STOCK PRICES PREDICTION USING LONG SHORT TERM MEMORY

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Nayanika Das
Electrical Engineering
Assam Engineering College
Guwahati,India
dasnayanika24@gmail.com

Barnali Goswami
Electrical Engineering
Assam Engineering College
Guwahati,India
goswamibarnali@yahoo.co.in

Ritu Nazneen Ara Begum
Electrical Engineering
Assam Engineering College
Guwahati,India
aecritu7@gmail.com

Abstract —In this study, we propose to use a Long Short Term Memory (LSTM) to forecast stock price and subsequently investigate the model's defenses against epochs and batch size. Stock market is a trading and investing alternative. Predicting the stock price for the future is a very sensitive process. Knowing the future price, or the unborn price, is useful for investors and dealers so they can enter and exit the market at the appropriate time and price. New algorithms and machine learning fared reasonably well in this, despite the fact that there are numerous ways to estimate unborn or future prices. In this investigation, a new stock price forecasting framework and exercising model are provided. i.e. model for long-short-term memory (LSTM). The Root Mean Square Error (RMSE) for LSTM was assessed by altering the number of iterations, architectures, and different units used in the unseen layers in order to generate a more a reliable model that can be applied read future or unborn stock values. The computation results show that our proposed strategy can accurately predict future market trends by applying the LSTM with the right hyperactive parameter adjustment. It can be anticipated that this model can be used in real time stock market prediction.

Keywords—LSTM, Machine learning, Stock prices, prediction, Artificial Intelligence, RMSE

I. INTRODUCTION

A time series is a list of events over obeyed commands over a specific time frame. A multivariate time series is made up of the values that several variables take at the same periodic time cases throughout a period, as opposed to a uninvariate time series, which is made up of the values that one variable takes at periodic time cases over a period. The variation in temperature throughout the day, week, month, or time is the most basic example of a time series that every one of us encounters on a daily basis. A helpful perception of how a variable changes over time or how it is influenced by changes in the values of other variables can be obtained through the analysis of temporal data(s). Artificial intelligence has many uses for this relationship between a variable's current value and other variables, which can be examined for time series forecasting. Undoubtedly, the financial sector is unstable because stock prices are always fluctuating. With the use of current technology, namely the integration of financial analysis and machine learning techniques, this volatility may be comprehended and resolved [1].The stock market has a reputation for being unpredictable, random, and volatile. It's a chaotic area with a possible vast frequently changing flood of data which does anticipating and acting on such forecasts to create a profit veritably challenging. In fact, it's among the most difficult challenges in predicting time series. This design's utmost objective is to investigate and implement machine learning methods in order to the financial markets to lower investment risk and boost profit.

The major objective of this project is to research and use machine learning techniques in the stock or financial market to forecast the stock behaviour and then accept those recommendations to reduce investment hazard and make money. Machine learning will be used to accomplish the aim in order to benefit from neural network models that have already been constructed. After then, predictions are compared to actual historical stock price data. As for time series forecasting, where the LSTM model is unquestionably the best fit, this project will cover a straightforward an illustration of the best model.

Time series forecasting is now a particularly demanding topic of research because the huge potential it has in several applications, including stock price forecasting, business planning, weather forecasting, resource allocation, and many more. Although supervised regression issues may be thought of as a subset of prediction problems, specific techniques are necessary because of the idea of perceptions in the actual world. Popular time series forecasting methods include Autoregressive (AR), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA) [2] [3] [4]. It is common to discuss and view various stock market researches as a unique type of time series. Some significant patterns cannot be accurately identified using traditional methods that depend on linear regression strategies because of the complexity of time series models. A sizable portion of the time series display nonlinearity when these models are used [5]. It is also challenging to anticipate or estimate the amount of money exchanged without more trustworthy and extraordinary nonlinear displaying approaches [6] [7].

II. LITERATURE REVIEW

Due of the considerable financial advantages, stock price forecasting has drawn scholars' attention for a long time. The most often used system among the several types of procedures now being used is the Artificial Neural Network (ANN) created by Verma et al. [7]. The over-fitting problem mostly affects ANNs. An approach to this over fitting issue is to employ Support Vector Machines (SVMs) [8]. Usmani et al. advise that the day's closing be the major focus of this inquiry in order to forecast the trajectory of the Stock Exchange of Karachi (KSE) [9]. To forecast stock prices, they used antiquated statistical models like ARIMA and SMA. Additionally, various machine learning architectures are also employed, such as the MLP, SLP, and RBF (Radial

Basis Function) (Multi Layer Perceptron), and SVM (Support Vector Machine). The MLP algorithm performed better when compared with other methods [9]. Different time series forecasting applications also used the LSTM model. A methodology for forecasting parking spaces using an LSTM model was introduced by Shao et al. [10]. With the use of the present vehicle's trajectory and an encoder decoder LSTM model, Seong et al. [11] were able to forecast the future trajectory of the nearby automobiles' movements. Traffic flow was predicted by Rui et al. [12] using neural network methods such as LSTM and GRU. A flexible yet reliable statistical model was created [13] by Salman et al. to predict the weather around an airport in Indonesia. Using single and multiple layers of LSTM, they also looked into how the weather affected takeoff and departure for flights. An architecture incorporating LSTM and GRU is also described in order to properly predict the future load of the Virtual Machines (VMs) of the cloud [14].

III. METHODOLOGY

Long short term memory, or LSTM, is a kind of neural network, is particularly helpful when predicting time series. An LSTM network produces the best time series analysis and stock request prediction results, according to the composition of LSTMs and the fundamentals of deep learning Long Short Term Memory networks have been shown to be the best solution for almost all of these sequence prediction challenges given the latest innovations in data wisdom. LSTMs outperform intermittent neural networks and conventional feed-forward neural networks in many instances.

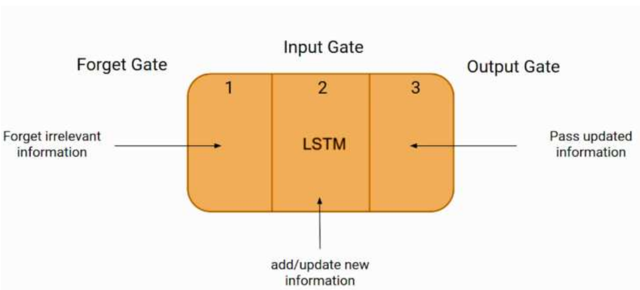

Fig.1. Simplified view of the LSTM cell

For a basic neural network, adding new information requires entirely transforming the existing information by using the sigmoid function. As a result, the entire body of information is altered. As a result, the distinction between "important" and "not so important" information is not taken into account. On the other hand, LSTMs add and multiply information in modest ways, changing it little. Information travels through the cell state medium in LSTMs. In this manner, LSTMs can extensively forget or flash back consequences.

An LSTM network's internal armature is shown in more depth in the accompanying figure:

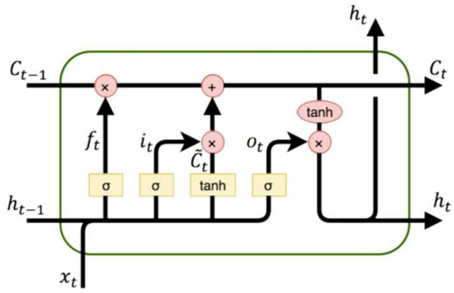

Fig.2. LSTM Architecture

A standard LSTM network is made up of numerous memory cells. The cell state and the hidden or concealed state are the two states that are being transferred to the new cell. The adjustments to this memory are made using three fundamental mechanisms known as gates, and the memory blocks are in charge of producing flashback effects:

A. Forget Gate

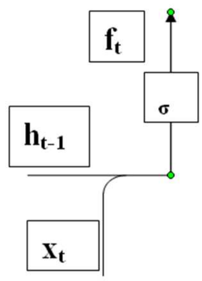

Fig.3. Forget Gate, Internal Architecture

Information from the cell state is eliminated by a forget gate. Information that is less important or no longer necessary for the LSTM function to interpret effects is eliminated. H_{t-1} and x_t are this gate's two inputs. The output of the previous cell, h_{t-1}, is the hidden state from that cell, and x_t is the input at that specific time step. Before a bias is applied, the weight matrices are multiplied by the inputs. Afterwards, this value is subjected to the sigmoid function. The sigmoid function yields a vector having values in the 0 to 1 range, one for each digit in the state of the cell. Most of the time, the sigmoid function determines which values to preserve and which to throw away. If a "0" is given for a particular value in the cell state, the forget gate wants the cell state to completely forget that piece of information. The forget gate wants to flash back the complete piece of information, which is indicated by a "1" as well. The sigmoid function's output vector is included in the cell's state.

B. Input Gate

The input gate is in tasked of upgrading the cell's state with new information. The three components that make up this information addition are depicted in the figure below.

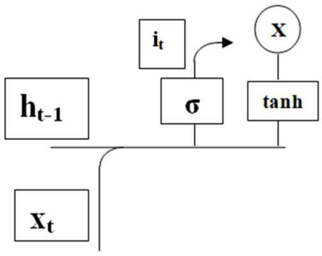

Fig.4. Input Gate, Internal Architecture

1. Control beyond such values should be incorporated applying the sigmoid function to the state of the cell. This provides as a screen for all the data from h_{t-1} and x_t and is essentially the forget gate's predecessor.

2. Generating a vector that includes all possible adjustments to the cell state (as determined by h_{t-1} and x_t). This is achieved by using the tanh function, which operates on numbers between -1 and 1.

3. Multiplying the value of the nonsupervisory cell (the sigmoid gate) by the created vector as well as adding this critical information to the cell state through addition operations (the tanh function). After completing these three steps, we make sure that only the most vital information is sent to the cell state.

4. Once the previous three processes have been completed, we ensure that the cell state only includes information that is required and not irrelevant.

C. Output Gate

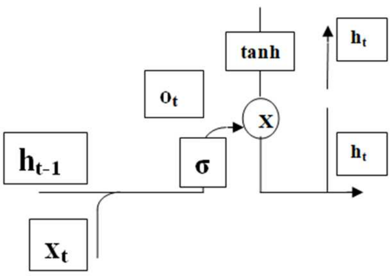

Fig.5. Output Gate, Internal Architecture

The output gate is responsible for choosing pertinent data from the current cell state and displaying it as an output. The operation of an output gate may once more be divided into three ways:

1. Through using tanh function to disperse the values of the cell state over a range of -1 to 1, we can produce a vector.

2. Constructing a cell with values of h_{t-1} and $x_t$to allow it to generate the values that must be collected from the vector produced over. Once more, this filter makes use of the sigmoid function.

3. The vector created in step 1 is multiplied by the value of this nonsupervisory cell before being delivered as an output and to the subsequent suppressed state of the cell.

D. Working model

Our proposed model has 100 epochs with batch size of 32 and a sequential unit of 50 with dropout of 0.2

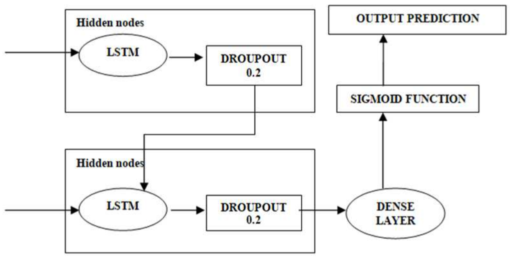

Fig.6. Working LSTM internal model

IV. MODELLING STUDY SETUP AND RESULT ANALYSIS

A. Dataset

The raw data is gathered from publicly accessible historical stock prices for Tata. We select the values from the data for the first and second columns ("Open" and "High," respectively) to serve as our training dataset. The "High" column displays the price at which shares finally closed, whereas the "Open" column displays the price at which shares opened on that specific day. Here, we predict using an adjusted opening value. The ultimate output value that the machine learning model will project is called the Adjusted Open Value.

The information includes historical stock price information for prominent company, like TATA Global [17].

B. Proposed Work

Below is the proposed algorithm.

Step 1 Importing the Repository

Step 2 Displaying the data used to estimate the stock market

Step 3 Using the DataFrame shape to publish a check for null values.

Step 4 Configuring the Goal Parameter and Choosing the Features

Step 5 Create a training set and a test set to make predictions about the stock market

Step 6 Market Projected for Stocks LSTM Model development blocks

Step 7 The Mechanism for Predicting the Stock Market Training

Step 8 Prediction

Step 9 Acclimated near Value comparison between unborn or projected and real - LSTM

C. System Flow Diagram

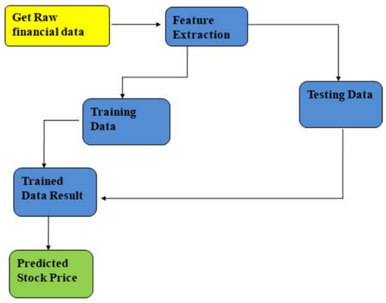

Fig.7. System Flow Diagram

V. EXPERIMENTAL RESULT

We can see that the model did a good job of fitting both the training and the test datasets.

The figure below shows predicting model. Here the blue colour bar indicating the real stock prices of TATA Global whereas for the red colour bar indicating the predicted stock prices of TATA Global for a week.

The graph below showing real stock prices v/s predicted stock prices.

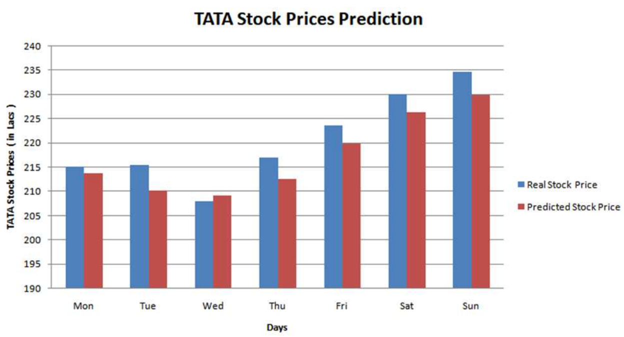

Fig.8. Real v/s Predicted TATA Stock Price

Here we can see in the table the arrangement of real & predicted values that we got from running the LSTM model.

TABLE I
Showing arrangement of real and predicted stock prices

Days	Real stock prices (in lacs)	Predicted stock prices (in lacs)
Mon	215	213.766
Tue	215.5	210.122
Wed	208	209.218
Thu	217	212.474
Fri	223.5	219.909
Sat	230	226.319
Sun	234.55	229.746

TABLE II
Comparison of the result with the recent report established

Sl.No.	Model	Dataset	Accuracy
1	KNN [18]	Amazon stock price	65.56%
2	Linear Regression [19]	Gold price	95%
3	ANN [20]	Stock price of Shenzhen company	66.1%
4	LSTM (Proposed model)	TATA Global stock price	75%

VI. CONCLUSION

Thanks to machine learning and its potent algorithms, contemporary advancements in request research and stock predicting the market has started to include comparable techniques for analyzing stock market data. Because the data was obtained from the internet, the forecasts are based on fact. The predictions were almost 75% accurate. From the fig.6. We found that on starting of week i.e. Monday the prices tends to fall and then it slows a slow rise from Friday to the weekend [15]. Stock returns on Mondays are frequently much lower than those of the previous Friday due to a phenomenon known as the weekend effect in the financial markets [16]. The accuracy of the forecasts can be improved through better data processing or the use of alternative techniques.

VII. FUTURE SCOPE

Machine learning solves a variety of issues. Machine learning tackles a variety of issues. In reality, machine learning has the potential to automate or improve almost every industry. The following are the areas where future work can be conducted on:

1. The effectiveness of this model can be experimented on various financial datasets of different organizations in future.
2. Including features and evaluating model performance with technical analysis.
3. Including elements from basic analysis and examining their effects on the mode.
4. Including sentiment analysis from social media, such as Twitter, and a new report to assess model performance.
5. To test the performance, the GRU network may also be attempted with other activations, such as a "soft sign".

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