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Stock Prediction using Neural Networks and Time Series Analysis Methods

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ABSTRACT
The stock market is considered to be one of the most highly complex financial systems which consist of various components or stocks, the price of which fluctuates greatly with respect to time. Stock market forecasting involves uncovering the market trends with respect to time. All the stock market investors aim to maximize the returns over their investments and minimize the risks associated. There are time series methods such as AR, MA, SARIMAX developed to predict the stock price but neural network methods such as CNN, LSTM also used to predict the stock price. This research paper describes the prediction of stock market using neural network alogorithms and also few time series methods.

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Keywords :- AutoRegressive Integrated Moving Average , AR- Autoregressive, CNN - Convolutional Neural Network, LSTM- Long Short Term Memory, MA- moving average, SARIMAX - Seasonal Autoregressive Integrated moving average.

I. INTRODUCTION

Predicting how the stock market will perform is one of the most difficult things to do. There are so many factors involved in the. All these aspects combine to make share prices volatile and very difficult to predict with a high degree of accuracy. For this, we can use machine learning algorithms as well as time series methods. In this paper, we will go through convolutional neural networks, long short term memory along with few time series analysis methods.

Machine learning has significant applications in the stock price prediction. Stock market is having a highly fluctuating and non-linear time series data. A time series is a set of data measured over time to acquire the status of some activity . Linear models like AR, ARMA, ARIMA have been used for stock market forecasting. The only problem with these models are, that they work only for a particular time series data, i.e the model identified for a particular company won't perform well for another. Due to the equivocal and unforeseeable nature of stock market, stock market forecasting takes higher risk compared to other sectors. It is one of the most important reason for the difficulty in stock market prediction. Here is where the application of deep-learning models in financial forecasting comes in. Deep neural network got its name due to the use of neural network architecture in DL models.

For the stock market, its volatility is complicated and nonlinear. It is obviously unreliable and inefficient to rely solely on a trader's personal experience and intuition for analysis and judgment. People need an intelligent, scientific, and effective research method to direct stock trading. With the rapid development of artificial intelligence, the application of deep learning in predicting stock prices has become a research hotspot. The neural network in deep learning has become a popular predictor due to its good nonlinear approximation ability and adaptive self-learning. Long short-term memory (LSTM) neural networks, Convolution neural network.

A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial in nature. Neural networks can adapt to changing input; so the network generates the best possible result without needing to redesign the output criteria. Stock prediction data is a time series data. Time series data is a collection of quantities that are assembled over even intervals in time and are ordered chronologically.

The time interval at which data is collected is generally referred as the time series frequency. A time series is a sequence of information that attaches a time to each value. The values can be pretty much anything measurable that depends on time in some way, like prices, humidity, or a number of people. As long as the values recorded are unambiguous, any medium can be measured with time series.

Due to the nonstationary, nonlinear, high-noise characteristics of financial time series,[1] traditional statistical models have difficulty predicting them with high precision. Although there are still some difficulties and problems in financial predictions using deep learning, people hope to establish a reliable stock market forecasting model.[2] Increased attempts are being made to apply deep learning to stock market forecasts. In 2014, Wanjawa et al. [3] proposed an artificial neural network using a feed-forward multilayer perceptron with error backpropagation to predict stock prices. The results show that the model can predict a typical stock market. There have been many recent studies on the application of LSTM neural networks to the stock market. A hybrid model of generalized autoregressive conditional heteroskedasticity (GARCH) combined with LSTM was proposed to predict stock price fluctuations.CNN was used to develop a quantitative stock selection strategy to determine stock trends and then predict stock prices using LSTM to promote a hybrid neural network model for quantitative timing strategies to increase profits[4].

Classical time series forecasting methods may be focused on linear relationships, nevertheless, they are sophisticated and perform well on a wide range of problems, assuming that your data is suitably prepared and the method is well configured.

II. METHODS AND MATERIAL

A. Long Short Term Memory Neural Network

Long short-term memory (LSTM) is an artificial recurrent neural network(RNN) architecture[1] used in the field of deep learning. Unlike standard feed forward neural networks LSTM has feedback connections. It can not only process single data points (such as images), but also entire sequences of data (such as speech or video). For example, LSTM is applicable to tasks such as unsegmented, connected and anomaly detection in network traffic or IDSs (intrusion detection systems).

A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell.

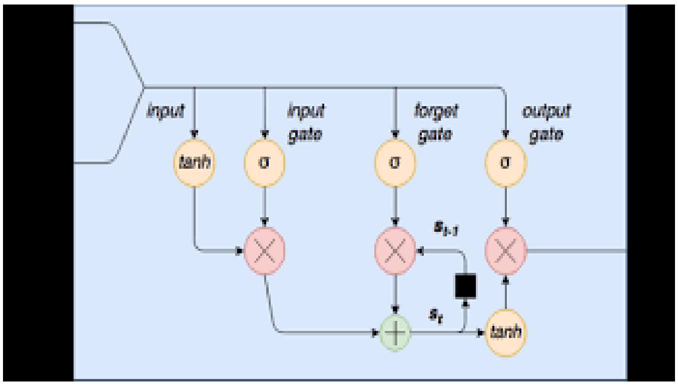

Fig 1 : Long Short Term Memory

The input gate determines how much of the current time network input is reserved into the cell state, which prevents insignificant content from entering the memory cells. It has two functions. One is to find the state of the cell that must be updated; the value to be updated is selected by the sigmoid layer. The other is to update the information to be updated to the cell state. A new candidate vector is created through the tanh layer to control how much new information is added. Finally is used to update the cell state of the memory cells.

The output gate controls how much of the current cell state is discarded. The output information is first determined by a sigmoid layer, and then the cell state is processed by tanh and multiplied by the output of the sigmoid layer to obtain the final output portion. The final output value of the cell is defined as:

$$h_t = O_t * \tanh(C_t).$$

B. Convolutional Neural Network

Convolutional Neural Network is a class of deep neural networks, most commonly applied to analyzing visual imagery. CNN is a regularised version of multilayer perceptrons. They contain the input layer, hidden layer, and output layer. The hidden layer can be one or more than one. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "fully-connectedness" of these networks makes them prone to overfitting data. Typical ways of regularization include adding some form of magnitude measurement of weights to the loss function.

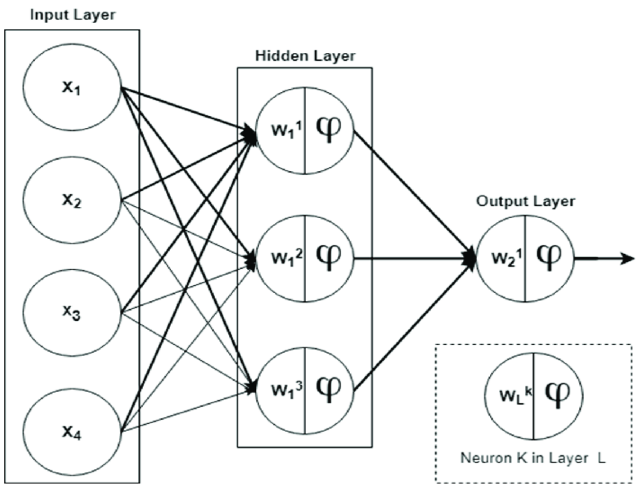

Fig 2 : Convolutional Neural Network

CNN take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns. Therefore, on the scale of connectedness and complexity, CNNs are on the lower extremity.

For time series analysis, 1D convolutional neural network is used to get result in this paper.

C. AutoRegressive Integrated Moving Average(ARIMA)

An autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. This model is fitted to time series data either to better understand the data or to predict future points in the series (forecasting). ARIMA models are applied in some cases where data show evidence of non-stationarity, where an initial differencing step (corresponding to the integrated part of the model) can be applied one or more times to eliminate the non-stationarity.

The AR part of ARIMA indicates that the evolving variable of interest is regressed on its own lagged (i.e., prior) values. The MA part indicates that the regression error is actually a linear combination of error terms whose values occurred contemporaneously and at various times in the past.

ARMA (p,q):

$$\phi(B)X_t = \psi(B)\varepsilon_t$$

ARIMA (p,d,q):

$$\phi(B)(1-B)^d X_t = \psi(B)\varepsilon_t; \quad d \in Z_+$$

fractional ARIMA (p,d,q): $d \in \left\langle -\frac{1}{2}; \frac{1}{2} \right\rangle$

$$(1-B)^d = \sum_{k=0}^{\infty} \binom{d}{k} (-1)^k B^k$$

Fig: Equations of ARIMA

Where, p is pacf value, q is acf value, d is difference.

The performance of ARIMA is calculated by Root Mean Squared Error(RMSE). The lesser the RMSE value the more accurate the prediction.

D.Holt Linear Method

Holt's two-parameter model, also known as linear exponential smoothing, is a popular smoothing model for forecasting data with trend. Holt's model has three separate equations that work together to generate a final forecast. The first is a basic smoothing equation that directly adjusts the last smoothed value for last period's trend.

The trend itself is updated over time through the second equation, where the trend is expressed as the difference between the last two smoothed values. Finally, the third equation is used to generate the final forecast. Holt's model uses two parameters, one for the overall smoothing and the other for the trend smoothing equation. The method is also called double exponential smoothing or trend-enhanced exponentialsmoothing.

$$\begin{aligned} \text{Forecast equation} \quad & \hat{y}_{t+h|t} = \ell_t + hb_t \\ \text{Level equation} \quad & \ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\ \text{Trend equation} \quad & b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}, \end{aligned}$$

Eq : Holt Linear method

III. RESULTS AND DISCUSSION

Here I have performed the analysis on time series data. For stock prediction used neural networks techniques such as CNN, LSTM, and time series analysis methods such as ARIMA, Holt's linear method.

The dataset initially contains eight columns. Out of eight columns, only two columns are considered to predict the stock which is the date and close values. The dataset is sorted based on the date in ascending order. The starting date is 2013-10-08 whereas the ending date is 2018-10-08. The dataset is split as training and validation data for predicting the result.

For time series analysis data need to be smooth.
To smooth the data I have used moving average smoothing with the window size 20. After smoothing the graph is as shown below:

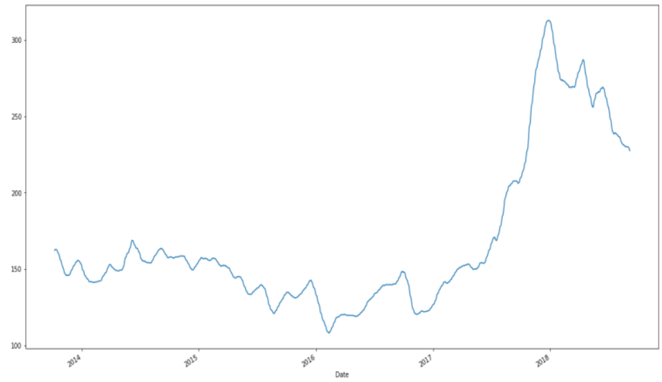

Fig 3 : Smooth data

The above graph looks clearly looks smooth.

The autocorrelation of the data is shown as follows:

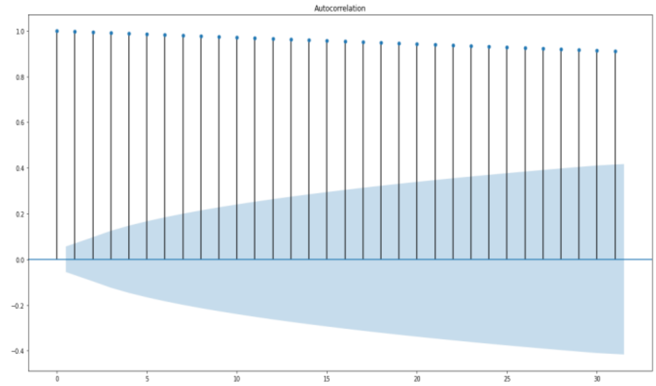

Fig 4 : Autocorrelation

From the above q value is observed as 2.

The Partial autocorrelation for the dataset is as follows:

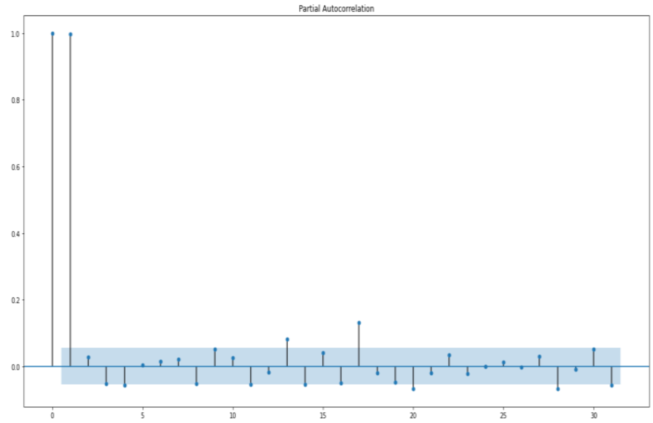

Fig 5: Partial Autocorrelation

From the above p value is observed as 2 and d value is observed as 1.

After applying ARIMA for the training and test data the predictions are plotted in the graph as follows:

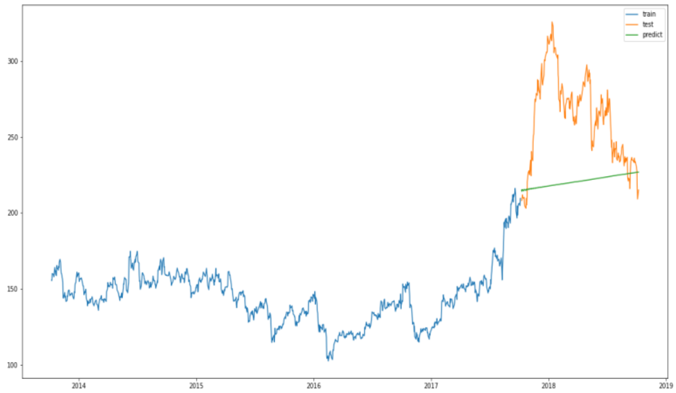

Fig 6: Result of ARIMA

The forecasting values for the Holt's linear model is observed as following:

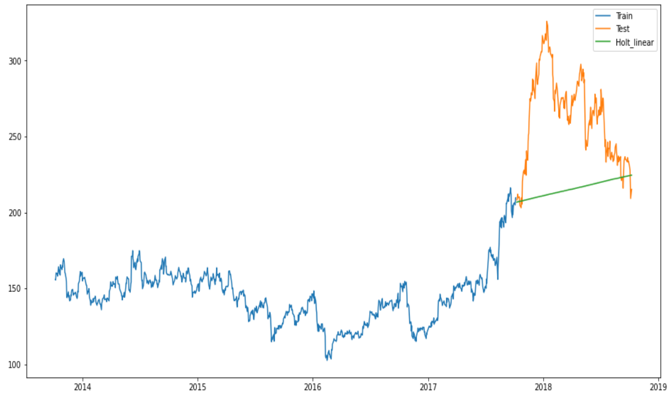

Fig 7 : Result of Holt's linear

The results obtained for ARIMA and Holt's linear model may not differ much for this dataset but they both produces different values for other datasets. Also, they varies with root mean squared error in the dataset i have taken.

The graph for LSTM predicted values is shown as below:

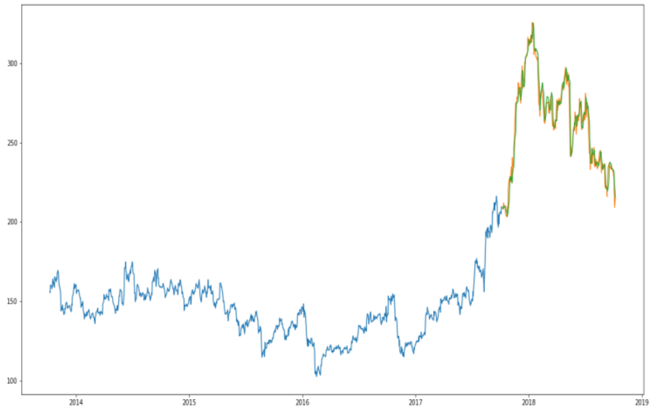

Fig 8: Result of LSTM

The loss used for LSTM is RMSE and optimizer used is adam.

The final neural network used for this dataset is CNN.

The result is as follows:

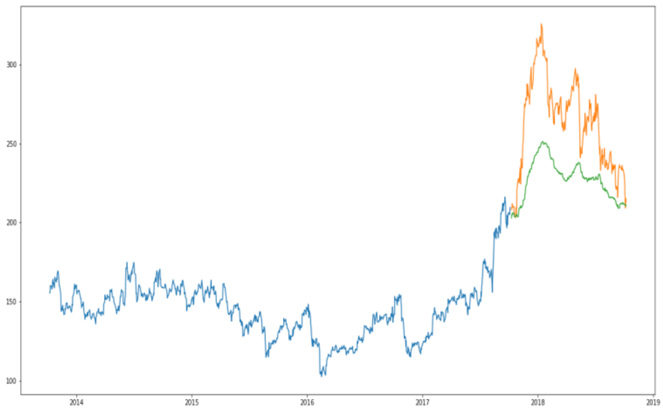

Fig 9 : Result of CNN

For this dataset, CNN result may not be much good but CNN really gives effective result for other time series data.

IV. CONCLUSION

The Root Mean Squared Error obtained for ARIMA model for the dataset taken is 51.245572 where as for Holt's Linear model is 56.000546. The RMSE value differs according to the dataset.

The LSTM and CNN neural networks works good for predicting the time series data. Sometimes, neural networks gives good performance than some time series methods which depends on the dataset taken.

V. REFERENCES

[1]. Bontempi G, Taieb S B, Yann-Aël Le Borgne. Machine learning strategies for time series forecasting[C]// European Business Intelligence Summer School. ULB—Universite Libre de Bruxelles, 2013.8.

[2]. Tay F E H, Cao L. Application of support vector machines in financial time series forecasting[J]. Journal of University of Electronic Science & Technology of China, 2007, 29(4):309–317.

[3]. Wanjawa B W, Muchemi L. ANN Model to Predict Stock Prices at Stock Exchange Markets[J]. Papers, 2014.

[4]. Ha Young Kim,Chang Hyun Won. Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models[J]. Expert Systems With Applications,2018,103.

[5]. Jiang Q, Tang C, Chen C, et al. Stock Price Forecast Based on LSTM Neural Network[J]. 2018.

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