A predictive analytics framework for opportunity sensing in stock market

Shruti Mittal*, Chander Kumar Nagpal
Dept. of Computer Engg., J. C. Bose Univ. of Sci. & Tech., YMCA, Faridabad 121 006, INDIA.
**Corresponding author: shruti.mattu@gmail.com*

Abstract

Large volume, random fluctuations and distractive patterns in raw price data lead to overfitting in stock price prediction. Thus research papers in this area suffer from multiple limitations: Very short prediction period from one day to one week, consideration of few stocks only instead of whole of stock market spectrum, exploration of more suitable machine learning algorithms. By overcoming the problems of raw data these limitations can be conquered. Proposed work uses a supervised machine learning approach on statistically learned macro features obtained from gist of input data, free from raw data drawbacks, to predict the price band for the upcoming month and a half for almost all NIFTY50 stocks. The predicted bands are tested for precision in comparison with actual stock price bands. Motivating outcomes so obtained were used for automated sensing of opportunity to make buy / sell / wait decision using fuzzy logic. The results show that the price bands are quite accurate with reasonable tolerance. Monetization capability of the predicted bands has also been enhanced by using an opportunity controller k.

Keywords: Fuzzy logic; machine learning; macro features; predictive analytics; risk management; statistical learning; stock market.

1. Introduction

Easy access to stock market data in electronic form has provided the researchers, a platform for extracting useful patterns for making future price predictions. In India, this data is available on various websites such as (NSE India, 2021; Rediff Money, 2021; Money Control, 2021; Yahoo Finance, 2021) etc. Most of the predictive systems are based upon pure machine learning algorithms and their designer hope that the machine will identify the underlying pattern in the data and make the predictions (Marian, 2019; Jarlath, 2020; Chung, 2018; Ismail, 2021; Jin *et al.*, 2020; Long *et al.*, 2020; Chen *et al.*, 2019; Li *et al.*, 2018; Cheng, 2018; Shah *et al.*, 2018; Lin *et al.*, 2018; Skehin *et al.*, 2018; Singh, 2022; Niu *et al.*, 2020; Wang *et al.*, 2019; Xu *et al.*, 2019). Reasons for the immense popularity of machine learning include: ability to handle large amount of data, ability to map between well-defined inputs and outputs, availability of large digital data sets, eradication of long chains of logical reasoning, tolerance for error, special skills not required for the user. The availability of the open source machine learning APIs have fuelled these engines. The problem with the stock market price data is that the stock prices fluctuate many times a day and over a period of month leading to a large number of random variations. If this data is used as such, then there are two possibilities. A rigorously trained system is likely to fall in the trap of overfitting leading to quite erroneous results while in the validation phase. An ordinarily trained system would fall in the trap of underfitting and will not be able to provide accurate results. It is for this reason that most of the research papers available in the stock market prediction domain predict for a very small period from one day to one week (Aifaa & Ariff, 2021; DiPersio *et al.*, 2017; Leigh *et al.*, 2008; Bao *et al.*, 2017; Jiawei, 2019; Najva & Saleem, 2022; Ngo & Troung, 2019; Ticknor, 2013; Yeh *et al.*, 2011; Fayyad, 1996; Zhong & Enke, 2017; Moghaddam *et al.*, 2016; Gupta & Dhingra, 2012).

Keeping this aspect in view, we propose that the design of a predictive system should ideally be based upon macro features (Jonathan, 2019; Carriero *et al.*, 2019), which can be created through a mathematical function based upon multiple low level features. These new reduced set of features should then be able to summarize most of the information contained in the original set of features. These features shall be more informative and interpretable in a better way. A system designed on the basis of these features shall have the following advantages over the conventionally designed purely machine learning based system: improved data visualization, increase in the explainability of the model, overfitting risk reduction, improved accuracy, easy to debug and transfer learning ability (reusability of modules). In case of stock market, many such macro features are available, created by various statistical researchers. These macro features have been developed over time and interpreted for their utility. Number of these macro features is quite large and the information provided by them is quite overlapping many times. It is possible to identify the non-overlapping macro features and to combine the pieces of semi-processed information provided by them to create a meaningful prediction system based upon machine learning. The work carried out in this paper undertakes this task by applying supervised learning on the combination of macro features.

The task includes the extraction of non-overlapping macro features from the past price data over a period of 120 working days (almost 6 months) for creating the unified input feature vector and the data of next 30 working days (almost month and a half) as desired output. The learning mechanism so created is used for prediction on similar future data. This completes the cycle. The output obtained, is a predicted price band which is likely to prevail in the upcoming month and a half. 4 such cycles have been used to demonstrate the precision of the proposed mechanism. The ensuring of the precision is an academic task that requires monetization aspect for its commercial usage. The price band so obtained has been used for signalling the various opportunities like buying/selling/wait keeping in view the prevailing price position. The results show that the system is effective and can be used for continuous gain.

The paper is organized as follows: section 2 talks about the literature survey. Section 3 defines the problem and the associated objectives. Section 4 defines the details of the proposed framework and Section 5 provides details about conduct of the experiment. Section 6 provides the details about opportunity signal generation which have been validated in section 7. Section 8 concludes the paper and talks about the future extension possibilities.

2. Literature Survey

In the current scenario, most of the available literature related to stock market prediction is based upon machine learning. The researchers have tried to identify many features which contribute to the change in the stock price. These features include various macroeconomic factors, stock fundamentals, market sentiments, news and social media etc. Despite all these issues, many people feel that the stock market behavior is random by nature. (Richard & Kenneth, 1983), amazed the researchers by showing that a random walk "no change" forecast for exchange rates is more accurate than model based forecasting. Similarly, (Duffee,G.R., 2002; Duffee, 2013) showed that a random walk forecast for future interest rates is much superior than the model based predictions.

(Eicher *et al.*, 2019) in their work evaluated predictions utilizing three measurements: (i) predisposition, which estimates predictions from actual values; (ii) effectiveness, which estimates whether the prediction errors were unusual and (iii) content, which estimates the worth of predictions compared to the naïve prediction models. They concluded that these predictions are ideal when they are impartial and effective. (Goyal & Welch, 2008) in their work conducted a comprehensive evaluation of many predictors for stock market index returns, but found that none of them could convincingly beat the unconditional mean. (Nikou, 2019) tried to assess the forecasting power of machine learning models for stock price prediction using daily close price value of iShares MSCI United Kingdom exchange-traded fund from January 2015 to June 2018. Their results indicated that the machine learning model outperforms the conventional stock prediction techniques. (Baek & Kim, 2018) proposed a hybrid model ModAugNet having two LSTM modules: overfitting Prevention Module and Prediction Module. Their model uses S&P500 and Korea Composite Stock Price Index 200 (KOSPI200) for evaluation. They confirmed that ModAugNet performed better than any other similar model without Prevention Module. They concluded that the test performance was entirely dependent on the prediction LSTM module. (Kim & Won, 2018) in their work proposed a new hybrid long short-term memory (LSTM) model with various Generalized Auto Regressive Conditional Heteroskedasticity (GARCH)-type models to improve the stock price prediction. They compared the performance of their system with other single models, like the GARCH, exponential

GARCH, exponentially weighted moving average, a deep feed forward neural network (DFN), and the LSTM, as well as the hybrid DFN models combining a DFN with one GARCH-type model. The work concludes with the fact that it improve the overall prediction performance in stock market volatility.

(Pang *et al.*, 2020), in their work proposed a LSTM based neural network with automatic encoder to predict the stock market price based on the concept of "stock vector" using deep learning. The experimental results depict that the deep LSTM with embedded layer outperforms for the Shanghai A-shares composite index. (Feng *et al.*, 2019), in their work, introduced a deep learning solution based on relational stock ranking model using temporal graph convolution for stock price prediction. The results were validated on the historical data of two stock markets, NYSE and NASDAQ. The experimental results showed that the model supersedes the state-of-the-art stock prediction solutions achieving an average return ratio of 98percent and 71percent on NYSE and NASDAQ, respectively. Few more references taken up during the literature survey have been listed in Table 1

Table 1: Additional papers studied in Literature Survey

Reference	Year	Technique used	Data source
Sirignano *et al.*	2018	Deep learning with stochastic gradient descent as optimizer	NASDAQ Stocks
Ni *et al.*	2011	SVM & fractal feature selection process	Shanghai Stock Exchange Composite Index
Mcnally	2018	RNN and LSTM Feature Engg. using Boruta Algorithm, Bayesian algorithm to select LSTM parameters	Bit coin price prediction
Kara *et al.*	2011	ANN and SVM	Istanbul Stock Exchange 1997-2007
Fischer *et al.*	2018	Comparison between deep learning and LSTM	
Long *et al.*	2019	Multi filter neural network, stochastic gradient descent, back propagation	Chinese stock market index CSI 300
JingyiShen *et al.*	2020	Customized Feature engineering, Deep Learning	
Kong *et al.*	2021	Multiple techniques	
Lei	2018	Rough Sets and Wavelet Neural networks	SSE Composite Index (China) CSI 300 (China) All Ordinaries Index (Ausrralia) Nikkei (Japan) Dow Jones (USA)
Pimenta *et al.*	2018	Multi objective genetic programming	Brazilian Stock Exchange (BOVESPA)
Idrees *et al.*	2019	Time Series based model, customized ARIMA model	
Weng *et al.*	2018	Ensemble based learning	20 US market stocks
Nekoeiqachkanloo *et al.*	2019	Time Series	25 shares
Jeon *et al.*	2018	Pattern Graph, ANN, Hadoop, RHive	KOSCOM Aug. 2014-Oct. 2014 continuous data
Amit K Sinha	2021	Probability	S&P 500 Index
He *et al.*	2021	Autoregressive model, Huber loss function	

2.1 Shortcoming identified in the literature

All these papers are using conventional machine learning mechanisms which suffer from the usual drawbacks of opacity, overfitting and short term prediction scenarios. Moreover, the random fluctuations in the stock price data which is a very common element, in the stock prices, is a big hindrance to the proper convergence. Most of the papers go for the few prominent stocks without taking care of the spectrum as a whole. All these issues need to be taken care of for making any genuine stock market prediction.

2.2 Highlights of the proposed scheme

Highlights of proposed work are as follows:

- *The work is spread across the entire NIFTY50 spectrum with 46/50(92%) companies being the part of the prediction process. NIFTY50 includes the top 50 companies of the Indian stock market. Thus, the work is not biased towards any particular company or sector.*
- *Prediction process captures the macro details from the historic price data before applying the supervised learning process, making it free from the random price fluctuations leading to faster convergence.*
- *The chosen macro features provide different views of the data thereby increasing the dimensionality of the problem and making it more effectively solvable (Cover, 1965).*
- *The work can be used in all the stock exchanges amongst all types of the stocks, across the globe.*
- *The precise results obtained indicate the success of academic research and its possible monetization makes it a successful financial research as well.*
- *The system is easily automatable.*

3. Problem Definition and Objectives

Before taking up details of the proposed work, let us explicitly define the problem and the associated objectives.

3.1 Problem Definition

To predict the future price band of the NIFTY50 stocks by using different macro features created on historic price data.

3.2 Objectives

- To design a framework using regression based supervised learning to predict maximum, minimum and average price of the stock for upcoming 30 working days from historical data of past 120 working days.
- Input feature vector of the supervised learning process should be created from component feature vectors obtained from the different macro features.
- The macro features used for the purpose should have the different dimensions in order to represent multiple aspects of the data.

4. Proposed Framework

The proposed work is based upon different macro features capable of providing complete and nearly non-overlapping views. We start the discussion with the selection of macro features.

4.1 Selection of macro features

The first view involves the comparative strength in the price movement wherein it is observed for how many days the price went up or down and by what magnitude in the period under consideration. The stock markets normally use Relative Strength Index RSI (14) for this purpose to measure the relative strength of the price in the past 14 working days. This macro feature was developed by (Wilder, 1978). RSI is a short term momentum indicator whose value oscillates between the 0 and 100. The value of the index is has been calculated for the recent past using a single-step formula as shown in Eq1 :

$$RSI = 100 - \frac{100}{1 + \frac{AverageGain}{AverageLoss}} \tag{1}$$

The detailed excel sheet based calculations for RSI can be seen at various websites such as (Duffee,G.R., 2002). We have used RSI (120), RSI (60), RSI (30), RSI (15) and RSI (5) to create the component feature set.

The second view involves the moving average for the past period which conveys the basic direction of the price movement. This movement can also be generally increasing, oscillating or generally decreasing. To take the historical account, Simple Moving Average (SMA) was computed for the period of 5, 15, 30, 60 and 120 days and was represented as SMAk where k is the number of days. SMA (Investopedia, 2021) is the arithmetic mean of the close price and is given by Eq2:

$$SMA_k = \frac{1}{k}\sum_{i=n-k+1}^{n} P_i \tag{2}$$

The third view involves the possible upward or downward movement of the price to anticipate the risk. For this purpose, the stock market uses Bollinger Bands for past 20 days with 2 levels of standard deviation represented as BB (20, 2). The component feature set relating to this view has been created using BB (120, 2), BB (60, 2), BB (30, 2), BB (15, 2) and BB (5, 2). (Bollinger-Bands, 2021) uses central tendency, such as moving average, as the base for defining highs and lows of the band referred to as upper band (UB) and lower band (LB). Formula for computing the UB and LB are shown in Eq 3 and 4.

$$UpperBB = MA + D\sqrt{\frac{\sum_{i=1}^{n}(Y_i - MA)^2}{n}} \tag{3}$$

$$LowerBB = MA - D\sqrt{\frac{\sum_{i=1}^{n}(Y_i - MA)^2}{n}} \tag{4}$$

where MA is the Moving Average and D represents the number of standard deviations.
The fourth view of component feature set is the actual closing price on the start and ending date of the cycle represented as Day1_CP and Day120_CP respectively.
These four views take care of multiple aspects of the price data which consider the basic direction of price movement, dispersion in price movement and relative magnitude of upward / downward movement on the daily basis thereby completing the entire spectrum. Here it is worth mentioning that the input data so created is almost free from random fluctuations, distractive patterns and much lesser in volume. Moreover, supervised learning model created from such a data would be much more transparent than the one created on the raw data.

4.2 Overview and working of the proposed framework

Figure 1 shows the overview of the proposed predictive framework. The work begins with the identification of the macro features keeping their applicability in view. As described in the previous subsection, the identified macro features are RSI, SMA and BB with their computations at various junctures for past 120 working days. Next Step involves the design of unified input feature vector. Figure 2 shows the components of three input feature vectors used for predicting the maximum, minimum and the average output. The feature vector for maximum price prediction uses Upper Bollinger Band (UB) only. Feature vector for minimum price prediction uses Lower Bollinger Band (LB) only. Feature vector for average price prediction uses both UB and LB. Now raw data relating to past 120 working days is picked up and unified input feature vector is created for all the companies under consideration. Thereafter, the data for next 30 working days is taken as target output for training purpose. Trained module, so obtained, is applied on 120 future working days as input data to obtain the predicted output. The obtained predicted output is compared with the actual output to validate the results. The process is repeated many times to ensure the consistency and accuracy of results. The trained module, so obtained, is also used to sense opportunity for the purpose of monetization. The design of the opportunity sensing module is shown in Figure 3. It is based upon the normalization of the min and max value to range [0,100]. Fuzzy sets are created over this normalized range. The current price is then applied to the normalized range to identify the corresponding fuzzy set(s) with its membership. Fuzzy set(s) and their corresponding memberships are used to identify the applicable opportunity with associated rewards. If the rewards obtained exceed the threshold then corresponding opportunity is signalled. The significance of signalled opportunities is validated through their monetization abilities.

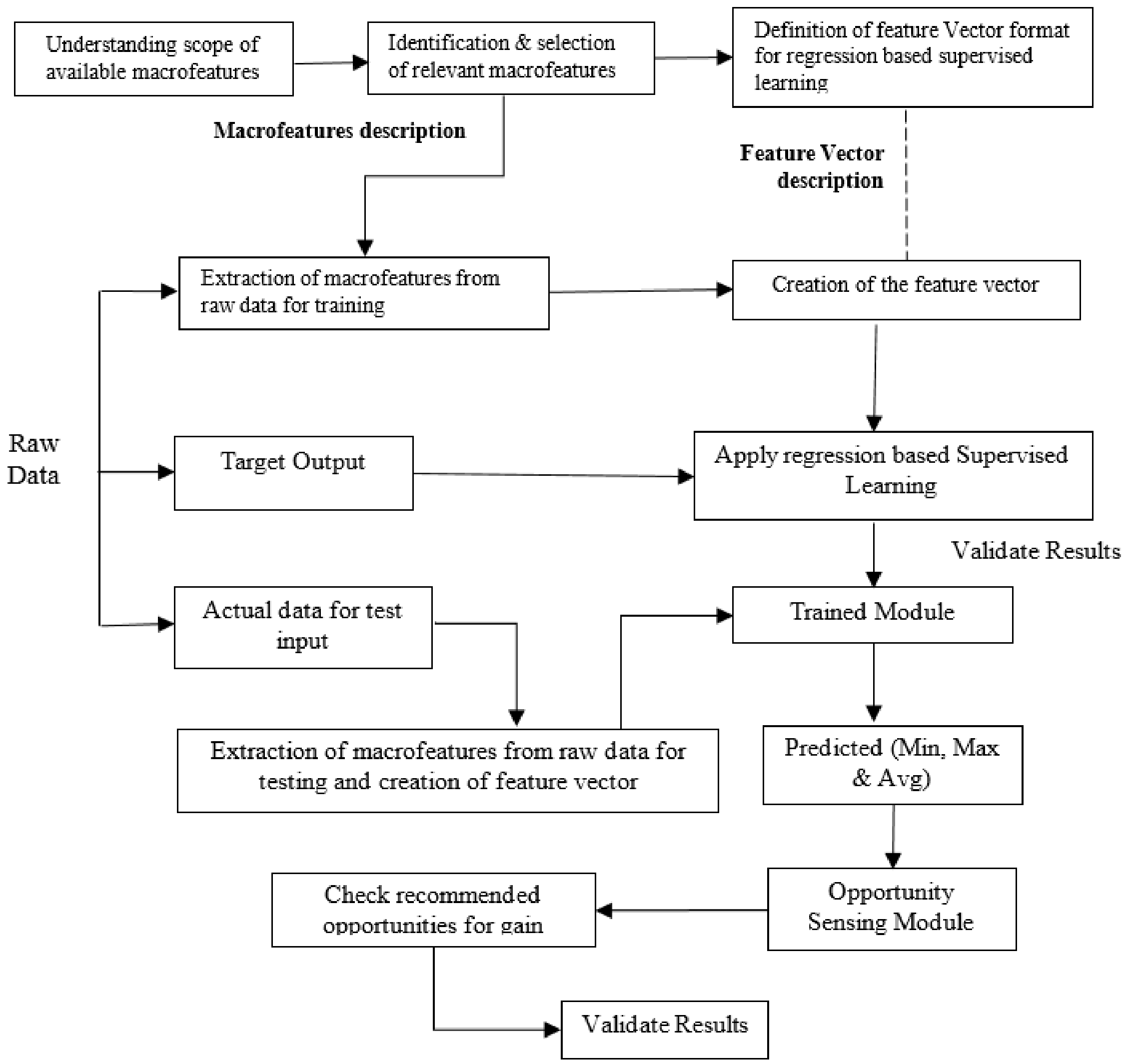

Fig. 1. Overview of the Proposed Predictive Framework.

Feature Vector For Maximum Price Prediction
RSI120
RSI60
RSI 30
RSI 15
RSI 5
UB120
UB60
UB30
UB15
UB05
SMA120
SMA60
SMA30
SMA15
SMA05
Day1_CP
Day120_CP
Pred_MAX

Feature Vector For Minimum Price Prediction
RSI120
RSI60
RSI 30
RSI 15
RSI 5
LB120
LB60
LB30
LB15
LB05
SMA120
SMA60
SMA30
SMA15
SMA05
Day1_CP
Day120_CP
Pred_MIN

Feature Vector For Average Price Prediction
RSI120
RSI60
RSI 30
RSI 15
RSI 5
UB120
UB60
UB30
UB15
UB05
LB120
LB60
LB30
LB15
LB05
SMA120
SMA60
SMA30
SMA15
SMA05
Day1_CP
Day120_CP
Pred_AVG

Fig. 2. Feature Vectors for Maximum, minimum and Average Price Prediction.

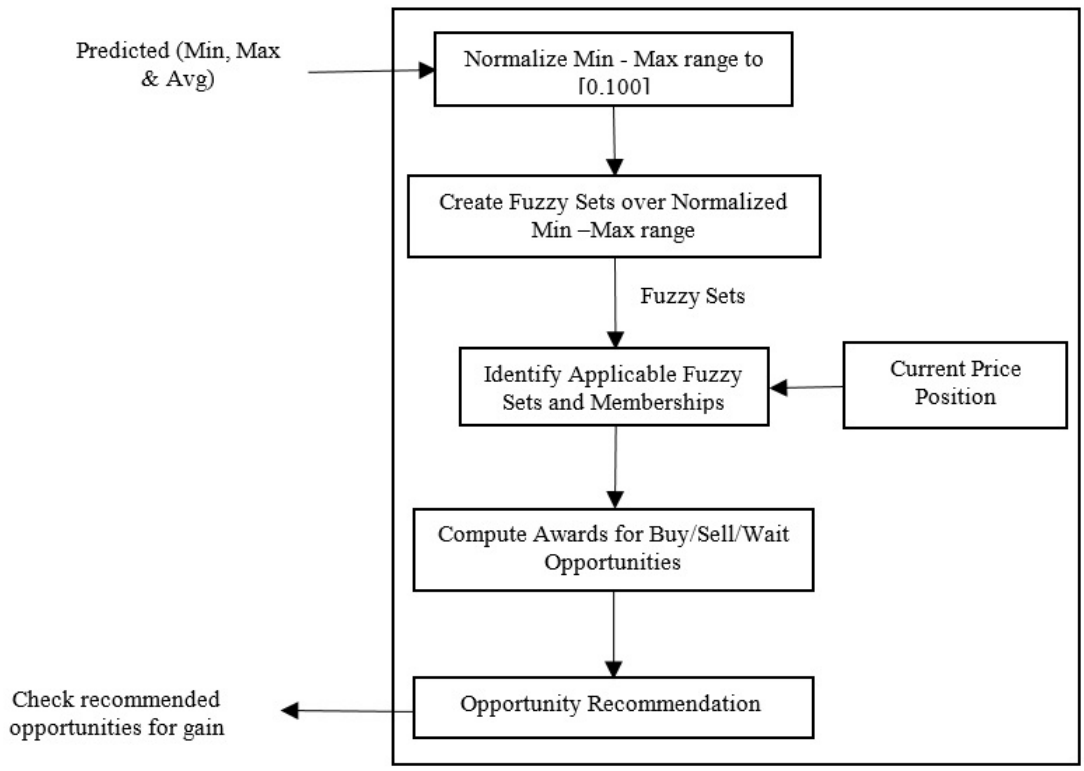

Fig. 3. Design of the Opportunity Sensing Module

The subsequent section talks about the conduct of the experiment based upon the proposed predictive framework.

5. The Experiment

5.1 Experimental Setup

As described earlier, the experiment was repeated for 4 cycles by taking the data for 46 NIFTY50 companies, listed in Table 2 from the various websites (NSE India, 2021)(Rediff Money, 2021)(Money Control, 2021)(Yahoo Finance, 2021) for evaluating the framework. Detail of various cycles is given in Table 3. An artificial neural network (ANN) with 4 hidden layers each having 50 neurons and ReLU as activation function, was trained on the input/output using Python 3.7 After reducing the mean square error (MSE) to its minimum, trained module was applied on the input data of prediction phase. The results so obtained were checked with the actual output for the purpose of validation.

Table 2: List of NIFTY50 companies under consideration

Co.No.	STOCK	Co.No.	STOCK
1	Adani Ports & Special Economic Zone	24	ITC Ltd.(L)
2	Asian Paints Ltd.(L)	25	JSW Steel Ltd.(L)
3	Axis Bank Ltd.(L)	26	Kotak Mahindra Bank Ltd.(L)
4	Bajaj Auto Ltd.(L)	27	Larsen & Toubro Ltd.(L)
5	Bajaj Finance Ltd.(L)	28	Mahindra & Mahindra Ltd.(L)
6	Bajaj Finserv Ltd.(L)	29	Maruti Suzuki India Ltd.(L)
7	Bharat Petroleum Corporation Ltd.(L)	30	Nestle India Ltd.(L)
8	Bharti Airtel Ltd.(L)	31	NTPC Ltd.(L)
9	Britannia Industries Ltd.(L)	32	Oil & Natural Gas Corporation Ltd.(L)
10	Cipla Ltd.(L)	33	Power Grid Corporation Of India
11	Coal India Ltd.(L)	34	Reliance Industries Ltd.(L)
12	Dr. Reddys Laboratories Ltd.(L)	35	Shree Cement Ltd.(L)
13	Eicher Motors Ltd.(L)	36	State Bank Of India(L)
14	GAIL (India) Ltd.(L)	37	Tata Consultancy Services Ltd.(L)
15	Grasim Industries Ltd.(L)	38	Tata Motors Ltd.(L)
16	HCL Technologies Ltd.(L)	39	Tata Steel Ltd.(L)
17	HDFC Bank Ltd.(L)	40	Tech Mahindra Ltd.(L)
18	Hero MotoCorp Ltd.(L)	41	Titan Company Ltd.(L)
19	Hindalco Industries Ltd.(L)	42	Ultratech Cement Ltd.(L)
20	Hindustan Unilever Ltd.(L)	43	UPL Ltd.(L)
21	HDFC	44	Vedanta Ltd.(L)
22	ICICI Bank Ltd.(L)	45	Wipro Ltd.(L)
23	Infosys Ltd.(L)	46	Zee Entertainment Enterprises Ltd

5.2 Experimental Observations

The output of the experiment for various cycles has been depicted in Figure 4 to Figure 10. The results can be divided into two segments: First Segment from Figure 4 to Figure 7 depicts the cycle wise performance of the proposed model. To evaluate the performance, the obtained output has been classified into Prediction Accuracy Bands (PABs) of size ±3%, ±5%, ±7%, ±10% and ±15%. The results of the min prediction are quite remarkable and majority of the stocks are covered within ±10% band. Next performer is average price prediction. Max price prediction comes in the last. The reason for the same is that the Indian stock markets have seen significantly high upward trend in the post pandemic (COVID) scenario. The beauty of the output is that it is consistent amongst all the cycles. Second Segment from Figure 8 to Figure 10 depicts the consolidated performance which quantifies the average performance across all cycles and endorses the above mentioned results. Figure 11 to Figure 13 show the stock wise actual performance through the use of scatter diagram. The purpose of these diagrams is to show that a significant portion of predictions results are bound in the narrow band and numbers of outliers are very few ensuring the good fitness of results. Since the stock price are different for different stocks, a stock may have the price as 230 and other as 15600 therefore while plotting these graph the actual price (max, min or average) was normalized to 100. Figure 13 shows a particular case where the numbers of outliers are quite high. This is an indication of the volatility in the stock market which supports our methodology. We observed that though the minimum and the maximum limits were not that violated

(Figure 11 and Figure 12) but the internal movement within the stocks were quite high which eventually generated the proposed opportunities and resulted in the effective monetization. Such things are quite likely and common in a random environment like stock market.

Table 3 Training, Testing and Validation details

CYCLE	Training Phase		Prediction & Validation Phase	
	Period for input training data feature extraction (120 working days)	Period for output data used for supervised learning (30 working days)	Input data period for feature extraction for testing (120 working days)	Prediction period for validation (30 working days)
Cycle1	1 July 20-18 Dec. 20	21 Dec.20-2 Feb. 21	3 Aug 20- 21 Jan. 21	22 Jan. 21-5 March 21
Cycle2	3 Aug 20- 21 Jan. 21	22 Jan. 21-5 March 21	1st Sept, 20 – 22nd Feb, 21	23rd Feb, 21 – 8th April, 21
Cycle 3	1st Sept, 20 – 22nd Feb, 21	23rd Feb, 21 – 8th April, 21	1st Oct, 20 – 25th Mar, 21	26th March , 21- 12th May, 21
Cycle 4	1st Oct, 20 – 25th Mar, 21	26th March , 21- 12th May, 21	2nd Nov, 20- 29th April, 21	30thApril, 21- 11th June, 21

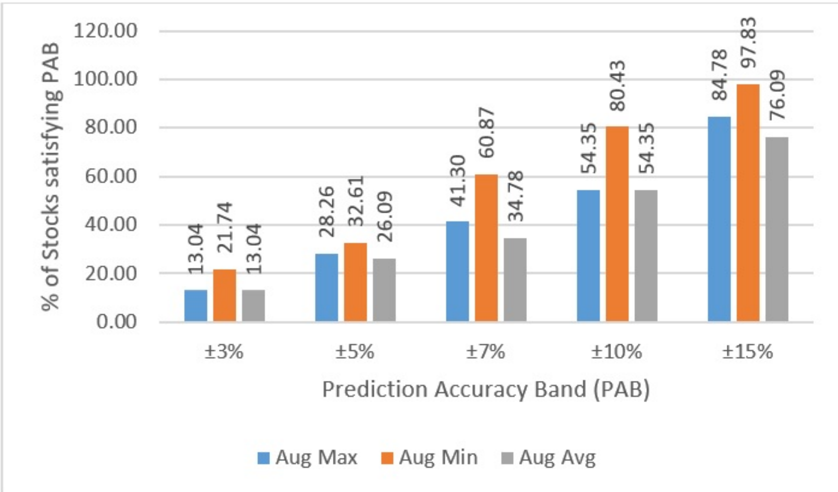

Fig. 4. Prediction Accuracy in Cycle 1

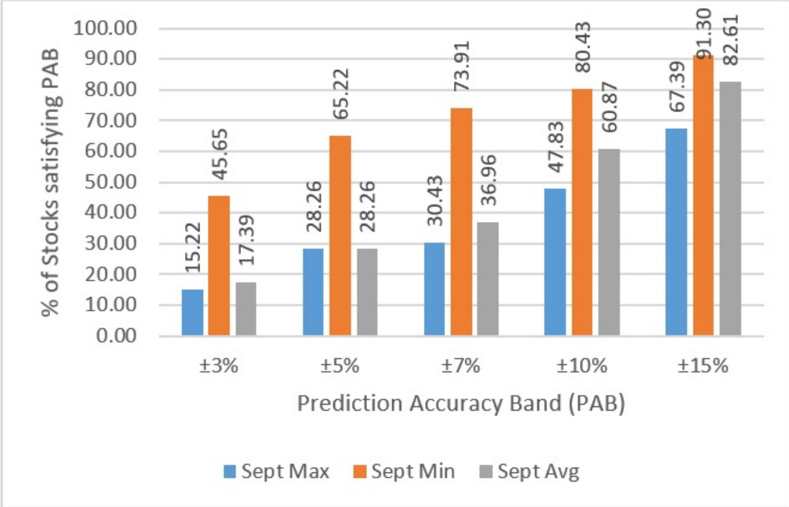

Fig. 5. Prediction Accuracy in Cycle 2

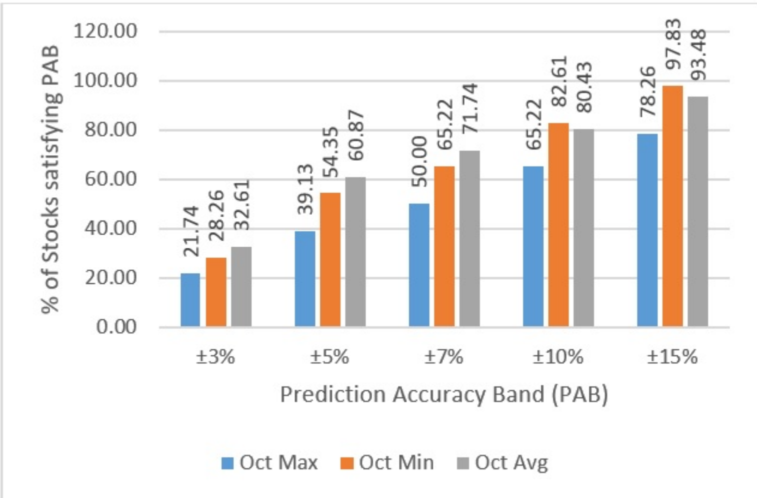

Fig. 6. Prediction Accuracy in Cycle 3

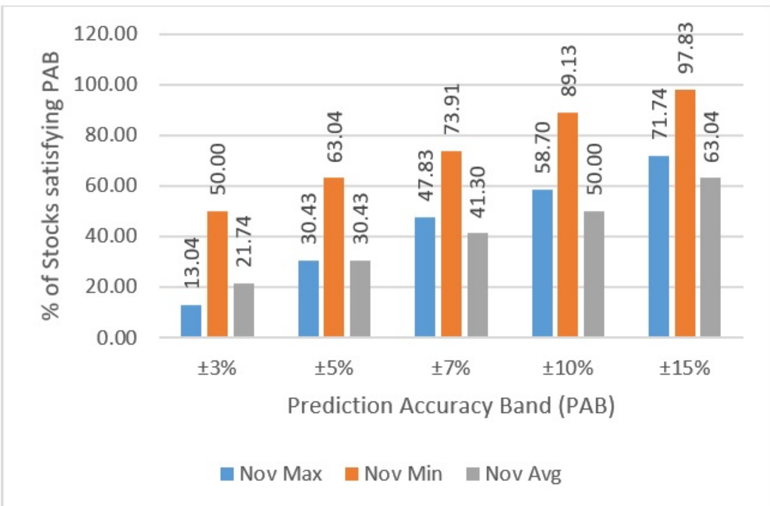

Fig. 7. Prediction Accuracy in Cycle 4

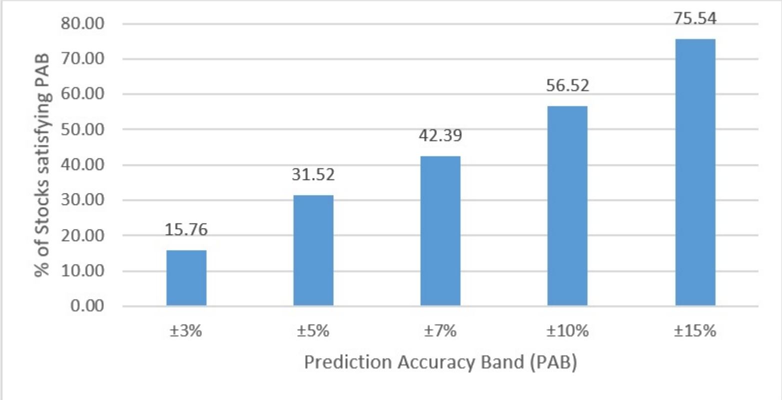

Fig. 8. Maximum Price Prediction Trend across all cycles

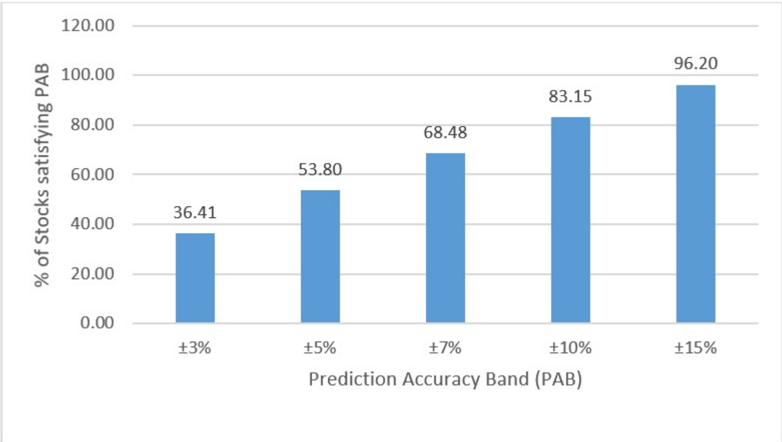

Fig. 9. Minimum Price Prediction Trend across all cycles

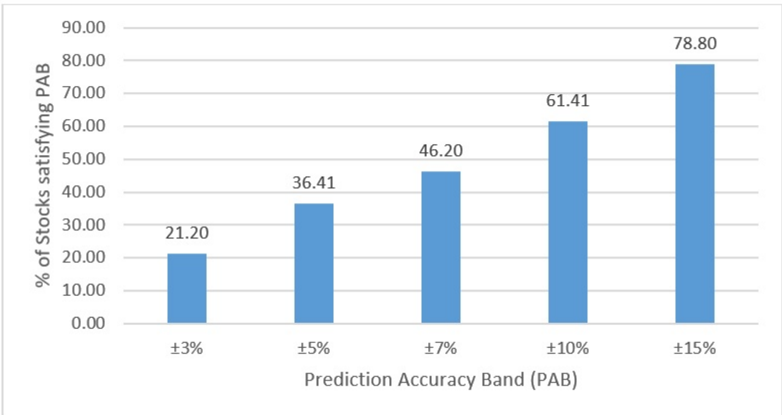

Fig. 10. Average Price Prediction Trend across all cycles

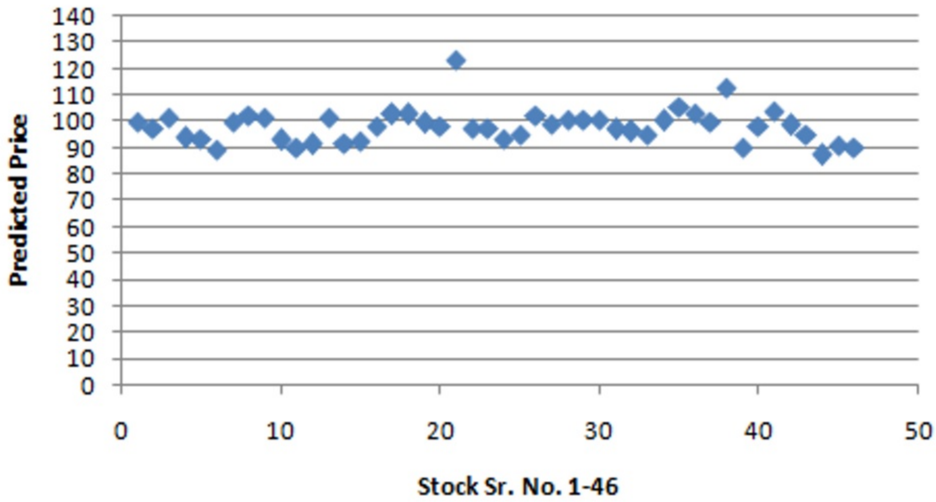

Fig. 11. Normalized Minimum Price Prediction in Cycle 4

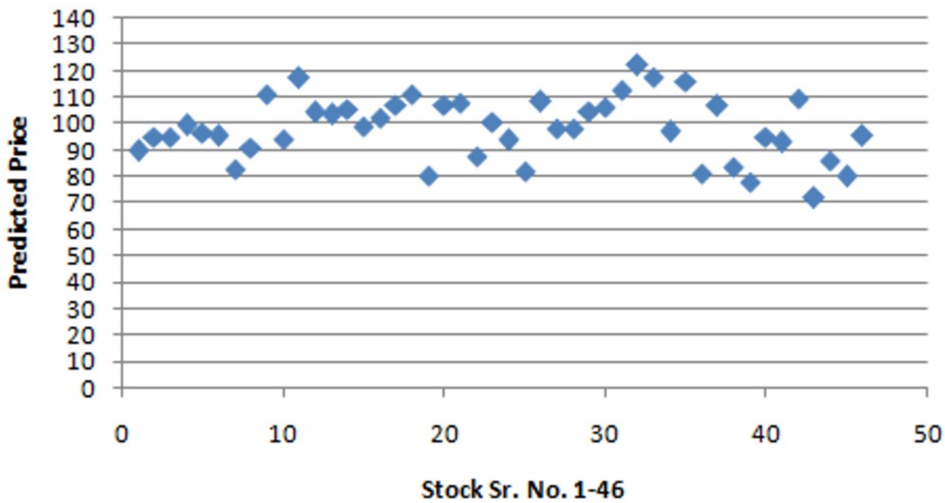

Fig. 12. Normalized Maximum Price Prediction in Cycle 4

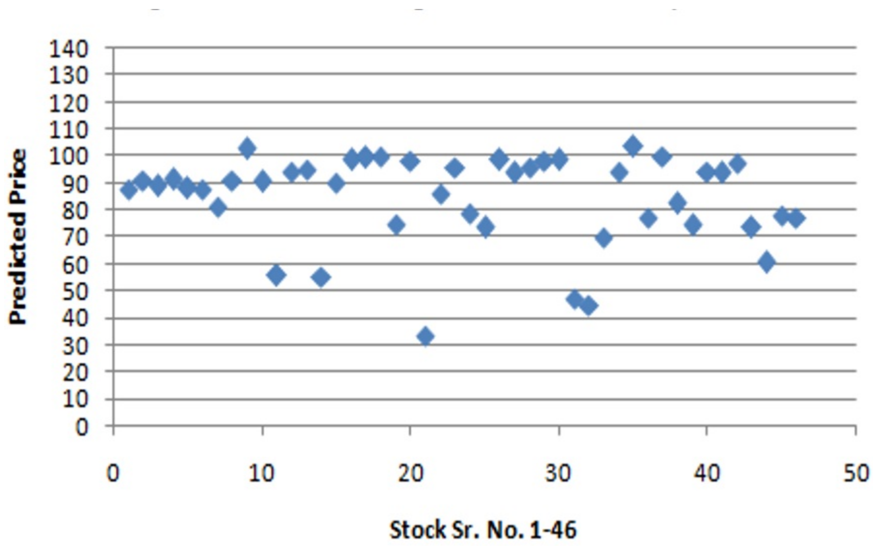

Fig. 13. Normalized Average Price Prediction in Cycle 4

6. Opportunity Signal Generation

The goal of this system is automated generation of an opportunity signal (indicating the advice to buy/sell/wait) with appropriate rewards. To accomplish the same, following methodology was adopted:

- The range between maximum and minimum prediction was normalized to [0, 100] range using a scaling factor. For example, for a stock say X, if the minimum predicted value is a and maximum predicted value is b then the Scaling Factor (S) for normalization is 100/(b-a). Now, for a current price Cp, the normalized value will be (Cp-a)*S

- This normalized range [0,100] is now fuzzified to three fuzzy sets namely Top, Mid and Bottom as shown in the Figure 14. For a given current price, a situation can be classified into one of the above fuzzy sets.

- Depending upon the fuzzy set(s) and the memberships obtained, the fuzzy sets Top/Mid/Bottom can be classified into sell/wait/buy opportunity call respectively on the basis of reward points.

- The simplest reward point system would be 100 * x, where x is the membership in the fuzzy set. Such a system would create 50 or more reward points as and when x exceeds 0.5.However, to make the system safer it is advisable to adopt a formula like

$$100 * x^k$$

where k is greater than 1, is the proposed Opportunity Controller, used to weaken the opportunity call generated at lower memberships (as per the expert advice). Table 4 illustrates the mechanism described above for k=2. An increment in value of k reduces the number of opportunities generated but increases the gain per opportunity thereby maintaining the overall gain reducing the risk factor at the same time. The same has been shown in the next section wherein the opportunities have been explored with value of k from 1 to 7.

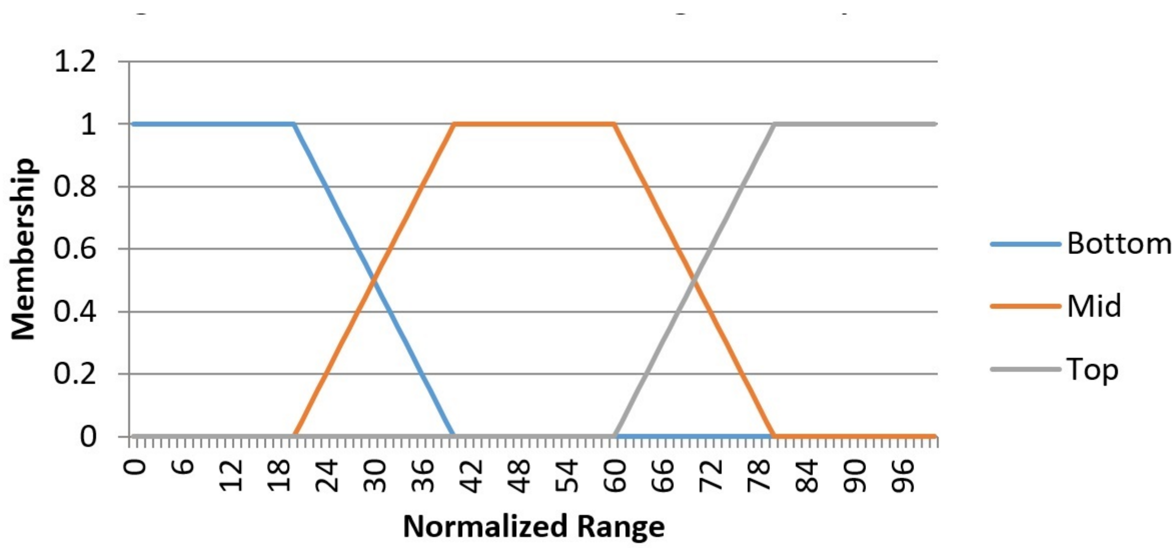

Fig. 14. Classification of normalized range into fuzzy sets

Table 4: Opportunity Signal Generation illustration								
Company	Predicted High price (b)	Predicted low price (a)	Range (b-a)	Normalization factor S= 100/(b-a)	Current Price Cp	Normalized Value	Fuzzy set(s) with membership	Opportunity Signal (Rewards at k=2)
A	18000	16500	1500	0.07	17234	48.93	Mid (1.0)	No action (100)
B	1200	750	450	0.22	903	34.00	Bottom (0.3) Mid (0.7)	Buy (9) No action (49)
C	1100	700	400	0.25	988	72.00	Mid(0.4) Top(0.6)	No Action (16) Sell(36)
D	1500	1250	250	0.4	1310	24.00	Bottom(0.8) Mid(0.2)	Buy (64) No Action (4)
E	1000	800	200	0.50	980	90.00	Top(1)	Sell (100)

Table 5 : Opportunity Analysis at k=2							
No of Stocks under Consideration = 46							
	CASE 1	**CASE 2**	**CASE 3**	**CASE 4**	**Profit**	**Loss**	**Net Gain**
Cycle 1	18	18	2	8	4250.8	-1576	2674.99
Cycle 2	12	20	4	10	5839.1	-1421	4417.85
Cycle 3	24	7	4	11	2724	-151.5	2604.98
Cycle 4	15	13	7	11	2124.5	-98.26	2026.22
Average Occurrence	17.25	14.5	4.25	10	3734.6	-811.7	2931.01
Success (%)	37.5	31.5	9.24	22	100	-21.78	78.22

Table 6: Detailed Computation Scenarios for Cycle 1 at k=2											
Co. No.	Ac_MIN	Ac_MAX	Pr_min	Pr_MAX	Range	BO POINT	SO POINT	BO status	SO status	RETURNS	Price on 5/Mar/21
1	509.70	752.45	514.48	639.11	124.63	546.71	606.89	Y	Y	60.17	748.95
2	2277.20	2596.65	2597.73	3029.33	431.60	2709.34	2917.72	N	N	0.00	2,387.10
3	632.10	794.00	668.55	786.68	118.13	699.10	756.13	Y	Y	57.03	730.75
4	3798.70	4237.45	3452.04	4002.53	550.50	3594.39	3860.18	N	Y	0.00	3,852.85
5	4734.55	5779.85	4820.55	5583.47	762.93	5017.84	5386.18	Y	Y	368.34	5,444.90
6	8722.75	10537.70	8460.35	9748.72	1288.37	8793.52	9415.55	Y	Y	622.02	9,958.10
7	380.60	469.00	402.60	493.74	91.14	426.17	470.17	Y	N	35.63	461.8
8	532.20	608.85	563.40	688.36	124.96	595.71	656.04	Y	N	-62.91	532.8
9	3331.20	3613.55	3501.86	4040.18	538.32	3641.07	3900.97	N	N	0.00	3,491.75
10	787.05	863.40	804.50	964.08	159.58	845.77	922.82	Y	N	-40.62	805.15
11	125.90	156.10	139.14	176.65	37.51	148.84	166.95	Y	N	2.26	151.1
12	4404.70	5082.40	4927.87	5761.24	833.37	5143.38	5545.73	N	N	0.00	4,492.50
13	2482.35	2972.60	2710.96	3185.99	475.03	2833.80	3063.15	Y	N	-246.05	2,587.75
14	125.30	150.80	131.45	158.41	26.96	138.42	151.44	Y	N	8.73	147.15
15	1004.00	1350.40	996.97	1176.63	179.66	1043.43	1130.17	Y	Y	86.74	1,339.35
16	909.45	985.80	971.82	1156.43	184.61	1019.56	1108.69	N	N	0.00	941.5
17	2377.80	2860.45	2566.76	2964.53	397.77	2669.63	2861.67	Y	N	-125.73	2,543.90
18	3224.00	3584.00	3082.53	3636.13	553.61	3225.69	3492.97	Y	Y	267.28	3,461.70
19	226.30	359.35	251.16	319.65	68.49	268.87	301.94	Y	Y	33.07	337.85
20	2132.05	2409.35	2304.64	2648.63	343.98	2393.60	2559.67	Y	N	-192.50	2,201.10
21	68.84	83.26	73.49	79.31	5.82	74.99	77.80	Y	Y	2.81	82.28
22	522.35	673.95	548.07	647.74	99.67	573.84	621.96	Y	Y	48.12	609.45
23	1239.05	1343.55	1305.89	1526.00	220.11	1362.81	1469.08	N	N	0.00	1,039.90
24	203.25	234.35	214.57	277.16	62.58	230.76	260.97	Y	N	-22.21	208.55
25	366.85	428.15	386.55	481.11	94.56	411.00	456.66	Y	N	-4.60	406.4
26	1712.95	2019.65	1887.49	2144.60	257.11	1953.98	2078.11	Y	N	-31.48	1,922.50
27	1334.70	1566.45	1357.13	1543.97	186.84	1405.45	1495.65	Y	Y	90.21	1,463.55
28	749.60	928.40	770.72	938.61	167.89	814.13	895.19	Y	Y	81.06	840.4
29	6866.15	8048.85	7456.63	8864.92	1408.30	7820.81	8500.74	Y	N	-571.81	7,249.00
30	16096.30	17589.60	17063.90	19737.29	2673.39	17755.24	19045.95	N	N	0.00	16,782.90
31	88.95	112.70	99.07	117.38	18.31	103.81	112.64	Y	Y	8.84	108.7
32	88.30	119.05	98.09	111.95	13.86	101.67	108.37	Y	Y	6.69	114.95
33	184.45	236.50	195.70	256.80	61.10	211.50	241.00	Y	N	-46.31	165.19
34	1841.95	2202.10	1993.22	2305.06	311.85	2073.86	2224.42	Y	N	104.84	2,178.70
35	22773.35	28676.60	22987.02	26739.89	3752.87	23957.51	25769.40	Y	Y	1811.88	27,848.60
36	275.65	415.20	287.62	365.59	77.96	307.79	345.43	Y	Y	37.64	383.65
37	2894.30	3303.10	3058.85	3596.08	537.23	3197.78	3457.15	Y	N	-189.73	3,008.05
38	262.70	348.50	228.45	337.05	108.60	256.54	308.97	N	Y	0.00	325.15
39	601.00	777.15	693.01	798.99	105.98	720.42	771.58	Y	Y	51.17	733.3
40	918.85	1010.60	999.83	1176.61	176.78	1045.54	1130.89	N	N	0.00	959.7
41	1405.25	1563.15	1510.46	1730.34	219.88	1567.32	1673.48	N	N	0.00	1,474.20
42	5327.25	6810.30	5238.84	6063.22	824.38	5452.02	5850.03	Y	Y	398.01	6,810.30
43	534.10	615.45	506.18	672.90	166.71	549.29	629.78	Y	N	42.26	591.55
44	161.25	219.30	164.75	218.60	53.85	178.67	204.67	Y	Y	26.00	219.25
45	410.30	446.45	411.26	536.20	124.93	443.57	503.89	Y	N	-22.72	420.85
46	201.00	249.45	217.94	292.39	74.44	237.19	273.14	Y	N	-19.14	218.05

7. Validation of Results

To validate the results, every cycle was checked for the occurrence of buying / selling opportunity for each of the 46 stocks. If the opportunity occurred, then one number of stock of the company was bought / sold. The data so obtained has been shown in Table 5. Let us represent the occurrence / non-occurrence of the buying / selling opportunity by “Y” / “N” and BO / SO respectively. Now there can be four cases:

- Case 1: BO = “Y” and SO = “Y” In this case both buying and selling opportunities have occurred, during the validation period of 30 working days, leading to profit generation.
- Case 2: BO = “Y” and SO = “N” In this case only buying opportunity has occurred. Since selling opportunity did not occur, there are two possible options: selling can be postponed to subsequent cycle(s) or selling can be done on the last day of the cycle, be it profit or loss. We have gone for the second option in order to finish the task with in the same cycle.

- Case 3: BO = "N" and SO = "Y" Here no buying opportunity has occurred so there is no possibility for selling leading to no transaction.
- Case 4: BO = "N" and SO = "N" Here neither buying nor selling opportunity has occurred, so there is no transaction.

Table 5 shows the opportunity analysis at k=2. The analysis in Table 5 shows that in 37.5% cases the both buying and selling opportunities were generated leading to majority profit. In 31.5% cases, selling opportunity did not occur leading to distress selling on the last day of the cycle which resulted in the loss in many cases but there was overall gain. In the overall scenario, on the average 21.78% profit (809/3713) was wiped out due to distress selling resulting in overall gain of 78.22% (2911/3713). Table 6 shows the detailed computation scenario for cycle 1 at k=2. Table 7, 8, 9 and 10 show real net gain obtained in various cycles by varying the value of k from 1 to 7. The results endorse the hypothesis that increase in the value of k, decreases the risk factor without affecting the net gain. Overall gain across all the cycles show that the proposed mechanism is quite trust worthy. These tables also include the precision and recall parameters for the predictions made. Here precision refers to the number of case 1 stock instances where in both buying and selling opportunity was created against the total number of stocks under consideration (46). For example, in Table 7, there are 21 stock instances at k=1 in Case 1 category leading to a precision of 21/46=0.46. For the purpose of the recall, the numerator is the case 1 instances and the denominator is the sum of case 1 and case 2 instances. For example, in Table 7, there are 21 stock instances at k=1 in Case 1 category and 14 in Case 2 category leading to a recall of 21/(21+14)=0.60. Since no buying opportunity was created in case 3 and case 4 therefore these cases have not been considered for making recall computations.

Table 7: Cycle 1

K	CASE 1	CASE 2	CASE 3	CASE 4	Precision	Recall	Gain	Loss	Net
1	21	14	2	9	0.46	0.6	3695.63	-1576.36	2119.273
2	18	18	2	8	0.39	0.58	4250.802	-1575.81	2674.991
3	16	19	3	8	0.35	0.6	4261.828	-1504.51	2757.321
4	16	20	3	7	0.35	0.58	4416.822	-1552.58	2864.237
5	16	20	3	7	0.35	0.58	4513.081	-1526.97	2986.111
6	16	20	3	7	0.35	0.58	4579.973	-1509.17	3070.803
7	16	20	3	7	0.35	0.58	4627.287	-1496.58	3130.707

Table 8: Cycle 2

K	CASE 1	CASE 2	CASE 3	CASE 4	Precision	Recall	Gain	Loss	Net
1	15	19	3	9	0.33	0.62	4911.198	-1655.89	3255.309
2	12	20	4	10	0.26	0.66	5839.135	-1421.28	4417.852
3	11	22	4	9	0.24	0.64	6239.678	-1519.58	4720.095
4	9	24	5	8	0.2	0.64	6407.916	-1605.61	4802.308
5	9	24	5	8	0.2	0.64	6544.296	-1564.79	4979.511
6	8	23	6	9	0.17	0.68	6414.57	-1536.42	4878.153
7	8	23	5	10	0.17	0.68	6479.152	-1516.35	4962.801

Table 9: Cycle 3

K	CASE 1	CASE 2	CASE 3	CASE 4	Precision	Recall	Gain	Loss	Net
1	25	6	3	12	0.54	0.68	2326.338	-148.893	2204.388
2	24	7	4	11	0.52	0.68	2723.972	-151.51	2604.981
3	24	8	4	10	0.52	0.66	2919.586	-147.211	2791.468
4	24	8	4	10	0.52	0.66	3027.005	-144.849	2902.862
5	24	8	4	10	0.52	0.66	3093.717	-143.383	2972.043
6	24	8	4	10	0.52	0.66	3140.76	-143.048	3020.119
7	24	8	4	10	0.52	0.66	3174.207	-142.983	3054.123

Table 10: Cycle 4

K	CASE 1	CASE 2	CASE 3	CASE 4	Precision	Recall	Gain	Loss	Net
1	15	12	7	12	0.33	0.78	1707.628	-106.433	1601.195
2	15	13	7	11	0.33	0.75	2124.479	-98.2612	2026.217
3	15	13	6	12	0.33	0.75	2309.646	-84.7642	2224.882
4	15	13	6	12	0.33	0.75	2411.327	-77.3526	2333.975
5	15	13	6	12	0.33	0.75	2474.5	-72.7726	2401.727
6	15	13	6	12	0.33	0.75	2519.296	-70.4859	2448.81
7	15	13	6	12	0.33	0.75	2550.98	-68.8685	2482.112

8. Conclusion and Future Scope

The proposed work is able to make a reasonable stock price band prediction for the upcoming one and a half month with quite significant accuracy. In Indian Stock Market, to prevent the undesirable manipulations of stock prices a circuit of 5% or 10% is imposed on the stock price on the daily basis. Most of the NIFTY50 stocks are in the 10% band. Thus, for a market undergoing a strong trend, whether upward or downward, it is not uncommon to have a change in the range of 30% to 60% in a period of one month and a half. The post pandemic rally, after September 2020, raised stock price 2 to 3 folds in the period under review (spread across all cycles) for a quite a significant fraction of the popular stocks. 50-60% rise has been seen in majority of stocks. The NSE bench mark index has risen by one and a half times.Under the circumstances, the predictions made by our system are quite accurate, appropriate and reliable wherein a majority of stocks (more than 75%) fall in 15% accuracy band as shown in Figure 4-10. Tables 7-10 show that monetization capability of the system increases with the increase in the value of Opportunity Controller k. Thus a bigger value of k is desirable but an extremely high value of k (more than 10) can result in missing of the opportunities to a large extent. The price band results obtained in the proposed model can be classified in the good fit category as they are consistent across all the cycles. We tried to extend the work with the inclusion of more features through the inclusion of their component features. This led to the deviation of the results due to overfitting. It will be a good exercise for new researchers if they can include more component features without falling in the trap of overfitting.

Conflict of Interest The work carried out in this paper is a pure academic research work without making any financial gain as such.

References

AIFAA, MOHD, ARIFF,MOHD (2021) , A new intelligent time-series prediction technique for coherency identification performance enhancement, Kuwait Journal of Science, Vol. 48 No. 4, Aug 2021, DOI: 10.48129/kjs.15051

Baek, Y., Kim, H.Y., (2018), ModAugNet: A new forecasting framework for stock market index value with an overfitting prevention LSTM module and a prediction LSTM module. Expert Syst. Appl., 113, pp. 457–480.

Bao, W., Yue, J. and Rao, Y. (2017), A deep learning framework for financial time series using stacked autoencoders and long-short term memory, PLoS ONE, https://doi.org/10.1371/journal.pone.0180944.

Bollinger-Bands (2021), https://www.bollingerbands.com/bollinger-bands accessed on 3rd July, 2021

Carriero A, Galvão A.B., Kapetanios G. (2019), A comprehensive evaluation of macroeconomic forecasting methods, International Journal of Forecasting, Volume 35, Issue 4, pp. 1226-1239

Chen, M.-Y.; Liao, C.H.; Hsieh, R.-P.(2019), Modeling public mood and emotion: Stock market trend prediction with anticipatory computing approach. Comput. Hum. Behav., 101, 402–408.

Cheng, L.-C.; Huang, Y.-H.; Wu, M.-E., (2018), Applied attention-based LSTM neural networks in stock prediction. In Proceedings of the IEEE International Conference on Big Data (Big Data), Seattle, WA, USA.

Chung, H.; Shin, K.-S., 2018, Genetic algorithm-optimized long short-term memory network for stock market prediction. Sustainability, 10, 3765.

Cover, T.M. (1965), Geometrical and Statistical properties of systems of linear inequalities with applications in pattern recognition, IEEE Transactions on Electronic Computers. EC-14 (3): pp. 326–334

Di Persio, Luca, Oleksandr H. 2017, Recurrent Neural Networks Approach to the Financial Forecast of Google Assets. International Journal of Mathematics and Computers in simulation 11: 7–13.

Duffee G., (2013), Handbook of Economic Forecasting, Chapter 7 - Forecasting Interest Rates, Elsevier,Volume 2, Part A

Duffee G.R., (2002), Term Premia and Interest Rate Forecasts in Affine Models. The Journal of Finance, 57: pp. 405-443.

Eicher S.,Kuenzel D.J., Papageorgiou C., Christofides C., (2019), Forecasts in times of crises, International Journal of Forecasting, Volume 35, Issue 3, pp. 1143-1159

Fayyad U.M., Haussler D., Stolorz, P.E., (1996), KDD for science data analysis: Issues and examples, in: KDD, 1996, pp. 50–56

Feng, F., He, X., Wang, X., Luo, C., Liu, Y., Chua, T.S., (2019), Temporal relational ranking for stock prediction. ACM Trans. Inf. Syst. (TOIS), 37, pp. 1–30.

Fischer T, Krauss C., (2018), Deep learning with long short-term memory networks for financial market predictions European Journal of Operational Research, Volume 270, Issue 2, pp. 654-669

Goyal A., Welch I., (2008), A Comprehensive Look at The Empirical Performance of Equity Premium Prediction, The Review of Financial Studies, Volume 21, Issue 4, pp. 1455–1508,

Gupta A., Dhingra B., (2012), Stock market prediction using hidden markov models, in: Proceedings of Students Conference on Engineering and Systems, pp. 1–4.

He, M, Hao, X, Zhang, Y, Meng, F., (2021), Forecasting stock return volatility using a robust regression model. Journal of Forecasting.

Idrees SM, Alam MA, Agarwal P., (2019), A prediction approach for stock market volatility based on time series data, IEEE Access;7:172, pp. 87–98.

Investopedia (2021), https://www.investopedia.com/terms/s/sma.asp accessed on 25th May, 2021

Ismail,A.Haj, (2021), Prediction of Global Solar Radiation from Sunrise Duration Using Regression Functions, Kuwait Journal of Science, DOI: 10.48129/kjs.15051

Jarlath Q., 2020, An overview of the four main approaches to predictive analytics

Jeon S, Hong B, Chang V., (2018), Pattern graph tracking-based stock price prediction using big data. Future Generation Computer Systems, Volume 80, pp. 171-187

Jiawei, X. and Murata, T., (2019), Stock market trend prediction with sentiment analysis based on LSTM neural network, Proceedings of the International MultiConference of Engineers and Computer Scientists, IMECS

Jin, Z.; Yang, Y.; Liu, Y. , (2020), Stock closing price prediction based on sentiment analysis and LSTM. Neural Comput. Appl. , 32, 9713–9729.

Jonathan H. Wright, (2019), Some observations on forecasting and policy, International Journal of Forecasting, Volume 35, Issue 3, pp. 1186-1192

Kara Y, Acar B.M., Baykan ÖK, (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, Volume 38, Issue 5, pp. 5311-5319

Kim, H.Y., Won, C.H.,(2018), Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models. Expert Syst. Appl., 103, pp. 25–37.

Kong, A, Zhu, H, Azencott, R., (2021), Predicting intraday jumps in stock prices using liquidity measures and technical indicators. Journal of Forecasting:40:, pp. 416-438

Lei L., (2018), Wavelet neural network prediction method of stock price trend based on rough set attribute reduction. Applied Soft Computing, Volume 62, pp. 923-932

Leigh, William, Cheryl J. Frohlich, Steven Hornik, Russell L. Purvis, and Tom L. Roberts. 2008, Trading with a Stock Chart Heuristic. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans 38: 93–104

Li, H.; Shen, Y.; Zhu, Y. (2018), Stock price prediction using attention-based multi-input LSTM. In Proceedings of the Asian Conference on Machine Learning, Beijing, China, 14–16 November 2018.

Lin, B.-S.; Chu, W.-T.; Wang, C.-M., (2018), Application of stock analysis using deep learning. In Proceedings of the 7th International Congress on Advanced Applied Informatics (IIAI-AAI), Yonago, Japan.

Long W, Lu Z, Cui L., (2019), Deep learning-based feature engineering for stock price movement prediction, Knowledge-Based Systems, Volume 164, pp. 163-173

Long, J.; Chen, Z.; He, W.; Wu, T.; Ren, J. (2020), An integrated framework of deep learning and knowledge graph for prediction of stock price trend: An ap-plication in Chinese stock exchange market. Appl. Soft Comput.

Marian R., 2019, Combining wavelet decomposition with machine learning to forecast gold returns, International Journal of Forecasting, Volume 35, Issue 2, Pages 601-615

McNally S, Roche J, Caton S. (2018), Predicting the price of bitcoin using machine learning, 26th Euromicro international conference on parallel, distributed, and networkbased processing, pp 339–43

Moghaddam A.H., Moghaddam M.H., Esfandyari M., (2016), Stock market index prediction using artificial neural network, J. Econ. Financ. Adm. Sci. 21 (41), pp. 89–93.

Money Control(2021) https://www.moneycontrol.com/ last accessed on 20th July, 2021

Najva Abdul, Saleem P.K, (2022) Real time obstacle motion prediction using neural network based extended Kalman filter for robot path planning, DOI: https://doi.org/10.48129/kjs.18361, Kuwait Journal of Science.

Nekoeiqachkanloo H, Ghojogh B, Pasand AS, Crowley M., (2019), Artificial counselor system for stock investment, Proceedings of the AAAI Conference on Artificial Intelligence, pp. 9558–9564

Ngo, N.T. and Truong, T.T.H., (2019), 'Forecasting time series data using moving-window swarm intelligence-optimised machine learning regression', International Journal of Intelligent Engineering Informatics (IJIEI), Vol. 7, No. 5, pp.422 – 440

Ni LP, Ni ZW, Gao YZ., (2011), Stock trend prediction based on fractal feature selection and support vector machine. Expert Systems with Applications, Volume 38, Issue 5, pp. 5569-5576

Nikou, M., Mansourfar, G., Bagherzadeh, J., (2019), Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms. Intell. Syst. Account. Financ. Manag., 26, pp.164–174.

Niu, H., Xu, K. & Wang, W. (2020), A hybrid stock price index forecasting model based on variational mode decomposition and LSTM network. ApplIntell 50, 4296–4309, https://doi.org/10.1007/s10489-020-01814-0

NSE India(2021), https://www.nseindia.com/ last accessed on 20th July, 2021

Pang, X., Zhou, Y., Wang, P., Lin, W., Chang, V,(2020), An innovative neural network approach for stock market prediction. J. Supercomput., 76, pp. 2098–2118.

Pimenta A, Nametala CAL, Guimarães FG, Carrano EG., (2018), An automated investing method for stock market based on multiobjective genetic programming. Computational Economics, 52; pp. 125-144

Rediff Money (2021) https://money.rediff.com/index.html last accessed on 20th July, 2021

Richard A. M., Kenneth R., (1983), Empirical exchange rate models of the seventies: Do they fit out of sample?, Journal of International Economics, Volume 14, Issues 1–2,pp. 3-24

Shah, D.; Campbell, W.; Zulkernine, (2018), F.H. A comparative study of LSTM and DNN for stock market forecasting. In Proceedings of the IEEE International Conference on Big Data (Big Data), Seattle, WA, USA.

Shen, J., Shafiq, M.O., (2020), Short-term stock market price trend prediction using a comprehensive deep learning system. Journal of Big Data 7, 66

Singh, Manpreet (2022), A hybrid approach based on k-nearest neighbors and decision tree for software fault prediction, Kuwait Journal of Science, DOI: https://doi.org/10.48129/kjs.18331

Sinha, AK., (2021), THE RELIABILITY OF GEOMETRIC BROWNIAN MOTION FORECASTS OF S&P 500 INDEX VALUES. Journal of Forecasting.

Sirignano J, Cont R., (2018), Universal features of price formation in financial markets: perspectives from deep learning. Ssrn.

Skehin, T.; Crane, M.; Bezbradica, M. (2018), Day ahead forecasting of FAANG stocks using ARIMA, LSTM networks and wavelets. In Proceedings of the 26th AIAI Irish Conference on Artificial Intelligence and Cognitive Science, Dublin, Ireland.

Ticknor J.L.,2013 A Bayesian regularized artificial neural network for stock market forecasting, Expert Syst. Appl. 40 (14),pp. 5501–5506.

Wang Q, Xu W, Huang X, Yang K, (2019) Enhancing intraday stock price manipulation detection by leveraging recurrent neural networks with ensemble learning. Neurocomputing 47:46–58

Weng B, Lu L, Wang X, Megahed FM, Martinez W., (2018), Predicting short-term stock prices using ensemble methods and online data sources. Expert Systems with Applications, Volume 112, pp. 258-2732.

Wilder, J. Welles, (1978), New Concepts in Technical Trading Systems, Greensboro, N.C. : Trend Research

Xu, W., Peng, H., Zeng, X. et al. (2019), A hybrid modelling method for time series forecasting based on a linear regression model and deep learning. ApplIntell 49, 3002–3015. https://doi.org/10.1007/s10489-019-01426-3

Yahoo Finance (2021) https://in.finance.yahoo.com/ last accessed on 20th July, 2021

Yeh, C.Y., Huang, C.W., Lee, S.J., (2011), A multiple-kernel support vector regression approach for stock market price casting, Expert Syst. Appl. 38 (3), pp. 2177–2186

Zhong X., Enke D., (2017), Forecasting daily stock market return using dimensionality reduction, Expert Syst. Appl. 67, pp. 126–139.

Submitted:	19/02/2022
Revised:	02/06/2022
Accepted:	03/06/2022
DOI:	10.48129/kjs.splml.18993