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Stock Trend Prediction: A Comparative Study using Different Approaches

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***Abstract*—With proper knowledge of any company's stock and insight, one can gain large profits sitting at home. The stock market of a company is a time-series data and stock price prediction is one of the fields where many researchers have gathered interest to predict the stock prices or trends of the future using historical data and technical indicators with high accuracy. A Simple Moving Average is very useful in predicting the future price direction and gives a good assumption about the future price. A good prediction model of a stock's future price will increase the trader's profits. This research proposed a novel model by utilizing the deep learning model, LSTM (Long Short-Term Memory) to predict the stock trend with two different approaches - with and without using a sliding window. The results are then compared and analyzed.**

Keywords—Stock Trend Prediction, LSTM, RNN, ANN

I. INTRODUCTION

Stock price prediction is a domain that attracts many data researchers and data analysts as a good stock prediction can capitulate notable profit. The stock of a company cannot be predicted easily. The stock market is volatile, haywire, and uncertain that operates on non-linear data [1]. The stock price of any given company is very much uncertain. Finding patterns in these stocks is a quite challenging task. The random changes in the stock market are referred to as the random-walk behavior of stock prices with time [2]. This statement holds very much true as there are many uncertain factors such as a country's progress, any natural disasters, or the political status of a country that affect the stock prices.

To predict the stock price based on the available data, some pattern in the stock chart is required to be identified using the raw data or by extracting useful technical indicators. The first step in the prediction of any stock price is to analyze the data. This analysis helps in forming an opinion about the volatility of the stock market. The analysis can be carried out by extracting technical indicators from data. For analysis, two approaches are used: i) Forecasting stock prices using fundamental indicators and ii) Forecasting stock prices using technical indicators. Fundamental analysis usually deals with the cause of the market and it takes all the macroeconomic factors such as the company's growth, the climate, etc. to predict the trend of future stocks. Technical analysis uses stock charts to analyze the patterns in the stock prices that are usually derived from the raw data using mathematical formulas. After analyzing the data various linear and non-linear models are being used to predict the data like ARIMA (Auto-Regressive Integrated Moving Average) and ANNs (Artificial Neural Networks).

Artificial Neural Networks (ANN) like RNN (Recurrent Neural Network), CNN (Convolutional Neural Network), and LSTM (Long Short Term Memory) are commonly used for stock price prediction [3]. ANN was inspired by the function of the human brain and implemented as a complex network of neurons. In [4], the authors proposed a fusion model to implement HMM (Hidden Markov Model), ANN, and GA (Genetic Algorithms) for predicting stock prices. These models are widely used in the areas like Image Processing, Natural Language Processing, Time Series Analysis, etc. Over-fitting and under-fitting of data is a big problem when using the ANN model for stock price prediction [5]. ANNs are very useful for short-term forecasting. While the non-linear model is a better choice to predict stocks, many factual researchers had shown that non-linear models might not outperform linear models every time [6] [7] [8]. Recently in [9], the authors carried out a comparison between the linear model and the nonlinear model and computed the accuracy, which proved how the nonlinear model outperformed the linear model. The linear model in the comparison was ARIMA whereas the nonlinear model was GRU (Gated Recurrent Unit) and LSTM in which the LSTM outperformed every other model. Also, in [10], researchers predicted the effect of demonetization on the stocks of Indian companies such as CNX and NIFTY50. ANNs were used to predict the future values of these stocks. In [11], the authors used Deep learning models to predict the stock price movement and analyzed the accuracy of many models such as LSTM, CNN, RNN, and many other nonlinear models. Moreover, in [12], a comparison among SVM, backpropagation, and LSTM was done and the accuracy was also analyzed.

In this work, a comparative analysis of two different approaches for time series forecasting using LSTM, with and without a sliding window approach, is presented. Sliding window approach predicts F(t+1) values considering the values of F(t), F(t-1), F(t-2) etc. A similar idea is also discussed in [13]. In our work, a comparison of the LSTM model with and without the sliding window approach is carried out which shows how without using any sliding window approach better results can be obtained compared to the model which uses the sliding window approach. LSTM is used to predict the future prices for both models. LSTM was first proposed in [14] by Felix Gers and his advisers Jurgen Schmidhuber and Fred Cummins who introduced the forget gate to deal with the vanishing gradient problem. LSTM is one of the most important models because of the introduction of the forgetting gate and memory cells. In this model, the information flows through a mechanism known as cell states. Due to the memory cells, LSTM selects and remembers or forgets things according to their importance. Therefore, LSTM can learn and identify patterns of data dynamically with time and produce huge prediction accuracy. As described in [14], the authors first used LSTM for time series forecasting long back in 2002 which is analyzed in [15]. Inspired by [16], we carried out a comparison among LSTM, RNN, and CNN using the sliding window approach.

II. PROPOSED METHOD

For the prediction of the stock market, it is required to deal with a huge amount of data that is historical as well as nonlinear [17] [18]. This high non-linearity imposes the need to find hidden patterns in the given data and analyze them for the prediction of future prices [19]. However, pattern identification based on nonlinear data is a difficult task, and therefore there is a need for a dynamic model that could analyze the data and find all the hidden patterns [20]. ANNs are very useful and capable of finding all the hidden patterns and exploiting the data to predict future prices through self-learning. These Neural networks are very efficient to predict the stock's future prices and therefore are widely used. An approach to predict financial time series data using neural networks was introduced in [21]. This research work has used Long Short-Term Memory (LSTM) as a prediction model to predict the stock price of Netflix using historical data of the past 17 years from https://finance.yahoo.com/.

A. *Data Gathering*

In this work, 17 years of data of Netflix from March 2004 to March 2021 is used. All the data has been collected from https://finance.yahoo.com/ and downloaded under the historical data section. This historical data is used to predict future stock prices using LSTM Architecture.

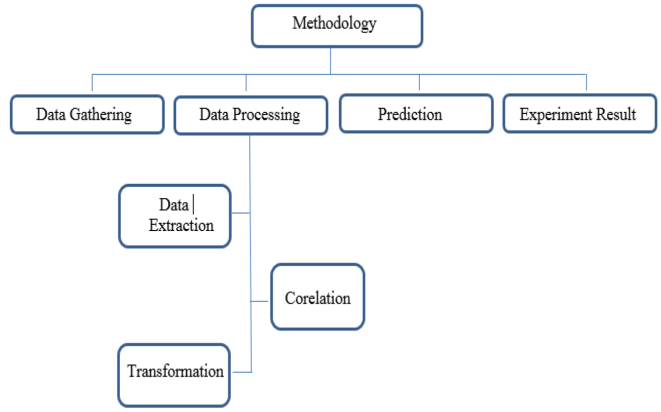

Fig. 1. Flow of Proposed Methodology

B. *Data Processing*

Before training the LSTM model, it is needed to process the data. Processing is done by extracting some of the features from the stock price and normalizing the data.

Simple Moving Average - SMA
Exponential Moving Average - EMA
Triple Exponential Moving Average - TEMA
Kaufman's Adaptive Moving Average - KAMA
Moving Average Convergence/Divergence - MACD
Bollinger Bands %B
Relative Strength Index - RSI
Average True Range - ATR
Chandelier Exit - CE
Chande Momentum Oscillator - CMO
Force Index - FI
Elder ray
Stochastic %k
Stochastic %D
Williams %R
Accumulation Distribution Oscillation - ADO
Commodity Channel Index – CCI

TABLE I. Technical indicators

- ***Feature Extraction***

The historical data gathered was raw unprocessed data with high volatility. Prediction using this raw data is not a good option. Therefore, processing this data is the first task to be carried out by calculating technical indicators [22] [23]. The computation of technical indicators involves the detailed analysis of past market actions for the purpose of forecasting future prices [24] [25]. It helps in forecasting the price directions and the current trends [26] [27]. Some of the technical indicators that are used in this work are listed in Table 1.

- ***Correlation***

After extracting the features, it is required to identify only the features relevant to the selected model. This action is needed to avoid features that are irrelevant, noisy, and redundant to maintain minimal computational time and resources. Hence, only those features are to be selected that are related to the stock prices and the remaining ones can be discarded. The correlation techniques used in this paper are Scatter plotting and calculating Pearson Correlation Coefficient [28] [29].

- ***Scatter Diagram***

The selection of features has been done based on the correlation coefficient value of all the features with the original stock's closing prices. The features with the highest correlation value are selected. Scatter diagram plotting and calculation of Pearson Correlation Coefficient value are done for finding the correlation. A scatter plot is a type of plot or mathematical diagram that uses Cartesian coordinates to display values of typically two variables for a set of data. One variable is plotted on the horizontal axis and the other is plotted on the vertical axis. If the points are coded, one additional variable can be displayed. The scatter diagram for SMA and the closing price of the data are shown in Fig. 2.

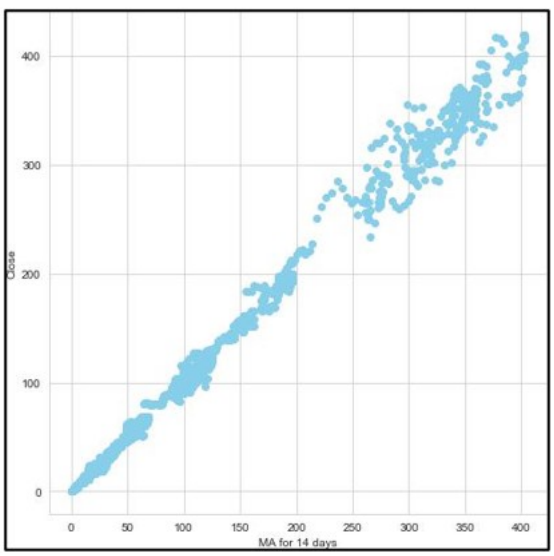

Fig. 2. Scatter Diagram for SMA for 14 days vs Closing prices

- ***Pearson Correlation***

Pearson Correlation gives a numerical response for finding the relationship between different data sets. It assigns a number to the extent of the relation between two data sets. Its value lies from -1 to 1, 1 representing exactly linear relation between two data sets and 0 representing no relation. The formula for calculating the Pearson correlation coefficient is as follows:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

After analyzing the data using Pearson correlation and verifying the same using a scatter diagram, a simple moving average for 14 days has been selected as the parameter for the input of stock prediction for Netflix. An SMA for 14 days of the closing price of a stock is defined as the rolling average of the closing price of the stocks over the last 14 days. The SMA helps in smoothing out the curve which helps in reducing the volatility in the curve. Here, SMA is used for predicting the trend of the direction of prices in the future.

- ***Data Transformation***

After obtaining the best feature, the next thing to do is data transformation. Data transformation is used to normalize the data and make the data stationary, which helps in pattern-finding. Normalization helps improve the convergence of the data. In our work, the data is transformed/mapped in the range of 0 to 1. Once the data set is transformed into a clean data set, it is divided into training and testing sets to evaluate the prediction accuracy of the proposed model. The training set is 95 percent of the total data set and the testing data is the rest of the data (5 percent).

C. *Prediction Models*

This paper presents the implementation of the LSTM architecture and a comparative analysis of two different approaches with and without sliding windows to understand which one performs better. LSTM is introduced to have long termed dependencies and deal with the vanishing gradient problem.

- ***LSTM with Sliding Window Approach***

The model was trained for 40 epochs and a batch size of 60. 60-day sliding window approach was used to predict the future trend. Initially, the number of epochs was 100 and changed accordingly to build a good prediction model. This LSTM model was initialized with an input sequential layer, led by 4 LSTM layers each having neurons lesser than the previous, and then finally a dense output layer with Adam optimizer and loss mean square error.

- ***LSTM without Sliding Window Approach***

The input to the proposed architecture is the moving average of the previous day to predict the next day's moving average. The architecture of this LSTM model is the same as the previous one with 40 epochs and a batch size of 60. Also, the network consists of one input layer with any sliding window. This LSTM model was initialized with an input sequential layer, led by 4 LSTM layers each having neurons lesser than the previous, and then finally a dense output layer with Adam optimizer and loss mean square error.

III. RESULTS AND DISCUSSIONS

Root Mean Square Error (RMSE) method is used to calculate the errors for each model. The parameter setting for both models is given in Table 2.

Value	Parameter
Input	SMA 14
Hidden Layer	4
Optimizer	Adam
Loss Function	mean square error
Epoch	40
Batch Size	60

TABLE II. Parameter setting for both the models

- ***LSTM with Sliding Window Approach***

The result for training and testing data is shown in Fig. 3 and Fig. 4 respectively. The RMSE for training and testing data is shown in Table 3.

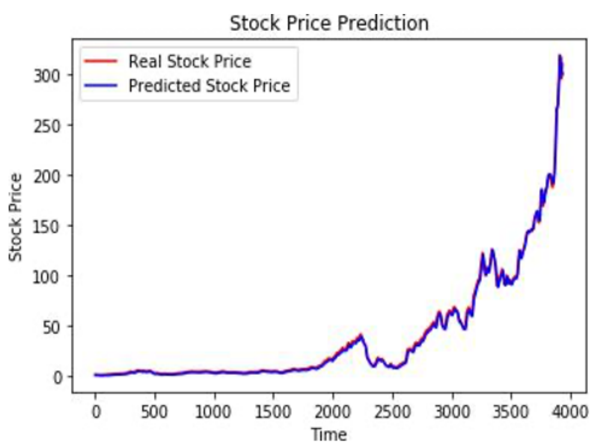

Fig. 3. Result of LSTM with sliding window model for Train data set

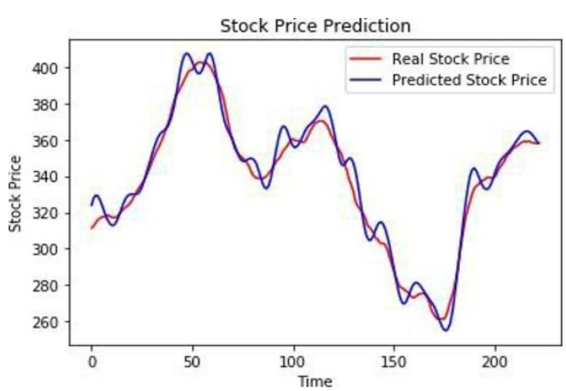

Fig. 4. Result of LSTM with sliding window model for Test data set

Input	RMSE	Size
Train	2.5983	3934
Test	6.3923	223

TABLE III. Result for LSTM with Sliding Window Model

- ***LSTM without Sliding Window Approach***

The result for training and testing data is shown in Fig. 5 and Fig. 6. The RMSE for training and testing data is shown in Table 4.

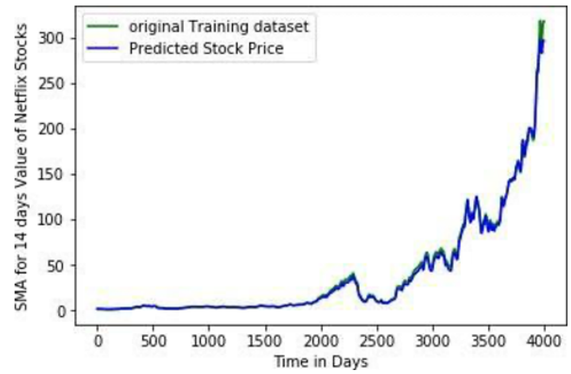

Fig. 5. Result of LSTM without sliding window model for Train data set

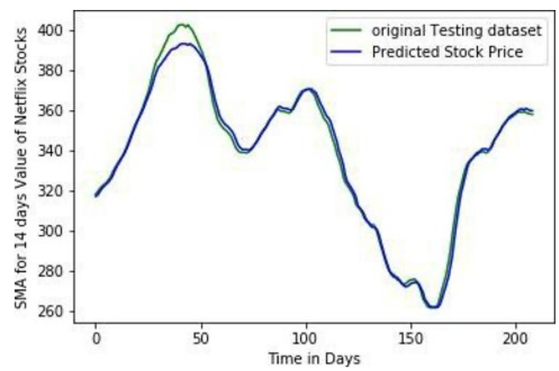

Fig. 6. Result of LSTM without sliding window model for Test data set

Input	RMSE	Size
Train	2.8778	3994
Test	3.5498	211

TABLE IV. Result for LSTM without Sliding Window Model

IV. CONCLUSION

In this work, the prediction of the trend of stocks of Netflix using the Sliding window and without using the Sliding window is done to identify which one performs better. Based on the obtained results, it is clear that the approach without using a sliding window gives better results compared to that with using a sliding window. SMA for 14 days is used as an input parameter for the approaches. From the result analysis, it is evident that forecasting stock prices or trends are highly useful to investors for earning huge profit. The need of predicting future prices or trends of a given stock to produce accurate results motivates the researchers to find new techniques to improve the accuracy of prediction. RNNs like LSTM are very good at processing sequential time series data. LSTM has been proven a very good solution while dealing with sequential data streams. In this work, significantly good results are obtained without using sliding window approach and LSTM architecture to predict the future trend of Netflix stocks by predicting the SMA for the stock.

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