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Predicting Stock Price Movements with Low Power Consumption LSTM

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Abstract - A new method of predicting time-series-based stock prices and a new model of an investment portfolio based on predictions obtained is proposed here. A new regression scheme is implemented on a long-short-term-memory-based deep neural network with increased efficiency, performance and decrease in processing time requiring low computing power consumption. The predictions once obtained are used to define the trend of the stock in a well defined line chart. The prediction by this model is objectified to provide trend identification to traders. A large set of experiments have been carried on data of multiple stocks which include All Indian stocks listed on NSE, Major Global exchanges and Listed Currencies. The results confirm that the proposed model outperforms various standard predictive models.

1. INTRODUCTION

The model uses Long-Short Term Model to predict the closing price of the stock on a very large dataset including all the listed stock data on NSE. Long Short-Term Memory (LSTM) models are a type of recurrent neural network (RNN) architecture that is well-suited for sequential data and time-series analysis [1]. widely used in the prediction of stock markets and financial time series data due to their ability to capture long-term dependencies and handle information over extended periods [2].

The model only will get trained over a single feature of data that means a single time series data of either close, high, low, open, volume or any other single individual column of data related.

Data is available at resources like Yahoo! Finance or MarketWatch contain years of trading data for every publicly traded company or Kaggle which have user uploaded datasets. [2] A prediction model can be used to help less experienced traders check their stock analyses against a predicted model for confirmation or further optimize profits for experienced day traders. [3] Programs that utilize an accurate prediction model can then be used to trade for individuals and cut out the emotions involved.

2. Objective

Primary objective of predicting stock market movements is to gain insights into potential future price changes, enabling investors and traders to make informed decisions. Numerous studies have explored the application of various predictive models to forecast stock prices, with the goal of achieving better returns and managing investment risks.

3. Dataset & Modules

The dataset provided to the model for training, testing, and for making prediction included Global Stock Exchanges, National Stock Exchanges and all the stock listed over NSE, the data is arranged form NSE official module.

The prediction uses the following modules in order to creating the model and predicting it:

- numpy (imported as np): Numerical computing library in Python.
- Pandas (imported as pd): Data manipulation and analysis library in Python.
- MinMaxScaler from sklearn.preprocessing: Part of scikit-learn library for preprocessing data, specifically used for feature scaling.
- Sequential from tensorflow.keras.models: Sequential model for linear stack of layers in Keras (Tensor Flow's high-level neural networks API).
- LSTM from tensorflow.keras.layers: Long Short-Term Memory layer for building LSTM networks in Keras [4][5].
- Dense from tensorflow.keras.layers: Fully connected layer for building neural network architectures.
- yfinance (imported as yf): Library for downloading financial data from Yahoo Finance.
- matplotlib.pyplot (imported as plt): Library for creating static, animated, and interactive visualizations in Python.
- tensor flow (imported as tf): An open-source machine learning library developed by the Tensor Flow team.
- load_model from tensorflow.keras.models: Function for loading a pre-trained model in Keras.
- plt (re-imported): Matplotlib library for creating visualizations.

1. Power Grid Corporation Of India	11. Bajaj Finserv	21. ITC	31. JSW Steel	41. Bharti Airtel
2. NTPC	12. Hero MotoCorp	22. Bajaj Auto	32. Nestle India	42. Grasim Industries
3. Axis Bank	13. Tata Steel	23. Tata Consultancy Services	33. Cipla	43. Hindalco Industries
4. IndusInd Bank	14. Maruti Suzuki India	24. Sun Pharmaceutical Industries	34. UPL	44. Hindustan Unilever
5. HDFC Life Insurance	15. Asian Paints	25. HDFC Bank	35. Larsen & Toubro	45. Tech Mahindra
6. Bharat Petroleum Corporation	16. Indian Oil Corporation	26. HCL Technologies	36. Infosys	46. Wipro
7. Coal India	17. State Bank Of India	27. Bajaj Finance	37. Titan Company	47. Dr. Reddys Laboratories
8. SBI Life Insurance Company	18. Kotak Mahindra Bank	28. Ultratech Cement	38. Shree Cement	48. Mahindra & Mahindra
9. Housing Development Finance Corporation	19. Reliance Industries	29. Oil & Natural Gas Corporation	39. ICICI Bank	49. GAIL (India)
10. Divis Laboratories	20. Tata Motors	30. Eicher Motors	40. Adani Ports & Special Economic Zone	50. Britannia Industries

Figure 1 :List Of Some Of The Stock Used To Train The Model Which is Also LISTED ON NSE

The training data distribution includes :

- All the stocks listed on NSE
- All the Major Global Indices
- USD to INR currency

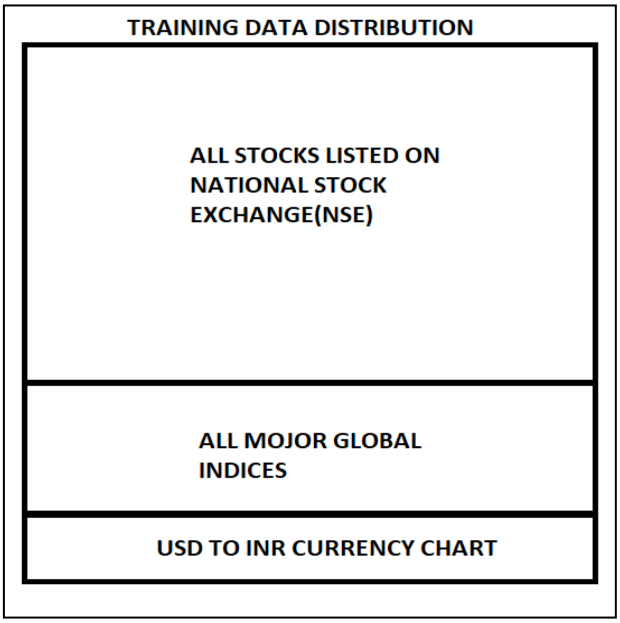

Figure 2: Training Data Distribution

This wide range of data to be feed to the model gives the vast knowledge base to take into account major and common activities to predict the future trends of a particular listing.

4. Cell Architecture of LSTM:

There are memory cell and gate cell in the following model the architecture. The cells have an architecture that allows for constant error through special, self-connected units without the disadvantages of the naive approach[11]. The internal diagram of cell of a LSTM is in figure 2.

Here, the notations in the structures are given by: Ft is Forget gate, It is Input gate, Ct1 is Cell update, Ct is Cell state Ot is Output gate, Ht is Output of the whole cell[12].

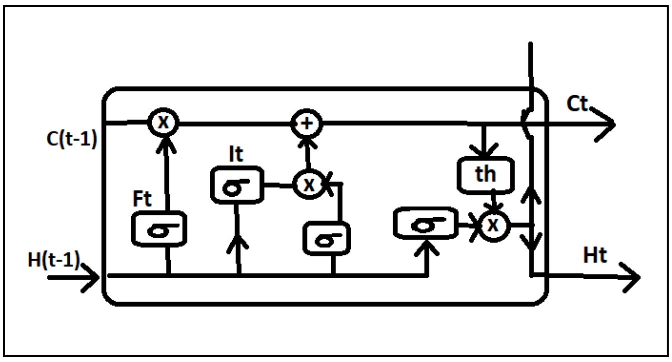

Figure 3: Internal Cell Diagram of LSTM

Likewise, the datathat hast to be stored is moved error free to memory cell. It is a more complex unit, each memory cell is built around a central unit which is linear in nature and memory cell is limmited to number of self connections.

The self recurrent connection indicates the feedback with the delay of 1 time step[11].

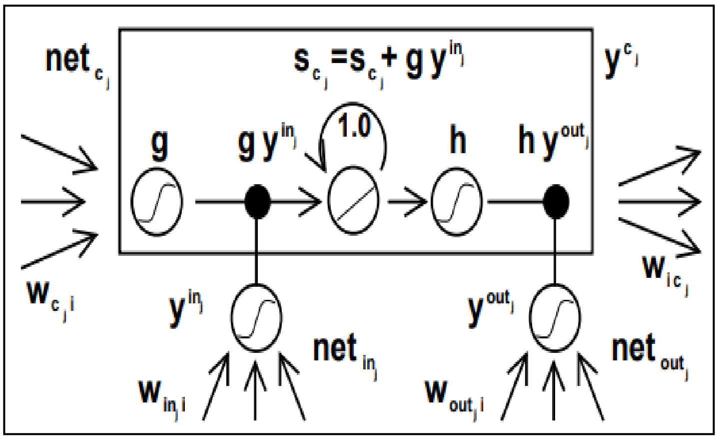

Figure 4: Architecture of memory cell and its gate

5. Model Development:

The data set of all the stock is attained from reliable sources but the size and the length of the data is very large (around 6.6 million data points) making it consume RAM equivalent of 50-64GB which increases the computing power consumption to large extent and also the model doesn't prove to be efficient we overcome this problem by doing a simple architectural change in data processing and training of the model that the requirement of RAM for LSTM reduced to less than 4GB at a time but increasing marginal inefficacy but as the data is very large the increase in inefficiency is negligible and the predictive model have less loss and higher correctness in predicting the trend.

In traditional LSTM the data is collected and concatenated to a single column, then after pre-processing the whole data is the feed to the model to get trained after dividing it for testing, training, and validating. [6][7][8] Here, if the concatenated data is large the RAM consumption increases (as in our case we have more than 6600000 data points) and to process it the power consumption increases leaving its carbon footprint.[8]

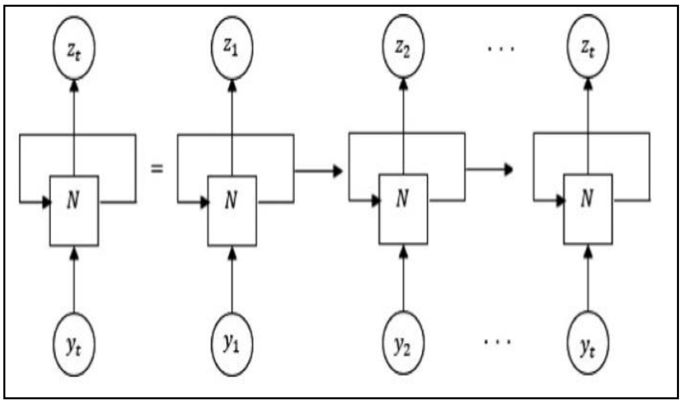

Figure 5: RNN & LSTM

Whereas, in updated architecture designed, LSTM is being processed with limited data. That is the data is collected for a particular stock from the data list of stocks and then the model is trained on it then the next stock data is feed to the system and likewise all the data iterate through the LSTM model, so that the model gets trained over all the data and increases its correctness and as the data size now reduced, the RAM consumption also reduce to large extent.

The model uses the Leaky-ReLU as activation function of the perceptron. Leaky Rectified Linear Unit (Leaky ReLU) is an activation function commonly used in neural networks, including Long Short-Term Memory (LSTM) models. It is an extension of the standard Rectified Linear Unit (ReLU) activation function and is designed to address the "dying ReLU" problem [5].

We are using 100 LSTM Layers and 1 (one) fully connected dense layer as increasing dense layer will provide multi column prediction and increasing or decreasing the layer may tend the model to be over fitting or under fitting, the epoch size used on a single stock data is 10 as the processing data length is small at a particular point of time in the model and batch size considered to be 32 with training, testing, validation spilt to be 75%, 15%, 10% respectively. And as of optimizer the model uses Adam optimizer and for losses the mean squared error method is being used for the calculation.

The prediction of a single value is being done based on previous 25 values as the sequence length is 25 this is used as the dataset is of daily so that the sequence length of 25 gives us the view of a moth on daily chart allowing the model to take the pattern of stock in previous month into consideration.

The prediction is visually represented in a line chart generally we are using the LSTM model to predict the data between 5-15 days to get the trend as the data is daily candle values.

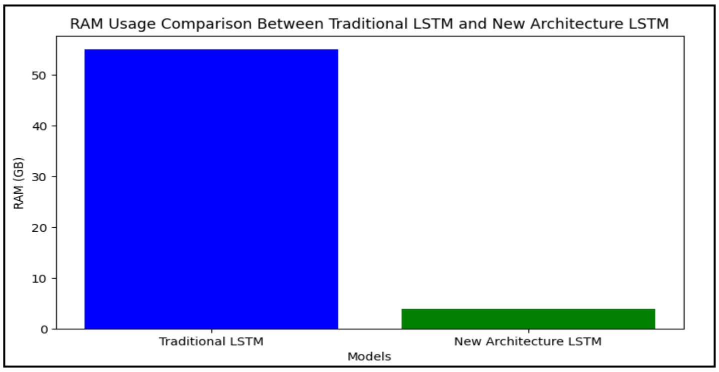

Figure 6: RAM Reduction between Traditional Model and New Architecture

6. Prediction and Result

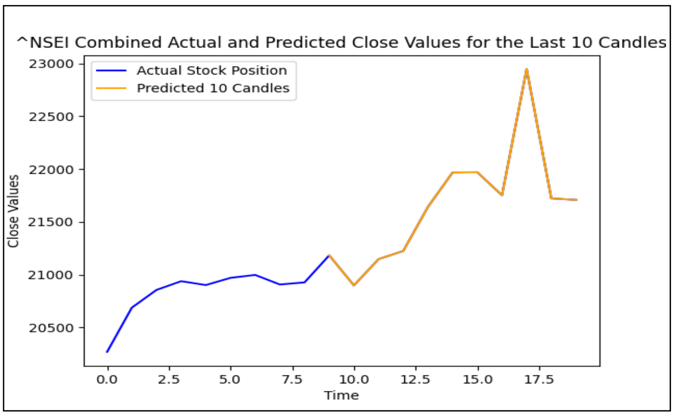

Figure 7: Prediction of ^NSEI (Dated as: 15-12-2023 – DD-MM-YYYY)

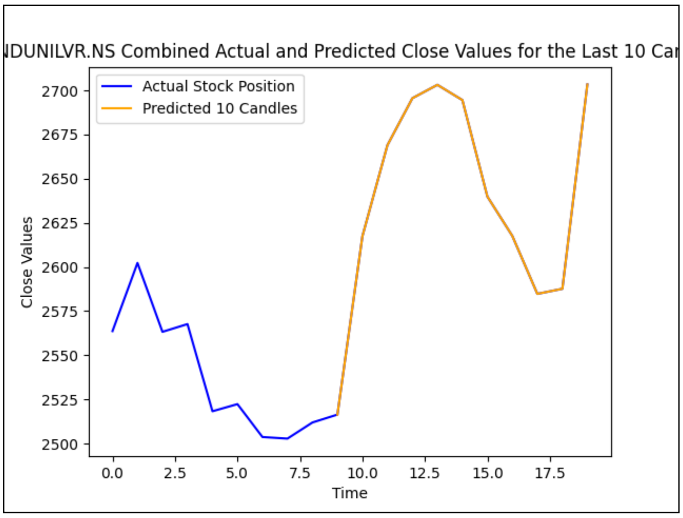

Figure 8:Prediction of HINDUNILVR.NS (Dated as: 15-12-2023 – DD-MM-YYYY)

7. Conclusion & Future Work

In conclusion, this research paper has presented an innovative approach to predicting stock market trends and prices using a deep learning Long Short-Term Memory (LSTM) model while addressing the critical aspect of power consumption. The proposed LSTM model not only demonstrates significant accuracy in forecasting market trends but also incorporates a novel data feeding architecture, contributing to more efficient power utilization in the prediction process. This model aids in making informed trading decisions for both large-scale and retail investments by leveraging computational power over human judgment.

The current model architecture can be enhanced by adjusting layers in LSTM, hyper parameters and utilizing high-capacity computational systems to achieve predictions closer to actual outcomes.

REFERENCES

1. LSTM-based Deep Learning Model for Stock Prediction and Predictive Optimization Model----Akhter Mohiuddin Rather
2. Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780. doi: 10.1162/neco.1997.9.8.1735
3. Predicting Stocks with LSTM-based DRNN and GAN --Duy Ngo
4. Tsantekidis, A., Passalis, N., Tefas, A., & Kanniainen, J. (2017). Forecasting stock prices from the limit order book using convolutional neural networks. In 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 4924-4930). IEEE. doi: 10.1109/IROS.2017.8206432
5. Maas, A. L., Hannun, A. Y., & Ng, A. Y. (2013). Rectifier nonlinearities improve neural network acoustic models. In Proceedings of the 30th International Conference on Machine Learning (ICML-13) (pp. 3-11).
6. "Deep learning with long short-term memory networks for financial market predictions"--Xinyi Wang, Feng Yu, Heng Zou
7. "A deep learning framework for financial time series using stacked autoencoders and long-short term memory"--Xiaoke Huang, Yuying Zhang, Daniel S. Yeung
8. "Stock price prediction using attention-based multi-input LSTM"--Lei Lin, Bing Qiao, Depei Qian
9. "Financial market forecasting using a mixture of Gaussian processes"--Hao Ding, Hengjian Cui, Hao Zhou, Xiongfei Jiang, Shihong Deng
10. LONG SHORT-TERM MEMORY Neural Computation 9(8):1735{1780, 1997 Sepp Hochreiter Fakult□at f□ur Informatik Technische Universit□at M□unchen
11. Stock Market Prediction Using LSTM Recurrent Neural Network Adil MOGHARa * ,Mhamed HAMICHEb
12. A survey on long short-term memory networks for time series prediction Benjamin Lindemann*, Timo Müller, Hannes Vietz, Nasser Jazdi, Michael Weyrich

BIOGRAPHIES

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