Import Libraries and perform Data Preprocessing

```
# STEP 1: Install necessary library
!pip install yfinance --quiet
```

```
# STEP 2: Import libraries
import yfinance as yf
import numpy as np
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
```

```
# STEP 3: Load stock data
ticker = 'AAPL'
df = yf.download(ticker, start='2022-01-01', end='2024-01-01')
df = df[['Open', 'High', 'Low', 'Close', 'Volume']]
df.dropna(inplace=True)
```

```
/tmp/ipython-input-3-3307097659.py:3: FutureWarning: YF.download() has changed argument auto_adjust default to True
  df = yf.download(ticker, start='2022-01-01', end='2024-01-01')
[*********************100%***********************]  1 of 1 completed
```

Data visualization

```
df.head()
```

Price	Open	High	Low	Close	Volume
Ticker	AAPL	AAPL	AAPL	AAPL	AAPL
Date					
2022-01-03	174.542932	179.499589	174.425155	178.645660	104487900
2022-01-04	179.254190	179.558457	175.809061	176.378342	99310400
2022-01-05	176.290033	176.839679	171.411899	171.686722	94537600
2022-01-06	169.507721	172.059668	168.467317	168.820663	96904000
2022-01-07	169.694226	170.921120	167.868606	168.987534	86709100

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
df.describe()
```

Price	Open	High	Low	Close	Volume
Ticker	AAPL	AAPL	AAPL	AAPL	AAPL
count	501.000000	501.000000	501.000000	501.000000	5.010000e+02
mean	161.460145	163.288978	159.788979	161.620328	7.359234e+07
std	17.813390	17.512542	18.043880	17.781002	2.536511e+07
min	124.398589	126.136083	122.582127	123.421249	2.404830e+07
25%	146.716186	148.842087	145.348158	147.230209	5.414710e+07
50%	162.136743	163.731955	160.200681	162.529846	6.924600e+07
75%	174.542932	176.057069	172.656490	174.569946	8.670910e+07
max	196.580427	198.168786	195.567834	196.669769	1.826020e+08

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 501 entries, 2022-01-03 to 2023-12-29
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   (Open, AAPL)    501 non-null    float64
 1   (High, AAPL)    501 non-null    float64
 2   (Low, AAPL)     501 non-null    float64
 3   (Close, AAPL)   501 non-null    float64
 4   (Volume, AAPL)  501 non-null    int64
dtypes: float64(4), int64(1)
memory usage: 23.5 KB
```

```
df.shape
```

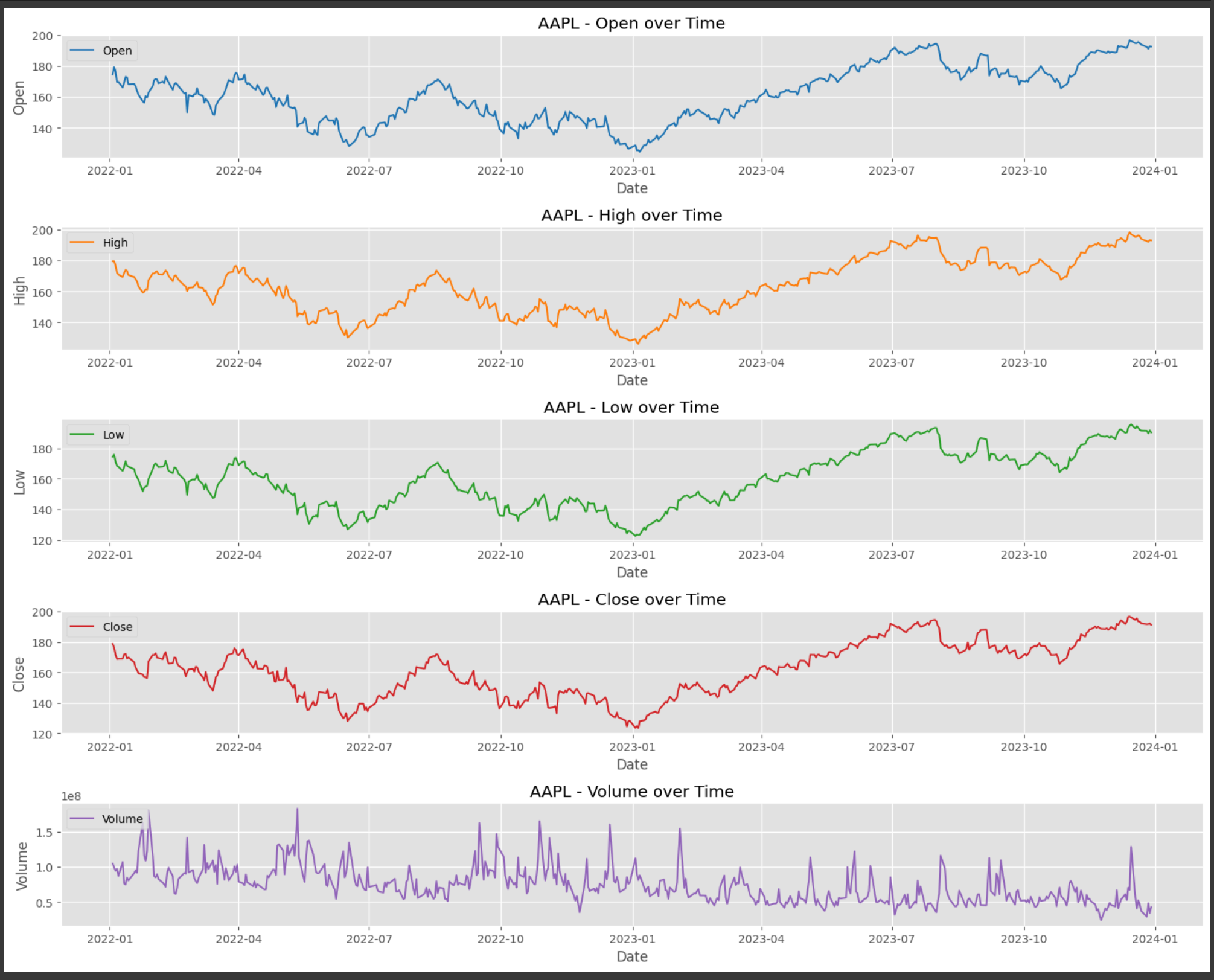
```
(501, 5)
```

```
df.columns
```

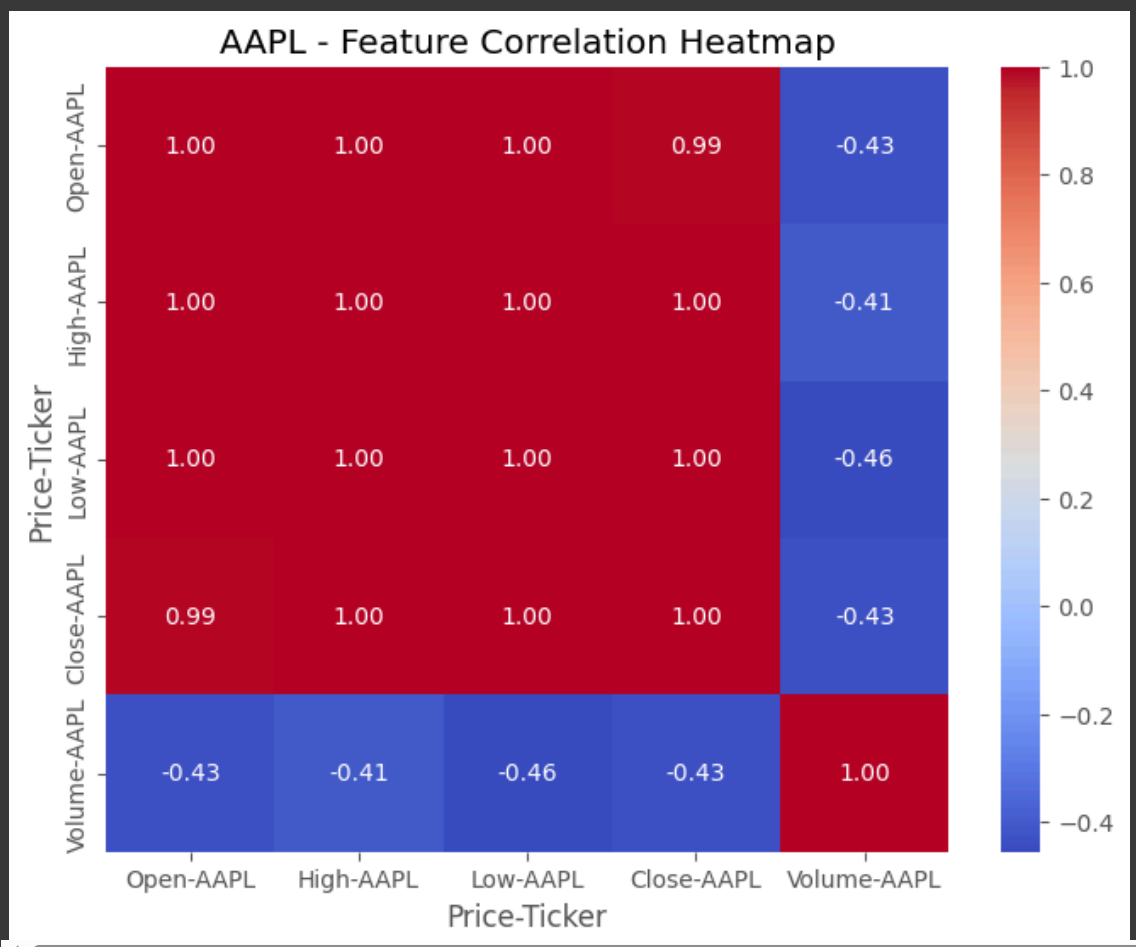
```
MultiIndex([(  'Open', 'AAPL'),
            (  'High', 'AAPL'),
            (   'Low', 'AAPL'),
            ( 'Close', 'AAPL'),
```

```
                ('Volume', 'AAPL')],
               names=['Price', 'Ticker'])
```

```
# Set style
plt.style.use('ggplot')

# Plot each column as individual time series
plt.figure(figsize=(15, 12))

columns = ['Open', 'High', 'Low', 'Close', 'Volume']

for i, col in enumerate(columns):
    plt.subplot(len(columns), 1, i + 1)
    plt.plot(df[col], label=col, color=sns.color_palette("tab10")[i])
    plt.title(f"{ticker} - {col} over Time")
    plt.xlabel("Date")
    plt.ylabel(col)
    plt.legend(loc="upper left")

plt.tight_layout()
plt.show()
```




```
# Correlation matrix
corr_matrix = df.corr()

# Plot heatmap
plt.figure(figsize=(8,6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title(f'{ticker} - Feature Correlation Heatmap')
plt.show()
```




```
!pip install plotly --quiet
```

```
import plotly.graph_objects as go
import plotly.express as px
```

```
# Ensure datetime index
# Access columns using the MultiIndex
df = df.dropna(subset=[('Open', ticker), ('High', ticker), ('Low', ticker), ('Close', ticker)])
df = df.copy()
df['Date'] = df.index  # Move datetime index to a column

# Plotly candlestick chart with fixes
fig = go.Figure(data=[go.Candlestick(
    x=df['Date'],
    open=df[('Open', ticker)],
    high=df[('High', ticker)],
    low=df[('Low', ticker)],
    close=df[('Close', ticker)],
    increasing_line_color='green',
    decreasing_line_color='red'
)])

fig.update_layout(
    title=f'{ticker} Candlestick Chart',
    xaxis_title='Date',
    yaxis_title='Price (USD)',
    xaxis_rangeslider_visible=True,
    template='plotly_dark'
)

fig.show()
```

LSTM model training

```
# STEP 5: Normalize features
scaler = MinMaxScaler()
```

```
# Drop the 'Date' column before scaling as it's not numerical
scaled_data = scaler.fit_transform(df.drop('Date', axis=1))
```

```
/tmp/ipython-input-71-2726385231.py:4: PerformanceWarning:

dropping on a non-lexsorted multi-index without a level parameter may impact performance.
```

```
# STEP 6: Create sequences for LSTM
def create_sequences_multivariate(data, seq_length=180):
    X, y = [], []
    for i in range(seq_length, len(data)):
        X.append(data[i-seq_length:i])
        y.append(data[i, 3])  # Index 3 = 'Close'
    return np.array(X), np.array(y)
```

```
sequence_length = 180
X, y = create_sequences_multivariate(scaled_data, seq_length = 180)
```

```
# STEP 7: Train-test split
split = int(0.8 * len(X))
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]
```

```
# STEP 8: Build the LSTM model
model = Sequential()
model.add(LSTM(64, return_sequences=True, input_shape=(X.shape[1], X.shape[2])))
model.add(Dropout(0.2))
model.add(LSTM(64))
model.add(Dropout(0.2))
model.add(Dense(1))
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning:

Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in t
```

```
history = model.compile(optimizer='adam', loss='mean_squared_error')
history = model.fit(X_train, y_train, epochs=20, batch_size=32, verbose=1)
```

```
Epoch 1/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 5s 143ms/step - loss: 0.1391
Epoch 2/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 153ms/step - loss: 0.0155
Epoch 3/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 169ms/step - loss: 0.0129
Epoch 4/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 2s 265ms/step - loss: 0.0117
Epoch 5/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 2s 153ms/step - loss: 0.0090
Epoch 6/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 157ms/step - loss: 0.0095
Epoch 7/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 161ms/step - loss: 0.0087
Epoch 8/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 160ms/step - loss: 0.0083
Epoch 9/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 2s 158ms/step - loss: 0.0071
Epoch 10/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 171ms/step - loss: 0.0068
Epoch 11/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 179ms/step - loss: 0.0082
Epoch 12/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 3s 187ms/step - loss: 0.0070
Epoch 13/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 2s 147ms/step - loss: 0.0066
Epoch 14/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 156ms/step - loss: 0.0071
Epoch 15/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 174ms/step - loss: 0.0080
Epoch 16/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 2s 155ms/step - loss: 0.0071
Epoch 17/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 3s 234ms/step - loss: 0.0058
Epoch 18/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 2s 162ms/step - loss: 0.0066
Epoch 19/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 3s 156ms/step - loss: 0.0067
Epoch 20/20
8/8 ━━━━━━━━━━━━━━━━━━━━ 2s 153ms/step - loss: 0.0076
```

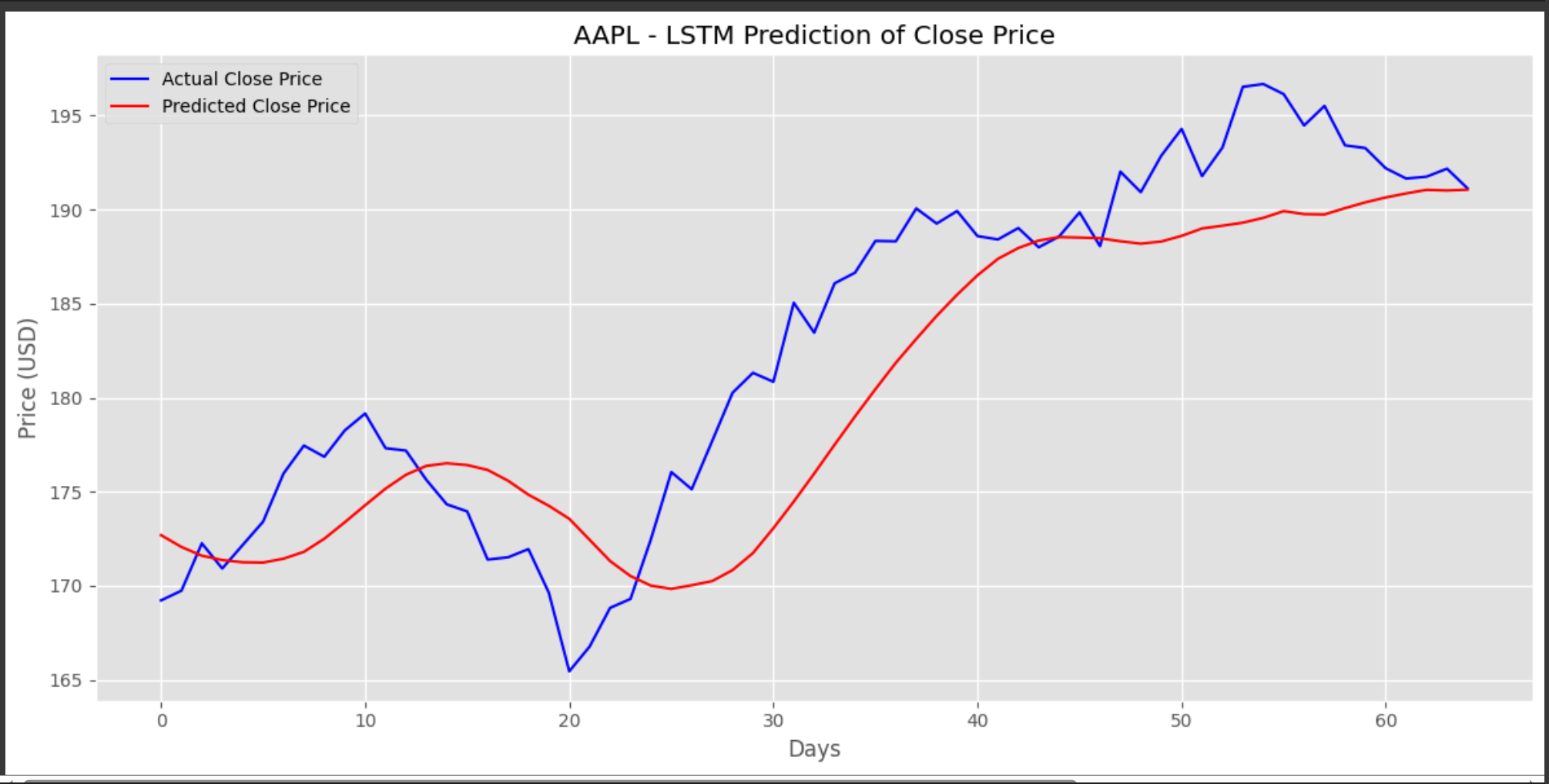
```
# STEP 9: Make predictions
predicted_scaled = model.predict(X_test)
predicted_full = np.zeros((predicted_scaled.shape[0], scaled_data.shape[1]))
predicted_full[:, 3] = predicted_scaled[:, 0]  # Fill only the Close column
```

```
WARNING:tensorflow:5 out of the last 7 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x7ab60bfc85e0
2/3 ━━━━━━━━━━━━━━━━━━━━ 0s 52ms/step WARNING:tensorflow:6 out of the last 9 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step
3/3 ━━━━━━━━━━━━━━━━━━━━ 1s 204ms/step
```

```
# Reverse scale only Close values
actual_scaled = np.zeros((len(y_test), scaled_data.shape[1]))
actual_scaled[:, 3] = y_test
```

```
predicted_prices = scaler.inverse_transform(predicted_full)[:, 3]
actual_prices = scaler.inverse_transform(actual_scaled)[:, 3]
```

```
# STEP 10: Visualize predictions vs actual
plt.figure(figsize=(12,6))
plt.plot(actual_prices, label='Actual Close Price', color='blue')
plt.plot(predicted_prices, label='Predicted Close Price', color='red')
plt.title(f'{ticker} - LSTM Prediction of Close Price')
plt.xlabel('Days')
plt.ylabel('Price (USD)')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
mae = mean_absolute_error(actual_prices, predicted_prices)
rmse = np.sqrt(mean_squared_error(actual_prices, predicted_prices))
r2 = r2_score(actual_prices, predicted_prices)

print(f"MAE: {mae:.2f}")
print(f"RMSE: {rmse:.2f}")
print(f"R² Score: {r2:.4f}")
```

```
MAE: 4.02
RMSE: 4.85
R² Score: 0.7217
```

```
# Plot training loss
plt.plot(history.history['loss'])
plt.title("Training Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.grid(True)
plt.show()
```