APPLIED DATA SCIENCE - PHASE 3

STOCK PRICE PREDICTION

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FEATURE ENGINEERING:

It involves creating and selecting relevant features (input variables) from the available data that can be used to train the model. Effective feature engineering can significantly improve the model's predictive performance.

Historical Price Data:

Close Price: The closing price of the stock on a given day.

Open Price: The opening price of the stock on a given day.

High and Low Prices: The highest and lowest prices of the stock during a trading day.

Time Series Features:

Lagged Returns: The returns of the stock in the previous days, which can capture trends and momentum.

Moving Averages: Simple moving averages (SMA) or exponential moving averages (EMA) to capture short-term and long-term trends.

After selecting and creating these features, it's important to preprocess the data, handle missing values, and potentially scale or normalize the features as needed before using them to train your stock price prediction model. Additionally, feature selection techniques (e.g., feature importance analysis or correlation analysis) can help identify the most relevant features and improve the model's efficiency and interpretability.

Code:

```
import pandas as pd

data = pd.read_csv('MSFT.csv')


print(data.head())

data['Date'] = pd.to_datetime(data['Date'])

data['Day'] = data['Date'].dt.day

data['Month'] = data['Date'].dt.month

data['Year'] = data['Date'].dt.year


data['Daily_Return'] = data['Adj Close'].pct_change()

data['Lagged_Return_1'] = data['Daily_Return'].shift(1)

data['Lagged_Return_7'] = data['Daily_Return'].shift(7)


data['SMA_5'] = data['Adj Close'].rolling(window=5).mean()

data['SMA_30'] = data['Adj Close'].rolling(window=30).mean()

data['EMA_12'] = data['Adj Close'].ewm(span=12, adjust=False).mean()



data['Avg_Volume_5'] = data['Volume'].rolling(window=5).mean()

data['Volume_Change'] = data['Volume'].pct_change()



def calculate_rsi(data, window=14):

    delta = data['Adj Close'].diff(1)

    gain = delta.where(delta > 0, 0)
```

```
    loss = -delta.where(delta < 0, 0)

    avg_gain = gain.rolling(window=window).mean()
    avg_loss = loss.rolling(window=window).mean()

    rs = avg_gain / avg_loss
    rsi = 100 - (100 / (1 + rs))

    return rsi

data['RSI_14'] = calculate_rsi(data)
print(data.head(100))
```

Output:

```
Date      Open      High       Low     Close  Adj Close      Volume  \
0  1986-03-13  0.088542  0.101563  0.088542  0.097222   0.062549
1031788800
1  1986-03-14  0.097222  0.102431  0.097222  0.100694   0.064783
308160000
2  1986-03-17  0.100694  0.103299  0.100694  0.102431   0.065899
133171200
3  1986-03-18  0.102431  0.103299  0.098958  0.099826   0.064224    67766400
4  1986-03-19  0.099826  0.100694  0.097222  0.098090   0.063107    47894400
5  1986-03-20  0.098090  0.098090  0.094618  0.095486   0.061432    58435200
6  1986-03-21  0.095486  0.097222  0.091146  0.092882   0.059756    59990400
7  1986-03-24  0.092882  0.092882  0.089410  0.090278   0.058081    65289600
8  1986-03-25  0.090278  0.092014  0.089410  0.092014   0.059198    32083200
9  1986-03-26  0.092014  0.095486  0.091146  0.094618   0.060873    22752000
10 1986-03-27  0.094618  0.096354  0.094618  0.096354   0.061990
16848000
```

11	1986-03-31	0.096354	0.096354	0.093750	0.095486	0.061432	12873600
12	1986-04-01	0.095486	0.095486	0.094618	0.094618	0.060873	11088000
13	1986-04-02	0.094618	0.097222	0.094618	0.095486	0.061432	27014400
14	1986-04-03	0.096354	0.098958	0.096354	0.096354	0.061990	23040000
15	1986-04-04	0.096354	0.097222	0.096354	0.096354	0.061990	26582400
16	1986-04-07	0.096354	0.097222	0.092882	0.094618	0.060873	16560000
17	1986-04-08	0.094618	0.097222	0.094618	0.095486	0.061432	10252800
18	1986-04-09	0.095486	0.098090	0.095486	0.097222	0.062549	12153600
19	1986-04-10	0.097222	0.098958	0.095486	0.098090	0.063107	13881600
20	1986-04-11	0.098958	0.101563	0.098958	0.099826	0.064224	17222400
21	1986-04-14	0.099826	0.101563	0.099826	0.100694	0.064783	12153600
22	1986-04-15	0.100694	0.100694	0.097222	0.100694	0.064783	9302400
23	1986-04-16	0.100694	0.105035	0.099826	0.104167	0.067016	31910400
24	1986-04-17	0.104167	0.105035	0.104167	0.105035	0.067575	22003200
25	1986-04-18	0.105035	0.105035	0.100694	0.101563	0.065341	21628800
26	1986-04-21	0.101563	0.102431	0.098958	0.101563	0.065341	22924800
27	1986-04-22	0.101563	0.101563	0.099826	0.099826	0.064224	15552000

28	1986-04-23	0.099826	0.100694	0.098958	0.100260	0.064503	15609600
29	1986-04-24	0.100260	0.111979	0.099826	0.110243	0.070926	62352000
30	1986-04-25	0.111111	0.121962	0.111111	0.117188	0.075393	85795200
31	1986-04-28	0.117188	0.118924	0.116319	0.118056	0.075952	28886400
32	1986-04-29	0.118056	0.118056	0.113715	0.114583	0.073718	30326400
33	1986-04-30	0.114583	0.115451	0.109375	0.111979	0.072043	30902400
34	1986-05-01	0.111979	0.111979	0.108507	0.110243	0.070926	54345600
35	1986-05-02	0.110243	0.111979	0.109375	0.110243	0.070926	20246400
36	1986-05-05	0.110243	0.110243	0.109375	0.109375	0.070367	3254400
37	1986-05-06	0.110243	0.111979	0.110243	0.110243	0.070926	9734400
38	1986-05-07	0.110243	0.111111	0.108507	0.110243	0.070926	5155200
39	1986-05-08	0.110243	0.111111	0.109375	0.111111	0.071484	3542400
40	1986-05-09	0.111111	0.111111	0.110243	0.110243	0.070926	6076800
41	1986-05-12	0.110243	0.113715	0.110243	0.111111	0.071484	10483200
42	1986-05-13	0.111111	0.112847	0.111111	0.111979	0.072043	3830400
43	1986-05-14	0.111979	0.111979	0.111111	0.111111	0.071484	9302400
44	1986-05-15	0.111111	0.112847	0.111111	0.111111	0.071484	3801600
45	1986-05-16	0.111111	0.114583	0.111111	0.111979	0.072043	11952000
46	1986-05-19	0.111979	0.111979	0.109375	0.110243	0.070926	11001600
47	1986-05-20	0.110243	0.110243	0.108507	0.109375	0.070367	61977600
48	1986-05-21	0.109375	0.110243	0.107639	0.107639	0.069250	8092800
49	1986-05-22	0.107639	0.108507	0.107639	0.107639	0.069250	4406400
50	1986-05-23	0.107639	0.109375	0.107639	0.107639	0.069250	4089600

51	1986-05-27	0.107639	0.111111	0.107639	0.111111	0.071484	13881600
52	1986-05-28	0.111111	0.114583	0.111111	0.114583	0.073718	15523200
53	1986-05-29	0.114583	0.118924	0.113715	0.117188	0.075393	45676800
54	1986-05-30	0.118056	0.123264	0.118056	0.121528	0.078186	27072000
55	1986-06-02	0.121528	0.121528	0.118056	0.118056	0.075952	19728000
56	1986-06-03	0.118056	0.118056	0.116319	0.118056	0.075952	5011200
57	1986-06-04	0.118056	0.118924	0.116319	0.117188	0.075393	4723200
58	1986-06-05	0.117188	0.118924	0.116319	0.118924	0.076510	13708800
59	1986-06-06	0.118924	0.118924	0.117188	0.118924	0.076510	3427200

	RSI_14	Day	Month	Year	Daily_Return	Lagged_Return_1 \
0	NaN	13	3	1986	NaN	NaN
1	NaN	14	3	1986	0.035716	NaN
2	NaN	17	3	1986	0.017227	0.035716
3	NaN	18	3	1986	-0.025418	0.017227
4	NaN	19	3	1986	-0.017392	-0.025418
5	NaN	20	3	1986	-0.026542	-0.017392
6	NaN	21	3	1986	-0.027282	-0.026542
7	NaN	24	3	1986	-0.028031	-0.027282
8	NaN	25	3	1986	0.019232	-0.028031
9	NaN	26	3	1986	0.028295	0.019232
10	NaN	27	3	1986	0.018350	0.028295
11	NaN	31	3	1986	-0.009001	0.018350
12	NaN	1	4	1986	-0.009099	-0.009001
13	46.666269	2	4	1986	0.009183	-0.009099

14	48.385420	3	4	1986	0.009083	0.009183
15	40.737547	4	4	1986	0.000000	0.009083
16	33.333333	7	4	1986	-0.018019	0.000000
17	40.001432	8	4	1986	0.009183	-0.018019
18	48.001719	9	4	1986	0.018183	0.009183
19	56.520047	10	4	1986	0.008921	0.018183
20	68.183298	11	4	1986	0.017700	0.008921
21	80.000000	14	4	1986	0.008704	0.017700
22	77.777778	15	4	1986	0.000000	0.008704
23	78.946376	16	4	1986	0.034469	0.000000
24	77.777778	17	4	1986	0.008341	0.034469
25	66.663825	18	4	1986	-0.033060	0.008341
26	70.000000	21	4	1986	0.000000	-0.033060
27	61.903138	22	4	1986	-0.017095	0.000000
28	60.974758	23	4	1986	0.004344	-0.017095
29	75.000000	24	4	1986	0.099577	0.004344
30	84.209782	25	4	1986	0.062981	0.099577
31	84.209782	28	4	1986	0.007414	0.062981
32	74.998881	29	4	1986	-0.029413	0.007414
33	69.048431	30	4	1986	-0.022722	-0.029413
34	64.286323	1	5	1986	-0.015505	-0.022722
35	63.414421	2	5	1986	0.000000	-0.015505
36	61.903138	5	5	1986	-0.007881	0.000000
37	58.975301	6	5	1986	0.007944	-0.007881
38	57.894737	7	5	1986	0.000000	0.007944
39	65.713409	8	5	1986	0.007867	0.000000
40	63.889580	9	5	1986	-0.007806	0.007867
41	68.571575	12	5	1986	0.007867	-0.007806

42	69.015434	13	5	1986	0.007820	0.007867
43	51.998281	14	5	1986	-0.007759	0.007820
44	29.415482	15	5	1986	0.000000	-0.007759
45	29.415482	16	5	1986	0.007820	0.000000
46	33.337312	19	5	1986	-0.015505	0.007820
47	38.460479	20	5	1986	-0.007881	-0.015505
48	38.460479	21	5	1986	-0.015874	-0.007881
49	38.460479	22	5	1986	0.000000	-0.015874
50	41.667910	23	5	1986	0.000000	0.000000
51	53.330150	27	5	1986	0.032260	0.000000
52	63.154919	28	5	1986	0.031252	0.032260
53	66.663825	29	5	1986	0.022722	0.031252
54	75.995417	30	5	1986	0.037046	0.022722
55	64.283887	2	6	1986	-0.028573	0.037046
56	62.960016	3	6	1986	0.000000	-0.028573
57	62.960016	4	6	1986	-0.007360	0.000000
58	65.514261	5	6	1986	0.014816	-0.007360
59	64.281604	6	6	1986	0.000000	0.014816

	Lagged_Return_7	SMA_5	SMA_30	EMA_12	Avg_Volume_5	Volume_Change
0	NaN	NaN	NaN	0.062549	NaN	NaN
1	NaN	NaN	NaN	0.062893	NaN	-0.701334
2	NaN	NaN	NaN	0.063355	NaN	-0.567850
3	NaN	NaN	NaN	0.063489	NaN	-0.491133
4	NaN	0.064112	NaN	0.063430	317756160.0	-0.293243
5	NaN	0.063889	NaN	0.063123	123085440.0	0.220084
6	NaN	0.062884	NaN	0.062605	73451520.0	0.026614

7	NaN	0.061320	NaN	0.061909	59875200.0	0.088334
8	0.035716	0.060315	NaN	0.061492	52738560.0	-0.508602
9	0.017227	0.059868	NaN	0.061397	47710080.0	-0.290844
10	-0.025418	0.059980	NaN	0.061488	39392640.0	-0.259494
11	-0.017392	0.060315	NaN	0.061479	29969280.0	-0.235897
12	-0.026542	0.060873	NaN	0.061386	19128960.0	-0.138702
13	-0.027282	0.061320	NaN	0.061393	18115200.0	1.436364
14	-0.028031	0.061543	NaN	0.061485	18172800.0	-0.147122
15	0.019232	0.061543	NaN	0.061563	20119680.0	0.153750
16	0.028295	0.061432	NaN	0.061457	20856960.0	-0.377031
17	0.018350	0.061543	NaN	0.061453	20689920.0	-0.380870
18	-0.009001	0.061767	NaN	0.061621	17717760.0	0.185393
19	-0.009099	0.061990	NaN	0.061850	15886080.0	0.142180
20	0.009183	0.062437	NaN	0.062215	14014080.0	0.240664
21	0.009083	0.063219	NaN	0.062610	13132800.0	-0.294314
22	0.000000	0.063889	NaN	0.062945	12942720.0	-0.234597
23	-0.018019	0.064783	NaN	0.063571	16894080.0	2.430341
24	0.009183	0.065676	NaN	0.064187	18518400.0	-0.310469
25	0.018183	0.065900	NaN	0.064364	19399680.0	-0.017016
26	0.008921	0.066011	NaN	0.064515	21553920.0	0.059920
27	0.017700	0.065899	NaN	0.064470	22803840.0	-0.321608
28	0.008704	0.065397	NaN	0.064475	19543680.0	0.003704
29	0.000000	0.066067	0.063210	0.065468	27613440.0	2.994465
30	0.034469	0.068077	0.063638	0.066995	40446720.0	0.375982
31	0.008341	0.070200	0.064010	0.068373	41639040.0	-0.663310
32	-0.033060	0.072098	0.064271	0.069195	44593920.0	0.049850
33	0.000000	0.073606	0.064531	0.069633	47652480.0	0.018993
34	-0.017095	0.073606	0.064792	0.069832	46051200.0	0.758621

35	0.004344	0.072713	0.065108	0.070000	32941440.0	-0.627451
36	0.099577	0.071596	0.065462	0.070057	27815040.0	-0.839260
37	0.062981	0.071038	0.065890	0.070190	23696640.0	1.991150
38	0.007414	0.070814	0.066281	0.070304	18547200.0	-0.470414
39	-0.029413	0.070926	0.066635	0.070485	8386560.0	-0.312849
40	-0.022722	0.070926	0.066933	0.070553	5552640.0	0.715447
41	-0.015505	0.071149	0.067268	0.070696	6998400.0	0.725118
42	0.000000	0.071373	0.067640	0.070903	5817600.0	-0.634615
43	-0.007881	0.071484	0.067975	0.070993	6647040.0	1.428571
44	0.007944	0.071484	0.068292	0.071068	6698880.0	-0.591331
45	0.000000	0.071708	0.068627	0.071218	7873920.0	2.143939
46	0.007867	0.071596	0.068962	0.071173	7977600.0	-0.079518
47	-0.007806	0.071261	0.069260	0.071049	19607040.0	4.633508
48	0.007867	0.070814	0.069483	0.070772	19365120.0	-0.869424
49	0.007820	0.070367	0.069688	0.070538	19486080.0	-0.455516
50	-0.007759	0.069809	0.069855	0.070340	17913600.0	-0.071895
51	0.000000	0.069920	0.070079	0.070516	18489600.0	2.394366
52	0.007820	0.070590	0.070377	0.071009	9198720.0	0.118257
53	-0.015505	0.071819	0.070656	0.071683	16715520.0	1.942486
54	-0.007881	0.073606	0.071009	0.072684	21248640.0	-0.407314
55	-0.015874	0.074947	0.071363	0.073186	24376320.0	-0.271277
56	0.000000	0.075840	0.071717	0.073612	22602240.0	-0.745985
57	0.000000	0.076175	0.072089	0.073886	20442240.0	-0.057471
58	0.032260	0.076399	0.072489	0.074290	14048640.0	1.902439
59	0.031252	0.076063	0.072676	0.074631	9319680.0	-0.750000

Evaluation:

In stock price prediction, the evaluation of a model's performance is crucial to assess its accuracy and effectiveness. Common evaluation metrics include:

Mean Squared Error (MSE): Measures the average squared difference between predicted and actual stock prices. Lower MSE indicates better accuracy.

Mean Absolute Error (MAE): Calculates the average absolute difference between predicted and actual prices. It provides a straightforward measure of prediction error.

Root Mean Squared Error (RMSE): RMSE is the square root of MSE, providing a measure in the same unit as the target variable. Lower RMSE suggests better predictive performance.

Code:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

from sklearn.preprocessing import MinMaxScaler

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import LSTM, Dense, Dropout


# Load the stock price data

data = pd.read_csv('MSFT.csv')  # Replace 'stock_data.csv' with your dataset


# Select the 'Close' prices as the target variable

prices = data['Close'].values.reshape(-1, 1)


# Normalize the data

scaler = MinMaxScaler(feature_range=(0, 1))

prices_scaled = scaler.fit_transform(prices)
```

```
# Split the data into training and test sets
train_size = int(len(prices_scaled) * 0.8)
train_data = prices_scaled[:train_size]
test_data = prices_scaled[train_size:]

# Create sequences of data for training
def create_sequences(data, sequence_length):
    X, y = [], []
    for i in range(len(data) - sequence_length):
        X.append(data[i:i+sequence_length])
        y.append(data[i+sequence_length])
    return np.array(X), np.array(y)

sequence_length = 10  # You can adjust this value
X_train, y_train = create_sequences(train_data, sequence_length)
X_test, y_test = create_sequences(test_data, sequence_length)

# Build the LSTM model
model = Sequential()
model.add(LSTM(units=50, return_sequences=True,
input_shape=(X_train.shape[1], 1)))
model.add(LSTM(units=50))
model.add(Dense(units=1))
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32)
```

```
# Evaluate the model
train_loss = model.evaluate(X_train, y_train, verbose=0)
test_loss = model.evaluate(X_test, y_test, verbose=0)
print(f"Train Loss: {train_loss:.4f}, Test Loss: {test_loss:.4f}")

# Make predictions
train_predictions = model.predict(X_train)
test_predictions = model.predict(X_test)

# Inverse transform the predictions to the original scale
train_predictions = scaler.inverse_transform(train_predictions)
test_predictions = scaler.inverse_transform(test_predictions)

# Plot the results
plt.figure(figsize=(12, 6))
plt.plot(prices, label='Actual Prices', color='b')
plt.plot(range(sequence_length, train_size), train_predictions, label='Train Predictions', color='g')
plt.plot(range(train_size + sequence_length, len(prices)), test_predictions, label='Test Predictions', color='r')
plt.legend()
plt.show()
```

Output:

```
Epoch 1/10
213/213 [==============================] - 8s 14ms/step - loss: 5.6418e-04
Epoch 2/10
```

213/213 [==============================] - 3s 13ms/step - loss: 4.2065e-05

Epoch 3/10

213/213 [==============================] - 3s 15ms/step - loss: 4.1125e-05

Epoch 4/10

213/213 [==============================] - 6s 27ms/step - loss: 4.0485e-05

Epoch 5/10

213/213 [==============================] - 6s 27ms/step - loss: 4.4396e-05

Epoch 6/10

213/213 [==============================] - 5s 26ms/step - loss: 3.7652e-05

Epoch 7/10

213/213 [==============================] - 3s 14ms/step - loss: 3.3948e-05

Epoch 8/10

213/213 [==============================] - 3s 13ms/step - loss: 3.4644e-05

Epoch 9/10

213/213 [==============================] - 3s 14ms/step - loss: 3.2606e-05

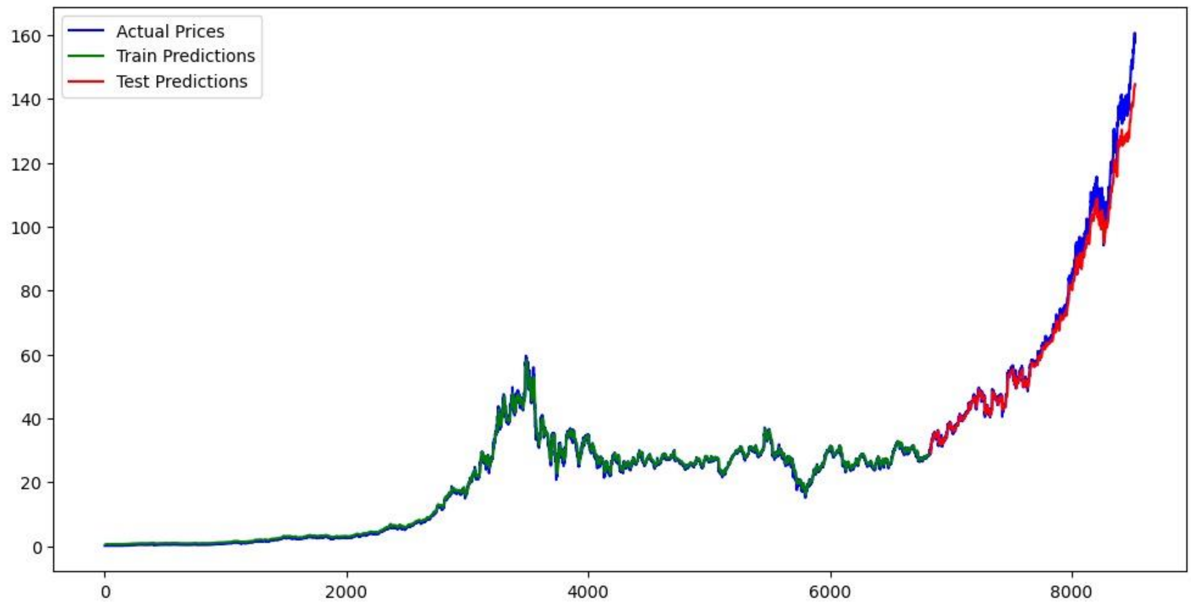
Epoch 10/10

213/213 [==============================] - 4s 18ms/step - loss: 2.8910e-05

Train Loss: 0.0000, Test Loss: 0.0008

213/213 [==============================] - 2s 4ms/step

53/53 [==============================] - 0s 5ms/step



MODEL SELECTION:

The LSTM model provides better results when the data set is large and has fewer Nan values.

Whereas, despite providing better accuracy than LSTM, the ARIMA model requires more time in terms of processing and works well when all the attributes of the data set provide legitimate values.

Different LSTM variants (e.g., Bidirectional LSTM, stacked LSTM).Attention mechanisms to focus on important time steps or features.

Incorporating other types of neural networks like CNNs for feature extraction.

Hybrid models that combine LSTMs with other architectures like Transformer models.

Reinforcement Learning for dynamic trading strategies.

Activation Functions:

Consider using appropriate activation functions for LSTM units. Common choices are 'tanh' for the recurrent activation and 'sigmoid' for the input and output gates.

Loss Function and Optimization Algorithm:

For regression tasks like stock price prediction, use a loss function like Mean Squared Error (MSE) to measure the model's prediction error.

Choose an optimization algorithm, such as Adam, RMSprop, or stochastic gradient descent (SGD), and experiment with different learning rates.

CODE FOR LSTM:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense, Dropout
# Load historical stock price data (e.g., CSV file with 'Date'
and 'Close' columns)
data = pd.read_csv('MSFT.csv')
# Extract the 'Close' prices as the target variable
prices = data*'Close'+.values.reshape(-1, 1)

# Normalize the data using Min-Max scaling
scaler = MinMaxScaler(feature_range=(0, 1))
prices_scaled = scaler.fit_transform(prices)
# Define a function to create sequences of data for training
the LSTM model
def create_sequences(data, seq_length):
 X, y = *+, *+
 for i in range(len(data) - seq_length):
 X.append(data*i:i+seq_length+)
 y.append(data*i+seq_length+)
```

```
return np.array(X), np.array(y)
# Set the sequence length and split the data into training and
testing sets
sequence_length = 10
X, y = create_sequences(prices_scaled, sequence_length)
train_size = int(len(X) * 0.8)
X_train, X_test = X*:train_size+, X*train_size:+
y_train, y_test = y*:train_size+, y*train_size:+
# Create an LSTM model
model = Sequential()
model.add(LSTM(units=50, return_sequences=True,
input_shape=(X_train.shape*1+, 1)))
model.add(LSTM(units=50))
model.add(Dense(1))
# Compile the model
model.compile(optimizer='adam',
loss='mean_squared_error')
# Train the model
model.fit(X_train, y_train, epochs=50, batch_size=64)
# Make predictions on the test set
predictions = model.predict(X_test)
# Inverse transform the predictions to get actual price values
predictions_actual = scaler.inverse_transform(predictions)
y_test_actual = scaler.inverse_transform(y_test)
# Plot the actual vs. predicted prices
plt.figure(figsize=(12, 6))
plt.plot(predictions_actual, label='Predicted Prices',
color='red')
```

```
plt.plot(y_test_actual, label='Actual Prices', color='blue')
plt.title('Stock Price Prediction with LSTM')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.show()
```

Output:

```
Epoch 1/50
107/107 *================================+ - 7s
20ms/step - loss: 0.0011
Epoch 2/50
107/107 *================================+ - 2s
19ms/step - loss: 3.8592e-05
Epoch 3/50
107/107 *================================+ - 2s
20ms/step - loss: 3.8419e-05
Epoch 4/50
107/107 *================================+ - 2s
14ms/step - loss: 3.7421e-05
Epoch 5/50
107/107 *================================+ - 1s
13ms/step - loss: 3.6841e-05
Epoch 6/50
107/107 *================================+ - 2s
15ms/step - loss: 3.6274e-05
Epoch 7/50
107/107 *================================+ - 2s
22ms/step - loss: 3.6100e-05
```

Epoch 8/50

107/107 *==============================+ - 2s

15ms/step - loss: 3.6038e-05

Epoch 9/50

107/107 *==============================+ - 2s

21ms/step - loss: 3.4980e-05

Epoch 10/50

107/107 *==============================+ - 2s

21ms/step - loss: 3.3884e-05

Epoch 11/50

107/107 *==============================+ - 2s

21ms/step - loss: 3.1855e-05

Epoch 12/50

107/107 *==============================+ - 2s

21ms/step - loss: 3.1442e-05

Epoch 13/50

107/107 *==============================+ - 2s

16ms/step - loss: 3.2507e-05

Epoch 14/50

107/107 *==============================+ - 2s

18ms/step - loss: 3.1582e-05

Epoch 15/50

107/107 *==============================+ - 2s

14ms/step - loss: 2.8938e-05

Epoch 16/50

107/107 *==============================+ - 2s

23ms/step - loss: 2.6421e-05

Epoch 17/50

107/107 *===============================+ - 2s

22ms/step - loss: 2.6747e-05

Epoch 18/50

107/107 *===============================+ - 2s

19ms/step - loss: 2.4096e-05

Epoch 19/50

107/107 *===============================+ - 2s

18ms/step - loss: 2.5314e-05

Epoch 20/50

107/107 *===============================+ - 2s

20ms/step - loss: 2.5337e-05

Epoch 21/50

107/107 *===============================+ - 2s

23ms/step - loss: 2.2405e-05

Epoch 22/50

107/107 *===============================+ - 2s

22ms/step - loss: 2.4915e-05

Epoch 23/50

107/107 *===============================+ - 1s

14ms/step - loss: 2.1624e-05

Epoch 24/50

107/107 *===============================+ - 2s

19ms/step - loss: 2.1545e-05

Epoch 25/50

107/107 *===============================+ - 2s

22ms/step - loss: 2.2694e-05

Epoch 26/50

107/107 *===============================+ - 2s

22ms/step - loss: 2.0566e-05

Epoch 27/50

107/107 *==============================+ - 2s

19ms/step - loss: 2.2009e-05

Epoch 28/50

107/107 *==============================+ - 2s

18ms/step - loss: 2.2940e-05

Epoch 29/50

107/107 *==============================+ - 2s

15ms/step - loss: 2.0115e-05

Epoch 30/50

107/107 *==============================+ - 2s

22ms/step - loss: 1.8910e-05

Epoch 31/50

107/107 *==============================+ - 2s

23ms/step - loss: 2.3294e-05

Epoch 32/50

107/107 *==============================+ - 2s

19ms/step - loss: 1.8463e-05

Epoch 33/50

107/107 *==============================+ - 2s

19ms/step - loss: 2.0214e-05

Epoch 34/50

107/107 *==============================+ - 2s

22ms/step - loss: 1.8284e-05

Epoch 35/50

107/107 *==============================+ - 2s

23ms/step - loss: 1.7490e-05

Epoch 36/50

107/107 *================================+ - 2s

21ms/step - loss: 1.8360e-05

Epoch 37/50

107/107 *================================+ - 2s

19ms/step - loss: 1.7240e-05

Epoch 38/50

107/107 *================================+ - 2s

21ms/step - loss: 1.6853e-05

Epoch 39/50

107/107 *================================+ - 3s

24ms/step - loss: 1.5736e-05

Epoch 40/50

107/107 *================================+ - 2s

22ms/step - loss: 1.5684e-05

Epoch 41/50

107/107 *================================+ - 2s

15ms/step - loss: 1.7331e-05

Epoch 42/50

107/107 *================================+ - 2s

23ms/step - loss: 1.6515e-05

Epoch 43/50

107/107 *================================+ - 2s

21ms/step - loss: 1.6822e-05

Epoch 44/50

107/107 *================================+ - 2s

16ms/step - loss: 1.4114e-05

Epoch 45/50

107/107 *==================================+ - 2s

23ms/step - loss: 1.4346e-05

Epoch 46/50

107/107 *================================+ - 2s

21ms/step - loss: 1.5537e-05

Epoch 47/50

107/107 *================================+ - 2s

19ms/step - loss: 1.4485e-05

Epoch 48/50

107/107 *================================+ - 2s

23ms/step - loss: 1.4945e-05

Epoch 49/50

107/107 *================================+ - 2s

22ms/step - loss: 1.3325e-05

Epoch 50/50

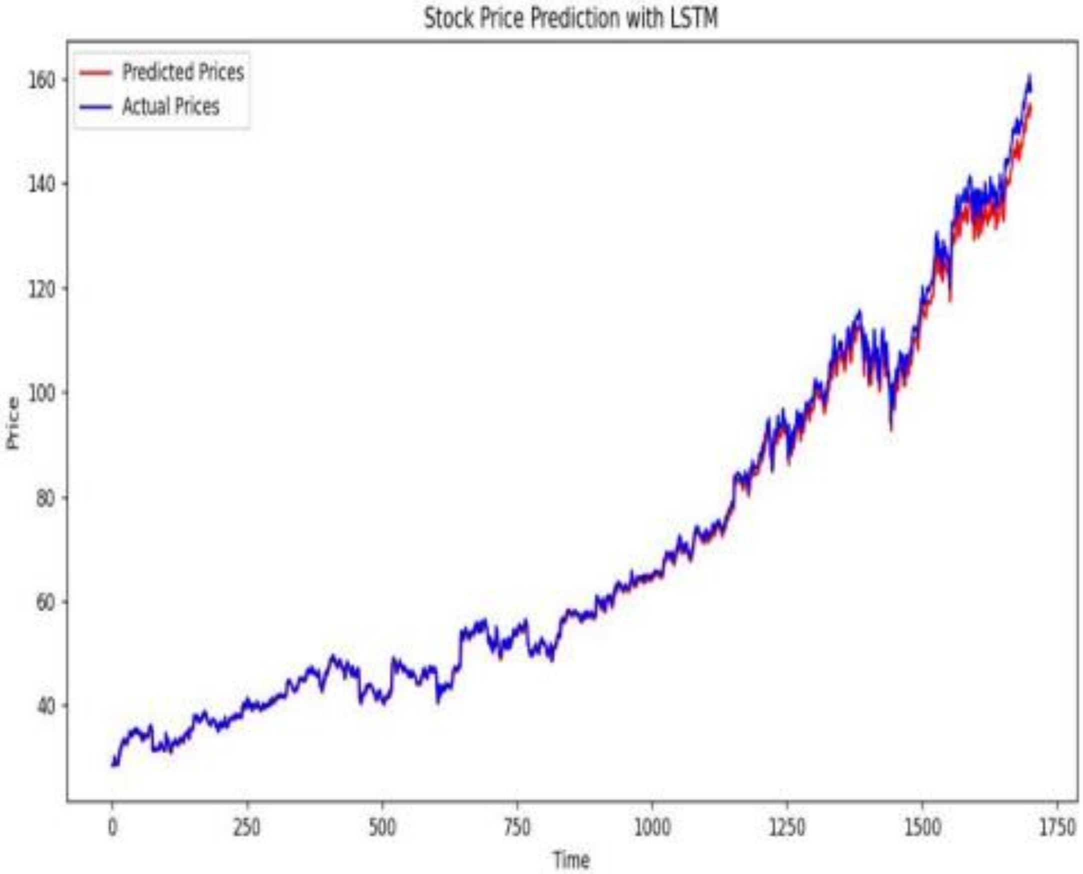
107/107 *================================+ - 2s

19ms/step - loss: 1.2995e-05

54/54 *================================+ - 1s 3ms/step

Process finished with exit code 0

Output:



Stock Price Prediction with LSTM
Predicted Prices
Actual Prices
Price
Time
160
140
120
100
80
60
40
0
250
500
750
1000
1250
1500
1750