

## ✓ Time Series Prediction of Coca-Cola Stock Prices Using LSTM

```
1 import pandas as pd
2 import numpy as np
3 from sklearn.preprocessing import MinMaxScaler
4 import matplotlib.pyplot as plt
5 from tensorflow.keras.models import Sequential
6 from tensorflow.keras.layers import LSTM, Dense, Dropout
7 from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, mean_absolute_percentage_e
```

```
1 # Load the data
2 data = pd.read_csv('/content/Coca-Cola_stock_history.csv')
```

```
1 # Convert Date to datetime format, handling extra characters
2 data['Date'] = pd.to_datetime(data['Date'], format='%Y-%m-%d %H:%M:%S%z', errors='coerce')
```

```
1 # Set Date as index
2 data.set_index('Date', inplace=True)
```

```
1 # Select relevant columns
2 features = data[['Close', 'Volume', 'Dividends', 'Stock Splits']]
```

```
1 # Normalize the data
2 scaler = MinMaxScaler(feature_range=(0, 1))
3 scaled_prices = scaler.fit_transform(prices)
```

```

1 # Create sequences of data
2 def create_sequences(data, seq_length):
3     X, y = [], []
4     for i in range(len(data) - seq_length):
5         X.append(data[i:i + seq_length])
6         y.append(data[i + seq_length])
7     return np.array(X), np.array(y)
8
9 seq_length = 50
10 X, y = create_sequences(scaled_prices, seq_length)

```

```

1 # Reshape X to fit the RNN input
2 X = X.reshape((X.shape[0], X.shape[1], 1))

```

```

1 # Split data into train and test sets
2 split = int(0.8 * len(X))
3 X_train, X_test = X[:split], X[split:]
4 y_train, y_test = y[:split], y[split:]

```

```

1 # Build the LSTM model
2 model = Sequential()
3 model.add(LSTM(50, return_sequences=True, input_shape=(seq_length, X.shape[2])))
4 model.add(Dropout(0.2))
5 model.add(LSTM(50))
6 model.add(Dropout(0.2))
7 model.add(Dense(1))
8
9 model.compile(optimizer='adam', loss='mean_squared_error')
10 model.summary()

```

➡ Model: "sequential\_8"

Layer (type)	Output Shape	Param #
=====		
lstm_6 (LSTM)	(None, 50, 50)	10400
dropout_16 (Dropout)	(None, 50, 50)	0

lstm_7 (LSTM)	(None, 50)	20200
dropout_17 (Dropout)	(None, 50)	0
dense_8 (Dense)	(None, 1)	51

=====  
Total params: 30651 (119.73 KB)  
Trainable params: 30651 (119.73 KB)  
Non-trainable params: 0 (0.00 Byte)  
=====

```
1 # Train the model
2 history = model.fit(X_train, y_train, epochs=50, batch_size=32, validation_data=(X_test, y_test))
```



```
382/382 [=====] - 21s 54ms/step - loss: 8.2354e-05 - val_loss: 0.0022
Epoch 35/50
382/382 [=====] - 21s 54ms/step - loss: 8.3430e-05 - val_loss: 0.0045
Epoch 36/50
382/382 [=====] - 21s 55ms/step - loss: 8.2163e-05 - val_loss: 0.0036
Epoch 37/50
382/382 [=====] - 20s 53ms/step - loss: 8.1604e-05 - val_loss: 0.0049
Epoch 38/50
382/382 [=====] - 21s 56ms/step - loss: 8.0913e-05 - val_loss: 0.0023
Epoch 39/50
382/382 [=====] - 20s 53ms/step - loss: 8.2749e-05 - val_loss: 0.0037
Epoch 40/50
382/382 [=====] - 21s 55ms/step - loss: 7.8992e-05 - val_loss: 0.0033
Epoch 41/50
382/382 [=====] - 20s 52ms/step - loss: 7.8135e-05 - val_loss: 0.0074
Epoch 42/50
382/382 [=====] - 21s 56ms/step - loss: 8.1521e-05 - val_loss: 0.0039
Epoch 43/50
382/382 [=====] - 20s 51ms/step - loss: 7.6379e-05 - val_loss: 0.0051
Epoch 44/50
382/382 [=====] - 21s 56ms/step - loss: 7.8489e-05 - val_loss: 0.0057
Epoch 45/50
382/382 [=====] - 20s 52ms/step - loss: 7.7944e-05 - val_loss: 0.0053
Epoch 46/50
382/382 [=====] - 21s 56ms/step - loss: 8.1946e-05 - val_loss: 0.0055
Epoch 47/50
382/382 [=====] - 20s 51ms/step - loss: 7.9614e-05 - val_loss: 0.0048
Epoch 48/50
382/382 [=====] - 21s 56ms/step - loss: 8.0926e-05 - val_loss: 0.0087
Epoch 49/50
382/382 [=====] - 20s 52ms/step - loss: 7.7035e-05 - val_loss: 0.0054
Epoch 50/50
382/382 [=====] - 21s 55ms/step - loss: 7.7047e-05 - val_loss: 0.0059
```

```
1 # Evaluate the model performance
2 predicted_prices = model.predict(X_test)
3 predicted_prices = scaler.inverse_transform(np.concatenate((predicted_prices, np.zeros((predicted_prices.shape[0], 3))))
4 actual_prices = scaler.inverse_transform(np.concatenate((y_test.reshape(-1, 1), np.zeros((y_test.shape[0], 3))), axis=1
```

```
⇒ 96/96 [=====] - 2s 14ms/step
```

```
1 # Calculate Mean Squared Error (MSE) and Mean Absolute Error (MAE)
2 mse = mean_squared_error(actual_prices, predicted_prices)
3 mae = mean_absolute_error(actual_prices, predicted_prices)
4 r2 = r2_score(actual_prices, predicted_prices)
5 mape = mean_absolute_percentage_error(actual_prices, predicted_prices)
6 print(f"Mean Squared Error (MSE): {mse}")
7 print(f"Mean Absolute Error (MAE): {mae}")
8 print(f"R-squared (R2): {r2}")
9 print(f"Mean Absolute Percentage Error (MAPE): {mape}")
```

➞ Mean Squared Error (MSE): 25.244215153620342  
Mean Absolute Error (MAE): 3.680703339364588  
R-squared (R2): 0.7800762457145903  
Mean Absolute Percentage Error (MAPE): 0.08267929786686115

```
1 # Plotting the actual vs predicted prices
2 plt.figure(figsize=(14, 7))
3 plt.plot(actual_prices, color='blue', label='Actual Coca-Cola Stock Price')
4 plt.plot(predicted_prices, color='red', label='Predicted Coca-Cola Stock Price')
5 plt.title('Coca-Cola Stock Price Prediction')
6 plt.xlabel('Time')
7 plt.ylabel('Stock Price')
8 plt.legend()
9 plt.show()
```



Coca-Cola Stock Price Prediction

