PROJECT REPORT ON STOCK MARKET PRICE PREDICTION

MODEL GENERATION TEAM

MULTILAYER LSTM MODEL

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Machine learning has significant applications in the stock price prediction. In this machine learning project, we will be talking about predicting the returns on stocks. This is a very complex task and has uncertainties.

DATASET:

To build the stock price prediction model, we will use the NIFTY dataset. This is a dataset of NIFTY stock prices from January 2021 to March 2021.

Stock price prediction using LSTM

1. Importing the required libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import math
from keras.models import Sequential
from keras.layers import Dense, LSTM
from sklearn.preprocessing import MinMaxScaler
import datetime
```

2. Reading the dataset

```
[ ] df = pd.read_csv(io.BytesIO(uploaded['NIFTY dataset.csv']))
```

```
[ ] df.head()
```

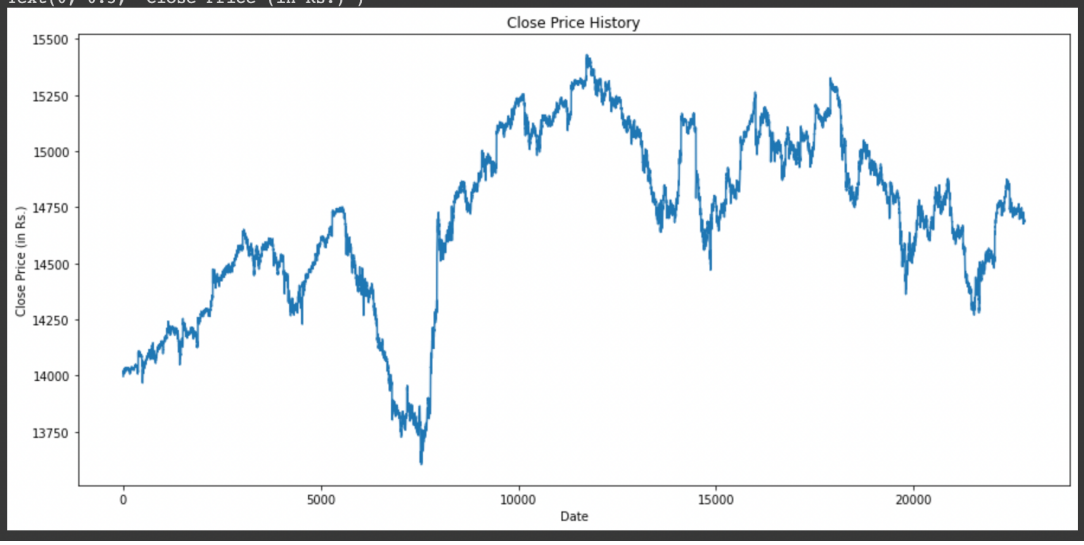
	Type	Date	Time	open	high	low	close
0	NIFTY	20210101	09:08	13996.10	13996.10	13996.10	13996.10
1	NIFTY	20210101	09:16	13997.90	14020.85	13991.35	14013.15
2	NIFTY	20210101	09:17	14014.85	14018.55	14008.15	14009.05
3	NIFTY	20210101	09:18	14008.05	14013.10	14005.05	14012.70
4	NIFTY	20210101	09:19	14013.65	14019.10	14013.65	14016.20

3. Information about the Nifty dataset

```
[ ] df['Date'].dtype

    dtype('int64')

[ ] df.isnull().sum()

    Type      0
    Date      0
    Time      0
    open      0
    high      0
    low       0
    close     0
    dtype: int64

[ ] df.shape

    (22806, 7)
```

4. Visualizing the “close” price history in the dataset

```
[ ] #Vizualizing the closing price history
    plt.figure(figsize=(15,7))
    plt.title('Close Price History')
    plt.plot(df['close'])
    plt.xlabel('Date')
    plt.ylabel('Close Price (in Rs.)')

    Text(0, 0.5, 'Close Price (in Rs.)')
```



5. Creating a new dataframe and normalizing it

```
[ ] #Creating a new dataframe with only close column
    data = df.filter(['close'])

    #Convert dataframe to numpy
    dataset = data.values

    training_data_len = math.ceil( len(dataset) * 0.65 )
    training_data_len
```

```
    14824
```

```
[ ] scaler = MinMaxScaler(feature_range=(0,1))
    scaled_data = scaler.fit_transform(dataset)
    scaled_data
```

```
    array([[0.21522382],
           [0.22455401],
           [0.22231039],
           ...,
           [0.59565503],
           [0.59661267],
           [0.59532669]])
```

```
[ ] time_step = 1
```

6. Creating scaled train data with time step = 1 and then reshaping it

```
[ ] time_step = 1
```

```
[ ] #create scaled training dataset
    train_data = scaled_data[0:training_data_len, :]

    x_train = []
    y_train = []

    for i in range(time_step, len(train_data) ):
      x_train.append(train_data[i-time_step:i, 0])
      y_train.append(train_data[i, 0])
```

```
[ ] #converting training data to numpy for using LSTM model
    x_train , y_train = np.array(x_train) , np.array(y_train)
```

```
[ ] #Reshape the data
    x_train = np.reshape(x_train , (x_train.shape[0], x_train.shape[1], 1))
    x_train.shape
```

```
    (14823, 1, 1)
```

7. Building and training the LSTM model

```
#Creating the LSTM model
model = Sequential()
model.add(LSTM(50, return_sequences=True, input_shape=(x_train.shape[1],1) ))
model.add(LSTM(50, return_sequences=True))
model.add(LSTM(50))
model.add(Dense(25))
model.add(Dense(1))
```

```
[ ] model.compile( optimizer = 'adam', loss = 'mean_squared_error')
```

```
[ ] #Training the model
    model.fit(x_train, y_train, batch_size= 10, epochs= 100)
```

```
Epoch 1/100
1483/1483 [==============================] - 7s 5ms/step - loss: 3.6170e-05
Epoch 2/100
1483/1483 [==============================] - 7s 5ms/step - loss: 3.1523e-05
Epoch 3/100
1483/1483 [==============================] - 7s 5ms/step - loss: 3.4244e-05
Epoch 4/100
1483/1483 [==============================] - 8s 6ms/step - loss: 3.4502e-05
Epoch 5/100
1483/1483 [==============================] - 7s 5ms/step - loss: 3.4589e-05
Epoch 6/100
1483/1483 [==============================] - 7s 5ms/step - loss: 3.4044e-05
Epoch 7/100
1483/1483 [==============================] - 7s 5ms/step - loss: 3.2284e-05
Epoch 8/100
1483/1483 [==============================] - 7s 5ms/step - loss: 3.3239e-05
Epoch 9/100
1483/1483 [==============================] - 7s 5ms/step - loss: 3.2550e-05
Epoch 10/100
1483/1483 [==============================] - 7s 5ms/step - loss: 3.1465e-05
Epoch 11/100
1483/1483 [==============================] - 7s 5ms/step - loss: 3.2498e-05
```

8. Take a sample of a dataset (test data) to make stock price predictions using the LSTM model

```
[ ] #testing dataset
    test_data = scaled_data[training_data_len - time_step: , :]

    x_test = []
    y_test = dataset[training_data_len: , :]

    for i in range(time_step, len(test_data)):
      x_test.append(test_data[i-time_step:i, 0])
```

```
[ ] #convert to numpy and reshape
    x_test = np.array(x_test)
    x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1))
```

```
[ ] #Model's predicted values
    predictions = model.predict(x_test)
    predictions = scaler.inverse_transform(predictions)
```

9. Error rate

```
[ ] #Error
    rmse = np.sqrt((np.mean(predictions - y_test)**2))
    print("The error rate of the model is", rmse)
```

```
The error rate of the model is 0.38309798119988636
```

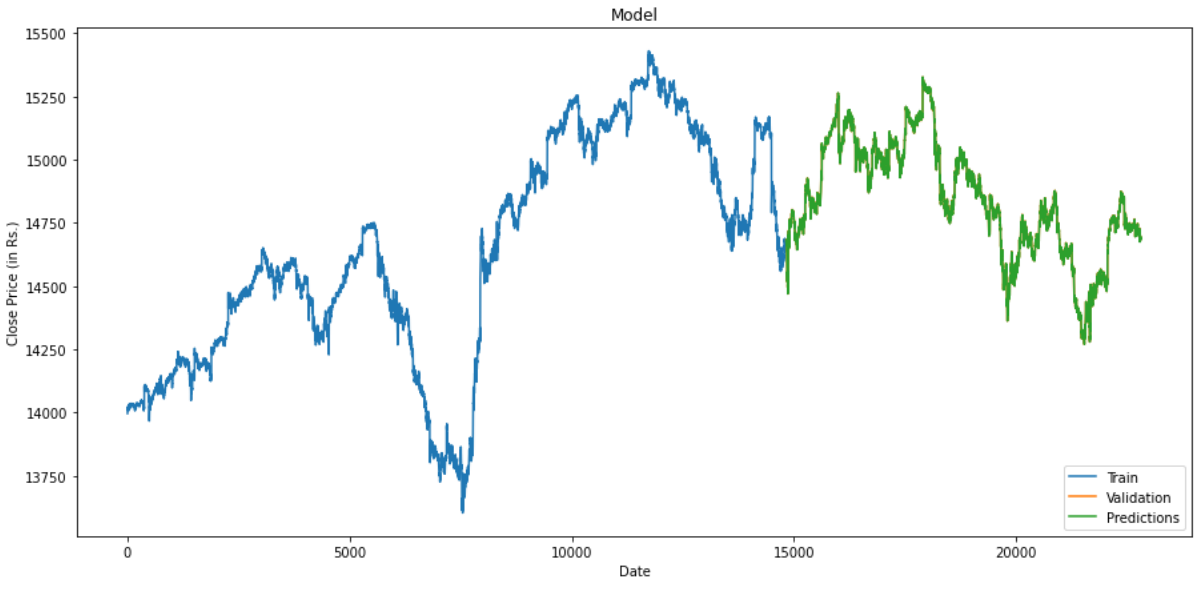
Made by Shrey Soni

10. Visualize the predicted stock costs with actual stock costs

```
[ ]  train = data[:training_data_len]
     validation_dataset = data[training_data_len:]
     validation_dataset['Predictions'] = predictions

     plt.figure(figsize=(15,7))
     plt.title('Model')
     plt.xlabel('Date')
     plt.ylabel('Close Price (in Rs.)')
     plt.plot(train['close'])
     plt.plot(validation_dataset[['close','Predictions']])
     plt.legend(['Train', 'Validation' , 'Predictions'], loc= 'lower right')
     plt.show()
```

i) For test data

ii) For the whole dataset



11. Original test data price and predicted price

```
[ ] validation_dataset
```

	close	Predictions
14824	14681.75	14675.378906
14825	14679.45	14680.609375
14826	14684.70	14678.317383
14827	14676.45	14683.548828
14828	14679.20	14675.328125
...	...	...
22801	14690.60	14686.491211
22802	14689.30	14689.430664
22803	14691.30	14688.133789
22804	14693.05	14690.127930
22805	14690.70	14691.874023

7982 rows × 2 columns

Benchmark:

The error rate of the multilayer LSTM model is **0.38**