 1$ vector y_t, has as the i^{th} element, $y_{i,t}$, the observation at time "t" of the i^{th} variable. (Figures 13, 14 and 15). The model fit obtained is R^2=.976 with AIC= 16.78, longest lag of 11 and P/E as significant predictor.

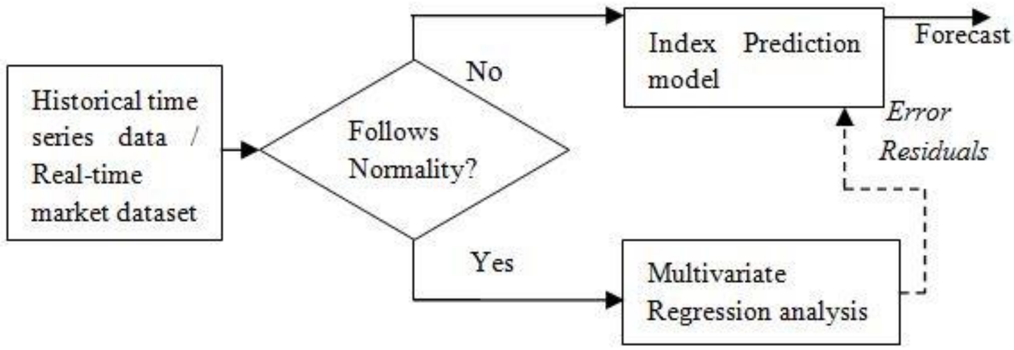

Figure 2: Proposed method of intelligent stock index prediction

A qualitative interpretation of results hints that the investing behavior in BSE index is more sensitive to market technical such as index high and risk factor in sector. In case of NSE, market index varies based on quarterly performance of companies and volatility doesn't impact over long term with BSE index. This supports hypothesis that Beta is nothing but investment choice determined by investor attitude to risk [Samaras et al., 2008]. It partly contrasts Patra, and Padhi, 2015 study that shows long memory of BSE index return. Comparatively the RBF models had lesser model fit and accuracy in forecasts while both architectures lack standard confidence intervals.

Radial basis function based models gave very less performance results that directly contradict with findings of Komo et al. 1994. Figure 2 outlines overall methodology to augment existing intelligent stock forecast systems. In first stage the historical data or real time market data must be preprocessed and fed into the decision unit of normality check. Based on normality check, a multivariate regression or index prediction built on MLP computes estimated. The model must also be fine-tuned to forecast horizon with current time (t+1...6) day/week/month depending on data availability and required accuracy parameters [Jang and Lee 2019]. Here retraining model from regression is to adjust coefficients, optimal learning rate of hidden nodes of model ensure the rigor of intelligent prediction system.

Multivariate regression analysis even though beneficial in earlier works [Hu et al. 2017, Paliwal and Kumar, 2011, Pokhriyal et al. 2011 and Refenes et al. 1994] gets contested in light of empirical results in hand. One good proposition is that a Vector auto regression (VAR) system for the BSE index since that even with less variables, model captures non-linearity associated among predictors. Durbin Watson statistic value 1.97 shows near positive autocorrelation and BIC (Bayesian information criterion) = 17.12 in the BSE index [Table 1]. While same VAR model efficacy needs to be tested in NSE data-sets remain as extension work [Suroso et al., 2018]. A MLP (Multi perceptron) prediction model has much scope for forecasting power of NSE index as proven in simulation results. Econometric and automatic modeling techniques are apt when variable information cannot be integrated in model parameters priori [Mullainathan, and Spiess, 2017].

6 Conclusions

Here, an exploratory research was carried out after systematic literature survey digging out the earliest research work up to current state-of-the-art in the field. The first obvious inference drawn is that more research advances are expected in future due to progression in terms of availability of data-sets, bigger computing power, industry interaction and economic demand in associated technologies [Nardo et al., 2016]. Secondly, there is increased attention to develop hybrid models for combining artificial neural networks, econometric models and multiple information fusion since it overcomes inherent limitations [Deng et al., 2018] [Mullainathan, and Spiess, 2017]. The price-to-book ratio was significant predictor of NSE Bank index which means that earnings value resulting from bank assets or liabilities or liquidation decisions has vital impact as opined by Wu and Hu, 2012. For BSE, volatility played major role in the index fluctuations. Back propagation algorithm that is tried and tested learning method provided best results on the both indices data-sets consistently. Hence there is reasonable clue to implement prediction frameworks using the techniques. This is verified in linear and ANN models and NSE index has lesser risk effects observed from market risk in large time frames. The BSE Bank index was affected more from technical indicators as bull/ bear effects and also dividend yield of the banks. As found by Weng et al. 2018, macroeconomic factor like the foreign exchange rate has a major role due to association with US markets.

7 Limitations and Future work

First obvious limitation in work is that from diverse set of factors on stock market, only few major variables are chosen lesser explored in Indian context. Various forecast methods using recent deep learning algorithms [Hiransha et al., 2018], multiple information fusion [Zhang et al. 2018] and text mining [Feuerriegel and Gordon, 2018] exists nevertheless only four approaches could be tested and validated. Since NSE data is not available prior 2005, and BSE index data is from 2004, restricts the properties of event window sampling. An out-of-sample model with qualitative data input such as stock price search interest and macro-economic factors remains to explore [Weng et al. 2018]. Index options and financial hypothesis in prediction model has scope for different dimension of empirical research [Jang and Lee, 2019]. Thereby the main contributions of study are in body of knowledge enabling better informed decisions for stakeholders in Indian stock market environment and developing economies [Sheu et al., 2018].

Acknowledgments: The article is modified and rewritten conference paper presented in ISDA2018, Vellore, India. The first author gratefully acknowledges National Institute of Technology Karnataka, Surathkal for permitting the usage of resources and providing research support through scholarship. All the authors thank reviewers for their helpful comments to greatly improve the initial version.

8 Appendix

Table 1. Summary of simulations (Source: *Simulation outputs*)

FORECAST TECHNIQUE	PREDICTION PERFORMANCE		INDEPENDENT VARIABLES IMPORTANCE (NORMALIZED IMPORTANCE)	
	BSE BANKEX INDEX	NSE NIFTY BANK INDEX	BSE BANKEX	NSE NIFTY BANK
Automatic Linear Modeling	AIC = 218.660 Accuracy=91.5%	AIC = 214.58. Accuracy = 83.3%	On scale of Least important (0) to most important (1) High index (0.85) Div. Yield (0.25)	1. High index (0.65) 2. P/B ratio (0.19) 3. P/E ratio (0.1) 4. Beta(0.05)
ARIMA (Auto-Regressive Integrated Moving Average) model	Stationary R- Squared value R^2= .976	Stationary R-squared R^2 = .955	*NA*	
Multi –Layer perceptron (MLP) model	Sum of squares error (SSE) = .005 Relative error = 0.001	Sum of squares error (SSE)= .002 Relative error= .000	1. Div. Yield = 100% 2. High index= 90.2% 3. Beta=87.5% 4. P/B ratio = 81.2% 5. P/E ratio = 75.5%	1. P/B ratio = 100% 2. P/E ratio = 88.3% 3. Div. Yield =78.6% 4. High index=61.2 5. Beta =38.6%
Radial Basis function (RBF) model	Sum of squares error (SSE) = 1.652 Relative error = 0.254	Sum of squares error (SSE) = 3.669 Relative error = 0.667	Beta = 100% Div. Yield = 9.1% All other factors = 9.4%	Beta = 100% All other factors = 17.7%
Vector Auto regression (VAR) model	Adjusted R^2 = .97 BIC = 17.12 Durbin-Watson = 1.97	*NA*	*NA*	

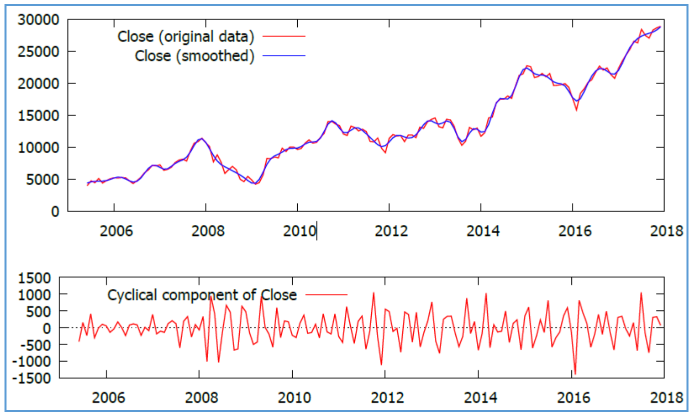

Figure 3: BSE index closing data and cyclical component separation (Source: Gretl)

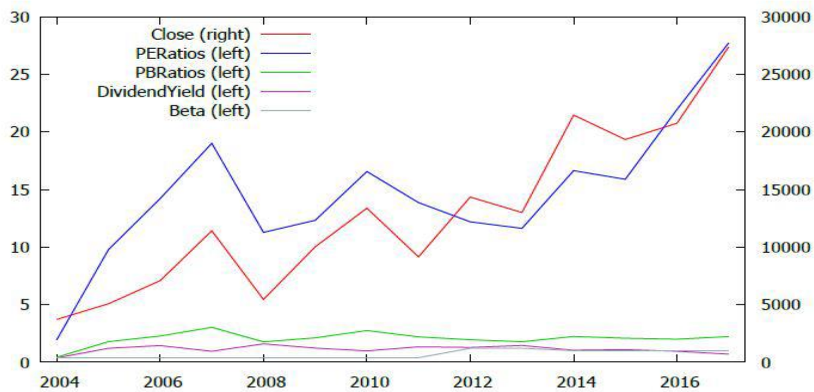

Figure 4: BSE Index data (source: Gretl)

Summary Statistics, using the observations 2004–2017

Variable	Mean	Median	Minimum	Maximum
Open	11253.	10754.	2817.5	21489.
High	14764.	14048.	3729.3	27406.
Low	8915.4	9003.1	2153.6	20358.
Close	12970.	12210.	3722.0	27375.
PERatios	14.642	14.035	1.9500	27.730
PBRatios	2.0507	2.1050	0.44000	3.0300
DividendYield	1.1243	1.1600	0.38000	1.6000
Beta	0.69143	0.40000	0.40000	1.2200

Variable	Std. Dev.	C.V.	Skewness	Ex. kurtosis
Open	6206.6	0.55156	0.33071	−1.0581
High	7180.7	0.48638	0.23618	−0.88891
Low	5692.7	0.63853	0.70249	−0.57938
Close	7054.9	0.54393	0.53107	−0.67861
PERatios	6.0125	0.41063	0.17586	0.76225
PBRatios	0.58433	0.28494	−1.1661	2.6319
DividendYield	0.32143	0.28590	−0.71734	0.23176
Beta	0.35563	0.51435	0.40228	−1.6793

Table 2: Summary statistics of BSE data (source: Gretl)

Correlation coefficients, using the observations 2004–2017
5% critical value (two-tailed) = 0.5324 for n = 14

Close	PERatios	PBRatios	DividendYield	Beta	
1.0000	0.8230	0.3669	−0.2744	0.7279	Close
	1.0000	0.6879	−0.0940	0.3569	PERatios
		1.0000	0.2916	−0.0268	PBRatios
			1.0000	−0.0013	DividendYield
				1.0000	Beta

Figure 5: Cross correlations (source: Gretl)

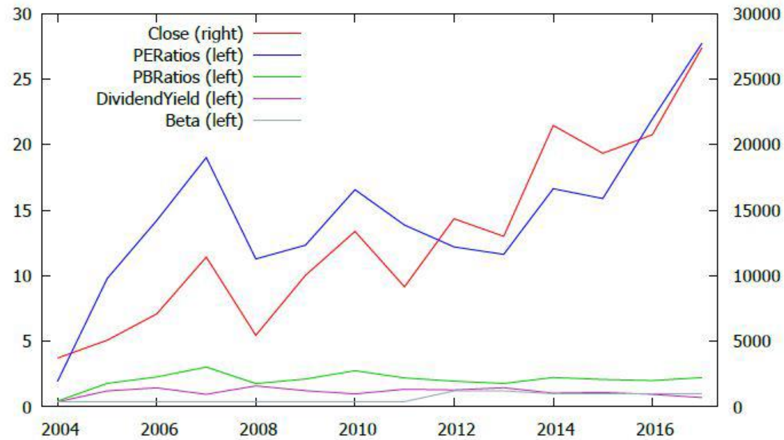

Figure 6: NSE index data

Summary Statistics, using the observations 2005–2016

Variable	Mean	Median	Minimum	Maximum
High	12792.	12275.	4704.4	20908.
Low	7523.5	7827.3	3314.6	15762.
Close	10995.	10624.	4534.2	18737.
PERatios	15.712	15.411	11.461	23.540
PBRatios	2.3884	2.3556	1.8091	3.0005
DividendYield	1.3441	1.3057	0.99389	2.2361
Beta	1.1733	1.1150	1.0600	1.3100

Variable	Std. Dev.	C.V.	Skewness	Ex. kurtosis
High	5138.0	0.40166	0.28756	−0.81673
Low	4050.4	0.53836	0.72064	−0.45336
Close	4914.6	0.44699	0.32582	−1.0973
PERatios	3.3519	0.21334	0.90621	0.56441
PBRatios	0.29246	0.12245	0.21309	0.59368
DividendYield	0.34147	0.25406	1.5050	1.9183
Beta	0.12449	0.10610	0.19830	−1.8709

Table 3: Summary statistics of NSE data (source: Gretl)

Correlation coefficients, using the observations 2005–2016
5% critical value (two-tailed) = 0.5760 for n = 12

Close	PERatios	PBRatios	DividendYield	Beta	
1.0000	0.6591	0.1763	−0.5918	0.5816	Close
	1.0000	0.4923	−0.7799	0.1846	PERatios
		1.0000	−0.5768	−0.0117	PBRatios
			1.0000	−0.3186	DividendYield
				1.0000	Beta

Figure 7: Cross correlations (source: Gretl)

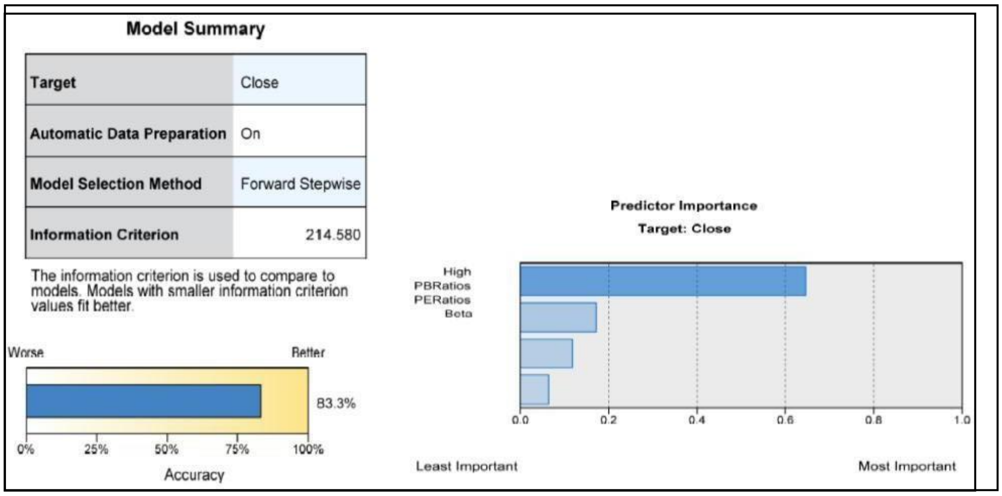

Figure 8: Automatic Linear Modeling (ALM) in NSE index data-sets (source: SPSS)

Network Information

Input Layer	Factors	1	PERatios
		2	PBRatios
		3	DividendYield
		4	Beta
		5	High
	Number of Units[a]		51
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		4
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Close
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

Model Summary

Training	Sum of Squares Error	.002
	Relative Error	.000
	Stopping Rule Used	Training error ratio criterion (.001) achieved
	Training Time	0:00:00.00

Dependent Variable: Close

Figure 9: MLP based artificial neural network model for NSE (source: SPSS)

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
Close-Model_1	5	.976	.	0	.	0

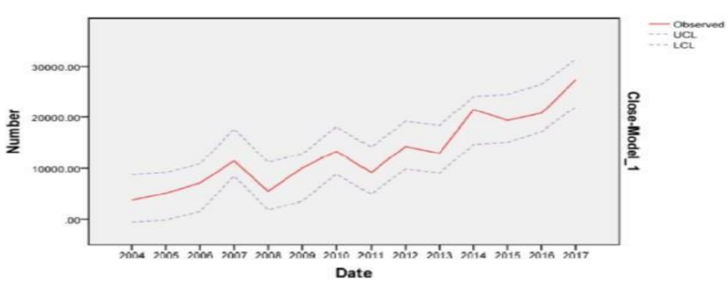

Figure 10: ARIMA (0, 0, 0) model in BSE index data (source: SPSS)

Model 3: ARMAX, using observations 2005–2017 ($T = 13$)
Dependent variable: $(1 - L)$Close

	Coefficient	Std. Error	z	p-value
const	650.767	440.246	1.4782	0.1394
PERatios	170.314	151.070	1.1274	0.2596
PBRatios	36.1980	1041.76	0.0347	0.9723
DividendYield	−1595.09	1084.74	−1.4705	0.1414
Beta	939.052	1554.49	0.6041	0.5458
Open	−0.788923	0.151427	−5.2099	0.0000
High	0.681018	0.171579	3.9691	0.0001
Low	0.481001	0.196719	2.4451	0.0145

Mean dependent var	1819.491	S.D. dependent var	4261.305
Mean of innovations	0.000000	S.D. of innovations	620.2946
Log-likelihood	−102.0387	Akaike criterion	220.0775
Schwarz criterion	224.5971	Hannan–Quinn	219.1485

Figure 11: ARMAX model BSE data (source: Gretl)

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Model 1: OLS, using observations 2005:06-2017:12 (T = 151)
Dependent variable: Close
HAC standard errors, bandwidth 3 (Bartlett kernel)

                  coefficient   std. error     z       p-value
  ------------------------------------------------------------
  const            35419.7      10765.4       3.290    0.0010   ***
  PERatios           721.816      197.694     3.651    0.0003   ***
  PBRatios         -8518.07      1539.23     -5.534    3.13e-08 ***
  DividendYield   -12309.2       3969.37     -3.101    0.0019   ***

Mean dependent var   13074.02   S.D. dependent var   6492.674
Sum squared resid    1.33e+09   S.E. of regression   3006.046
R-squared            0.789927   Adjusted R-squared   0.785640
F(3, 147)            123.1185   P-value(F)           6.49e-40
Log-likelihood      -1421.498   Akaike criterion     2850.997
Schwarz criterion    2863.066   Hannan-Quinn         2855.900
rho                  0.739736   Durbin-Watson        0.333978
```

Figure 12: OLS model estimates for BSE index close data (source: Gretl)

```
VAR system, lag order 12
OLS estimates, observations 2006:06-2017:12 (T = 139)
Log-likelihood = -1150.3613
Determinant of covariance matrix = 903548.1
AIC = 16.7822
BIC = 17.1200
HQC = 16.9194
Portmanteau test: LB(34) = 14.2679, df = 22 [0.8917]

Equation 1: Close
Heteroskedasticity-robust standard errors, variant HC1

                 coefficient    std. error   t-ratio    p-value
  --------------------------------------------------------------
  const          1760.43        2186.70        0.8051    0.4223
  Close_1           1.04740        0.102642   10.20      4.36e-018 ***
  Close_2          -0.191345       0.130916   -1.462     0.1464
  Close_3           0.122269       0.132287    0.9243    0.3572
  Close_4          -0.106627       0.114303   -0.9328    0.3527
  Close_5           0.156707       0.133313    1.175     0.2421
  Close_6          -0.0680498      0.145307   -0.4683    0.6404
  Close_7          -0.0332215      0.161361   -0.2059    0.8372
  Close_8           0.00778092     0.143400    0.05426   0.9568
  Close_9          -0.0444830      0.139421   -0.3191    0.7502
  Close_10          0.101476       0.134751    0.7531    0.4529
  Close_11         -0.0433722      0.139925   -0.3100    0.7571
  Close_12         -0.00215455     0.0900648  -0.02392   0.9810
  PERatios         66.2848        30.1599      2.198     0.0298    **
  PBRatios       -591.929        392.147      -1.509     0.1337
  DividendYield  -517.850        866.328      -0.5978    0.5511
```

Figure 13: VAR model for BSE index (source: Gretl)

```
Mean dependent var    13782.50   S.D. dependent var    6280.581
Sum squared resid     1.26e+08   S.E. of regression    1010.486
R-squared             0.976928   Adjusted R-squared    0.974114
F(15, 123)            455.5764   P-value(F)            4.9e-100
rho                   0.012648   Durbin-Watson         1.971584

F-tests of zero restrictions:

All lags of Close          F(12, 123) =   78.896 [0.0000]
All vars, lag 12            F(1, 123) = 0.00057227 [0.9810]

For the system as a whole:

  Null hypothesis: the longest lag is 11
  Alternative hypothesis: the longest lag is 12
  Likelihood ratio test: Chi-square(1) = 0.000578685 [0.9808]
```

Figure 14: VAR model summary (source: Gretl)

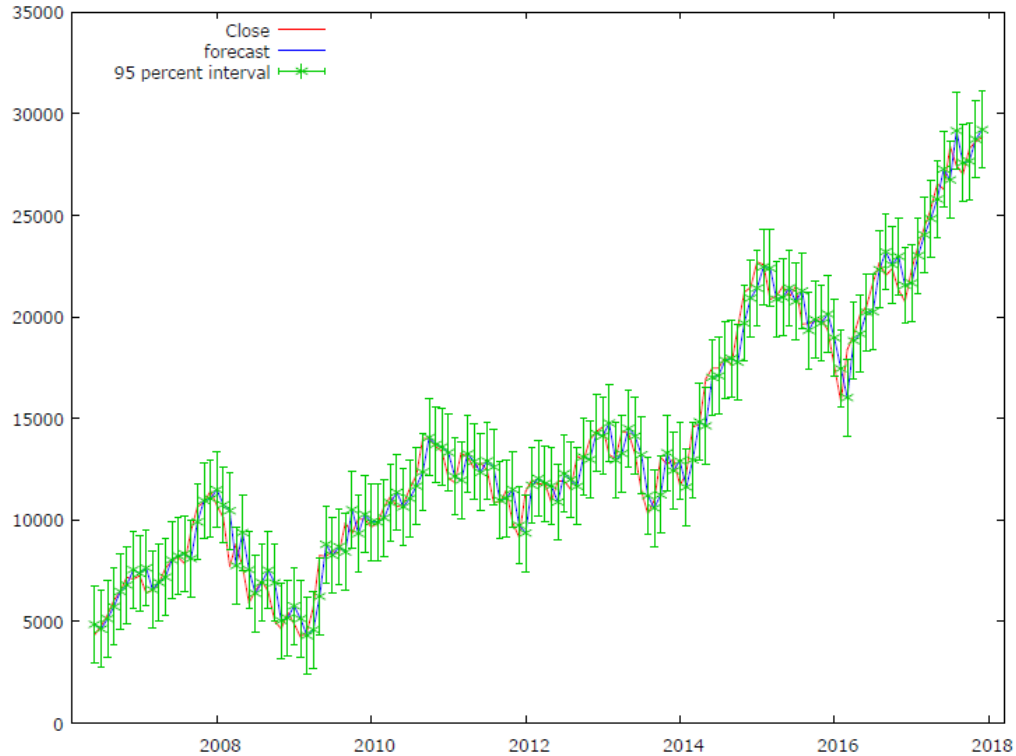

Figure 15: VAR model performance (source: Gretl)

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