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Stock Indices Price Prediction Based on Technical Indicators using Deep Learning Model

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ABSTRACT: The pattern of stock market data is highly complex and volatile. However, notion of stock price predictability is typical, many researchers suggest that the prices are predictable and investor can make above-average profits using efficient Technical Analysis (TA). Most of the earlier prediction models predict individual stocks and the results are mostly influenced by company's reputation, news, sentiments and other fundamental issues while stock indices are less affected by these issues. In this work, an effort is made to predict the prices of stock indices by utilizing Stock Technical Indicators (STIs) which in turn helps to take buy-sell decision over long and short term. Two different models are built, one for future price trend prediction of indices and other for taking Buy-Sell decision at the end of day. As a part of prediction model the optimized Long Short Term Memory (LSTM) model is combined with highly correlated STIs. The models are implemented in Python language using popular deep learning libraries TensorFlow and Keras. The experiments are carried out with three popular indices of National Stock Exchange (NSE) of India: Bank, Automobile and Metal. The concept of applying adaptive TA on stock indices along with Optimized-LSTM is demonstrated successfully in this work. The price trend prediction model presents monthly trend correctly and indicates nature of indices over long term, i.e. Profit, Loss and Neutral. The daily prediction model observed up to 68.45% accuracy and average accuracy of 61.51%.

Keywords: Deep Learning, Machine Learning, Long Short Term Memory, National Stock Exchange, Stock Indices, Stock Prediction model, Stock Technical Indicators, Technical Analysis

I. INTRODUCTION

The analysis and prediction of stock market data have got a significant role in today's economy. The prediction models are based on various algorithms and can be categorized into linear models such as 'Auto-Regressive Integrated Moving Average' (ARIMA) [1], and non-linear models like Neural Network (NN) and Deep Learning [2, 3]. Numerous researchers have attempted to construct an efficient model for prediction of prices for the individual stocks and indices. Deep Neural Networks (Deep Learning) a sub field of Machine Learning (ML) has changed forms gradually over the past decade as it allures many researchers for prediction of stock indices price trends [4, 5, 18-20].

The approaches, for stock price prediction, are generally classified into four categories [6]:

-Fundamental Analysis: Utilizes news, earnings, profits and other economic factors for forecasting.

-Technical Analysis (TA): Utilizes some indicators like Moving Averages (MAs) and Stochastic Oscillator etc.

-Hybrid Method: Utilizes combination of both of the above methods.

-Time series analysis: utilizes analysis of time series data.

The stock indices are generally not affected by fundamental issues, so technical analysis is a better option for indices prediction. In this work, we applied adaptive TA along with deep learning for building the predictive model. The abstract concept of TA is utilization of Stock Technical Indicators (STIs). STIs are statistical calculations based on the price, volume or significance for a share, security or contract. STIs are independent of fundamentals of a business, like earnings, revenue, or profit margins.

The TA is useful while predicting the future prices of assets so it can also be integrated into automated trading systems. The TA anticipates what is "likely" to happen to prices over time, while the deep leaning algorithms give strength to such anticipations by improving accuracy.

In this work, the importance of applying adaptive TA along with Optimized-LSTM over past prices of stocks traded in the asset market is demonstrated.

Finally two predictive models are presented, one for prediction of future prices which helps in determining trends. The other model is for daily prediction which helps in taking buy-sell decision.

Motivation. Most of the works predicts individual stocks and these are mostly affected by social media, news, sentiments and other fundamental issues. Also, earlier works predicts single stock price or pattern. On the other hand stock indices are less affected by these issues. So, prediction of stock indices with adaptive STIs and modern deep learning algorithms can give better profits. Here, adaptive signifies the highly correlative STIs to particular indices.

Another motivation is that the most of the works apply traditional ML algorithms and simplest form of deep learning which do not analyse the prices and volume data over long and short term. The earlier works are either classifying or calculating the accuracy of classifier.

Key Contributions of this work:

Following are the key benefits of proposed model/s

-Prediction of the future prices of stock indices.
-Prediction of price trends over long and short term.
-Decisions of buy-sell of stock indices at the end of day.
-Determines adaptive Stock Technical Indicators.
-Determines Entry and Exit points in long and short term.
-Higher Prediction Accuracy so higher profits.
-Determines Nature of Indices: Profit, Loss, Neutral.

The remaining of the paper is organized as follows: Section II, discuss the related work. Proposed work is presented in section III. The experiments and results are presented in section IV. This section also discusses the results. The paper is concluded in section V with future remarks.

II. LITERATURE REVIEW

TA utilizes historical stock prices and trading volume for predicting what the stock price will be and making a trading decision [7]. de Souza *et al.* [8] investigated the profitability of TA as applied to the stock markets. An automated trading system is developed to simulate transactions in this portfolio using technical analysis techniques. The sample portfolio from Russia and India showed very strong returns. The work utilized two types of moving average: SMA, EMA over varying number of days.

Pang X *et al.* [9] proposed the deep LSTM Neural Network (NN) with embedded layer and the LSTM-NN network with automatic encoder to forecast the stock as traditional NN algorithms may incorrectly predict the stock market. The accuracy achieved with LSTM –NN with embedded layer is better. The maximum accuracy achieved is 57.2%.

To enhance the profitability of investors, Chen, [10] proposed a novel technical analysis method. The techniques utilize trend based classification, indicator selection, and stock market trading signal forecasting.

In our earlier work [11] we predicted the stock prices and price trend of individual stocks by applying optimal-LSTM deep learning and adaptive STIs. To optimize the deep learning task we utilized the concept of Correlation-Tensor built with appropriate STIs. The results are analyzed and compared with LR, SVM and ELSTM [9] which is a deep learning approach. The analysis is done on data of 3 financial organizations (Banks) listed in National Stock Exchange (NSE) – India. The highest accuracy and mean accuracy achieved is 65.64% and 59.25% respectively.

Hasan *et al.* [12] applied several ML techniques along with two popular STIs to predict the future stock prices. Authors then utilized ensemble technique to combine the outcomes of different ML algorithms. The past prices of 15 months for three prominent stocks are used. The algorithms predicts the 1-day, 1-week and 1-month-ahead prices of these stocks. The results signify that ensemble ML approach in combination with technical indicators often provide better results and less prediction error.

Xiong *et al.* [13] used economic variables and LSTM to predict the volatility of the S&P index with the Google trend. Yu [14] applied the deep NN and LSTM to forecast the trading data of the Amazon stock. The highest prediction accuracy achieved is 54%. It is mentioned that the effect of the deep NN was better than LSTM.

Hiransha *et al.* [15], utilizes four deep learning architectures i.e. Multilayer Layer Perceptron (MLP), Recurrent Neural Network (RNN), LSTM and Convolution Neural Network (CNN) for predicting the stock price of a company based on the day-wise historical closing prices of NSE of India and NYSE. The CNN performed much better even it is trained on NSE data and was able to predict for NYSE also. The results obtained were compared with linear ARIMA model.

Silva IND *et al*. [16] utilized RNN to forecast the prices of the three stocks. When used economic variables as input and the historical data, he found that the forecast price fitted the actual price better.

Wang and Kim [17] applied moving average convergence divergence (MACD) which is a momentum based technical indicator along with the historical volatility index. Finally the results are compared with MACD to test the stability of proposed method over buy-sell and buy-hold strategies and achieved good results. Authors utilized the data of less than two years for experiments.

Formulae for calculating the most prevalent Stock Technical Indicators (STIs) is presented in Table 1. The Adaptive STIs are derived from these indicators.

Table 1: Stock Technical Indicators.

Stock Technical Indicators (STIs)	Mathematical Formula
Moving Average (MA) of n days	$\frac{1}{n}\sum_{i=1}^{n} C_i$
Exponential Moving Average (EMA)	$EMA_t = C_t\left(\frac{2}{T+1}\right) + EMA_{t-1}\left(1-\frac{2}{T+1}\right)$
Moving Average Convergence Divergence (MACD): most common is 12/26 MACD	$MACD = [(12-day\ EMA) - (26-day\ EMA)]$
Commodity Channel Index (CCI)	$CCI = \frac{Typical\ price - MA}{0.015 * Mean\ deviation}$ where: $Typical\ price = \sum_{1}^{p}((H+L+C)/3)$ $Mean\ deviation = (\sum_{1}^{p} \lvert Typical\ price - MA \rvert)/p$
Relative Strength Index (RSI)	$RSI = 100 - \left[\left(\frac{100}{1+\left(\frac{AG}{AL}\right)}\right)\right]$
Stochastic Oscillator (%K)	$\%K = \left[\frac{C_t - Lp}{Hp - Lp}\right] * 100$
William (%R)	$\%K = \left[\frac{Hp - C_t}{Hp - Lp}\right] * 100$

Where H_p and L_p are highest and lowest prices in the last **p** days, respectively and C_t is the current price of the day under consideration. **AG** is Average Gain and **AL** is Average Loss. H, L and C are high, low and close prices.

III. PROPOSED METHOD

A. Predictive Model
The proposed predictive model is depicted in Fig. 1. The difference between the two models lies at step 7, i.e. data preparation. The difference is mentioned below:

Predictive model 1: If we have to predict the indices price and long term future trend we utilize test data with proper shape and no close price appended.
Predictive model 2: If we have to predict the Buy-Sell signal at the end of the day, a new field must be appended for showing the signal i.e. (Buy (1) and Sell (0)).

B. Optimized – LSTM Algorithm
The O-LSTM algorithm which is tuned for model is presented below.

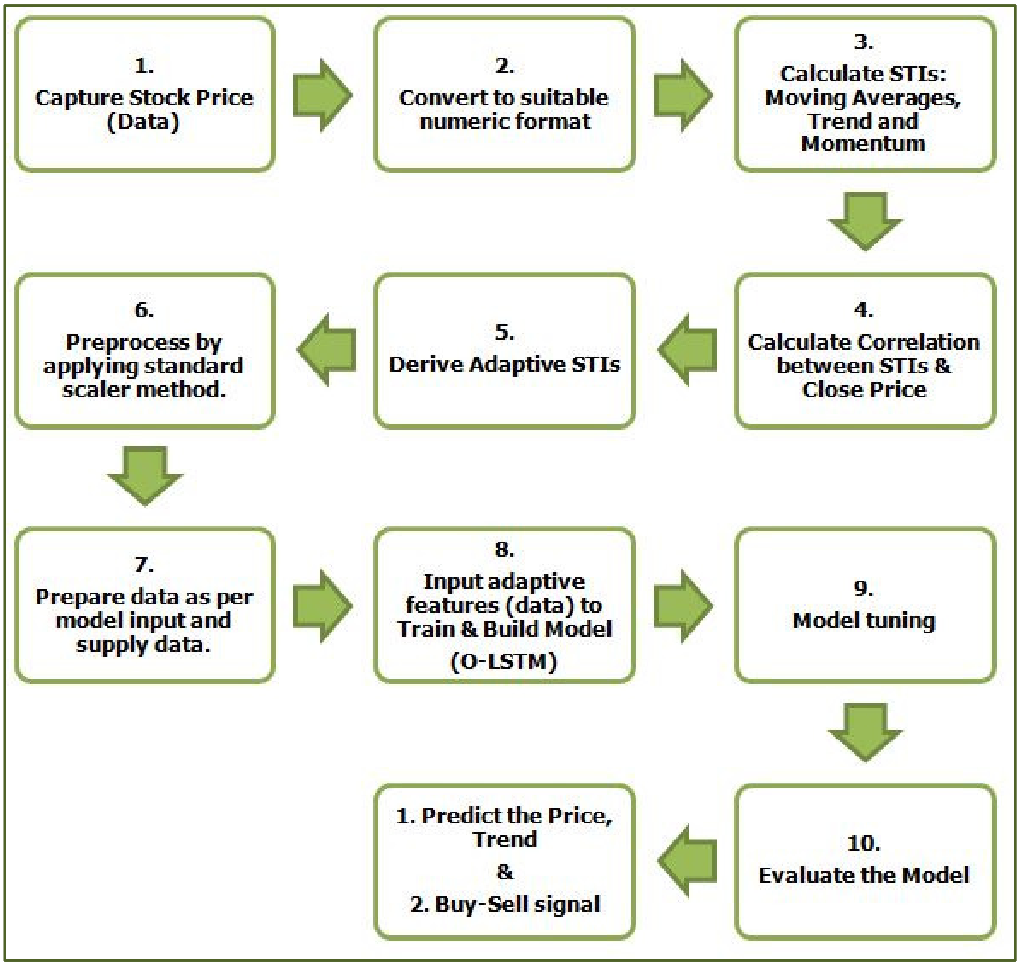

Fig. 1. Predictive models for stock Indices price, trend and buy-sell prediction.

Description of Notations	
Notation	**Description**
E_t	Input Event.
N_t	Memory output at time *t*.
i_t	Ignore factor.
f_t	Forget factor.
STM_{t0}	Short Term Memory from previous time.
LTM_{t0}	Long Term Memory from previous time.
STM_t	New Short Term output of OLSTM node.
LTM_t	New Long Term output of OLSTM node.
tanh	ReLU.
σ	Sigmoid Function.
U_t & V_t	Calculations with Use Phase inputs.
W_n, W_n, W_f and W_u	Linear Activation Functions applied to NN.
b_n, b_i, b_f , b_u and b_v	Bias applied at corresponding stages.

Algorithm: Optimized LSTM
Inputs: E_t , LTM_{t_0} & STM_{t_0} I. Learn Phase: 1. Input E_t and STM_{t_0} 2. Calculate: $$N_t * i_t$$ where: $$N_t = \tanh(W_n[STM_{t_0}, E_t] + b_n$$ & $$i_t = \sigma(W_i[STM_{t_0}, E_t] + b_i$$ II. Forget Phase: 3. Calculate: $$LTM_{t_0} * f_t$$ where: $$f_t = \sigma(W_f[STM_{t_0}, E_t] + b_f$$ III. Memory Phase: 4. Simply add the output of Forget and Learn Phase: $$LTM_t = [LTM_{t_0} * f_t] + N_t * i_t$$ IV. Use Phase: 5. Calculate $$U_t = \tanh(W_u[LTM_{t_0} * f_t] + b_u)$$ 6. Calculate $$V_t = \sigma(W_v[STM_{t_0}, E_t] + b_v)$$ 7. Calculate $$STM_t = U_t * V_t$$ Outputs: STM_t & LTM_t

IV. EXPERIMENTATION AND RESULTS

A. Dataset

Datasets are chosen from NSE for indices of three different sectors: Banking, Automobile and Metal. In these datasets Banking and Automobile are highly traded indices, while metal is considered as one among the most lucrative indices nowadays. The basic information contained in the dataset comprise of: Date; Price: Open, High, Low, Close; Shared traded and Turnover in Crores (INR).

The snapshot of top 5 rows of banking indices is shown in Fig. 2.

The see the impact of optimized LSTM on prices over long and short term, the data of 6 years is taken for algorithmic input. The duration for which the data is chosen is: 01.Apr.13 to 28.02.2019. The stock prices at the end of the day (i.e. close price), trend and decisions for Buy-Sell is predicted for the data of 1.03.2019 to 29.03.2019.

Date	Open	High	Low	Close	Shares_Traded	Turnover_Rs_Cr
01-Apr-13	11414.95	11460.6	11330.85	11425.55	11678537	925.5
02-Apr-13	11430.85	11548.05	11361.15	11523.4	14137032	1075.92
03-Apr-13	11512.75	11590.6	11283.4	11344.1	18106112	1535.92
04-Apr-13	11243.2	11254.25	11105.1	11126.25	17806888	1354.59
05-Apr-13	11120.15	11168.25	11021.4	11098.95	19214638	1546.91

Fig. 2. View of top 5 rows of dataset.

B. Tools and Libraries Utilized

The experimental setup is done on system with Intel Core i3 (2.0 GHz.) processor and 8GB RAM, running Microsoft - Windows – 10 (64-bit) operating system. The Python version 3.7.0 and 3.6.6 are utilized for implementation of models. The major Libraries utilized for experimentation purpose are listed in Table 2. The model is developed by utilizing powerful deep learning library: **Keras** as the high-level API developed for Google's **TensorFlow**.

C. Results & Discussion

The various results obtained from predictive models are presented in Table 3, 4 & 5. The results are separately shown for 3 different indices: Banking, Automobile and Metal.

Price and Price Trend Prediction. The predicted prices for each day are based on past prices.

Table 2: Libraries for experimentation.

Python Libraries	Version
Scikit-Learn	0.20.2
SciPy	1.1.0
NumPy	1.15.4
TensorFlow (deep learning library)	1.12.0
Keras (deep learning library)	2.2.4
Pandas	0.23.4

Table 3: Predictive Model Results - Bank Indices Prices (Actual v/s Predicted).

	Bank Indices Prices		BUY-SELL Signal			
Date	**Actual**	**Predicted**	**Actual**	**Predicted**	**Accuracy**	**Nature**
01-Mar-19	27043.9	27161.352	1	0	68.40%	Profit
05-Mar-19	27554.05	27155.994	1	0		
06-Mar-19	27625.65	27154.246	1	0		
07-Mar-19	27764.6	27158.896	0	0		
08-Mar-19	27761.8	27171.512	1	1		
11-Mar-19	27966.65	27191.791	1	1		
12-Mar-19	28443.7	27219.324	1	1		
13-Mar-19	28884.3	27255.74	1	1		
14-Mar-19	28923.1	27304.188	1	1		
15-Mar-19	29381.45	27366.234	1	1		
18-Mar-19	29596.1	27444.111	1	1		
19-Mar-19	29767.85	27539.807	1	1		
20-Mar-19	29832.2	27655.035	0	1		
22-Mar-19	29582.5	27791.115	0	1		
25-Mar-19	29281.2	27947.674	1	1		
26-Mar-19	29882.15	28121.896	1	1		
27-Mar-19	30019.8	28310.781	1	1		
28-Mar-19	30420.55	28507.354	1	1		
29-Mar-19	30426.8	28701.111	0	1		

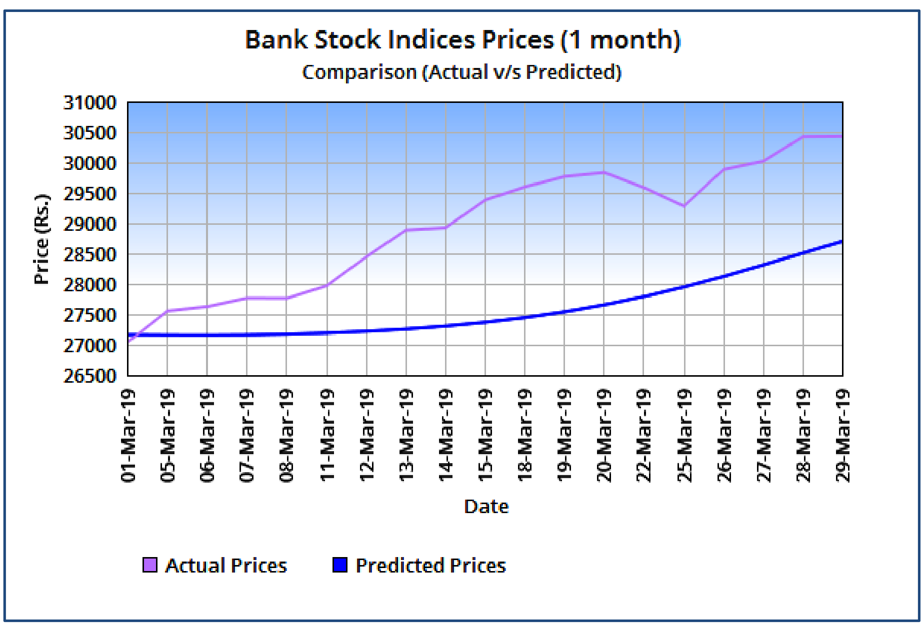

Fig. 3. Trend for Bank Stock Indices over 1 month.

The price trend prediction is depicted in Fig. 3, 4 and 5 shows the shows the direction (nature) of prices for particular indices. The nature of indices can be seen over a month or more than a month for long and short term investments and trading decisions.

Buy-Sell Prediction. The Buy-Sell decision for each day is presented in Table 3, 4, 5 for Banking, Automobile and Metal indices respectively. The Buy (1) and Sell (0) decision is measured on the basis of following formula, where y is decision Buy or Sell at the end of each day.

$$y = \begin{cases} 1, & (y_{i+1} - y_i) > 0 \\ 0, & otherwise \end{cases}$$

Table 4: Predictive Model Results - Automobile Indices Prices (Actual v/s Predicted).

	Automobile Indices Prices		BUY-SELL Signal			
Date	**Actual**	**Predicted**	**Actual**	**Predicted**	**Accuracy**	**Nature**
01-Mar-19	8413.65	8563.424	1	0		
05-Mar-19	8676.6	8549.807	0	0		
06-Mar-19	8651.75	8534.757	0	0		
07-Mar-19	8635.7	8520.214	0	0		
08-Mar-19	8582.6	8507.631	1	0		
11-Mar-19	8782.7	8497.823	1	0		
12-Mar-19	8802.9	8491.616	0	0		
13-Mar-19	8767.55	8489.706	0	0		
14-Mar-19	8725.5	8492.447	1	0		
15-Mar-19	8748.05	8499.739	0	0	**63.15%**	**Loss**
18-Mar-19	8627.05	8511.223	0	0		
19-Mar-19	8567.05	8525.916	0	0		
20-Mar-19	8445.1	8542.368	0	0		
22-Mar-19	8336.6	8558.643	0	0		
25-Mar-19	8238.55	8572.583	1	0		
26-Mar-19	8287.25	8582.199	0	0		
27-Mar-19	8215.35	8586.365	1	0		
28-Mar-19	8234.25	8584.6455	1	0		
29-Mar-19	8335.35	8577.359	0	0		

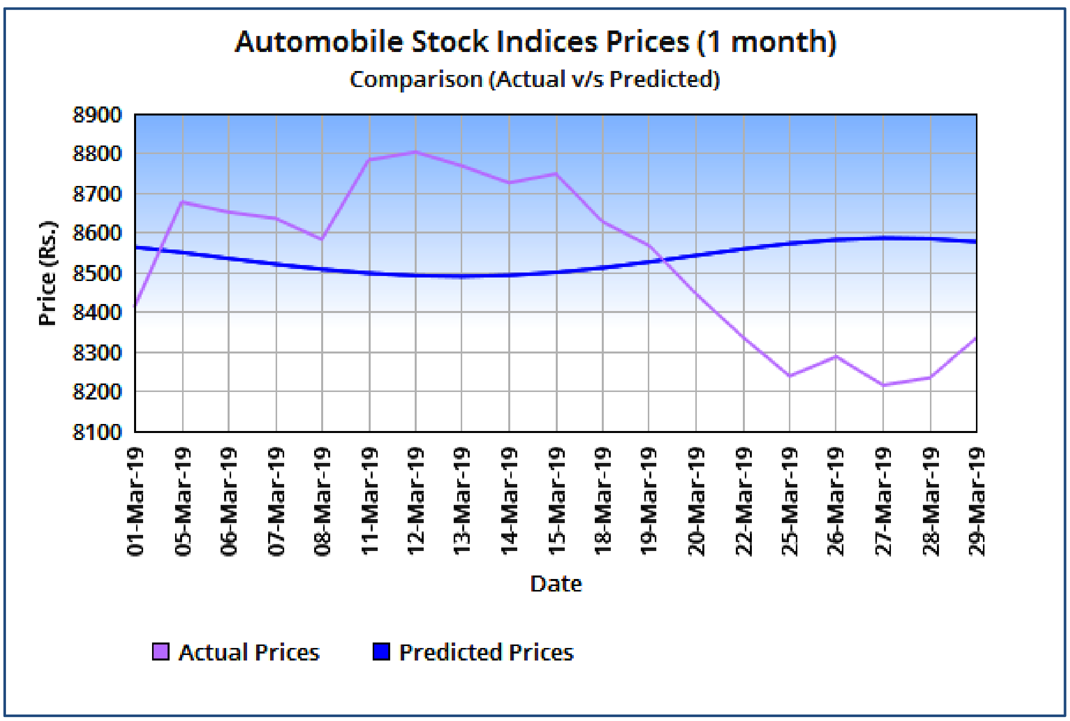

Fig. 4. Trend for Automobile Stock Indices over 1 month.

Table 5: Predictive Model Results - Metal Indices Prices (Actual v/s Predicted).

	Metal Indices Prices		BUY-SELL Signal			
Date	Actual	Predicted	Actual	Predicted	Accuracy	Nature
01-Mar-19	2922.7	3003.38	1	1	53%	Neutral
05-Mar-19	3000.2	2998.92	1	1		
06-Mar-19	3021.3	2994.84	0	1		
07-Mar-19	2992.85	2991.86	0	1		
08-Mar-19	2947.95	2990.13	1	1		
11-Mar-19	3028.85	2988.94	1	1		
12-Mar-19	3043.05	2988.56	0	1		
13-Mar-19	2985.75	2989.57	1	1		
14-Mar-19	3002.05	2991.54	1	1		
15-Mar-19	3008.25	2994.04	1	1		
18-Mar-19	3028.4	2996.76	0	1		
19-Mar-19	3027.4	2999.72	0	1		
20-Mar-19	2996.1	3002.95	0	1		
22-Mar-19	2983.2	3006.01	0	1		
25-Mar-19	2949.65	3008.24	1	1		
26-Mar-19	2980.6	3008.79	1	1		
27-Mar-19	2982.1	3007.58	0	1		
28-Mar-19	2973.7	3004.99	1	1		
29-Mar-19	3044.15	3001.41	0	1		

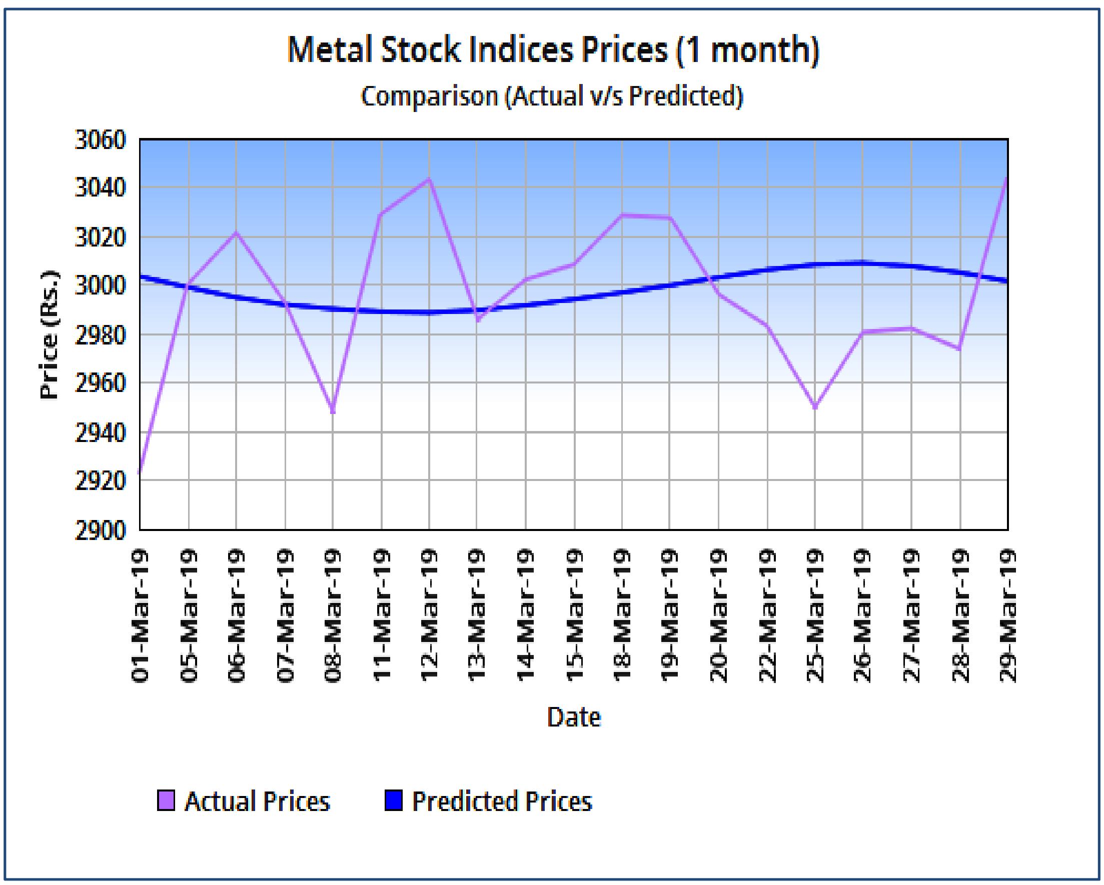

Fig. 5. Trend for Metal Stock Indices over 1 month.

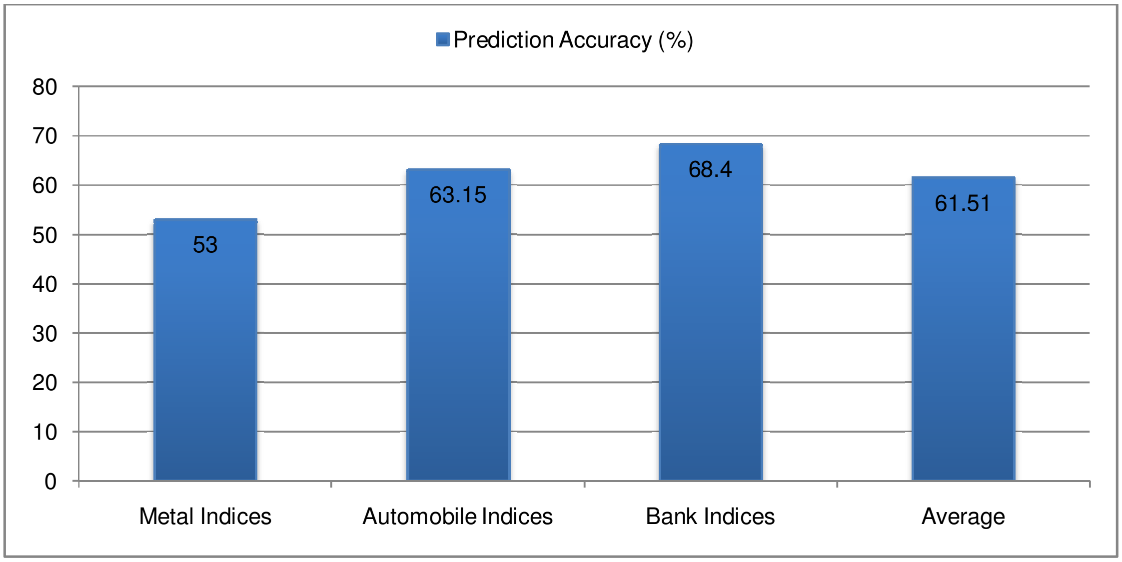

Fig. 6. Comparison of Prediction Accuracy for 3 Indices using O-LSTM.

Prediction Accuracy. The Buy (1) and Sell (0) decision is measured and then the average accuracy % for the month is calculated is also presented in Table 3, 4 & 5 for each of the indices. The model 2 is evaluated for prediction accuracy. The average accuracy given by model is 61.51%. Figure 6 showing the comparison of prediction accuracy using proposed O-LSTM.

Discussion. The results obtained from the proposed model are compared with the Logistic Regression (LR), Support Vector Machine (SVM) and ELSTM deep learning model proposed by Pang et al. [9]. As discussed most of the earlier model results are based on Accuracy. The Fig. 7 shows the accuracy comparison of various models for 3 stock indices.

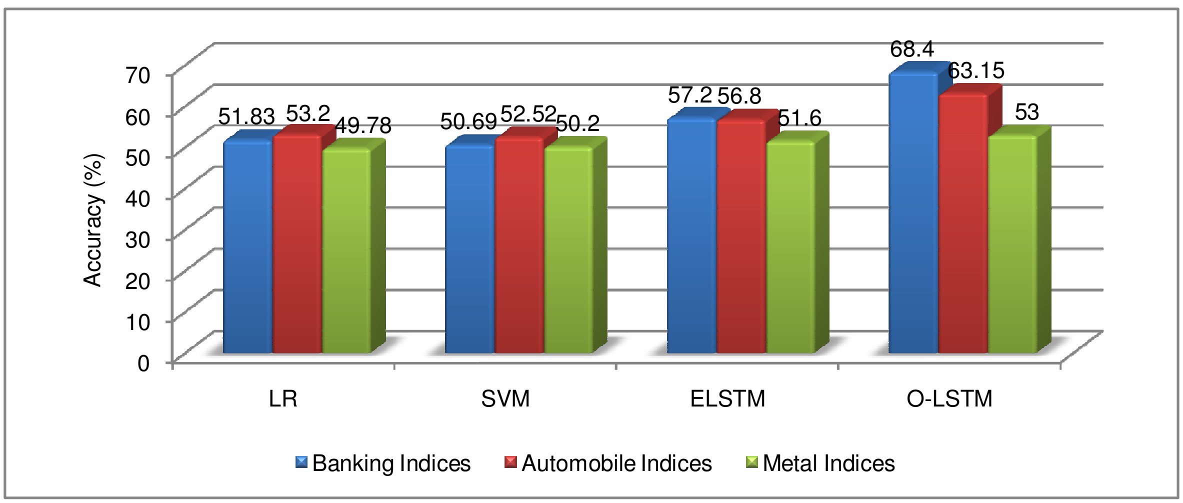

Fig. 7. Accuracy comparison of four models for 3 stock indices.

The earlier works only determines the price of individual stock or trend. In contrast to previous models we demonstrated the following for Stock Indices:

-The price trend prediction.
-Price prediction.
-Buy-Sell signal at the end of day.
-Prediction accuracy of model.
-Nature of Indices: Profit, Neutral & Loss.

The application of O-LSTM along with adaptive STIs improves the performance and fetches more profit. The highest accuracy achieved is 68.4% which is much higher than LR, SVM and ELSTM [9]. The adaptive STIs are chosen as per the highest correlation factor and passed as tensor to the model and this makes the proposed work distinguished in comparison to previous works. The STIs that are primarily used and highly correlated with outcome are presented in Table 1. The TA anticipates what is "likely" to happen to prices over time, while the OLSTM algorithm used in this work has given strength to such anticipations by improving accuracy.

V. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

The proposed work demonstrates the application of deep learning for stock Indices using technical indicators. The O-LSTM algorithm is applied along with adaptive STIs. The proposed O-LSTM is a market independent approach. The proposed approach is not fitting the data to a model or model to specific data. We are discovering the indicators that are potential for predicting the price, price trends and signal for daily trading. The application of O-LSTM dynamics of deep learning has given the boost to prediction accuracy. The model built is robust and is implemented with Deep Neural Network in Python using powerful Machine Learning (ML) and deep learning libraries: Google - TensorFlow and Keras. The models proposed in this work helps us to decide the stock trends as well as decision of selling or buying the stock. The proposed models thus decreasing the risk while increasing the returns on investments.

This work offers several confront on stock trends forecasting. In future, the proposed model can also be applied to individual stocks as it capable of determining the nature (profit, loss and neutral) of stock or indices. The model can also be evaluated against other ML and deep learning models. The proposed model can also be further optimized using several nature inspired algorithms. The model can be further integrated with automated system for stock trading.

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CONFLICT OF INTREST: Nil

REFERENCES

[1]. Zhang, G., Zhang, X., and Feng, H. (2016). Forecasting financial time series using a methodology based on autoregressive integrated moving average and Taylor expansion. *Expert Systems*, **33**(5), 501-516.

[2]. Althelaya, K.A., El-Alfy, E.M. and Mohammed, S. (2018). Evaluation of bidirectional LSTM for short-and long-term stock market prediction. *2018 9th International Conference on Information and Communication Systems (ICICS),* Irbid, pp. 151-156.

[3]. Selvin, S., Vinayakumar, R., Gopalakrishnan, E.A. Menon, V.K. and Soman, K.P. (2017). Stock price prediction using LSTM, RNN and CNN-sliding window model. *2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Udupi, 2017,* pp. 1643-1647.

[4]. Dang, L. Minh & Sadeghi-Niaraki, Abolghasem & Huynh, Huy & Min, Kyungbok & Moon, Hyeonjoon. (2018). Deep Learning Approach for Short-Term Stock Trends Prediction based on Two-stream Gated Recurrent Unit Network. IEEE Access. PP. 1-1.

[5]. Liu, Guang and Wang, Xiaojie (2018). A Numerical-based Attention Method for Stock Market Prediction with Dual Information. IEEE Access. PP. 1-1.

[6]. Oriani, F.B. and Coelho, G.P. (2016). Evaluating the impact of technical indicators on stock forecasting. *2016 IEEE Symposium Series on Computational Intelligence (SSCI),* Athens, 2016, pp. 1-8.

[7]. Thomsett, M.C. (2015). Getting Started Getting Started in Stock Analysis, Illustrated Edition. Hoboken, Singapore: John Wiley Publishing, 2015.

[8]. de Souza, M.J.S., Ramos, D.G.F., Pena, M.G. et al. (2018). *Financ Innov* **4**(3): 1-18.

[9]. Pang, X. Zhou, Y., Wang, P., Lin, W. and Chang, V. (2018). An innovative neural network approach for stock market prediction. *The Journal of Supercomputing*, 1-21.

[10]. Chen, Y.J., Chen, Y.M., Tsao, S.T., & Hsieh, S.F. (2018). A novel technical analysis-based method for stock market forecasting. *Soft Computing,* **22**(4), 1295-1312.

[11]. Agrawal, M., Khan, Asif Ullah, Shukla, P.K. (2019). Stock Price Prediction using Technical Indicators: A Predictive Model using Optimal Deep Learning. *International Journal of Recent Technology and Engineering (IJRTE),* Vol. **8** Issue 2, July 2019, 2297-2305.

[12]. Hasan, S.S., Rahman, R., Mannan, N., Khan, H., Moni, J.N., Rahman, R.M. (2017). Improved Stock Price Prediction by Integrating Data Mining Algorithms and Technical Indicators: A Case Study on Dhaka Stock Exchange. In: Nguyen N., Papadopoulos G., Jędrzejowicz P., Trawiński B., Vossen G. (eds) Computational Collective Intelligence. ICCCI 2017. Lecture Notes in Computer Science, Vol. **10448**. Springer, Cham, 288-297.

[13]. Xiong, R., Nichols, E.P., Shen, Y. (2015). Deep learning stock volatility with google domestic trends. Preprint arXiv:1512.04916, 1-6.

[14]. Yu, F.F. (2016). Based on the neural network of stock forecast [D]. Harbin Institute of Technology, Harbin.

[15]. Hiransha, M., Gopalakrishnan, E.A., Vijay Krishna, Menon, Soman, K.P., (2018). NSE Stock Market Prediction Using Deep-Learning Models. *Procedia Computer Science*, Vol. **132**, 2018, Pages 1351-1362, ISSN 1877-0509.

[16]. da Silva, I.N., Spatti, D.H., Flauzino, R.A., Liboni, L.H.B., & dos Reis Alves, S.F. (2017). Forecast of stock market trends using recurrent networks. In *Artificial Neural Networks* (pp. 221-227). Springer, Cham.

[17]. Jian Wang and Junseok Kim, (2018). Predicting Stock Price Trend Using MACD Optimized by Historical Volatility. Mathematical Problems in Engineering, vol. 2018, Article ID 9280590, 12 pages, 2018, 1-12.

[18]. Joshi, A. and Mehta, A. (2017). Comparative Analysis of Various Machine Learning Techniques for Diagnosis of Breast Cancer. *International Journal on Emerging Technologies* (Special Issue NCETST-2017) **8**(1): 522-526.

[19]. Motwani, A., Patel, V. and Yadav, A. (2015). Optimal Sampling for Class Balancing with Machine Learning Technique for Intrusion Detection System. *International Journal of Electrical, Electronics and Computer Engineering* ISSN No. (Online): 2277-2626 **4**(2): 47-51.

[20]. Fegade, K.G., Namdeo, V. and Gupta, R. (2017). Predictive Modelling for E-Commerce Data Classification Tasks: An Azure Machine Learning Approach. *International Journal of Electrical, Electronics and Computer Engineering* ISSN No. (Online): 2277-2626 **6**(2): 45-50.

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