stock-prediction

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0.1 Use Long Short-Term Memory (LSTM) for stock price prediction. Analyze apple company's stock data to forecast future prices effectively.

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1.0.1 THE DATA SCIENCE INTERNSHIP.

[ ]:
```
#install the prerequiments
!pip install yfinance
```

```
Requirement already satisfied: yfinance in /usr/local/lib/python3.10/dist-
packages (0.2.31)
Requirement already satisfied: pandas>=1.3.0 in /usr/local/lib/python3.10/dist-
packages (from yfinance) (1.5.3)
Requirement already satisfied: numpy>=1.16.5 in /usr/local/lib/python3.10/dist-
packages (from yfinance) (1.23.5)
Requirement already satisfied: requests>=2.31 in /usr/local/lib/python3.10/dist-
packages (from yfinance) (2.31.0)
Requirement already satisfied: multitasking>=0.0.7 in
/usr/local/lib/python3.10/dist-packages (from yfinance) (0.0.11)
Requirement already satisfied: lxml>=4.9.1 in /usr/local/lib/python3.10/dist-
packages (from yfinance) (4.9.3)
Requirement already satisfied: appdirs>=1.4.4 in /usr/local/lib/python3.10/dist-
packages (from yfinance) (1.4.4)
Requirement already satisfied: pytz>=2022.5 in /usr/local/lib/python3.10/dist-
packages (from yfinance) (2023.3.post1)
Requirement already satisfied: frozendict>=2.3.4 in
/usr/local/lib/python3.10/dist-packages (from yfinance) (2.3.8)
Requirement already satisfied: peewee>=3.16.2 in /usr/local/lib/python3.10/dist-
packages (from yfinance) (3.16.3)
Requirement already satisfied: beautifulsoup4>=4.11.1 in
/usr/local/lib/python3.10/dist-packages (from yfinance) (4.11.2)
Requirement already satisfied: html5lib>=1.1 in /usr/local/lib/python3.10/dist-
packages (from yfinance) (1.1)
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.10/dist-
packages (from beautifulsoup4>=4.11.1->yfinance) (2.5)
Requirement already satisfied: six>=1.9 in /usr/local/lib/python3.10/dist-
packages (from html5lib>=1.1->yfinance) (1.16.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-
```

```
packages (from html5lib>=1.1->yfinance) (0.5.1)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.3.0->yfinance) (2.8.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests>=2.31->yfinance) (3.3.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests>=2.31->yfinance) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests>=2.31->yfinance) (2.0.6)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests>=2.31->yfinance)
(2023.7.22)
```

2 Import the libraries

[ ]:
```
import math
import yfinance as yf
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
```

3 Processing the Data

[ ]:
```
stock_data = yf.download('AAPL', start='2016-01-01', end='2021-10-01')
stock_data.head()
```

```
[**********************100%%**********************]  1 of 1 completed
```

[ ]:

Date	Open	High	Low	Close	Adj Close	Volume
2016-01-04	25.652500	26.342501	25.500000	26.337500	24.009068	270597600
2016-01-05	26.437500	26.462500	25.602501	25.677500	23.407410	223164000
2016-01-06	25.139999	25.592501	24.967501	25.174999	22.949337	273829600
2016-01-07	24.670000	25.032499	24.107500	24.112499	21.980764	324377600
2016-01-08	24.637501	24.777500	24.190001	24.240000	22.096998	283192000

[ ]:
```
stock_data.describe()
```

[ ]:

	Open	High	Low	Close	Adj Close	\
count	1447.000000	1447.000000	1447.000000	1447.000000	1447.000000	
mean	62.548246	63.213274	61.897859	62.583359	60.639281	
std	37.286174	37.721778	36.792048	37.265635	37.330035	

```
min      22.500000    22.917500    22.367500    22.584999    20.826063
25%      36.879999    37.172501    36.490000    36.962500    34.898375
50%      47.252499    47.669998    46.882500    47.209999    45.402885
75%      79.118748    79.884998    78.435001    79.331249    77.554703
max     156.979996   157.259995   154.389999   156.690002   154.897964

              Volume
count   1.447000e+03
mean    1.280990e+08
std     5.997313e+07
min     4.544800e+07
25%     8.815295e+07
50%     1.115985e+08
75%     1.487286e+08
max     5.334788e+08
```

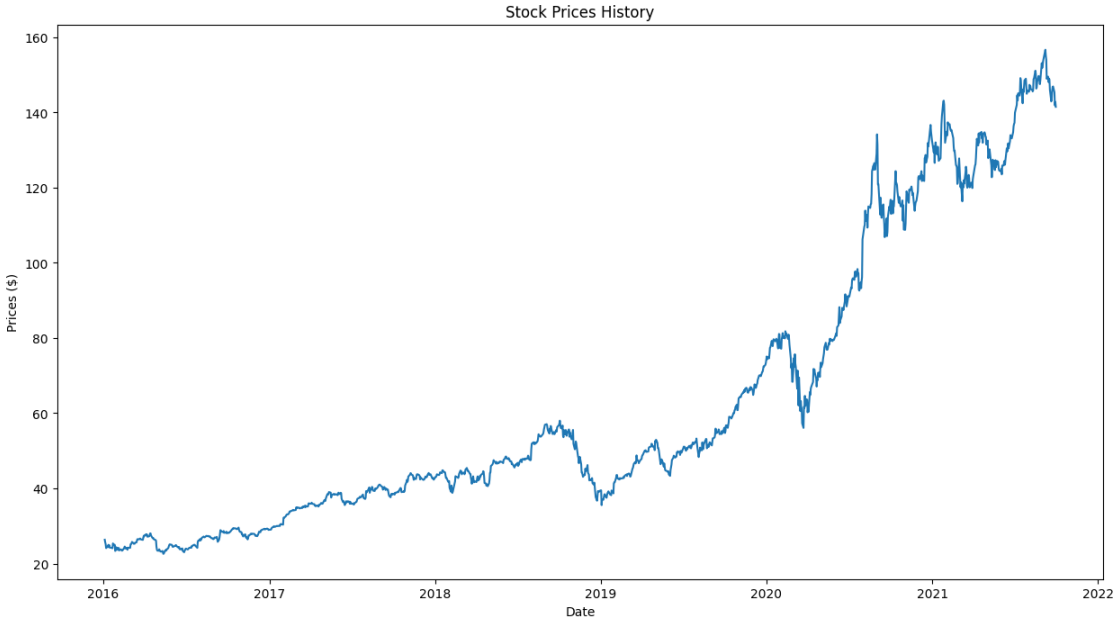
[ ]:
```
stock_data.isnull().sum()
```

[ ]:
```
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

4 Visualisation

[ ]:
```
plt.figure(figsize=(15, 8))
plt.title('Stock Prices History')
plt.plot(stock_data['Close'])
plt.xlabel('Date')
plt.ylabel('Prices ($)')
```

[ ]:
```
Text(0, 0.5, 'Prices ($)')
```



5 Splitting Data

[ ]:
```
close_prices = stock_data['Close']
values = close_prices.values
training_data_len = math.ceil(len(values)* 0.8)

scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(values.reshape(-1,1))

train_data = scaled_data[0: training_data_len, :]

x_train = []
y_train = []

for i in range(60, len(train_data)):
    x_train.append(train_data[i-60:i, 0])
    y_train.append(train_data[i, 0])

x_train, y_train = np.array(x_train), np.array(y_train)

x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
print(x_train)
print("*******")
print(y_train)
```

```
[[[0.02798181]
```

```
 [0.02306029]
 [0.01931323]
 …
 [0.02768354]
 [0.03232542]
 [0.03583013]]

[[0.02306029]
 [0.01931323]
 [0.01139033]
 …
 [0.03232542]
 [0.03583013]
 [0.03476753]]

[[0.01931323]
 [0.01139033]
 [0.01234108]
 …
 [0.03583013]
 [0.03476753]
 [0.03663175]]

…

[[0.41883227]
 [0.4121211 ]
 [0.40511165]
 …
 [0.62395139]
 [0.64391707]
 [0.64934193]]

[[0.4121211 ]
 [0.40511165]
 [0.40863504]
 …
 [0.64391707]
 [0.64934193]
 [0.65230602]]

[[0.40511165]
 [0.40863504]
 [0.4052235 ]
 …
 [0.64934193]
 [0.65230602]
 [0.68094027]]]
```

```
*******
[0.03476753 0.03663175 0.03873831 … 0.65230602 0.68094027 0.66013573]
```

[ ]:
```
test_data = scaled_data[training_data_len-60: , : ]
x_test = []
y_test = values[training_data_len:]

for i in range(60, len(test_data)):
  x_test.append(test_data[i-60:i, 0])

x_test = np.array(x_test)
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1))
print(x_test)
```

```
[[[0.40863504]
  [0.4052235 ]
  [0.41873903]
  …
  [0.65230602]
  [0.68094027]
  [0.66013573]]

 [[0.4052235 ]
  [0.41873903]
  [0.41534621]
  …
  [0.68094027]
  [0.66013573]
  [0.67217851]]

 [[0.41873903]
  [0.41534621]
  [0.42669924]
  …
  [0.66013573]
  [0.67217851]
  [0.64717944]]

 …

 [[0.87524704]
  [0.89060812]
  [0.9096231 ]
  …
  [0.92647552]
  [0.92714661]
  [0.91558848]]
```

```
 [[0.89060812]
  [0.9096231 ]
  [0.89970548]
  …
  [0.92714661]
  [0.91558848]
  [0.88978786]]

 [[0.9096231 ]
  [0.89970548]
  [0.91364974]
  …
  [0.91558848]
  [0.88978786]
  [0.89664815]]]
```

6 Model Definition

[ ]:
```
model = keras.Sequential()
model.add(layers.LSTM(100, return_sequences=True, input_shape=(x_train.
  ↪shape[1], 1)))
model.add(layers.LSTM(100, return_sequences=False))
model.add(layers.Dense(25))
model.add(layers.Dense(1))
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 lstm_4 (LSTM)                (None, 60, 100)           40800

 lstm_5 (LSTM)                (None, 100)               80400

 dense_4 (Dense)              (None, 25)                2525

 dense_5 (Dense)              (None, 1)                 26

=================================================================
Total params: 123,751
Trainable params: 123,751
Non-trainable params: 0
_________________________________________________________________
```

7 Training Configuration

[ ]:
```
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(x_train, y_train, batch_size= 1, epochs=20)
```

```
Epoch 1/20
1098/1098 [==============================] - 59s 50ms/step - loss: 6.4851e-04
Epoch 2/20
1098/1098 [==============================] - 55s 50ms/step - loss: 2.8510e-04
Epoch 3/20
1098/1098 [==============================] - 55s 50ms/step - loss: 3.5768e-04
Epoch 4/20
1098/1098 [==============================] - 68s 62ms/step - loss: 2.4070e-04
Epoch 5/20
1098/1098 [==============================] - 54s 50ms/step - loss: 1.6507e-04
Epoch 6/20
1098/1098 [==============================] - 57s 51ms/step - loss: 2.7093e-04
Epoch 7/20
1098/1098 [==============================] - 54s 50ms/step - loss: 1.7414e-04
Epoch 8/20
1098/1098 [==============================] - 57s 52ms/step - loss: 1.5812e-04
Epoch 9/20
1098/1098 [==============================] - 62s 57ms/step - loss: 2.2560e-04
Epoch 10/20
1098/1098 [==============================] - 55s 50ms/step - loss: 1.5827e-04
Epoch 11/20
1098/1098 [==============================] - 55s 50ms/step - loss: 1.7366e-04
Epoch 12/20
1098/1098 [==============================] - 55s 50ms/step - loss: 1.5815e-04
Epoch 13/20
1098/1098 [==============================] - 55s 50ms/step - loss: 1.5017e-04
Epoch 14/20
1098/1098 [==============================] - 55s 50ms/step - loss: 1.5087e-04
Epoch 15/20
1098/1098 [==============================] - 55s 50ms/step - loss: 1.4691e-04
Epoch 16/20
1098/1098 [==============================] - 55s 50ms/step - loss: 1.4955e-04
Epoch 17/20
1098/1098 [==============================] - 55s 50ms/step - loss: 1.5752e-04
Epoch 18/20
1098/1098 [==============================] - 55s 50ms/step - loss: 1.3704e-04
Epoch 19/20
1098/1098 [==============================] - 55s 50ms/step - loss: 1.5161e-04
Epoch 20/20
1098/1098 [==============================] - 62s 57ms/step - loss: 1.2613e-04
```

[ ]:
```
<keras.callbacks.History at 0x7ef98a6c75b0>
```

8 Prediction Evaluation

[ ]:
```
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)
rmse = np.sqrt(np.mean(predictions - y_test)**2)
rmse
```

```
10/10 [==============================] - 2s 33ms/step
```

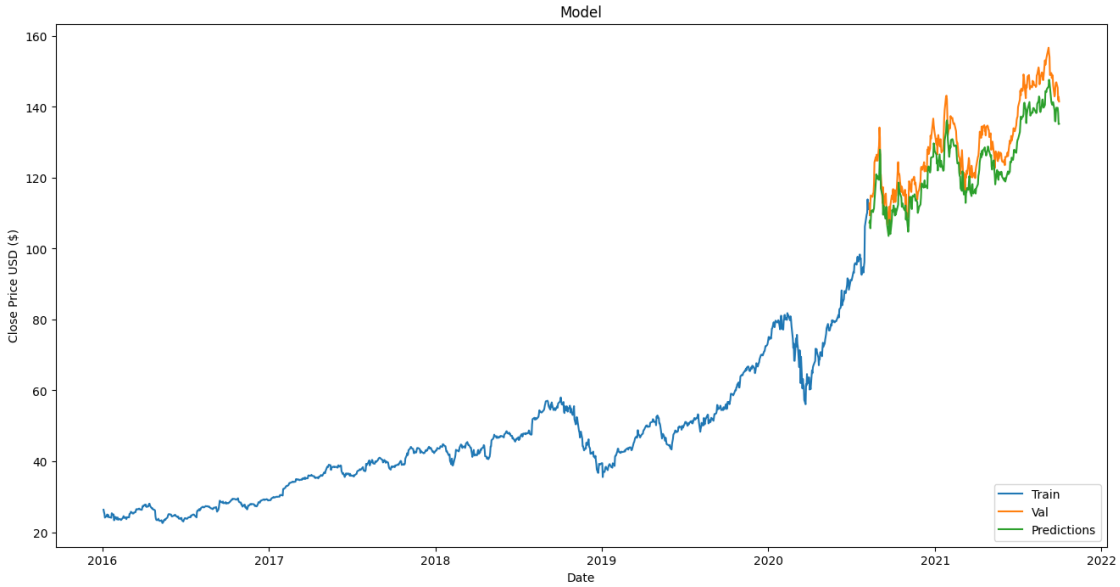
[ ]:
```
5.7677883161393
```

9 Prediction visualisation

[ ]:
```
data = stock_data.filter(['Close'])
train = data[:training_data_len]
validation = data[training_data_len:]
validation['Predictions'] = predictions
plt.figure(figsize=(16,8))
plt.title('Model')
plt.xlabel('Date')
plt.ylabel('Close Price USD ($)')
plt.plot(train)
plt.plot(validation[['Close', 'Predictions']])
plt.legend(['Train', 'Val', 'Predictions'], loc='lower right')
plt.show()
```

```
<ipython-input-23-d92c50f720f0>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  validation['Predictions'] = predictions
```


Model
Close Price USD ($)
Date
Train
Val
Predictions
160
140
120
100
80
60
40
20
2016
2017
2018
2019
2020
2021
2022

10 THANKS.