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TS Predictor - An Approach to Analyze and Forecast Time Series

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Abstract: In this work, a methodology has been proposed for analysis & forecasting of time series data. The methodology involves collecting historical stock data, preprocessing the data such as handling of incomplete data, duplicate data, and incorrectly formatted data, dealing with outliers, data normalization to ensure all inputs are on a similar scale, splitting the dataset into training and testing data sets, organize the dataset into sequential pattern. Train the proposed model using training dataset. Finally we have used the test dataset to evaluate the performance of the model. Our proposed model produces better accuracy in prediction when compared to the similar work done in the same field.

Index Terms **- Time series data analysis, data forecasting, training dataset, testing dataset, noise removal, data normalization, sequential pattern, Long short-term memory.**

I. INTRODUCTION

In this proposed model using Long-Short Term memory analysis on time series data has been done. As time series data, stock market data has taken into account for the present study. A time series is a sequence of observations taken at equally spaced points in time say days, weeks, months or years. It is helpful in investigating about changes of an entity over time. Time series analysis is the process of analyzing the time series data collected over a period of time.

In practical world time series data are widely used for forecasting of the upcoming events, by analyzing data over regular intervals. In this proposed work at first a time series data of historical stock market has been collected. Dataset may contain incomplete data, duplicate data, and incorrectly formatted data and outliers. These discrepancies might cause hindrance in producing accurate results. Data cleaning is one of the most important stages in creating an efficient model. Data gathered are passed through the process of data cleaning, before they are utilized into the main architecture.

The heart of the proposed architecture is a Long Short Term Memory based model. This proposed model is very sensitive to the scale of the data. If the proposed model is fit on unscaled data, it is possible for large input to slow down the learning and convergence of the model, even in some cases prevents the model from effectively learning the problem. So MinMax scalar has taken on to the crease to scale the data within range (0, 1). Consequently the data set is split into training and testing data sets, followed byorganization the dataset into sequential pattern. The proposed model is trained using the training dataset formed and finally the trained model is applied on testing dataset to evaluate the performance of the model.

II. PRELIMINARIES

This section deals with some fundamental concepts used for achieving the goal of time series data analysis and forecasting. First one is time series data. A time series is a sequence of observations taken at equally spaced points in time say days, weeks, months or years. It is helpful in investigating about changes of an entity over time. Time series analysis and forecasting is the process of analyzing the time series data collected over a period of time to anticipate upcoming events.

Next the concept of Long Short Term Memory (LSTM) , a variant of Recurrent Neural Network(RNN) has come onto the crease. It has designed to address the vanishing gradient problem is capable to capture complex patterns and dependencies in historical data. Incorporation of memory cells and gates in LSTM, enable it to selectively retain and propagate information over extended time intervals. This uniqueness allows LSTM based models to capture intricate temporal relationships in sequential data, making them particularly well-suited for predicting time series data.

III. METHODOLOGY

The proposed model starts with collecting the historical stock data. To make these collected data suitable for the present algorithm, a procedure of data cleaning is executed to tackle duplicate data, unformatted data, incomplete data and outliers.

Next, the data is normalized to ensure that all inputs are on a similar scale. The procedure of MinMax scalar is incorporated to scale data within range (0, 1) and consequently data are organized into the sequential pattern. The cleaned and normalized dataset are split into training and test sets. In the proposed architecture, we have used first 75% of data for training purpose and the rest25% of the data for testing purpose of the model. The proposed model is designed with LSTM layers and other layers like dense layers for additional processing. We utilize an appropriate loss function and optimizer during the model training. The proposed LSTM based model is next trained with training dataset. We have considered step size as 100, batch size 64 and number of epochs 200. During compilation of the model, we have used Adam optimizer to adjust the parameters of the model to improve the speed and accuracy of the model, mean squared error (MSE) for calculating the loss function. Finally, we have used the test dataset to evaluate the performance of the model. Use the trained model to make prediction on unseen data.

The schematic diagram for the heart of the methodology is as follows:

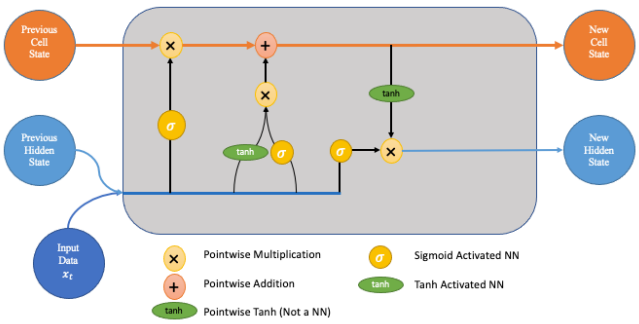

Fig. 1: Proposed Model

IV. RESULTS

For execution of the methodology mentioned above we have considered a machine with specifications 4 GB RAM and INTEL Core i3 Processor. The method been implemented using Python Jupyter Notebook IDE.

We have used here the NSE TATA GLOBAL dataset, which is a dataset of Tata Beverages from Tata Global Beverages Limited. Dataset contains data from 21-07-2010 to 28-09-2018. It contains a total of 2035 records. We have used first 75% of the data for model training purpose and remaining last 25% of the data for testing purpose. We compiled the model with an Adam optimizer, calculating the loss using mean squared error.

Figure 2 shows the snapshot of first 5 rows of the taken dataset.

	Date	Open	High	Low	Last	Close	Total Trade Quantity	Turnover (Lacs)
0	2018-09-28	234.05	235.95	230.20	233.50	233.75	3069914	7162.35
1	2018-09-27	234.55	236.80	231.10	233.80	233.25	5082859	11859.95
2	2018-09-26	240.00	240.00	232.50	235.00	234.25	2240909	5248.60
3	2018-09-25	233.30	236.75	232.00	236.25	236.10	2349368	5503.90
4	2018-09-24	233.55	239.20	230.75	234.00	233.30	3423509	7999.55

Fig. 2: Snapshot of data set

Figure 3 shows the summary of the proposed LSTM based model.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 100, 50)           10400

 lstm_1 (LSTM)               (None, 100, 50)           20200

 lstm_2 (LSTM)               (None, 50)                20200

 dense (Dense)               (None, 1)                 51

=================================================================
Total params: 50,851
Trainable params: 50,851
Non-trainable params: 0
```

Fig. 3: Summary of the model

Mean squared error (MSE) and Mean absolute error (MAE) values calculated for the model are 0.0002096385433105752 and 0.011509445495903492 respectively.

Root mean square error (RMSE) calculated for training data and predicted training data: 166.61411425830292

Root mean square error (RMSE) calculated for test data and predicted test data: 106.8973897846642

As shown both the calculated values are very close. It indicates the model accuracy is very good.

After execution of the proposed methodology on the fed time series data, the following plots have been generated.

Figure 4 shows the generated plot of actual dataset

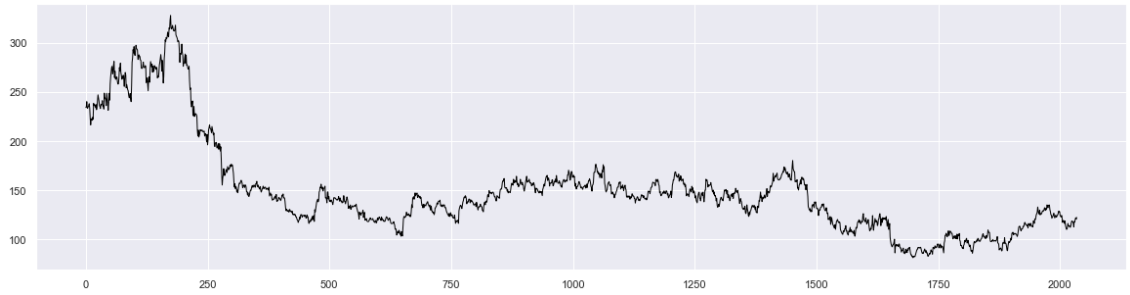

Fig. 4: Plot of actual Dataset

Figure 5 shows the generated plot of predicted training dataset

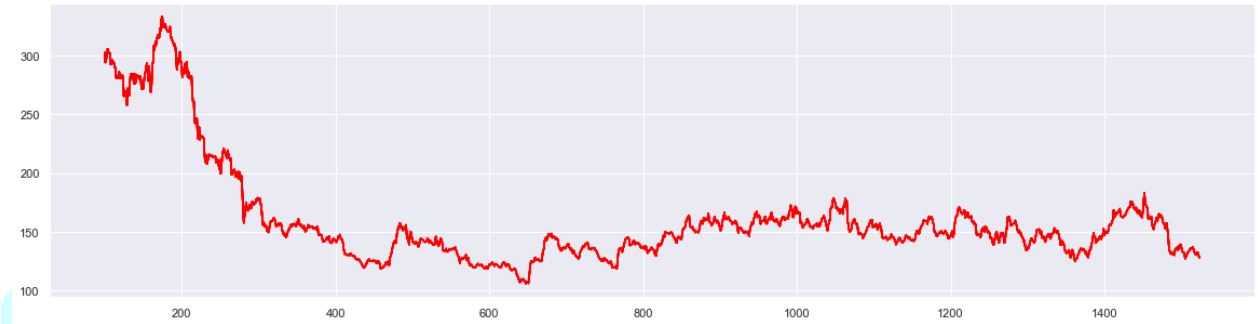

Fig. 5: Plot of predicted training dataset

Figure 6 shows the generated plot of predicted test dataset.

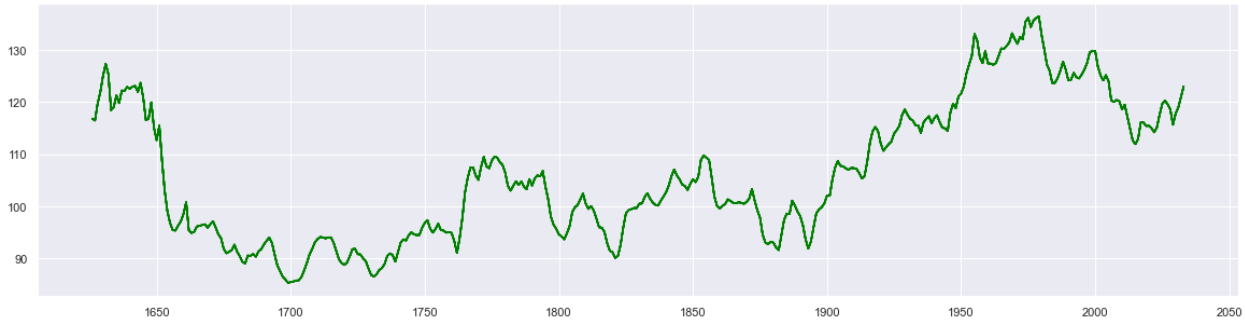

Fig. 6: Plot of predicted test dataset

Figure 7 shows the generated combined plot of predicted training and test dataset.

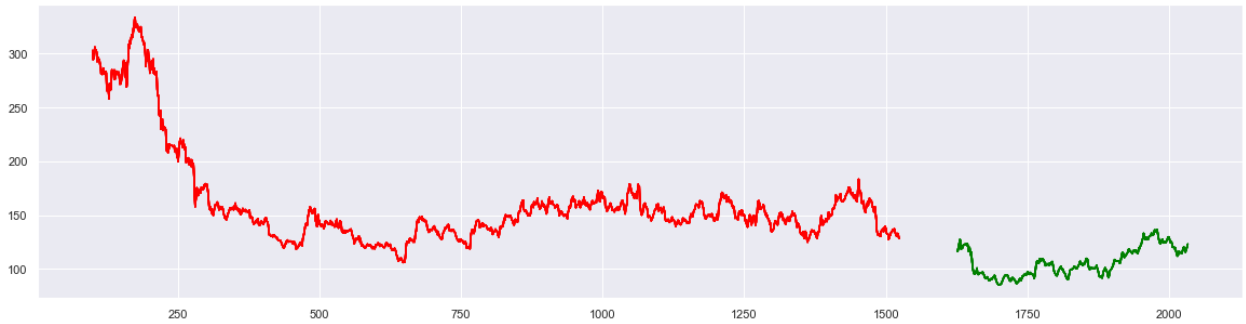

Fig. 7: Plot of combined predicted training (red) and test (green) dataset

Figure 8 shows the generated combined plot of actual , predicted training and test dataset.

Fig 8: Plot of combined actual (black), predicted training (red) and test (green) dataset.

Figure 8 clearly shows that our proposed model has predicted the stock open price very well.

V. CONCLUSIONS

This proposed Long Short-Term Memory based model works very efficiently for analyzing and forecasting the time series data. Deep learning power of LSTM unlocks insights into the unpredictable nature of the time series data. It overcomes the limitations of traditional RNN by incorporating memory cells and gates. The Incorporation of data cleaning makes it an efficient model, data normalization process makes learning and convergence of the model much faster for larger input sequence.

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