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CNN based Stock Market Prediction

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Abstract: ***Indian Stock market is highly dynamic and especially after globalization stock market modeling has become even more complex due to influence of multiple parameters. In presence of multiple parameters, some parameters have increased influence than others in prediction of stock market trends. This influence of individual parameters and their joint influence over time is better modeled with Convolutional Neural Network Classifiers. This work models the dynamics of stock market in terms of Convolutional Neural Networks and multiple parameters impacting the stock trend. The proposed solution is implemented for Indian stock market for stocks in different sectors to prove its prediction accuracy.***

I. INTRODUCTION

Companies list their stocks in Stock market where trading on stocks occurs day to day. The price of stock depends on demand and supply like all other commodities in open market. The demand and supply of a stock is influenced by multitude of parameters like company's performance, National economic indicators and policies, competitor's performance, forex impacts, social network sentiments, foreign institutional investments and withdrawals etc. Globalization has further added to the parameters influencing the stock market trends. Interest rates, oil prices, gold price etc., affect the sentiments of people trading in stocks and results in volatility of stock market prices. In this background there is increased need for prediction methods and tools to predict the stock market trend with high accuracy. Prediction of stock market trends based on company's performance alone (Fundamental analysis), historical prices of stocks (Technical analysis) or social network sentiments are not accurate and it is necessary to base the prediction based on multiple parameters influencing the stock.

Indian stock market started in 1855 is the hoariest market in Asia. Indian stock market has primitively three stock exchanges Bombay Stock Exchange (BSE), National Stock Exchange (NSE) and Multi Commodity Exchange (MCX). BSE recognized by the Indian Government in 1957, having the total market capitalization of Rs. 2.3 Lakh Crores is the world's 10th largest market. BSE SENSEX index measures the performance of exchange. NSE established in 1992 having the total market capitalization of Rs. 2.2 Lakh Crores is the world's 10th largest market. NIFTY 50 is the index of NSE is an indicator of Indian capital market for the world. NSE offers trading in equity, and derivatives while BSE only offers equity trading. The overall trading from both the exchanges per day is Rs.17 Lakh Crores which makes up to 4% of the country's economy. MCX established in 2003 is Nation's commodity derivatives exchange. MCX offers trade commodities in 3 main sectors: metals such as gold, silver zinc etc., energy sector such as crude oil and agro sector such as cotton, coconut etc., Turnover of MCX is Rs. 180 Crores.

With rapid economic progress after 1996, Indian stock market is most profitable in world with profitability more than 200% and it has attracted many domestic and international investors. This is reflected in the average turnover per day crossing Rs.12, 000 Crores in BSE and NSE. In this scenario, stock market prediction system for Indian stock market is of prime importance.

Convolutional Neural Networks (CNN) are the recent trend in classification methods. It has applied in different applications due to its capability to extract highly relevant features and their semantic relations. In this work use the CNN to forecast stock prices in Indian stock market. Many existing works (as in survey) has been proposed for stock market prediction using CNN, but existing approaches don't model the influence of different parameters on each stock. There is a lack of stock wise personalization in handling of features. Due to this accuracy of prediction is very low when applied to different stocks. In this work, this problem is solved by analyzing the features influencing a particular stock and continuously weighting the features affecting the stock price trend and retain the CNN to provide increased accuracy.

II. RELATED WORK

CNN based prediction of American stock index was proposed in [1]. Features from multiple sources like daily closing prices, technical indicators, economic data, world stock markets, US dollar exchange rate against other countries, commodities, future contrasts etc., are used to predict the moving trends of American stock indexes. The work is not for individual stocks and it is only for overall stock index. Though it can predict the overall trend of stock market, it cannot predict the prices of individual stocks and not much useful for investors. Outlier detection was not considered before training the CNN.

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Deep Neural Networks (DNN) was trained to forecast the next minute average price in [2]. Time series of past minute returns are used as training set for the DNN to predict the stock price. Use of DNN for the simple time series predication is complex and tick by tick transaction price prediction based only on past price of stock is not accurate.

Most investor are interested in next day average price, in this view the method proposed in [2] is not useful for investors. Restricted Boltzmann Machine is used in [3]. It extracted discriminative low-dimensional features from the data set by considering 324 dimensions, Support Vector Machine (SVM) is used for applying regression extracted features. Like [1], this approach was used to predict only the next day indexes and not used for individual stocks. Long Short Term Memory (LSTM) method based stock price prediction was proposed in [4]. Daily dataset of stock in terms of closing price, trade volume collected for some days is used to train the LSTM. Since the predicted price is based only on past price of stock, the prediction is not accurate. Deep Feature Learning is used for market price prediction in [5]. Principal component analysis, restricted Boltzmann machine and auto-encoder are used to construct 3 layer Deep Neural Networks (DNN) to predict the upcoming stock price based on the previous day stock prices. The dataset considered for prediction is limited, so the prediction accuracy is low in volatile market. LSTM networks based stock market prediction is proposed in [6]. Authors have found a common pattern among the stocks chosen for trading that these stocks have high volatility and quick price reversal. Based on this knowledge they formalized Rules Based Short Term Reversal strategy. In [7] authors have proposed an innovative application of Paragraph Vector, LSTM and Deep Learning models to time series forecasting of stock prices. Traders emotions about the market is driven by the news hence they make decision based on the factors such as Price Earnings (PE) ratio, consumer price index and other political or financial news. In [8] author proposed an approach to convert news articles into Paragraph Vector to obtain the distributed representations of news articles. This vector is used to study the time based effect on the opening prices of multiple companies based on the events using LSTM. The news feed which affect the buy or sell decision needs more efficient filtering mechanisms. Author proposed planar feature representation methods and deep convolutional neural networks for stock market prediction in [8].

The historical prices of stock are represented as time series and features extracted from it are used for deep CNN. Author proposed a deep learning approach based on CNN that forecasts the stock price variations using as large and high frequency time series data obtained from the order book of stock exchanges in [9]. This approach can only predict short time price movements.

The authors of [10] have proposed a hybrid and robust model for stock market prediction. This model is composed of 2 linear and 1 non-linear model. The linear models are exponential smoothing model and autoregressive moving average model. The non-linear model is recurrent neural network. The training data set for recurrent neural network is obtained by new regression model. The non-linear model gave a better predictions in compression with the linear models. A hybrid model was introduced to enhance the performance of the prediction by combining the forecasting obtained by linear and non-linear models. The model was optimized by using genetic algorithms which produce optimal weights for each prediction models.

Use of LSTM for stock market prediction based on historical stock prices and Technical analysis indicators is explored in [11]. The method provides only a decision of increase and decrease and does not provide the price of the stock.

CNN was used to predict the stock price variations of China market in [12]. Open, High, Low, Close (OHLC) prices and volume of trading is provided as input to CNN. This approaches predicts the price only based on historical prices hence inaccurate.

A recurrent CNN was applied to predict stock price in [13]. This model can extract useful information from news about the market without using any predesigned features. It uses Entity Embedding layer to learn entity embedding in the financial news. CNN extracts the important information impacting market movement, and LSTM neural network is used to learn context dependent relations between financial news and market trend. The approach is not secure against cascading errors due to outlier in the data.

A deep learning approach for prediction stock market is proposed in [14]. Events in the news text are extracted and represented in the form of Dense Vectors. These vectors are used to train Neural Tensor Network. A deep CNN is used to model the effect of events on market price trends in short-term and long-term. Though the approach is able to identify the events affecting the stock market prices, it cannot quantify the influence.

Recurrent Neural Networks and character-level language model pre-training for both intraday and positional stock price forecasting is proposed in [15]. Financial news are used as predictors for stock market prediction. The approach cannot provide quantitative estimation of stock prices from the news forecast and especially with diverse feeds from different market news, it is very difficult to predict the trend using financial news forecast alone.

III. PROPOSED SOLUTION

The architecture of the proposed solution is given below. Different from earlier works on CNN based stock market predictions following novelties are added in the proposed solution.

1. Feature Analysis
2. Training data personalization
3. Feedback Analysis

Feature Analysis: Not all the features collected from multiple sources influencing the stock market affect all stocks equally. The influence of a parameter on a stock varies and stock dependent. So the best set of features affecting the stock must be selected. A new feature selection approach is proposed to select the features personalized for each stock.

Training data personalization: Based on the features selected, the training data for CNN must be organized for the stock.

The data sampling duration is universal for all stocks in most of the existing approaches; this too must be made dependent on stock. A strategy to decide the sampling duration and organization of training data set personalized for stock is proposed.

Feedback Analysis: Feedback based correction in terms of CNN parameter tuning or Training data reorganization is done based on evaluation of prediction accuracy at regular intervals.

With these three novelties, the stock market prediction is made accurate and personalized.

The features used for stock market prediction is this work is given in table 1. The features are collected in different categories as below

1. Stock Specific Parameters
2. Global Influencing Parameters
3. Economic Indicators
4. Monetary Indicators
5. Sentiments

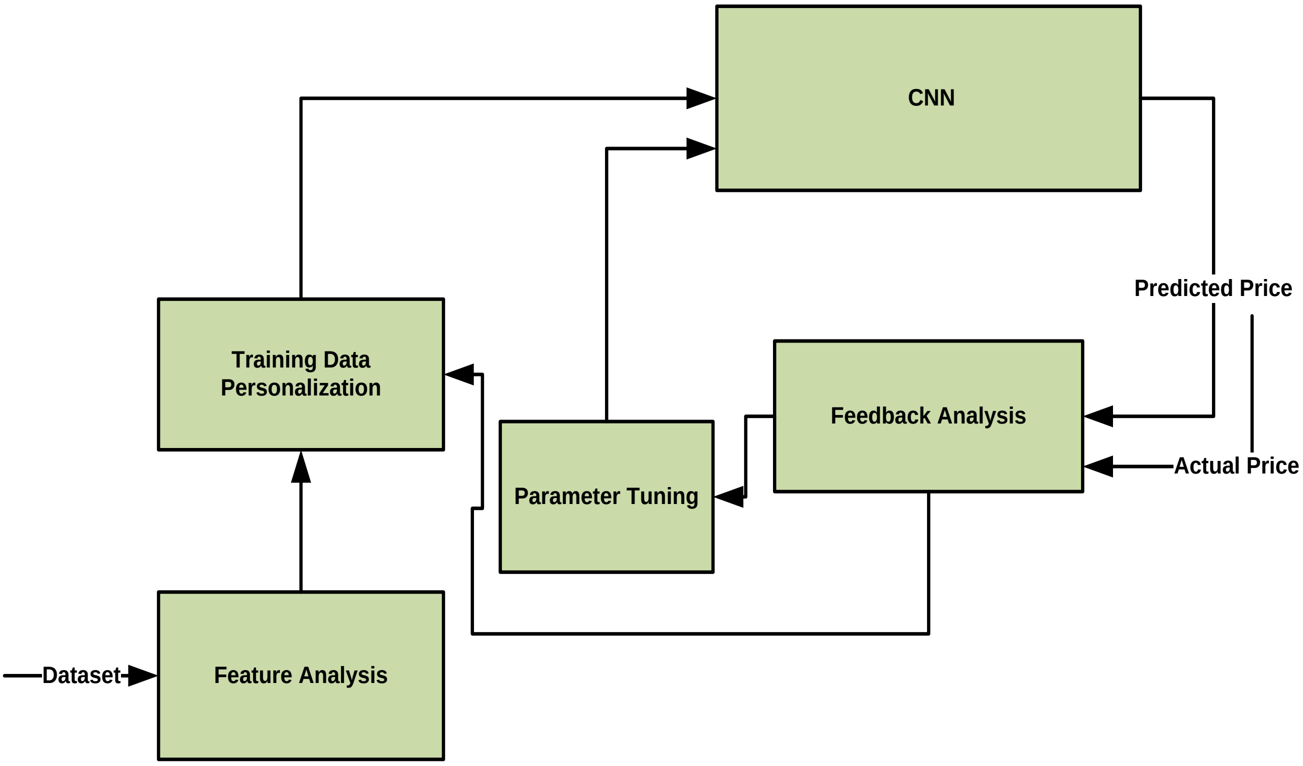


Fig 1: Figure 1 Proposed CNN Architecture

Table 1: Features Selected

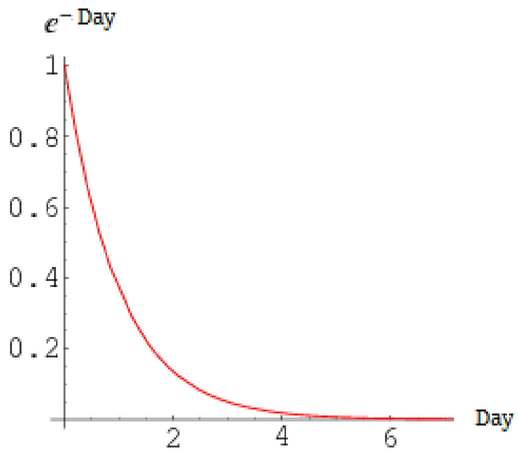
Category	Name	Description
Stock Specific	Closing Price at Day	Closing price of stock
	Segment Index value	The BSE segment index value in which stock comes in
	Quarterly Result Impact(QRI)	Impact due to Quarterly result announced by the company.
Global Influencing Parameters	Gold Price rise or fall (GPI)	Rise or fall in the international gold price on that day
	Oil Price rise or fall (OPI)	Rise or fall in the international crude oil price per barrel on that day
	Dollar rate rise or fall (DRI)	Rise or fall in the US dollar rate on that day
	US repo rate rise or fall (URI)	The US reserve bank repo rate
	Global Index Sentiment rise/fall (GI)	Rise and fall of average global index
Economic Indicators	RBI repo rate rise or fall (RI)	Reserve Bank of India repo rate fall or rise compared to past value
	GDP rise or fall (GDPI)	Gross domestic product fall or rise compared to past value
	IPI rise or fall (IPII)	Industrial product index fall or rise compared to past value
Monetary Indicators	FDI rise or fall	Rise or fall in FDI compared to previous results
	Debt rise or fall	Rise or fall in Debt value of the company

	Investment rise or fall	Rise or fall in investments of the company
Sentiments	Social sentiment vector about the stock from brokerages	The Social sentiments about the stock from brokerages (buy/sell) given as vector

A. Stock Specific Parameters

Stock specific parameters are the most dominant parameter influencing the stock price in the market. Closing data price of the stock, the value of segment index in which the stock comes in and Quarterly result impact are the stock specific parameters used in this work.

Quarterly result impact is modeled as continuous function. The impact of quarterly results last for certain days in stock market and slowly fades. The Quarterly result is modeled as an exponentially decreasing function over days for 7 days.



$$QRI = \begin{cases} e^{-Day}, & for\ postive\ results \\ -e^{-Day}, & for\ negative\ results \end{cases}$$

B. Global Influencing Parameters

Global influencing parameters are the external fluencies which impact the stock market trend. It is modeled in terms of rise or fall in Gold price, Oil price, Dollar rate, US repo rate and Global index sentiment. The influence of these parameter usually last for only one 2 days on the market.

$$GPI = \begin{cases} 1, & GFluct > T \\ -1, & -GFluct > T \\ 0, & otherwise \end{cases}$$

$$GFluct = \frac{GP_{current} - GP_{current-1}}{GP_{current}} * 100$$

Where GP is the gold price and T is 5.

$$OPI = \begin{cases} 1, & OFluct > T \\ -1, & -OFluct > T \\ 0, & otherwise \end{cases}$$

$$OFluct = \frac{OP_{current} - OP_{current-1}}{OP_{current}} * 100$$

Where OP is the crude oil price/barrel and T is 5.

$$DRI = \begin{cases} 1, & DFluct > T \\ -1, & -DFluct > T \\ 0, & otherwise \end{cases}$$

$$DFluct = \frac{DP_{current} - DP_{current-1}}{DP_{current}} * 100$$

Where DP is the US dollar value and T is 5.

$$URI = \begin{cases} 1, & UFluct > T \\ -1, & -UFluct > T \\ 0, & otherwise \end{cases}$$

$$UFluct = \frac{UR_{current} - UR_{current-1}}{UR_{current}} * 100$$

Where UR is the US repo rate and T is 5.

Global Index sentiment is modeled as vector of index variations in global stock index. Dow jones, Nikkei and Shanghai stock exchange trends affect Indian stock market. It is found taking the stock index values as time series as time series and calculating the correlation between BSE and the international stock exchange time series using

$$\sigma_{xy} = \frac{1}{N-1}\sum_{t=1}^{N}(x_{t-T} - \mu_x)(y_t - \mu_y)$$

The stock indexes are selected if their correlation value is above 0.8.

Global index Sentiment is modeled as

$$GI = [a, b, c]$$

$$a = \begin{cases} 1, & Dow\ JhonesIndexChange > 5\% \\ -1, & -Dow\ IndexChage > 5\% \\ 0, & otherwise \end{cases}$$

$$b = \begin{cases} 1, & \text{Nikkei}IndexChange > 5\% \\ -1, & -\text{Nikkei}IndexChage > 5\% \\ 0, & otherwise \end{cases}$$

$$c = \begin{cases} 1, & ShanghaiIndexChange > 5\% \\ -1, & -\text{Shanghai}\ IndexChage > 5\% \\ 0, & otherwise \end{cases}$$

C. Economic Indicators

Countries economic indicators influencing the stock market prices are captured by economic indicator features. The influence of these economic indicators lasts for around 7 days. Like Quarterly results, it is modeled as exponentially decreasing function.

$$RI = \begin{cases} e^{-Day}, & Rfluc > T \\ -e^{-Day}, & -Rfluc > T \\ 0, & otherwise \end{cases}$$

$$Rfluc = \frac{R_{current} - R_{current-1}}{R_{current}} * 100$$

Where R is the RBI repo rate.

GDP and IPI index are calculated similarly.

D. Monetary Indicators

Investments and debt affect the stock prices and three most dominating monetary parameters influencing stock market are FDI (Foreign Direct Investment) rise/fall, Dept rise/fall, local investments rise/fall. The impact of this news last for 7 days in a exponential decreasing manner. It can be modeled similar to RBI repo rate index.

E. Sentiment Indicators

Stock market news spread through news influences the sentiments of people and alters the demand supply of stocks. Stock market recommendations provided by the brokerages in India are the most influencing sentiment molding parameter. Each stock brokerage provides suggestion in terms of buy/sell for a stock. To model the stock sentiment, we use a vector with one element for each stock brokerage.

$$SI = \{x_1, x_2, x_3 \ldots x_n\}$$

Where n is the number of brokerages.

$$x = \begin{cases} 1, & Buy\ decision \\ -1, & Sell\ decision \\ 0, & No\ decision \end{cases}$$

F. Features Analysis

Each feature affect the stock price trend in a different manner. The most influential features affecting the stock market trend has to be selected for accurate prediction. Symmetric Uncertainty based feature selection is used for selecting the features.

$$SU(x,y) = \frac{2 * MI(x,y)}{H(x) + H(y)}$$

where

$$MI(x,y) = \sum_x \sum_y p(x,y) log \frac{p(x,y)}{p(x) * p(y)}$$

$$H(X) = -\int p(x) \log(p(x))dx$$

P(x) is the probability density function.

SU is calculated for each feature and the features whose *SU* values above decision threshold is selected as most important features. The initial value of decision threshold is fixed as 0.5.

G. Training Data personalization

The features selected from previous steps are extracted from the training dataset collected over a 5 year period. It is split to training and test set in ratio of 80.20. In the training dataset, each stock closing price is a time series and follows a repeatable trend at multiple levels. Say there are N levels of seasonal trend in the dataset. Initially top level (level 1) is selected for decomposition of the signal. Based on the start and end time of each decompose signal, the window period is set and the values of all selected features in each window period is arranged as row. It is repeated for entire duration of the signal and a 2 dimensional matrix is created from the features. For each matrix, the closing day price of the next window is the output.

This two dimensional matrix of features and the closing day price is used for training the CNN.

H. Feedback Analysis

The test dataset is created feature matrix as in previous step and passed to CNN classifier to predict the price and this price is compared to next closing price in the test data. If the accuracy of prediction is greater than 90%, then CNN classifier is stabilized and can be used for production. If the accuracy of prediction is less than 90%, parameter tuning must be done.

I. Parameter Tuning

Parameter tuning is done in terms of following parameters

1. Decision Threshold
2. Window Level Selection for training data preparation

Decision threshold is increased or decreased to get different feature selection and Window Level is modified for different organization of data in a trial and error manner and CNN is continuously retrained till the desired accuracy is met.

IV. PERFORMANCE ANALYSIS

To evaluate the performance of proposed solution 5 stocks in BSE across different segments are considered. Following 5 stocks are considered for study. The features collected over last 5 years are used for training the proposed solution. The performance of the proposed solution is compared against [7].

Table2: Stock and Segments

Stock	Segment
Infosys	IT
Reliance Industries	Manufacturing
Bharati Airtel	Telecom
Cipla	Pharmaceutical
Tata Motors	Automobile

The difference between the predicted and actual price of the stock for a weekly time period is given below.

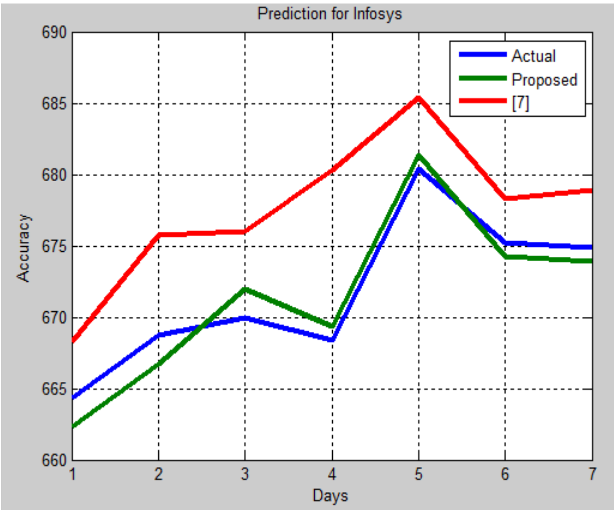


Fig2: Prediction of Infosys

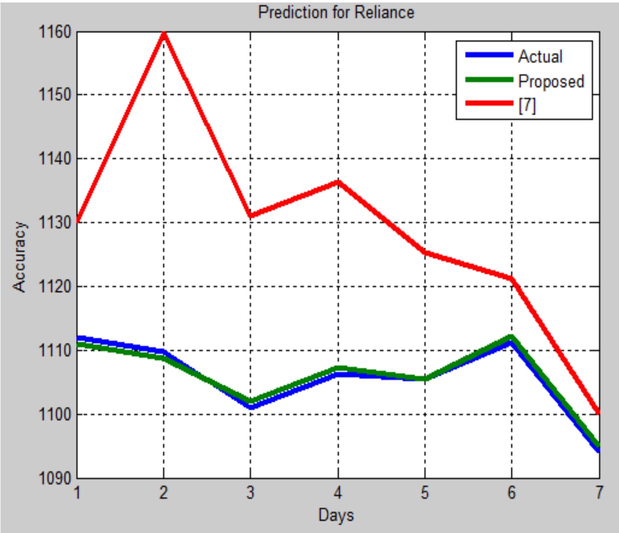


Fig3: Prediction of Reliance

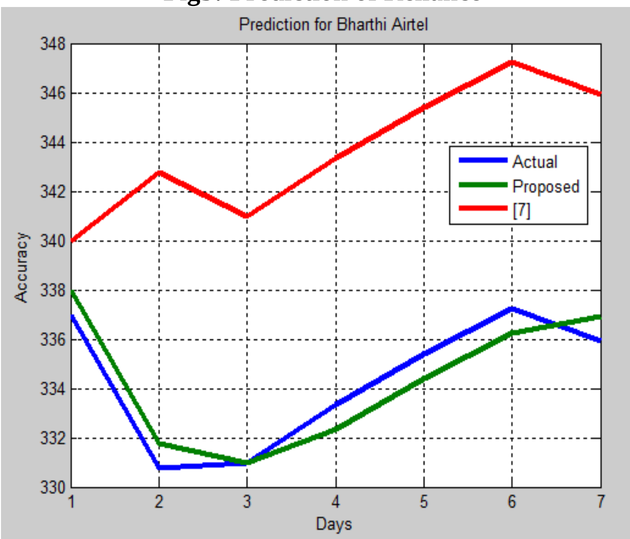


Fig4: Prediction of Bharathi Airtel

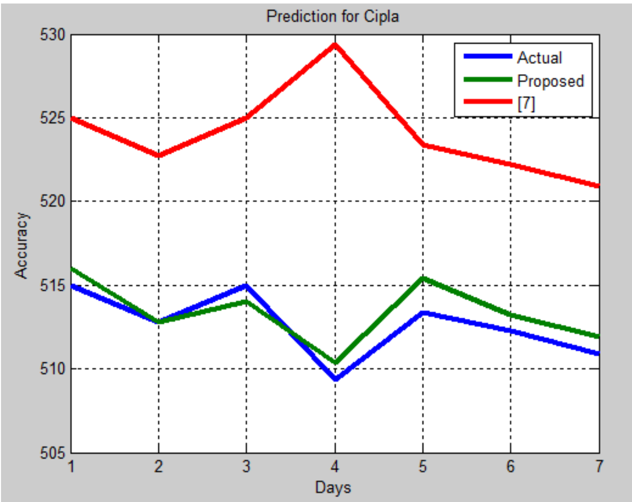


Fig5: Prediction of Cipla

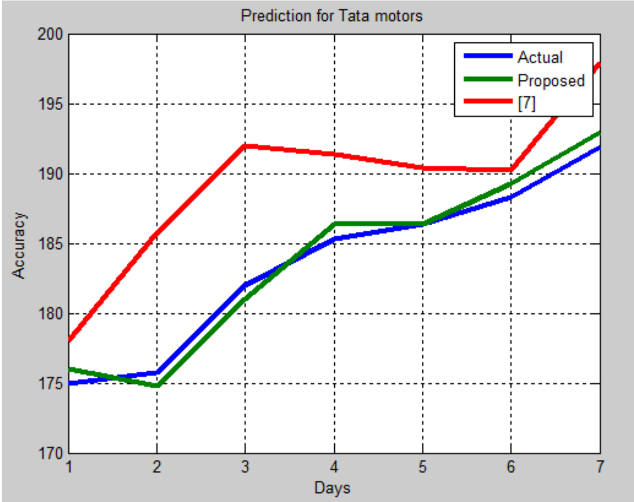


Fig6: Prediction of Tata Motars

The accuracy of prediction is measured for Last 1 year for every month beginning and end price and the result is below

Table 3: Prediction Accuracy of Infosys

Infosys Limited	
Method	**Accuracy**
[7]	82 %
Proposed	91 %

Table 4: Prediction Accuracy of Reliance Industries

Reliance Industries	
Method	**Accuracy**
[7]	83 %
Proposed	94 %

Table 5: Prediction Accuracy of Bharthi Airtel

Bharthi Airtel	
Method	**Accuracy**
[7]	81 %
Proposed	94 %

Table 6: Prediction Accuracy of Cipla

Cipla	
Method	**Accuracy**
[7]	82 %
Proposed	92 %

Table 7: Prediction Accuracy of Tata Motors

Tata Motors	
Method	**Accuracy**
[7]	84 %
Proposed	95 %

From the results, it can been that the accuracy of the proposed solution is better than solution [7]. The reason for higher accuracy is consideration of multiple features and parameter tuning to select the best features and window sampling period.

V. CONCLUSION AND ENHANCEMENTS

We have detailed our proposed solution for stock market based on CNN learning. We measured the accuracy of system and compared with methods based on historic stock prices and news feeds data. From the results we proved that the accuracy of the proposed system is higher than other methods. Currently we have explored only two method for performance tuning, in future multiple parameters for performance tuning will be explored to provide increased accuracy.

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