Impact of COVID-19 on the Indian stock market and price prediction using CNNs and RNNs

Submitted in partial fulfillment of the requirements of the course of
DS203 Programming for Data Science
Centre for Machine Intelligence and Data Sciences
Indian Institute of Technology Bombay
2020

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***Abstract*—The goal of this study is to investigate the impact of COVID-19 on Indian stock markets over the period February 10 – June 30, 2020 and comparison of various deep learning models to predict stock market prices. Findings reveal that the stock market prices had fallen sharply before the announcement of lockdown and different sectoral indices rose at different rates. The Pharmaceutical sector outperformed the market and all other sectors during this period. After comparison of different deep learning models to predict the prices, we found that LSTM's were able to predict future stock data very accurately. GRU's could predict it almost as effectively as LSTM's and simple RNN's predicted data worse than both of them. CNN's, when used to predict future stock data, were not very effective. Overall we found that we could rely on LSTM neural networks to predict the future stock data fairy accurately.**

***Index Terms*—COVID-19, Stock Market, Price Prediction**

I. Introduction

According to the World Health Organization (WHO, 2020), the coronavirus (COVID-19) outbreak which emerged from central China in late December has spread to 218 countries, areas or territories, and has resulted in over 67 million confirmed cases as well as over 1.5 million deaths across the globe as of December 7, 2020. Given the widespread and ongoing transmission of the novel coronavirus worldwide, the WHO officially declared a pandemic on March 11, 2020.

The rapid spread of the unprecedented COVID- 19 pandemic has put the world in jeopardy and changed the global outlook unexpectedly. Many countries have adopted various ways to deal with the pandemic and all the measures taken have resulted in a sudden shutdown of their economic activities. So this pandemic is not only a global health emergency but is a significant global economic downturn too. A pandemic can trigger a number of channels, including for example, labor markets, global supply chains, consumption behaviors, all of which can affect global economy. Among these channels, one of the most important components is definitely the stock markets The term "Black Swan" is used to emphasize unpredictable, rare events that have the potential to deeply affect the financial world and global economic systems. Many have declared COVID-19 as the "Black Swan" of 2020 with global economies starring at one of their worst recessions ever.

There had been several lockdowns announced in India to curb the effect of the pandemic. The dates were as follows :

1) Lockdown Phase 1 : 25 March to 14 April
2) Lockdown Phase 2 : 15 April to 3 May
3) Lockdown Phase 3 : 4 May to 17 May
4) Lockdown Phase 4 : 18 May to 31 May

We attempt to analyze the impact of COVID-19 on various sectors of the Indian markets using NIFTY 50 as the whole market index and other NIFTY sectoral indices as sector representatives. Using impact of COVID-19 as the base condition, we can predict the outcome of the impact on different economic sectors, if a similar situation happens in the future. Our project report will give individual as well as institutional investors an idea about they should respond if such a situation occurs again. Studying and evaluating past and current data helps investors and traders to gain an edge in the markets to make informed decisions. We will show how various sectors get impacted and how much risk investors will face and how much reward they will get in return when investing during such a period. Finally, we will use different deep learning models (such as Recurrent Neural Networks and Convolutional Neural Networks) to predict stock market prices and compare the predictions obtained from each model.

II. Related Work

Due to the high risk high reward nature of stock markets, and the immense amount of data available, they are heavily analyzed time to time. There has been financial analytics done on the effect of COVID-19 on stock market. Some of the works done in relation to the impact, and also the prediction of prices are listed below :

- "What India Could Have Done To Better Handle The Deadly Coronavirus" [Online]. https://www.outlookindia.com/website/story/opinion-what-india-could-have-done-to-better-handle-the-deadly-coronavirus/349649

- ”POLICY RESPONSES TO COVID-19” [Online]. https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19
- ”Stock market analysis prediction using LSTM” [Online]. Available: https://www.kaggle.com/faressayah/stock-market-analysis-prediction-using-lstm/
  (This source predicted data using LSTM’s only, on a different dataset, with different parameters for the training data and the LSTM neural network).

III. Datasets

The project deals with the analysis of stock market prices during COVID-19, and predicting stock market prices using deep learning model. Firstly, for the sector-wise analysis, we will require indices which can represent the whole sector together. For this, we chose NIFTY 50 to represent the entire market. Our analysis deals with six sectors which are Automobile, Banking, FMCG (Fast Moving Consumer Goods), IT/Software, Media and Pharmaceuticals. Moreover, since the analysis is related to COVID-19 period, we require a narrow spectrum of data, with dates ranging over the COVID-19 period. We chose February 10, 2020 to June 30, 2020 to be an optimal period. Secondly, for the prediction of stock market prices, we require a broader spectrum i.e our dataset should span over several years.

The first part of the report deals with the analysis of stock market during COVID-19 period. For this, the datasets have been collected from two sources :

1) Yahoo Finance : We have taken the NIFTY 50 data from this source. The data was taken over the period from 10 Feb, 2020 to 30 June, 2020. Table I displays the first two rows of this dataset. The columns are “Date”, “Open”, “High”, “Low”, “Close”, “Adj Close”and “Volume” which represent the date, opening value, highest value, lowest value, closing value, adjusted closing price of the stock and the volume of stock traded on that date. The date is of string type, volume of 64 bit integers and the rest are 64 bit floating points rounded off to 6 decimal places. (All values are in ₹)
   For the part where we predicted future stock prices, using various models, we used data from this same source. For that portion we used a large dataset containing the stock values over a period of 13 years, from 2007 to 2020.
2) NSE India : We have taken the NIFTY sectoral indices data from this source. The data was taken over the period from 10 Feb, 2020 to 30 June, 2020. Table II displays the first two rows of this dataset. The columns are “Date”, “Open”, “High”, “Low”, “Close”, “Shares traded”and “Turnover (Rs. Cr)” The date is of string type, shares traded of 64 bit integers and the rest are 64 bit floating points rounded off to 2 decimal places. (All values are in ₹)

We can see that the datasets from the two sources have different columns and different representation of data. Firstly, we drop the columns “Adj Close” from the NIFTY 50 dataset, and “Turnover (Rs. Cr)” from the sectoral indices datasets. Next, we see that the dates have different formats (YYYY-MM-DD and DD-Month-YYYY). To make them the same, we convert them to the ’DateTime’ format and set the index of the dataframe to the ’Date’ column which makes it compatible with mplfinance. Now, we have maintained uniformity across all datasets. These 7 datasets will be stored in a dictionary as {Name of index : dataset of index}.

Hence, in the end, the datasets have the columns “Open”, “High”, “Low”, “Close”, “Volume”.

IV. Analysis Pipeline

The analysis of various sectors during COVID-19 is done to help the investors prepare for such a situation. There is a potential to lose as well as gain a lot of money off the pandemic. To prevent huge losses and even earn a fortune off it such an analysis would help investors put their money in the right place at the right time. Using various technical indicators such as RSI (Relative Strength Index) and MAV (Moving Averages), we have tried to figure out various points in time where investors can hold long and short positions in the market.

We began our analysis by plotting candlestick charts for both the whole market index, and sectoral indices. This chart helps us analyze the open-high-low-close (ohlc) price variation together. Volume was also plotted along with Moving Averages (MAV) of 7 and 14 days. We calculate the moving average of a stock is to help smooth out the price data over a specified period of time by creating a constantly updated average price. A simple moving average takes the arithmetic mean of a given set of prices over the specific number of days in the past. In our case, we chose to plot MAV over 7 and 14 days. Exponential moving average (EMA) is a weighted average that

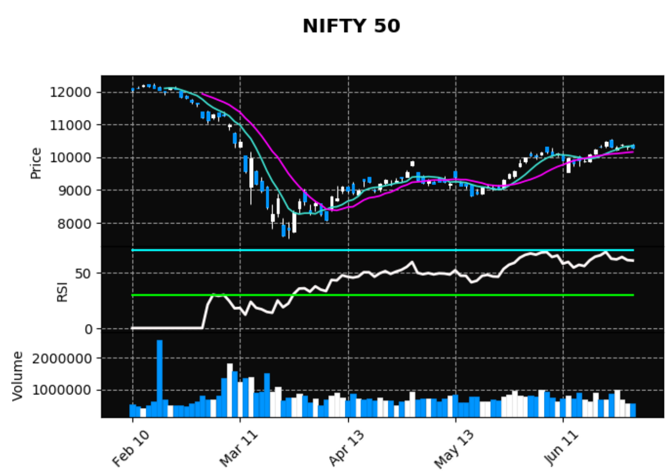


Fig. 1: NIFTY 50 index price with Relative Strength Index and Volume. In the candlestick chart, — represents 7 day MAV, — represents 14 day MAV. Below that, the white graph is the RSI values and — represents 30, — represents 70

TABLE I: NIFTY 50 Dataset : First two rows

Date	Open	High	Low	Close	Adj Close	Volume
2020-02-10	12102.349609	12103.549805	11990.750000	12031.500000	12031.500000	524700
2020-02-11	12108.400391	12172.299805	12099.000000	12107.900391	12107.900391	480000

TABLE II: NIFTY AUTO Dataset : First two rows

Date	Open	High	Low	Close	Shares Traded	Turnover (Rs. Cr)
10-Feb-2020	8065.40	8067.35	7820.30	7860.55	120638033	3697.57
11-Feb-2020	7923.00	7969.30	7881.35	7892.40	84781272	2719.71

gives greater importance to the price of a stock on more recent days, making it an indicator that is more responsive to new information. Whenever the 7 day MAV goes above the 14 day MAV, the view of the stock is bullish.

The relative strength index (RSI) is a momentum indicator used in technical analysis that measures the magnitude of recent price changes to evaluate overbought or oversold conditions in the price of a stock or other asset. The RSI is displayed as an oscillator (a line graph that moves between two extremes) and can have a reading from 0 to 100. Traditional interpretation and usage of the RSI are that values of 70 or above indicate that a security is becoming overbought or overvalued and may be primed for a trend reversal or corrective pullback in price. An RSI reading of 30 or below indicates an oversold or undervalued condition. To calculate RSI, we follow the following method :

1) Calculate Up move (U) and Down move (D) : We write
$$\Delta_i = CP_i - CP_{i-1} \tag{1}$$
If $\Delta_i \geq 0$ it is called an up move, and if $\Delta_i \leq 0$, it is a down move
2) Calculate average gain and average loss : We use Wilder smoothing method to do so. $\alpha = \frac{1}{14}$ (since we are finding average for the past 14 days)
$$avg(U_i) = \alpha U_i + (1 - \alpha)\ avg(U_{i-1}) \tag{2}$$
$$avg(D_i) = \alpha D_i + (1 - \alpha)\ avg(D_{i-1}) \tag{3}$$
3) Calculate Relative Strength (RS) : RS is the ratio of the two averages found above.
$$RS = \frac{avg(U_i)}{avg(D_i)} \tag{4}$$
4) Find RSI : Finally, we write
$$RSI = 100 - \frac{100}{1 + RS} \tag{5}$$

We can see the RSI plot for NIFTY 50 in Fig 1

Daily return of a stock on day i is given as
$$r_d(i) = \frac{CP_i - CP_{i-1}}{CP_{i-1}} \tag{6}$$
We modify this concept slightly and define dynamic return as
$$r_D(i) = \frac{CP_i - BP_i}{BP_i} \tag{7}$$
Here, BP_i (or Base Price) is the minimum of the closing prices before the current closing price, i.e
$$BP_i = min\{CP_j\} \text{ for } j < i \tag{8}$$
For each index, we take the maximum of the dynamic returns found. This maximum return has been converted to a monthly return as shown below
$$r_M = (max\{r_D(i)\} + 1)^{\frac{30}{N}} - 1 \tag{9}$$
Here, N denotes the number of days between the date of the base price and the current date (included). We have done this to determine the maximum amount of return that can be earned when invested at the best time.

V. Results

As seen from Fig 1 and Fig 2, even before Lockdown 1.0 was announced, prices of the indexes had started falling rapidly. Lockdown 1.0 was announced on 24th March, but by then, most of the indices had already taken most of their fall. This can be explained by noting the fact that prior to 24th March, numerous containment measures had already been imposed, varying in intensity across the country, including travel restrictions; closing educational establishments, gyms, museums, and theatres; bans on mass gatherings; and encouraging firms to promote remote work.

When market started to correct itself after the first lockdown, the sectoral indices showed different behaviour in their prices. After starting falling from around 20th February, all stock prices reached their minimum around 23rd March. After this period (until the end of April), index prices of Automobile and IT/Software sector started to rise slowly and steadily. The index prices of FMCG and Pharmaceuticals sector rose sharply and showed sudden jumps in their price. However, the index prices of Banking and Media/Entertainment sector remained fairly constant. Around the end of April, a second drop was seen in all the indices, and this was because of the second wave of COVID-19 striking India. The sudden increase in number of cases caused a similar effect as before.

From Fig 3, which is the barplot of Maximum Monthly Return (i.e r_M) of each index, we can see that an investor holds a great potential to earn off the pandemic for three continuous months accounting for around 60% return in the Pharmaceuticals sector, 50% return in the Automobile and Media sector and between 30% to 35% return in the other

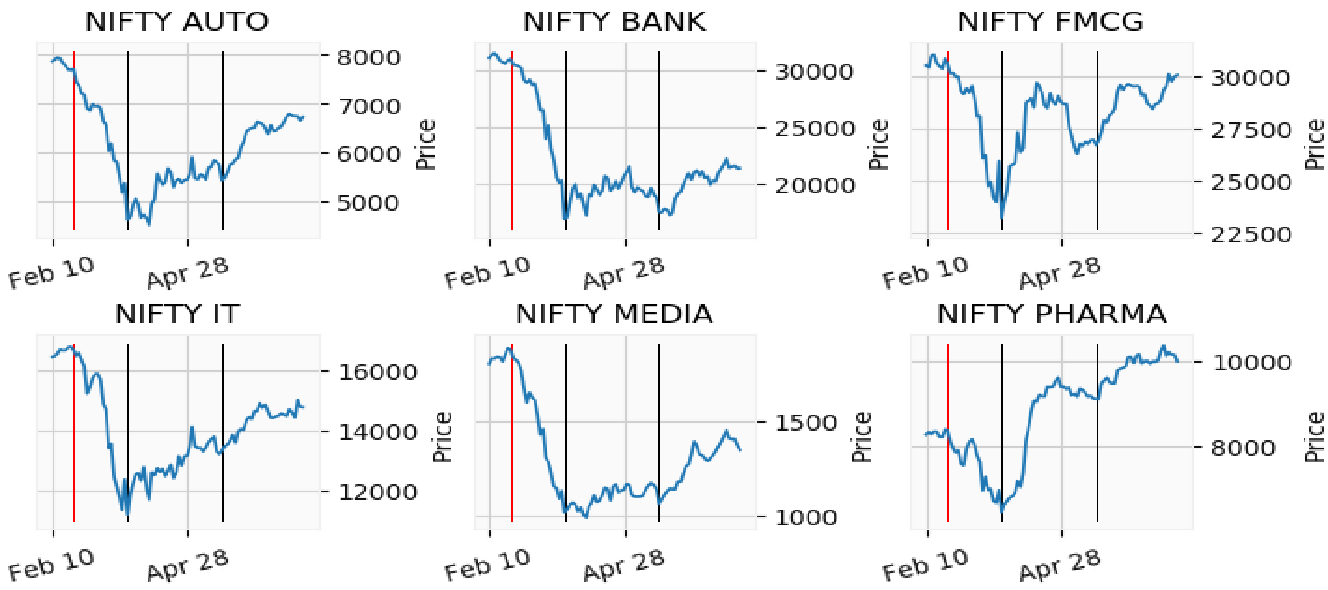


Fig. 2: Sectoral indices line plot. The — line indiciates the date (20th Feb, 2020) around which the indices start falling. The — lines are the dates when Lockdown 1.0 and Lockdown 4.0 started, i.e 25th March, 2020 and 18th May, 2020

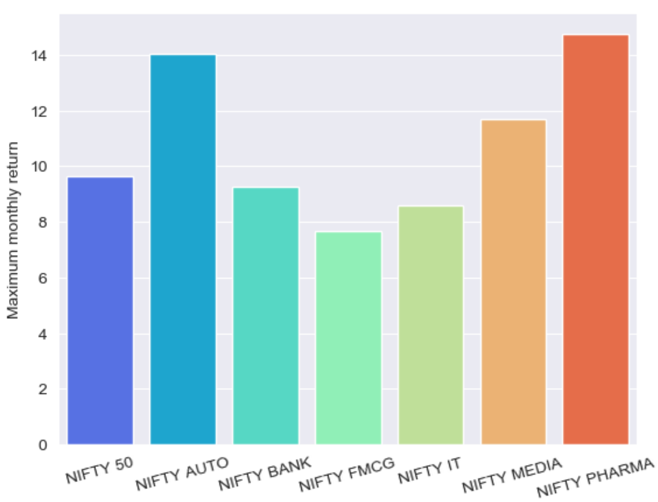


Fig. 3: Maximum monthly returns (r_M) for the indices

three sectors. The market as a whole saw an increase of 37.6%. Thus, Banking, IT and FMCG sector performed relatively poorer than the market while Pharma, Media and Automobile sector outperformed the market. Hence, for the investors, the latter three sectors prove to be the most profitable ones amongst all sectors.

We observe that although FMCG price index grew quickly, it did not outperform the market if compared by the value of return, owing to the sudden dip during the second wave of COVID-19 around end of April. In spite of this, investors can smartly invest in such a situation by holding a short position in this second dip and going long again after the market starts recovering.

The graphs for the RSI values of each sector can be found in the IPython Notebook. All the stocks are underbought during the end of March signalling the investors to hold a long position. In general, all indices' RSI values increased (but had falls around the second wave) and was touching 70 mark at the end. When the restrictions on theatres and other entertainment premises were relaxed, NIFTY Media got overbought. The RSI for NIFTY Pharma rose sharply touching the 70-mark around the beginning of April, and constantly stayed above the 50-mark, thus showing its overly-bullish nature during the pandemic.

VI. Discussion

Our analysis has given insights into the behaviour of various sectoral indices during a pandemic period. Through our analysis, we have shown that Pharmaceuticals, Automobile and Media sectors have been the most profitable sectors if invested at the correct time. FMCG has shown sudden jumps in prices twice between 20th February and 30th June and if invested smartly, this sector has a potential to bring huge profits. This sector suddenly went bullish after initial slowdown which according to analysts, may be attributed to some sector specific policies made by the government.

Whenever an announcement regarding restrictions on mobility, banks etc. are made, investors should become aware that prices will fall and soon enough will rise again. Adding to that, whenever consecutive waves of the pandemic are about to be realised, a similar pattern will be followed. The IT and Banking sector underperformed the market during this time. The IT sector saw an initial recession, but adapted to the scenario gradually and recovered steadily as compared to the

Banking sector. Due to many restrictions on operations, the Banking sector couldn't perform at par with the market.

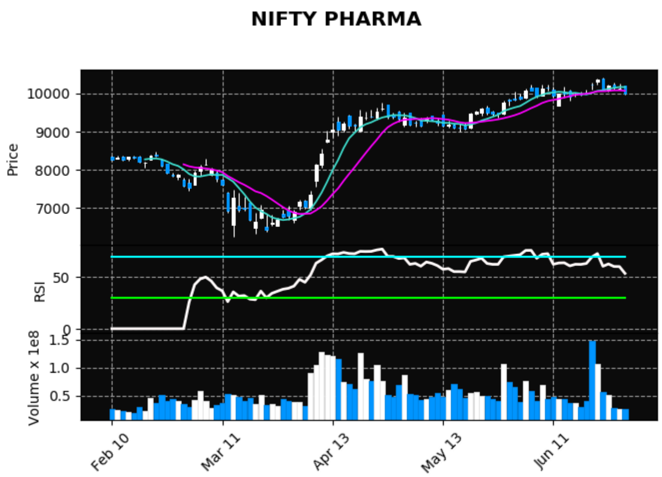


Fig. 4: NIFTY PHARMA index price with Relative Strength Index and Volume. In the candlestick chart, — represents 7 day MAV, — represents 14 day MAV. Below that, the white graph is the RSI values and — represents 30, — represents 70

We showed that the Pharmaceuticals sector was the most profitable sector to invest in during the COVID-19 period. The prices saw a sudden boom as people believed that pharmaceutical companies would be the most profitable coming out of the pandemic. The RSI for NIFTY PHARMA clearly shows how the index become overbought despite the COVID situation. It crossed the 70 mark around the beginning of the first lockdown itself. This confirms the belief of people in the pharmaceutical sector.

This pandemic made investors face an unprecedented situation and weren't quite familiar with the way they should manage their funds. With the above analysis, we have figured out particular profitable sectors to invest in incase such a situation occurs again. We have shown that there is a potential to earn huge profits during these recession times if we know when and where to invest

We had seen that the prices for NIFTY FMCG dropped considerably during the second wave, as compared to other sectoral indices. This behaviour may involve further analysis or sector specific policies made by the government during this time.

VII. Prediction

We thought it would be very interesting to try and predict future stock data using past information, using different machine learning models. This is very important as, people can know which stocks to invest in by seeing how much their prices rise and fall by this method. We tried to predict stock data using 4 different machine learning models. We tested the accuracy of the predictions made by LSTM's, Simple RNN's, GRU's and CNN's.

A. Pre-processing of data

- We first collected the stocks data of NIFTY 50 over a 13 year period.
- We only tried to predict the closing price of the stocks, so we only took the 'Close' and 'Date' columns of the stocks data.
- We dropped all the values which had NaN values in either of those columns.
- We then normalised all our data and scaled it to make our training more uniform.
- We then defined our training data length which was 0.8 of the entire dataset length.(Defined our test train split).
- Their accuracy not being so great, might be because they do not capture much data about the proximity of the previous stock prices on different days, with the stock price we are predicting. LSTM's, GRU's and simple RNN's do this.
- Then we created our x train, which consisted of the 70 previous stock prices, before the stock price we are trying to predict(which was our y train), corresponding to 1 value of y train. We took the number 70 as we wanted to include the most information without making it include information which was not necessary for the prediction. A little over 2 months seemed right.
- Then we trained our processed data using different models and compared the results.
- We used different loss metrics on our predictions and test data (Which we created in the same manner as our final train dataset, and we took the actual stock prices over the previous 70 days even for the test data, not the ones predicted by the model over the past 70 days) to find the relative accuracies of the model.

B. CNN

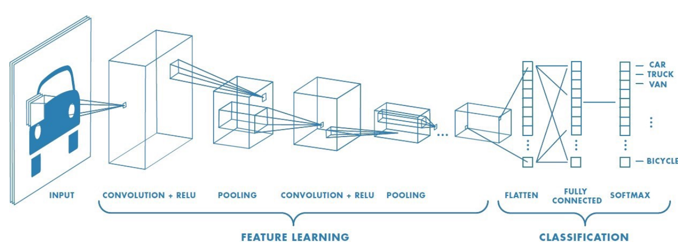


Fig. 5: BASIC 2D CNN

CNNs work the same way whether they have 1, 2, or 3 dimensions. The difference is the structure of the input data and how the filter, also known as a convolution kernel or feature detector, moves across the data.

Convolutional Neural Network (CNN) models were developed for image classification, in which the model accepts a two-dimensional input representing an image's pixels and color channels, in a process called feature learning.

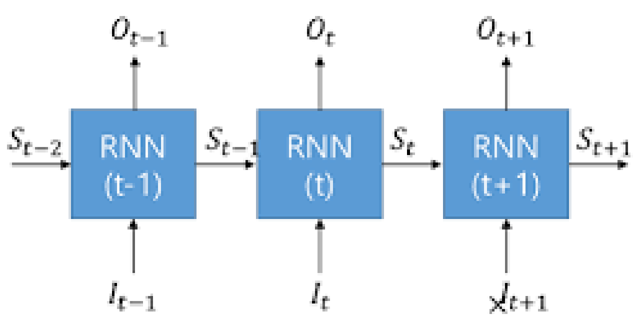
This same process can be applied to one-dimensional sequences of data. The model extracts features from sequences data and maps the internal features of the sequence. A 1D CNN is very effective for deriving features from a fixed-length segment of the overall dataset, where it is not so important where the feature is located in the segment.

They work well for analysis of a time series of sensor data, or a sequence of data of a fixed length, like an audio recording.

Our findings-

- CNN's predict the least accurate stock prices.
- They had the maximum RMSE with the test data, among all the model predictions.
- Their curve was considerable smoother and did not capture the small sharp fluctuations in the stock prices.
- They were not accurate at all with the same number of epochs as the rest of the data so we gave them more epochs to become fairly accurate
- Their accuracy not being so great, might be because they do not capture much data about the proximity of the previous stock prices on different days, with the stock price we are predicting. LSTM's, GRU's and simple RNN's do this.

C. Simple RNN



$$S_t = W_1 \times [I_t \ S_{t-1}] + b_1 \qquad (1)$$

$$O_t = W_2 \times S_t + b_2 \qquad (2)$$

Fig. 6: Basic RNN

Recurrent Neural Networks (RNN) are a type of Neural Network where the output from previous step are fed as input to the current step. In traditional neural networks, all the inputs and outputs are independent of each other, but in cases like when it is required to predict the next word of a sentence, the previous words are required and hence there is a need to remember the previous words. Thus RNN came into existence, which solved this issue with the help of a Hidden Layer. The main and most important feature of RNN is Hidden state, which remembers some information about a sequence.

Our findings-

- Simple RNN's predicted better than the CNN, but worse than the LSTM, and GRU.
- They had the second largest RMSE out of all the 4 models.
- This is probably as LSTM's, and GRU's are more complex than a simple RNN, and hence can capture more information about a dataset.

D. LSTM

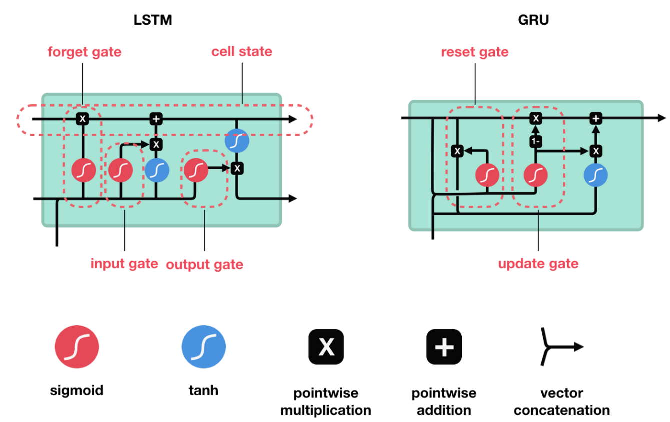


Fig. 7: LSTM and GRU

LSTM 's and GRU's were created as the solution to short-term memory. They have internal mechanisms called gates that can regulate the flow of information.

Core Concept :

The core concept of LSTM's are the cell state, and it's various gates. The cell state act as a transport highway that transfers relative information all the way down the sequence chain. You can think of it as the "memory" of the network. The cell state, in theory, can carry relevant information throughout the processing of the sequence. So even information from the earlier time steps can make it's way to later time steps, reducing the effects of short-term memory. As the cell state goes on its journey, information get's added or removed to the cell state via gates. The gates are different neural networks that decide which information is allowed on the cell state. The gates can learn what information is relevant to keep or forget during training.

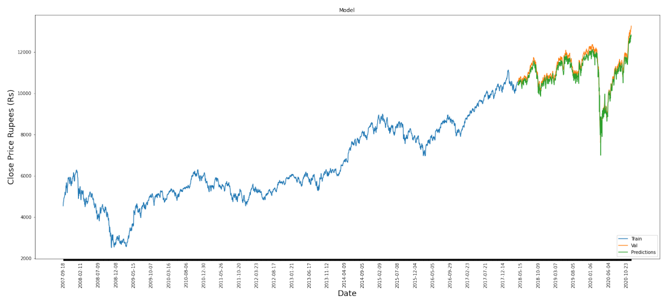
The Forget gate decides what is relevant to keep from prior steps. The input gate decides what information is relevant to add from the current step. The output gate determines what the next hidden state should be.

Our findings-

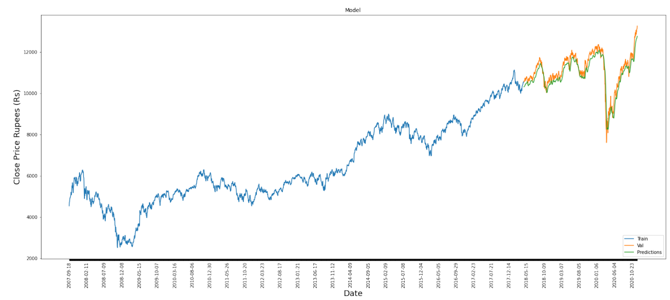
- LSTM's predicted future data very well, as seen from their graph.They performed the best, among all the 4 models.
- They had the lowest RMSE with the test data, out of all 4 models.

	Model type	RMSE	Mean Absolute Error	R2 score	Mean squared log error	Mean poisson deviance	Min error(Rs)	Max error(Rs)	Final loss with training data
0	LSTM	148.761758	96.763539	0.970979	0.000228	2.214611	0.187500	1376.044922	0.000158
1	CNN	333.473459	270.221026	0.854167	0.001011	10.537681	0.620118	1477.058593	0.000270
2	GRU	189.055832	149.588504	0.953128	0.000324	3.371220	0.010743	1209.598633	0.000158
3	Simple RNN	247.648167	210.943393	0.919573	0.000552	5.787208	2.163086	1251.557617	0.000293

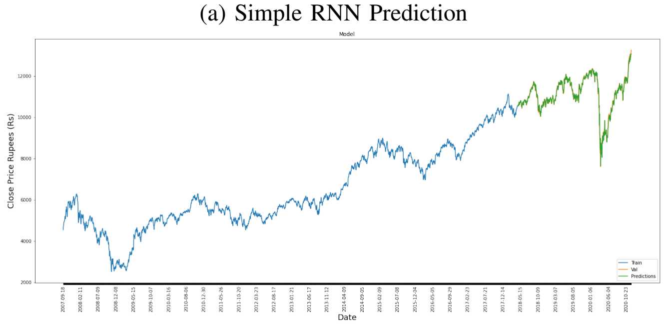
Fig. 8: Loss metrics table



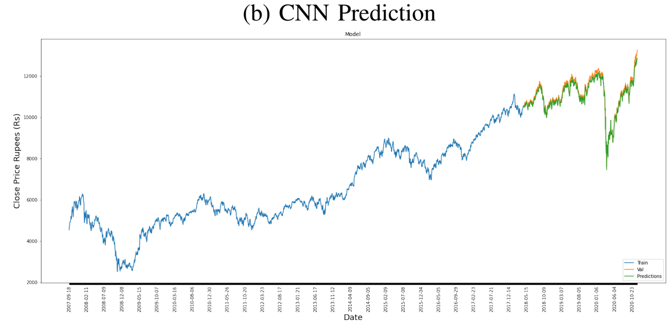
(a) Simple RNN Prediction



(b) CNN Prediction



(c) LSTM Prediction



(d) GRU Prediction

- This is probably because LSTM's are more complex than RNN's and have a structure more suitable for this particular task, than GRU's.

E. GRU

So now we know how an LSTM works, let's briefly look at the GRU. The GRU is the newer generation of Recurrent Neural networks and is pretty similar to an LSTM. GRU's got rid of the cell state and used the hidden state to transfer information. It also only has two gates, a reset gate and update gate.

- Update Gate-The update gate acts similar to the forget and input gate of an LSTM. It decides what information to throw away and what new information to add.
- Reset Gate-The reset gate is another gate is used to decide how much past information to forget.

And that's a GRU. GRU's has fewer tensor operations; therefore, they are a little speedier to train then LSTM's. There isn't a clear winner which one is better. Researchers and engineers usually try both to determine which one works better for their use case.

Our findings-

- GRU's predicted future data very well, second to only LSTM's, and not by a lot.
- They had the second lowest RMSE with the test data, although their RMSE with the test data was very close to that of the LSTM.
- This is probably because GRU's are more complex than RNN's, but LSTM's have a structure more suitable for this particular task, than GRU's.

Our Loss Metrics

- $RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(y_i - predicted)^2}$
- MAE = Sum of the absolute value of the errors between corresponding elements of the arrays.
- $SS_{\text{tot}} = \sum_i (y_i - \bar{y})^2$

  $$SS_{\text{res}} = \sum_i (y_i - predicted)^2 = \sum_i e_i^2$$

  $$R^2 score = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}}$$
- $MSLE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(\log(x_i + 1) - \log(predicted + 1))^2}$
- MPD = The Tweedie deviance (d) with p, the power parameter = 1. μ is the corresponding value predicted by

our model here.

$$d(y,\mu) = \frac{1}{n}\Sigma_{i=1}^{n-1}\begin{cases}(y-\mu)^2, & \text{for } p=0\\ 2(y\log(y/\mu)+\mu-y), & \text{for } p=1\\ 2(\log(\mu/y)+y/\mu-1), & \text{for } p=2\end{cases}$$

CONCLUSION

- We saw that using LSTM's, we can predict the future stock data very well.
- We found that CNN's are not useful for predicting sequential data, especially data which depends upon previous data in a way such that the entries closest to it are the most important.
- GRU's also work very well to predict future data.
- Simple RNN's predict data well, but more complex networks perform better, and understandably so.
- Hence we found out that machine learning can be used to reliably predict future data, as long as we aren't predicting too far into the future, which can in turn help people predict how the stocks will behave and which ones to invest in.

ACKNOWLEDGMENT

We would like to thank our professors, Prof. Amit Sethi, Prof. Manjesh K. Hanawal, Prof. Sunita Sarawagi and Prof. S. Sudarshan for teaching us this course, without which we would not have been able to complete this project. We would also like to thank all the TA's involved with this course, who helped us a lot in doing the various assignments, and completing this course. We would also like to thank Aaryan Gupta and Utakarsh Thakare for their help in this project, especially with regard to how stocks, and the stock market work.

REFERENCES

[1] ”Nifty indices dataset” [Online]. Available: https://www.kaggle.com/sudalairajkumar/nifty-indices-dataset?select=NIFTY+50.csv

[2] ”RNN theory”[Online]. Available: https://www.analyticsvidhya.com/blog/2017/12/introduction-to-recurrent-neural-networks

[3] ”LSTM and GRU theory”[Online]. Available: https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21

[4] ”CNN and LSTM's to predict future data” [Online]. Available: https://www.hindawi.com/journals/mpe/2020/2746845/

[5] ”Prediction of data using LSTM's” [Online]. Available: https://www.kaggle.com/faressayah/stock-market-analysis-prediction-using-lstm/

[6] ”An example of a 1D CNN” [Online]. Available:https://machinelearningmastery.com/cnn-models-for-human-activity-recognition-time-series-classification/

[7] Mert Topcu and Omer Serkan Gulal,”The impact of COVID-19 on emerging stock markets” [Online]. Available:https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7348595/pdf/main.pdf

[8] ”Stock indicators” [Online]. Available:https://www.investopedia.com/articles/active-trading/041814/four-most-commonlyused-indicators-trend-trading.asp