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Stock Market Prediction Using Deep Learning LSTM Model

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***Abstract*- Stock market is well known to all. It is an option for investment and trading. But it is a really difficult thing to predict the future stock price. It is helpful for the investors and traders to know the future price, so that they can enter and exit the market at the right time and right price. Although there are different methods to predict future price, new algorithms and deep learning performed quite well in this. In this paper Long Short Term Memory (LSTM) is used to predict stock price and here we studied the implications of epochs and batch size in the model.**

Keywords- Deep Learning, Long Short-Term Memory, Machine learning, Recurrent Neural Network, Stock prediction

I. INTRODUCTION

Stock price depends on multiple factors. It is basically based on demand and supply. It mainly depends on trends, news, policies, etc. Accurate prediction is very difficult. But it is extremely useful for investors and traders. It is helpful to earn profit. So people usually do the analysis manually. They take the help of charts, market indices, news, etc. But it is not an easy work. Nowadays it is becoming easy to use a huge dataset. These datasets can be from different sources. Machine learning techniques are used and this is proved to generate quite accurate predictions. Different algorithms, like Artificial Neural Network, Deep Learning, Long Short Term Memory are being used. By using these algorithms, now prediction has become more accurate and efficient. In this paper, the main motive is to predict the stock price of a Nifty 50 share. Here, we are using a LSTM deep learning model. Here our main aim is to study how epochs and batch-size influence the model. Here we have taken 2 batch sizes. For each batch size we used 4 epochs and calculated percentage error. Through this, we analysed how batch size and epochs influence a model's performance.

A. Related work

Author A Saini et al., in the paper [1], had compared many methods. These are like Random Forest, Support Vector Machine, Artificial Neural Network, etc. According to them, prediction of stock market was not easy. According to the authors, Long Short term Memory had performed better.

According to the Authors[2], the model had been trained using INFOSYS stock. Selvin et al., proposed a deep learning model. They predicted TCS, CIPLA, INFOSYS stocks. According to them Convolutional Neural Network's performance was good.

According to Authors, Sismanoglu et al. [3], time series is non-linear. This is why it was difficult to predict. Long Short Term Memory was used to predict stocks from NYSE, NASDAQ.

According to Ramesh et al. [4], backpropagation worked well. The authors' proposed model was compared with multiple linear regression model.

Authors Attigeri et al., used big data for prediction [5]. Their techniques used financial news, social media etc.

According to Hiransha et al., model used was trained using RNN, CNN, LSTM, MLP and predicted NSE and NYSE stocks[6].

Nabipore et al. [7], used ANN, RNN, LSTM etc. These were used to forecast stock prices of Tehran stock exchange.

Authors used LSTM to predict GOOGLE and NKE scrips[8].

According to Authors, NN model was used for prediction. Shanghai stock exchange composite index was predicted[9].

II. DEEP LEARNING METHODOLOGIES

A. Recurrent Neural Network

Abbreviated form of Recurrent neural network is RNN. It is a deep learning method.

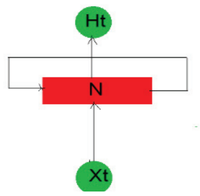


Fig 1: Recurrent neural network

In the above diagram, neural networks denoted as N, input as Xt and output as Ht. Information is passed from one to another. This is a loop. RNN is used for image captioning, speech recognition, etc. This is used for sequences. It has the ability to remember past input. The main disadvantages are exploding gradients and vanishing gradients[10].

B. Long short term memory

It is also known as LSTM. It is capable to remember long term dependencies. It is an extension of RNN. In LSTM cell state performs a great role. The model has the ability to add or remove information in cell state. It is regulated by gates. There are three types of gates.

i. Input gate
ii. Output gate
iii. Forget gate

Forget gate layer makes the decision. Input gates decides what part of information to update. Unlike RNN, LSTM can remember things from long past.

C. *Mean Absolute Percentage Error*

This is one of the best metrics used in forecasting. It is used for measuring accuracy.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \qquad (1)$$

Where,

At → actual value

Ft → forecasted value

n is no. of fitted points.

For calculating percentage error, this value is multiplied with 100. The value of t is observations, when the problem is generic regression. The value of t is time index, when it is time series problem. The main advantage is, it is a percentage error. So, it is independent of scale. It is used for forecasting problem. It can be used for comparing different results.

III. EXPERIMENT

A. *Data Source*

In this paper dataset is taken from Kaggle[11]. It is a NSE dataset. In the dataset, there were 50 stocks data. For this paper, 'HCL TECH' stock was used. Data was from 2000-2007. Here, a part of data was used for training and the other part as test data. After that, the original data and the predicted data were compared. It contains 2000 records. Data from 11/1/2000 to 27/12/2007 are there in the dataset. There are fifteen attributes. These are

i. Date
ii. Symbol
iii. Series
iv. Prev. Close
v. Open
vi. High
vii. Low
viii. Last
ix. Close
x. VWAP
xi. Volume
xii. Turnover
xiii. Trades
xiv. Deliverable Volume
xv. %Deliverble

The first five records of the dataset used are shown below in (Table I).

TABLE I

Date	Symbol	Series	Prev. Close	Open	High	Low	Last	Close	VWAP	Volume	Turnover	Trades	Deliverable Volume	%Deliverble
11-01-2000	HCLTECH	EQ	580	1550	1725	1492	1560	1554.45	1582.72	1192200	1.88691E+14			
12-01-2000	HCLTECH	EQ	1554.45	1560	1678.85	1560	1678.85	1678.85	1657.05	344850	5.71435E+13			
13-01-2000	HCLTECH	EQ	1678.85	1790	1813.2	1781	1813.2	1813.2	1804.69	53000	9.56488E+12			
14-01-2000	HCLTECH	EQ	1813.2	1958.3	1958.3	1835	1958.3	1958.3	1939.9	270950	5.25617E+13			
17-01-2000	HCLTECH	EQ	1958.3	2115	2115	1801.65	1801.65	1801.65	1990.55	428800	8.53547E+13			

B. *Method*

For the experiment, Python was used. Dataset was a NSE dataset. This is Stock price Dataset. It is Time series. Deep learning LSTM model was used.

C. *Result*

The dataset used, in the paper, is 'HCL TECH'. It is a NIFTY 50 share. Dataset is split into two parts. The first part is used for training. The second part is used for testing. With testing dataset, the output result was predicted. Then the actual and predicted values were compared. Python was used. LSTM model was used for prediction. Graphical representation was done based on the actual and predicted values. 'Open', 'Close', "High", "Low", and 'Volume' were given as input. 'Open' price was predicted. Here, 30 days values were given as input. Next day's 'Open' price was predicted as output. In this paper, we tried to train our model differently. We tried the same dataset to train the model with 2 batch sizes. Batch sizes are 30, 50. Now on these 2 batch sizes, the model was trained for 10 epochs, 20 epochs, 30 epochs, 50 epochs, 100 epochs. We plotted actual and predicted values in both the cases and the graphical representations are shown below. It has been seen that the epochs as well as the batch size, impacts the model significantly. The graphical representation is given below. Graphical representations of predicted and original values of batch size 30 are given below (Fig. 2).

Batch size=30

Epochs =10

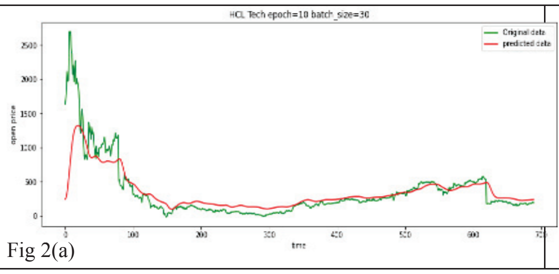


Fig 2(a)

Epochs =50

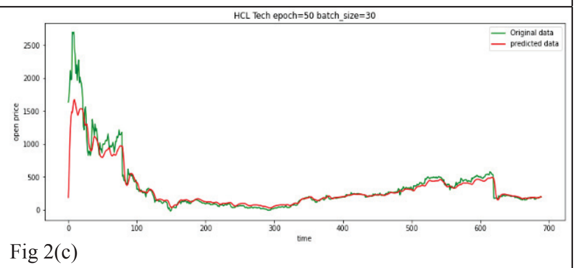


Fig 2(c)

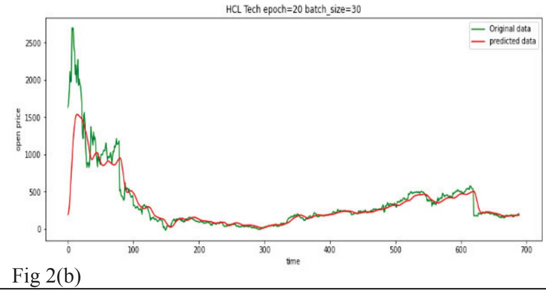
<table>
<tr><td>Epochs =20</td><td>

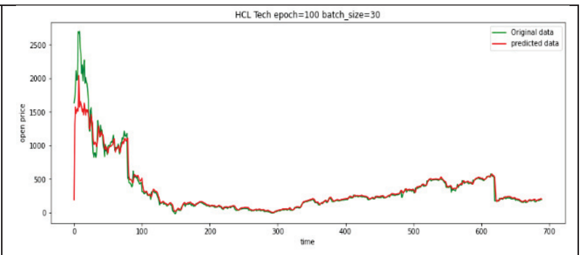
Fig 2(b)</td><td>Epochs =100</td><td>

Fig 2(d)</td></tr>
</table>

Fig 2: 2(a) original and predicted stock values graphical representation for 10 epochs, 2(b) original and predicted stock values graphical representation (for 20 epochs), 2(c) original and predicted stock values graphical representation (for 50 epochs), 2(d) original and predicted stock values graphical representation (for 100 epochs)

It can be seen from figure (Fig. 2) that as the epochs increases (from 10 to 100), the model predicted better. If we consider the figure (Fig. 2(a)), in the initial values model could not predict well. But as the no. of epochs increases, model started predicting the initial values better. Graphical representations of predicted and original values of batch size 50 are given below (Fig. 3) .

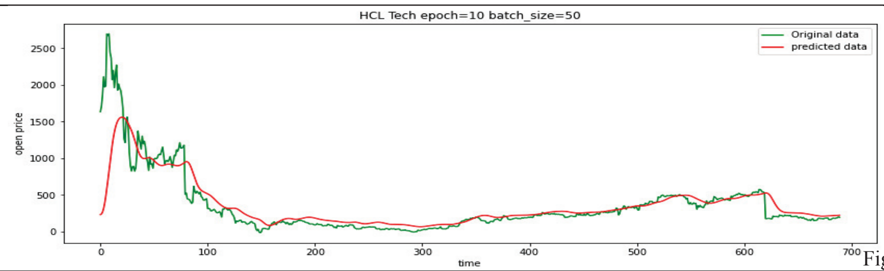
<table>
<tr><td colspan="2">Batch size=50</td></tr>
<tr><td>Epochs=10</td><td>

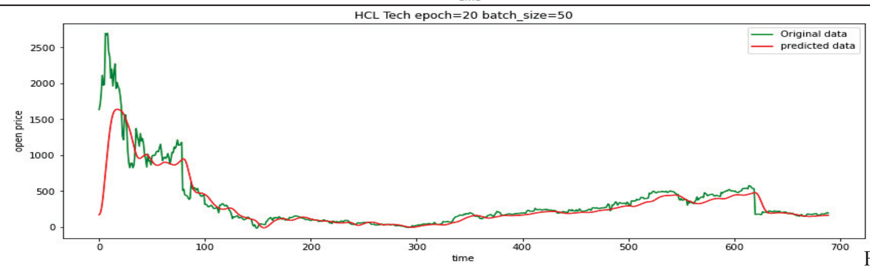
Fig 3(a)</td></tr>
<tr><td>Epochs =20</td><td>

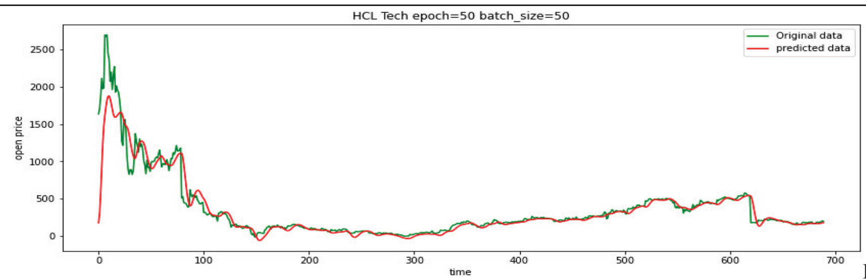
Fig 3(b)</td></tr>
<tr><td>Epochs =50</td><td>

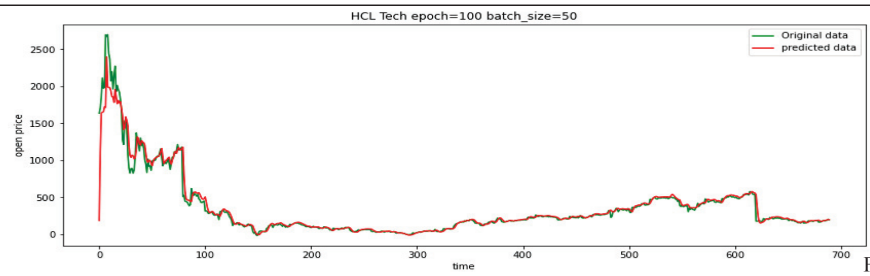
Fig 3(c)</td></tr>
<tr><td>Epochs =100</td><td>

Fig 3(d)</td></tr>
</table>

Fig 3: 3(a) original and predicted stock values graphical representation for 10 epochs, 3(b) original and predicted stock values graphical representation (for 20 epochs), 3(c) original and predicted stock values graphical representation (for 50 epochs), 3(d) original and predicted stock values graphical representation (for 100 epochs)

As discussed earlier for figure (Fig. 2), for figure (Fig. 3), it is evident that model performed better as the no. of epochs increased. Model could not predict well for the initial values. But if we consider, the way model predicted the initial values for epochs 10 and epochs 100, it is evident from the above figure (Fig. 3), model predicted the initial values better in the latter scenarios. Loss of the model depending on the batch size and epochs are shown in the Table below (Table II). It is evident from the table (Table II) that the loss of training for both the batch sizes, i.e., batch-size =30 and batch-size=50, for batch-size 50 it is minimum. In case of batch size 30, the value is 6.9042e-04 and for batch size 50 the value is 4.6535e-04.

TABLE II

Scrip name: HCL Tech	
Batch size=30	
Epochs	***Loss***
10	0.0025
20	0.0013
50	8.2505e-04
100	**6.9042e-04**
Batch size=50	
Epochs	***Loss***
10	0.0018
20	0.0013
50	0.0010
100	**4.6535e-04**

D. Evaluation

In this paper, evaluation is done based on percentage error or MAPE. Here, the stock used is 'HCL TECH'. For batch sizes 50 , 30 stock price is predicted for four different epochs. For each case, percentage error was calculated based on the predicted and actual values. It is evident from the results that for epoch=100 and batch size=50, our model performed best. MAPE was minimum in this case. MAPE or percentage error calculated, are shown in the below table (Table. 3).

TABLE III

Scrip Name:	HCL Tech	
Starting Date:	11-01-2000	
End Date:	27-12-2007	
Batch Size	50	30
	Percentage Error (MAPE)	
Epoch	***batch-size=50***	***batch-size=30***
10 epochs	114.4	152.7
20 epochs	33.7	45.4
50 epochs	46.1	53.5
100 epochs	**15.3**	**22.7**

From the table (Table III) , it can be seen that the for no. of epochs =100 , the percentage error was minimum. For batch size 30, it is 22.7 and for batch size 50, it is 15.7. The percentage error of the scrip, HCL tech, is shown below (Fig. 4) as a chart.

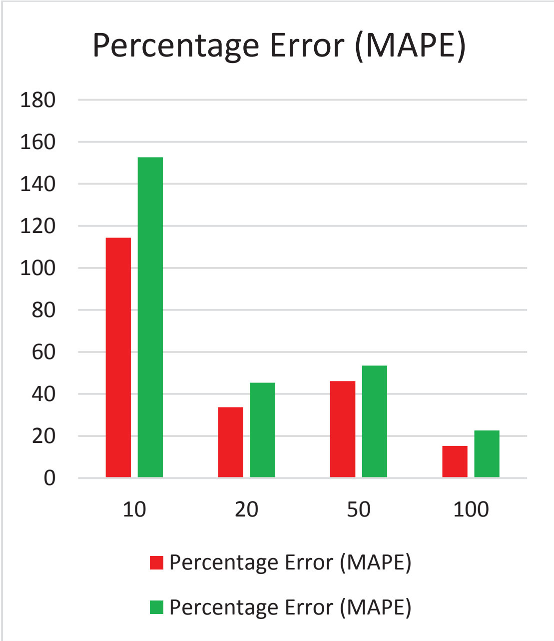


Fig 4: The chart of percentage error of shares

In the below figure (Fig. 5), loss for batch size 30, no. of epochs and loss are plotted in x axis and y axis respectively. It is evident from the graph that as the no. of epochs increases, the training loss is less. For epoch 10, it was 0.0025 and for epoch 100, it was 6.9042e-04, for batch size 30.

So, we can conclude that, our model performed well as the no. of epochs increased.

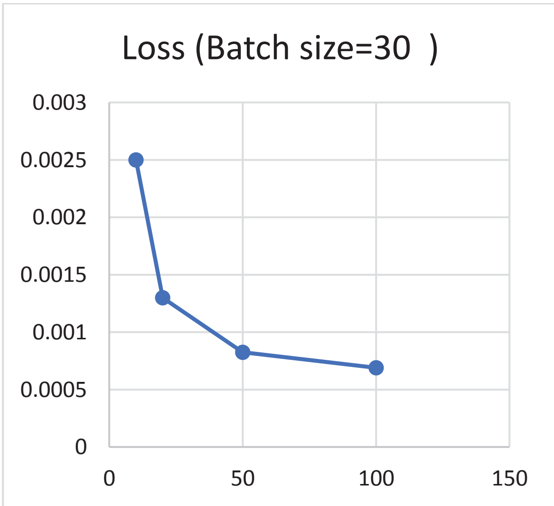


Fig 5: Chart of loss for batch-size=30

In the below figure (Fig. 6), loss for batch size 50, no. of epochs and loss are plotted in x axis and y axis respectively. It is evident from the graph that as the no. of epochs increases, the training loss is less. For epoch 10, it was 0.0018 and for epoch 100, it was 4.6535e-04, for batch size 50. Our model performed well as the no. of epochs increased. If we compare figs (Fig. 5) and (Fig. 6), the model performed better in the latter scenario.

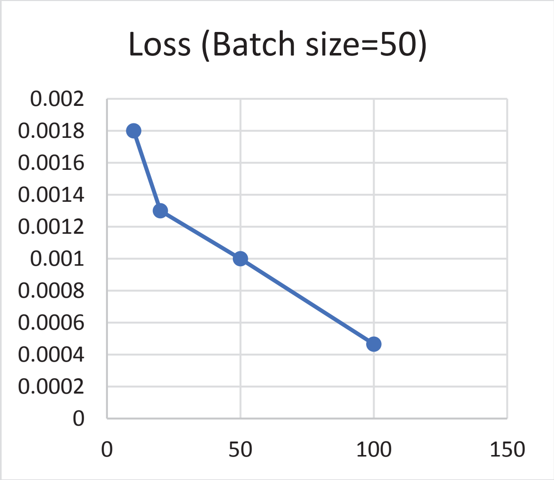


Fig 6: Chart of loss of batch size=50

IV. CONCLUSION

In this paper, we predicted stock price. Here, we used HCL Tech, a NSE Nifty 50 stock and we have studied the implication of the epochs as well as the Batch Size. Here 2 batch sizes, batch-size=30 and batch-size=50 are taken. For both the cases 4 different epochs are used. And percentage error (MAPE) was calculated in all the cases. And it is shown that with batch-size=50 and epochs=100 , the model worked best. It is shown that depending on the batch-size and epochs, the model performed differently.

ANN	**A**rtificial **N**eural **N**etwork
AI	**A**rtificial **I**ntelligence
ML	**M**achine **L**earning
LSTM	**L**ong **S**hort **T**erm **M**emory
RNN	**R**ecurrent **N**eural **N**etwork
CNN	**C**onvolution **N**eural **N**etwork

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