STOCK PREDICTION USING LSTM TECHNIQUE

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ABSTRACT

We attempt to use a machine learning approach to anticipate stock prices in this project. When it comes to stock price predictions, machine learning works well. The goal is to forecast future stock prices. make more accurate and better investment decisions We propose incorporating mathematical functions into stock prices. To arrive at an acceptable timescale, examine the prediction system, machine learning, and other external factors. delivers accurate stock predictions and lucrative trades There are some There are two types of stocks. Day trading is another name for intraday trading. The phrase "day trading" was thrown around. Interday traders invest in a diverse range of assets. at least one day after another, and frequently for several days or weeks, LSTMs are quite effective in solving sequence prediction problems. because they may store information from the past.

Keywords— Stock Price Prediction, LSTM, Neural Network, RNN, SVR

1. INTRODUCTION

We've all heard the term stock, without a doubt. Stock, in particular, is linked to partners and organisations that have become well-known and are settling into the marketization cosmos. The second word for the stock is share, which is commonly used in ordinary conversation. It's even referred to as a growth plan, and it's something that people perceive to be a long-term investment that generates and distributes abundant assets during retirement. A successful stock forecast can result in large gains for both the seller and the broker. Prediction is sometimes described as chaotic rather than random, meaning that it can be predicted by studying the history of the relevant stock market. Artificial intelligence in the form of machine learning

The dataset used in machine learning is crucial. The data source Because a small modification in the data might produce large changes in the conclusion, it should be as specific as possible. This project entails On a dataset collected, supervised machine learning is used. Yahoo Finance is a search engine for financial information. The following five variables make up this dataset: open, close, low, high, and volume are all options. The terms open, close, low, and high are used. multiple stock bid prices at different periods with virtually direct names. The volume is the number of shares that have passed from one person to another. During the historical period, one owner to another. The model is then put to the test. the test results For this, regression and LSTM models are used. separate speculation The goal of regression is to reduce error, and LSTM helps with that. helps you recall things

2. Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM)

Long Short Term Memory (LSTM) is one of several types of RNNs, which can also collect data from past stages and use it for future prediction [7]. In general, an artificial neural network (ANN) consists of three layers:

1). input layer

2). Hidden layers

3).output layer

dimension of the data, the nodes of the input layer connect to the hidden layer via links called 'synapses'. The relation between every two nodes from (input to the hidden layer), has a coefficient called weight, which is the decision-maker for signals. The process of learning is naturally a continuous adjustment of weights, after completing the process of learning, the Artificial NN will have optimal weights for each synapse. The hidden layer nodes apply a sigmoid or tangent hyperbolic (tanh) function on the sum of weights coming from the input layer which is called the activation function, this transformation will generate values, with a minimized error rate between the train and test data using the SoftMax function.

The values obtained after this transformation constitute the output layer of our NN, these values may not be the best output, in this case, a backpropagation process will be applied to target the optimal value of error, and the backpropagation process connects the output layer to the hidden layer, sending a signal conforming the best weight with

the optimal error for the number of epochs decided. This process will be repeated trying to improve our predictions and minimize the prediction error.After completing this process, the model will be trained. The class of NN that predict future value based on the passed sequence of observations is called Recurrent Neural Network (RNN) this type of NN makes use of earlier stages to learn data and forecast future trends. The earlier stages of data should be remembered to predict and guess future values, in this case, the hidden layer act as a stock for the past information from the sequential data. The term recurrent is used to describe the process of using elements of earlier sequences to forecast future data. Since RNNs cannot store long-term memories, the use of long-term memory (LSTM) based on " memory strings" has proven to be very useful for predicting when long-term data is present. In LSTM, the memorization of the previous step can be performed through the gate with the memory line active. This diagram illustrates aLSTM node configuration

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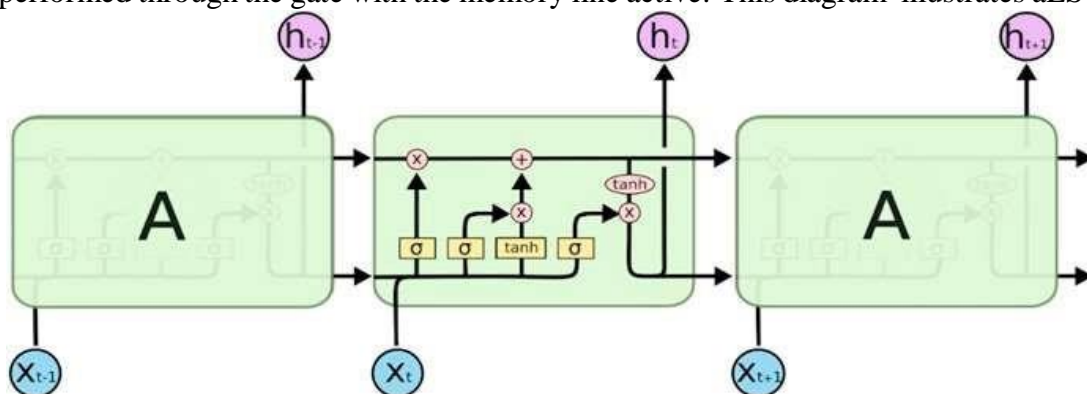
The ability to memorize the sequence of data makes the LSTM a special kind of RNN. Every LSTM node must be consisting of a set of cells responsible for storing passed data streams, the upper line in each cell links the models as a transport line handing over data from the past to the present ones, and the independence of cells helps the model dispose filter of add values of a cell to another. In the end, the sigmoidal neural network layer composing the gates drive the cell to an optimal value by disposing or letting data pass through. Each sigmoid layer has a binary value (0 or 1) with 0 "let nothing pass through"; and 1 "let everything pass through." The goal here is to control the state of each cell, the gates are controlled as follow: Forget Gate outputs a number between 0 and 1, where 1 illustrates "completely keep this"; whereas, 0 indicates "completely ignore this." Memory Gate chooses which new data will be stored in the cell. First, a sigmoid

layer "input door layer" chooses which values will be changed. Next, a tanh layer makes a vector of new candidate values that could be added to the state. The output gate determines the output of each cell. The output value is based on the status of the cell with the filtered and most recently added data.

3. Methodology and data

The data in this article consists of the daily market prices of two stocks on the New York Stock Exchange NYSE (GOOGL and TSLA) obtained from Yahoo Finance. For GOOGL, the data series covers the period from January 1, 2005, to May 10, 2022, and for TSLA, the data series covers the period from January 1, 2005, to May 10, 2022. To build our model we will use an LSTM RNN. Our model uses 70% of the data for training and 30% of the remaining data for testing. Optimize the model using root mean squared error for training. We also used 4, different epochs (12 epochs, 25 epochs, 50 epochs, and 100 epochs) for the training data, and the model consists of:

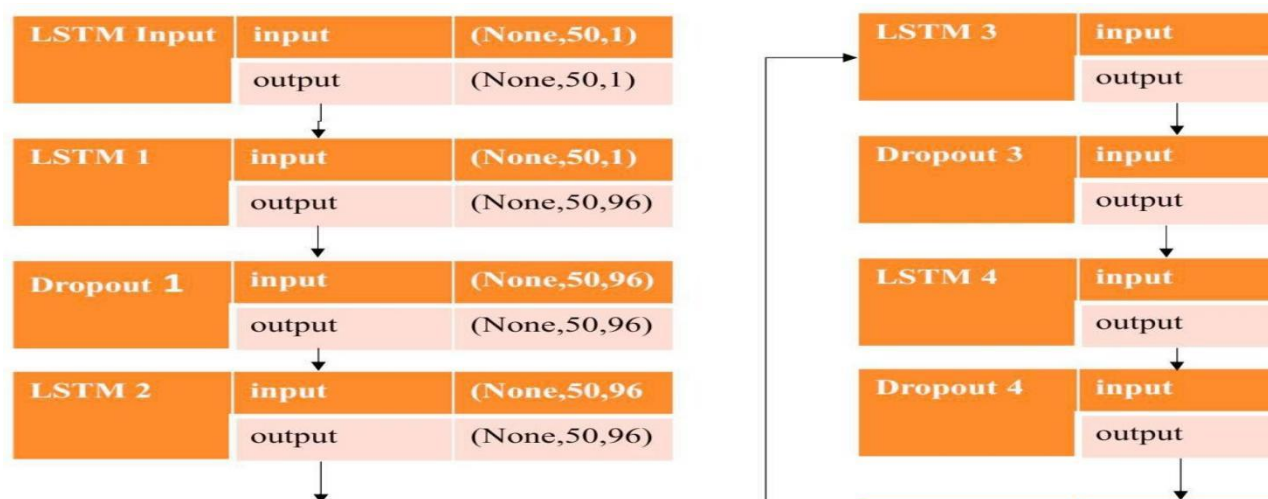| Layer (type)	Output Shape	Parameters
lstm_1 (LSTM)	(None, 50, 96)	37632
dropout_1 (Dropout)	(None, 50, 96)	0
lstm_2 (LSTM)	(None, 50, 96)	74112
dropout_2 (Dropout)	(None, 50, 96)	0
lstm_3 (LSTM)	(None, 50, 96)	74112
dropout_3 (Dropout)	(None, 50, 96)	0
lstm_4 (LSTM)	(None, 96)	74112
dropout_4 (Dropout)	(None, 96)	0
dense_1 (Dense)	(None, 1)	97

Figure 2: the LSTM model structure

4. Result and discussion

After training the NN, the test results showed different results, and the number of epochs and data length significantly affect the test results. For example, if we change the data set for TSLA from January 1, 2005 to May 10, 2022, the result is:
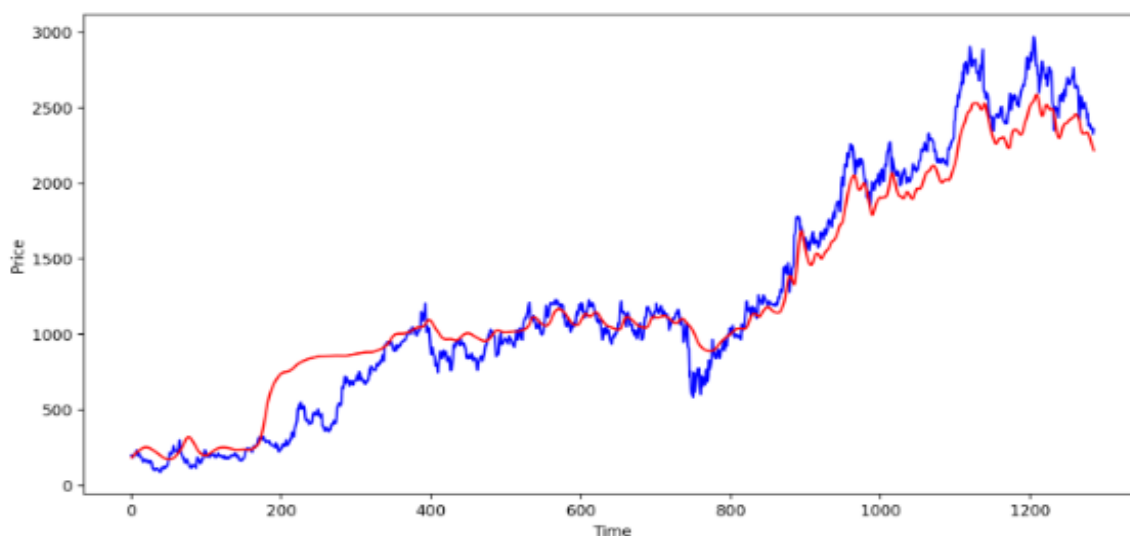

Closing price vs Time chart with 100 days Moving Average
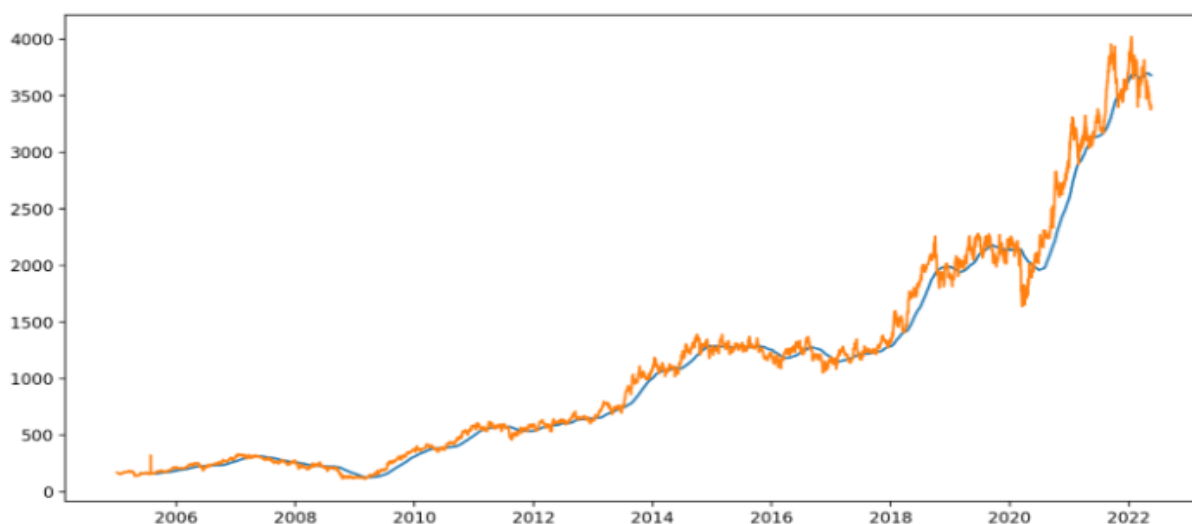
Closing price vs Time chart with 100 Moving Average & 200 days Moving Average

Prediction vs Original

Looking at the data, you can see that initially the data was less volatile and had lower values. In Figure, the Blue line represents the actual market value and the Redline represents the predicted price value after TSLA started peeking. A large value increases the volatility of the asset and changes its characteristics. In our case, it is better to avoid this kind of change. Our model lost its open price tracking over the 600-700 days we tested, consistent with changes in data characteristics.

5. Conclusion

This paper proposes an LSTM-based RNN built to predict the future value of GOOGL and TSLA assets, and the result of our model showed promising results.   The test results confirm that our model can track changes in the open price for both assets. For future work, we will try to find the best set of combat data lengths and the number of training periods that best fit our assets and maximize the accuracy of our predictions.

6. ACKNOWLEDGEMENT

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