IJCRT.ORG

ISSN : 2320-2882



## INTERNATIONAL JOURNAL OF CREATIVE **RESEARCH THOUGHTS (IJCRT)**

An International Open Access, Peer-reviewed, Refereed Journal

# A Review on Stock Price Prediction using LSTM Approach

Shweta Agarwal, Bhupesh kumar Singh

#### **Abstract**

In today's economy, the stock market, often known as the equity market, has a significant impact. The rise or decline in the share price has a outstanding impact on the investor's profit. The proposed method uses Long short-Term Memory(LSTM) Approach. Here I considering multi-column LSTM model which takes more than one column to analyse and train the model and based on that it will predict the values for future days. More than one features helps the model to predict the values more accurately than providing the single feature. Here, We are also adding two more features to our dataset to check whether it will improve the results or not.

#### Keywords: LSTM, RNN, Prediction

#### Introduction

Stocks, also known as company shares, symbolise ownership in a firm and provide shareholders with voting rights as well as earnings in the form of capital gains and dividends. Predicting how the stock market will move is one of the most difficult tasks due to many variables that go into stock forecasting, such as interest rates, politics, and economic growth, which make the stock market volatile and difficult to predict effectively.

Stock values depends on multiple factors, one of them is demand and supply. The demand and supply of a company's shares is a major factor in stock price fluctuations. Equities that are in high demand will rise in price, whereas stocks that are heavily sold will fall in price. Stock price fluctuations damage investor's confidence. necessitating the need forecast future stock value.

## Literature Review

To predict future stock market values, a model is built using Recurrent Neural Networks (RNN) and, in particular, the Long-Short Term Memory model (LSTM). It's main goal is to see how accurate a Machine Learning algorithm can predict and how much epochs can improve

the model. Different data sets were used in this study, and it was discovered that training with less data and more epochs can improve testing results[1].

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) in which the weights are updated for individual data points using stochastic gradient descent. When compared to existing stock price prediction systems, this will yield more accurate results[2].

The prediction in paper[3] is made using the KNN algorithm and non-linear regression.Lift graph is used to evaluate the performance of the KNN model, and plot curve is used to depict the relationship between real and predicted values. According to the paper, the error numbers are relatively minimal, indicating that the actual and predicted values are near, implying good accuracy.

#### **Dataset**

This section discusses about the dataset that has been used in the proposed work. The dataset is downloaded from the yahoo finance. Dataset consist of historical data of the companies. Here I am taking PETRONET LNG for the proposed work. The historical data for this company is available from 2004 to till date, but I am skipping the data from 2019 onwards, basically at the time of covid pandemic as it affected every sector and industry in different ways. Sudden fall and rise was there based on the affect of the pandemic. So I am taking the dataset till 2018 and will try to predict the next 30 days value based on that prediction.

### Methodology used

The proposed method used Long short-Term Memory (LSTM) Approach. Here We are considering multi-column LSTM model which takes more than one column to analyse and train the model and based on that it will predict the values for future days. More than one features helps the model to predict the values more accurately than providing the single feature.

Downloaded dataset consist of columns like Open values, Close values, High value of the day and some more. So, before using this dataset I will findout the momentum and volatility from the given data according to the dates.

Momentum: If the stock price is greater today than it was yesterday, the momentum for that day is +1 since there is a price increase; otherwise, it is -1.

Volatility: Represents the magnitude of the movement in stock closing prices. Volatility is a term that is used to describe how the market fluctuates. The difference between yesterday's closing price and today's closing price is divided by yesterday's closing price to measure volatility for a given day.

**Stock Momentum:** The average of a company's last five days momentum is used to calculate stock momentum.

Stock Price Volatility: The stock's price volatility is determined as the average of the previous five days' volatility.

Now after adding these two columns to the dataset we will use the dataset for our work.

Fig 1 shows the result after calculating 2 more features for the dataset I.e. volatility and momentum.

as	te Cop	/ ~ Format Painter	ви	2 - H - E	3 - 🖎 - 🛆		E ± ±	<u> </u>	lerge and W Center* T
	A1		(R), fx	Date					
al	Α	В	С	D	Е	F	G	н	1
	Date	Open	High	Low	Close	Adj Close	Volume	Stock_Price	Stock_Mon
	3/26/2004	8.5	8.5	6	7.325	5.230333	32036948		
	3/29/2004	7.375	7.475	7.25	7.325	5.230333	11272118		
	3/30/2004	7.325	7.575	7.3	7.375	5.266035	9214162		
	3/31/2004	7.375	7.5	7.325	7.35	5.248184	5874712		
	4/1/2004	7.425	7.7	7.375	7.65	5.462396	9260748		
	4/2/2004	7.75	8.625	7.65	8.5	6.069329	37970688	0.0324286	0.6
	4/5/2004	8.675	10.075		9.55	6.819068	97860558	0.0571345	0.8
	4/6/2004	9.75	10.35	9.475	9.875	7.051132	66634092	0.0625756	0.8
)	4/7/2004	9.975	10.175	9.7	10	7.140387	41154350	0.0644293	1
	4/8/2004	10.05	10.05	9.7	9.85	7.033282	25181032	0.059266	0.8
	4/9/2004	9.85	9.85	9.85	9.85	7.033282	0	0.0370438	0.6
3	4/12/2004	9.95	11.05	9.875	10.55	7.533107	57264840	0.0265511	0.6
ı	4/13/2004	10.7	10.725	10.075	10.4	7.426001	27663252	0.0225884	0.4
5	4/14/2004	10.4	10.4	10.4	10.4	7.426001	0	0.0200568	0.2
5	4/15/2004	10.5	10.8	10.325	10.575	7.550958	25511140	0.0204222	0.4
7	4/16/2004	10.625	11.075	10.5	10.95	7.818723	31238310	0.0275144	0.6
	4/19/2004	12.5	13.4	12.475	12.9	9.211099	70477720	0.0489176	0.6
)	4/20/2004	12.975	13.2	12.2	12.425	8.871931	42040052	0.0534384	0.6
	4/21/2004	12.3	12.75		12.625	9.014739	26804200	0.0566577	0.8
	4/22/2004	12.675	12.725	12.375	12.475	8.907632	17219094	0.0556685	0.6
<	4/23/2004	12.5 PETRO			12.15	8.675568	19614068	0.0537868	0.4

Fig 1

Fig 2 shows the predicted values when we didn't added the new features I.e. volatility and momentum.

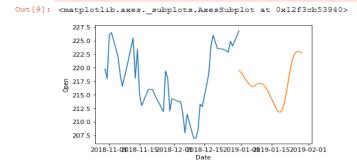


Fig 2

Fig 3 shows the predicted values when we have added two new features I.e. volatility and momentum.



Fig 3

#### Comparing the above results

plt.plot(data3['Date'],data3['Open'],color='blue')

Out[30]: [<matplotlib.lines.Line2D at 0x2124a8de7c0>]

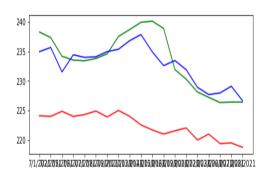


Fig 4

Fig 4 shows the comparison bewteen both the cases that we take. Red line shows the actual values on the particular date whereas green line shows predicted values when we use the data without adding new features. Blue line shows the predicted values when we have added more features. Results clearly shows that blues line is following actual trend more accuratly than green one. Hence adding new feature helps the model to to provide better results.

#### Conclusion

The approach used in this work is LSTM neural network that handles the time series data more efficiently as compare to other models. The result shows that after adding new feature the model is predicting better as compare to the model where these features were not added.

#### **Future work**

There are many researchers that uses different techniques such as SVM, CNN, ANN etc on the historical data. Adding more feature to the dataset make the model more accurate. So adding some more features can also be calculated and can be tested for the better accuracy. As, I added Volatility and momentum to the original data and this was calculated based on only previous 5 days. Now one thing that can be changed is this interval and may be it can improve the results as well. Not even that we can also add more extra features to improve the model.

#### References

Ding, G. and Qin, L. 2020. Study on the prediction of stock price based on the associated network model of LSTM. Int. J. Mach. Learn. Cybern, 11(3): 1307–1317.

Guray, U. and Kotrappa, S. 2020. Predict Stock Market's Fluctuating Behaviour: Role of Investor's Sentiments on Stock Market performance. *International* Journal Engineering Trends and Technology, 68(11): 72-80.

Guray, U. and Kotrappa, S. 2020. Sentiment Aware Stock Price Forecasting using an SA-Learning Model. Engineering, RNN-LBL Technology and Applied Science Research, 10(5): 6356-6361.

Guray, U. and Kotrappa, S. 2020. Lbl - Lstm: Log Bilinear And Long Short Term Memory Based Efficient Stock Forecasting Model Considering External Fluctuating Factor. International Journal of Engineering and Advanced Technology, 9(4): 2057-2063.

Mehar, V., Chandola, D., Tikkiwal, V. and 2020. Stock Closing Price Kumar, A. Prediction using Machine Learning Techniques. Procedia Computer Science, 167(4): 599-606.

Moghar, A. and Hamiche, M. 2020. Stock Market Prediction Using LSTM Recurrent Neural Network. 'In: International Workshop Methods Artificial Statistical and Intelligence (IWSMAI 2020)' at Poland, during. April 6-9. pp. 1168-1173.

Mohammad, A. I. S., Maswood, M. and Alharbi, A. G. 2020. Deep Learning- Based Stock Price Prediction Using LSTM and Bi-Directional LSTM Model. 'In: 2nd Novel Intelligent and Leading Emerging Sciences Conference' at Egypt, during. October 24-26. pp. 87-92.

Nandakumar, R., Uttamraj, K. R., Vishal, R. and Lokeswari, Y. V. 2018. Stock Price Prediction Using Long Short Term Memory. International Research Journal of Engineering and Technology, 5(3): 3342-3348.

Roondiwala, M., Patel, H. and Varma, S. 2017. Predicting Stock Prices Using International Journal of Science and Research, 6(4): 1754-1756.

Selvin, S., Ravi, V., Gopalakrishnan, E. A., Menon, V. and Soman. 2017. Stock price prediction using LSTM, RNN and CNN-sliding window model. In: International Conference on Advances in Computing, Communications and Informatics' at coimbatore, during. September 2017. pp. 1643-1647.

