

```
In [59]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import pandas_datareader as web
import datetime as dt

from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, LSTM

stock1 = pd.read_csv('/Users/ashiyabhandari/Desktop/apple_stock.csv', index_
```

```
In [60]: stock = stock.loc['2020-01-01':]
stock.head()
```

```
Out[60]:
```

	Adj Close	Close	High	Low	Open	Volume
<b>2020-01-02</b>	72.796043	75.087502	75.150002	73.797501	74.059998	135480400
<b>2020-01-03</b>	72.088303	74.357498	75.144997	74.125000	74.287498	146322800
<b>2020-01-06</b>	72.662712	74.949997	74.989998	73.187500	73.447502	118387200
<b>2020-01-07</b>	72.320969	74.597504	75.224998	74.370003	74.959999	108872000
<b>2020-01-08</b>	73.484375	75.797501	76.110001	74.290001	74.290001	132079200

```
In [61]: plt.title("Close Price of Apple from 2020 to 2024", size = 11)
plt.plot(stock['Close'])
plt.xlabel("Date", size = 10)
plt.ylabel("Closing Price", size = 10)
plt.show()
```



```
In [62]: #creating min max scaler
scaler = MinMaxScaler(feature_range=(0,1))

#fit the scaler to stock dataset, convert it into numpy using .values and th
scaled_data = scaler.fit_transform(stock['Close'].values.reshape(-1,1))
```

```
In [63]: #number of days you want the prediction for to see what the price is going t
#advise to not have only few days because model will only gather few informa
days_prediction = 60
```

```
train_size = int(len(scaled_data) * 0.8)
#first 80% for training
train_data = scaled_data[:train_size]
#20% for testing
test_data = scaled_data[train_size:]

x_train = []
y_train = []

x_test = []
y_test = []
```

```

#loops from the position of scaled_data starting from days_prediction
for x in range(days_prediction, len(train_data)):
    #creating a set of past data points that will be used to make prediction
    #collects the past data and adds it to the list, x-train. This helps model
    x_train.append(train_data[x - days_prediction: x])
    #y takes the value for today's price. (what we want to predict for today)
    y_train.append(train_data[x, 0])

for x in range(days_prediction, len(test_data)):
    x_test.append(test_data[x - days_prediction:x])
    y_test.append(test_data[x, 0])

#converting list to arrays as machine learning language mostly work with arrays
x_train = np.array(x_train)
y_train = np.array(y_train)

x_test = np.array(x_test)
y_test = np.array(y_test)

#using np.reshape() function to change the shape of x_train which is required
#ex: if you had 100 samples and each sample used 5 past days,
#the reshaped x_train would have the shape (100, 5, 1).
x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))

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

```

## Build a Model

```

In [65]: model = Sequential()

#more layers you add more sophisticated
model.add(LSTM(units=50, return_sequences=True, input_shape=(x_train.shape[1], 1)))
#drops at 20% randomly during training to prevent the model from memorizing
model.add(Dropout(0.2))
model.add(LSTM(units=50, return_sequences=True))
model.add(Dropout(0.2))
#return_sequence = False by default, learns from all the previous layers
model.add(LSTM(units=50))
model.add(Dropout(0.2))

#outputs the final stock price prediction
model.add(Dense(units=1))

```

```

In [66]: #Compiling the model. Need to specify optimizer, loss function, and any metrics
model.compile(optimizer='adam', loss='mean_squared_error')

```

```

#train the model on training data.
#model is going to see 32 batch at the same time.
model.fit(x_train, y_train, epochs=50, batch_size=32)

#make prediction
predicted_prices = model.predict(x_test)


#reverse the scaling to get the actual values
predicted_prices = scaler.inverse_transform(predicted_prices)
actual_prices = scaler.inverse_transform(y_test.reshape(-1, 1)) # Convert a


```


```


Epoch 1/50
30/30 ————— 2s 30ms/step - loss: 0.0902
Epoch 2/50
30/30 ————— 1s 31ms/step - loss: 0.0051
Epoch 3/50
30/30 ————— 1s 31ms/step - loss: 0.0035
Epoch 4/50
30/30 ————— 1s 32ms/step - loss: 0.0031
Epoch 5/50
30/30 ————— 1s 30ms/step - loss: 0.0036
Epoch 6/50
30/30 ————— 1s 30ms/step - loss: 0.0031
Epoch 7/50
30/30 ————— 1s 30ms/step - loss: 0.0029
Epoch 8/50
30/30 ————— 1s 45ms/step - loss: 0.0025
Epoch 9/50
30/30 ————— 1s 47ms/step - loss: 0.0028
Epoch 10/50
30/30 ————— 1s 31ms/step - loss: 0.0029
Epoch 11/50
30/30 ————— 1s 31ms/step - loss: 0.0026
Epoch 12/50
30/30 ————— 1s 33ms/step - loss: 0.0025
Epoch 13/50
30/30 ————— 1s 33ms/step - loss: 0.0028
Epoch 14/50
30/30 ————— 1s 48ms/step - loss: 0.0022
Epoch 15/50
30/30 ————— 1s 34ms/step - loss: 0.0024
Epoch 16/50
30/30 ————— 1s 44ms/step - loss: 0.0020
Epoch 17/50
30/30 ————— 1s 34ms/step - loss: 0.0025
Epoch 18/50
30/30 ————— 1s 32ms/step - loss: 0.0024
Epoch 19/50


```


**30/30**  **1s** 33ms/step - loss: 0.0024  
Epoch 20/50


**30/30**  **1s** 31ms/step - loss: 0.0021  
Epoch 21/50


**30/30**  **1s** 33ms/step - loss: 0.0026  
Epoch 22/50


**30/30**  **1s** 31ms/step - loss: 0.0021  
Epoch 23/50


**30/30**  **1s** 39ms/step - loss: 0.0022  
Epoch 24/50


**30/30**  **1s** 32ms/step - loss: 0.0022  
Epoch 25/50


**30/30**  **1s** 37ms/step - loss: 0.0020  
Epoch 26/50


**30/30**  **1s** 32ms/step - loss: 0.0018  
Epoch 27/50


**30/30**  **1s** 31ms/step - loss: 0.0019  
Epoch 28/50


**30/30**  **1s** 31ms/step - loss: 0.0017  
Epoch 29/50


**30/30**  **1s** 32ms/step - loss: 0.0019  
Epoch 30/50


**30/30**  **1s** 38ms/step - loss: 0.0016  
Epoch 31/50


**30/30**  **1s** 41ms/step - loss: 0.0016  
Epoch 32/50


**30/30**  **1s** 36ms/step - loss: 0.0017  
Epoch 33/50


**30/30**  **1s** 46ms/step - loss: 0.0019  
Epoch 34/50


**30/30**  **1s** 36ms/step - loss: 0.0018  
Epoch 35/50


**30/30**  **1s** 35ms/step - loss: 0.0016  
Epoch 36/50


**30/30**  **1s** 34ms/step - loss: 0.0016  
Epoch 37/50


**30/30**  **1s** 32ms/step - loss: 0.0016  
Epoch 38/50


**30/30**  **1s** 33ms/step - loss: 0.0016  
Epoch 39/50

**30/30**  **1s** 31ms/step - loss: 0.0016  
Epoch 40/50

**30/30**  **1s** 32ms/step - loss: 0.0016  
Epoch 41/50

**30/30**  **1s** 33ms/step - loss: 0.0017  
Epoch 42/50

**30/30**  **1s** 31ms/step - loss: 0.0016  
Epoch 43/50

**30/30**  **1s** 47ms/step - loss: 0.0016  
Epoch 44/50

```

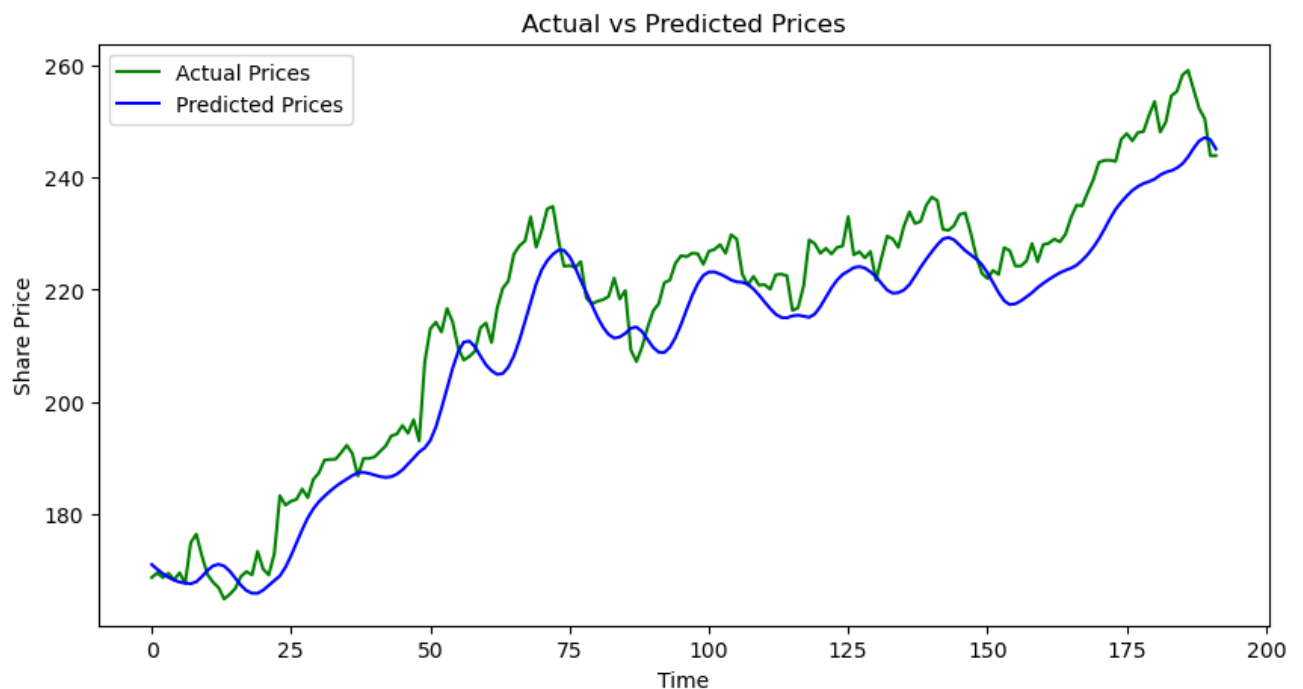
30/30 ————— 1s 32ms/step - loss: 0.0016
Epoch 45/50
30/30 ————— 1s 32ms/step - loss: 0.0016
Epoch 46/50
30/30 ————— 1s 31ms/step - loss: 0.0016
Epoch 47/50
30/30 ————— 1s 34ms/step - loss: 0.0016
Epoch 48/50
30/30 ————— 1s 39ms/step - loss: 0.0014
Epoch 49/50
30/30 ————— 1s 34ms/step - loss: 0.0014
Epoch 50/50
30/30 ————— 1s 32ms/step - loss: 0.0013
6/6 ————— 0s 10ms/step

```

```

In [67]: plt.figure(figsize=(10, 5))
plt.plot(actual_prices, color = 'green', label='Actual Prices')
plt.plot(predicted_prices, color = 'blue', label='Predicted Prices')
plt.title('Actual vs Predicted Prices')
plt.xlabel('Time')
plt.ylabel('Share Price')
plt.legend()
plt.show()

```



```

In [68]: print("Actual Price | Predicted Price")
print("-" * 30)

for x, y in zip(actual_prices.flatten(), predicted_prices.flatten()):
    print(f"    {float(x):.3f}          {float(y):.3f}")

```

## Actual Price | Predicted Price

168.840	171.140
169.650	170.290
168.820	169.524
169.580	168.860
168.450	168.375
169.670	168.018
167.780	167.847
175.040	167.729
176.550	168.075
172.690	168.993
169.380	170.094
168.000	170.910
167.040	171.187
165.000	170.870
165.840	169.964
166.900	168.723
169.020	167.460
169.890	166.511
169.300	166.047
173.500	166.023
170.330	166.592
169.300	167.435
173.030	168.256
183.380	169.129
181.710	170.666
182.400	172.722
182.740	175.044
184.570	177.330
183.050	179.427
186.280	181.054
187.430	182.315
189.720	183.301
189.840	184.190
189.870	185.002
191.040	185.705
192.350	186.338
190.900	186.971
186.880	187.477
189.980	187.532
189.990	187.345
190.290	187.049
191.290	186.768
192.250	186.639
194.030	186.759
194.350	187.225
195.870	187.987
194.480	189.016
196.890	190.067

193.120	191.147
207.150	191.896
213.070	193.218
214.240	195.601
212.490	198.897
216.670	202.460
214.290	206.027
209.680	208.996
207.490	210.693
208.140	210.885
209.070	209.879
213.250	208.202
214.100	206.633
210.620	205.596
216.750	204.956
220.270	205.110
221.550	206.250
226.340	208.237
227.820	211.049
228.680	214.364
232.980	217.743
227.570	221.072
230.540	223.567
234.400	225.205
234.820	226.320
228.880	227.057
224.180	227.008
224.310	225.881
223.960	223.957
225.010	221.651
218.540	219.475
217.490	217.270
217.960	215.144
218.240	213.341
218.800	212.055
222.080	211.401
218.360	211.600
219.860	212.237
209.270	213.167
207.230	213.376
209.820	212.570
213.310	211.145
216.240	209.740
217.530	208.899
221.270	208.850
221.720	209.785
224.720	211.498
226.050	213.830
225.890	216.472
226.510	218.992



226.400	221.090
224.530	222.551
226.840	223.159
227.180	223.169
228.030	222.804
226.490	222.319
229.790	221.738
229.000	221.408
222.770	221.333
220.850	220.978
222.380	220.142
220.820	219.059
220.910	217.832
220.110	216.659
222.660	215.642
222.770	215.075
222.500	215.012
216.320	215.353
216.790	215.476
220.690	215.275
228.870	215.096
228.200	215.686
226.470	217.007
227.370	218.652
226.370	220.340
227.520	221.722
227.790	222.718
233.000	223.309
226.210	223.940
226.780	224.122
225.670	223.860
226.800	223.176
221.690	222.322
225.770	221.088
229.540	219.944
229.040	219.395
227.550	219.480
231.300	219.961
233.850	220.933
231.780	222.419
232.150	224.009
235.000	225.443
236.480	226.767
235.860	228.007
230.760	229.023
230.570	229.315
231.410	228.866
233.400	227.938
233.670	226.964
230.100	226.199

225.910	225.467
222.910	224.458
222.010	223.003
223.450	221.220
222.720	219.495
227.480	218.039
226.960	217.369
224.230	217.495
224.230	218.035
225.120	218.735
228.220	219.480
225.000	220.396
228.020	221.139
228.280	221.828
229.000	222.453
228.520	223.025
229.870	223.465
232.870	223.841
235.060	224.385
234.930	225.244
237.330	226.300
239.590	227.565
242.650	229.049
243.010	230.809
243.040	232.650
242.840	234.317
246.750	235.585
247.770	236.676
246.490	237.658
247.960	238.374
248.130	238.896
251.040	239.244
253.480	239.678
248.050	240.412
249.790	240.907
254.490	241.184
255.270	241.656
258.200	242.414
259.020	243.615
255.590	245.157
252.200	246.480
250.420	247.057
243.850	246.698
243.860	245.044

## Prediction for Future Day

```
In [70]: model_inputs = scaled_data
```

```
real_data = model_inputs[len(model_inputs) - days_prediction : len(model_inputs)]
real_data = np.array(real_data)
real_data = np.reshape(real_data, (1, real_data.shape[0], 1)) # Reshape for

prediction = model.predict(real_data)
prediction = scaler.inverse_transform(prediction)
print(f"Prediction: {prediction}")
```

1/1  0s 161ms/step

Prediction: [[242.4975]]