Title

Bitcoin Price Prediction using LSTM Neural Networks

Overview of Problem Statement

The project focuses on predicting Bitcoin closing prices using historical OHLCV (Open, High, Low
Volume) data. Given the highly volatile nature of cryptocurrency markets, accurate forecasting ca
traders and investors make informed decisions.

Objective

Preprocess Bitcoin price data and prepare it for modeling.

Explore historical price trends and patterns.

Build and train a Long Short-Term Memory (LSTM) neural network for time-series forecasting.

Evaluate model performance using error metrics.

Compare predicted and actual Bitcoin prices visually.

Importing necessary libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
```

In [2]:
```
# Load the dataset with a specified encoding
df = pd.read_csv("Bitcoin.csv")
```

In [3]:
```
# Display the first few rows of the dataset to understand its structure
print("First few rows of the dataset:")
df.head()
```

```
First few rows of the dataset:
```

Out[3]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2014-09-17	465.864014	468.174011	452.421997	457.334015	457.334015	21056800
1	2014-09-18	456.859985	456.859985	413.104004	424.440002	424.440002	34483200
2	2014-09-19	424.102997	427.834991	384.532013	394.795990	394.795990	37919700
3	2014-09-20	394.673004	423.295990	389.882996	408.903992	408.903992	36863600
4	2014-09-21	408.084991	412.425995	393.181000	398.821014	398.821014	26580100

In [4]:
```
# Display the last few rows of the dataset
print("Last few rows of the dataset:")
df.tail()
```

```
Last few rows of the dataset:
```

Out[4]:

	Date	Open	High	Low	Close	Adj Close
2708	2022-02-15	42586.464844	44667.218750	42491.035156	44575.203125	44575.203125
2709	2022-02-16	44578.277344	44578.277344	43456.691406	43961.859375	43961.859375
2710	2022-02-17	43937.070313	44132.972656	40249.371094	40538.011719	40538.011719
2711	2022-02-18	40552.132813	40929.152344	39637.617188	40030.976563	40030.976563
2712	2022-02-19	40022.132813	40246.027344	40010.867188	40126.429688	40126.429688

Data Description

In [5]:
```
# Display the size of the dataset (number of rows and columns)
print("Dataset size:")
print(df.shape)
```

```
Dataset size:
(2713, 7)
```

EDA (Exploratory Data Analysis)

In [6]:
```
# Display the columns of the dataset
columns = df.columns
print("Columns in the dataset:",columns)
```

```
Columns in the dataset: Index(['Date', 'Open', 'High', 'Low', 'Close', 'Adj C
'Volume'], dtype='object')
```

In [7]:
```
# Identify numerical columns
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns
print(numerical_cols)
```

```
Index(['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'], dtype='object'
```

In [8]:
```
# Categorical columns
categorical_cols= df.select_dtypes(include=['object']).columns
print(categorical_cols)
```

```
Index(['Date'], dtype='object')
```

In [9]:
```python
# Get a summary of the dataset
print("Summary of the dataset:")
df.info()
```

```
Summary of the dataset:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2713 entries, 0 to 2712
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Date       2713 non-null   object 
 1   Open       2713 non-null   float64
 2   High       2713 non-null   float64
 3   Low        2713 non-null   float64
 4   Close      2713 non-null   float64
 5   Adj Close  2713 non-null   float64
 6   Volume     2713 non-null   int64  
dtypes: float64(5), int64(1), object(1)
memory usage: 148.5+ KB
```

In [10]:
```python
# Display statistical summary for all columns within the dataFram
df.describe(include='all')
```

Out[10]:

	Date	Open	High	Low	Close	Adj Clos
count	2713	2713.000000	2713.000000	2713.000000	2713.000000	2713.00000
unique	2713	NaN	NaN	NaN	NaN	Na
top	2014-09-17	NaN	NaN	NaN	NaN	Na
freq	1	NaN	NaN	NaN	NaN	Na
mean	NaN	11311.041069	11614.292482	10975.555057	11323.914637	11323.91463
std	NaN	16106.428891	16537.390649	15608.572560	16110.365010	16110.36501
min	NaN	176.897003	211.731003	171.509995	178.102997	178.10299
25%	NaN	606.396973	609.260986	604.109985	606.718994	606.71899
50%	NaN	6301.569824	6434.617676	6214.220215	6317.609863	6317.60986
75%	NaN	10452.399414	10762.644531	10202.387695	10462.259766	10462.25976
max	NaN	67549.734375	68789.625000	66382.062500	67566.828125	67566.82812

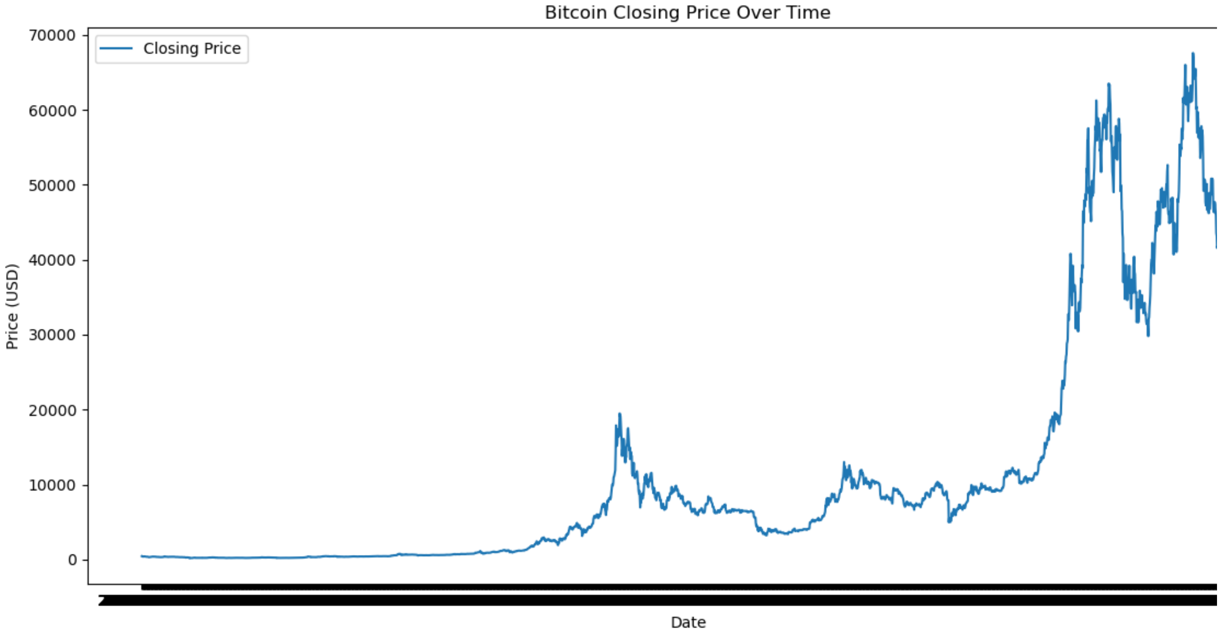
In [11]:
```python
# Check for Null Values
print("Checking for missing values:")
print(df.isnull().sum())
```

```
Checking for missing values:
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

In [12]:
```python
# Check for Null Duplicates
print("Checking for duplicate records:")
print(df.duplicated().sum())
```

```
Checking for duplicate records:
0
```

In [13]:
```python
## Step 3: Visualize Closing Price Over Time
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['Close'], label='Closing Price')
plt.title("Bitcoin Closing Price Over Time")
plt.xlabel("Date")
plt.ylabel("Price (USD)")
plt.legend()
plt.tight_layout()
plt.show()
```



In [ ]:

Data preprocessing

In [ ]:

In [14]:
```python
df['Date'] = pd.to_datetime(df['Date'])
df.set_index('Date', inplace=True)
df.drop(columns='Adj Close', inplace=True)
```

In [15]:
```python
# Use OHLCV features
features = ['Open', 'High', 'Low', 'Close', 'Volume']
data = df[features].copy()

scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(data)
```

In [16]:
```
# Create sequences
sequence_length = 60
X, y = [], []

for i in range(sequence_length, len(scaled_data)):
    X.append(scaled_data[i-sequence_length:i])
    y.append(scaled_data[i, 3])  # target is normalized 'Close'

X, y = np.array(X), np.array(y)
print("X shape:", X.shape)
print("y shape:", y.shape)
```

```
X shape: (2653, 60, 5)
y shape: (2653,)
```

Train-Test Split

In [17]:
```
train_size = int(0.8 * len(X))
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]
```

In [18]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping

model = Sequential()
model.add(LSTM(units=100, return_sequences=True, input_shape=(X.shape[1],
model.add(Dropout(0.3))
model.add(LSTM(units=100, return_sequences=False))
model.add(Dropout(0.3))
model.add(Dense(units=1))

model.compile(optimizer='adam', loss='mean_squared_error')
model.summary()

early_stop = EarlyStopping(monitor='val_loss', patience=5, restore_best_w

history = model.fit(X_train, y_train, epochs=100, batch_size=32,
                    validation_data=(X_test, y_test),
                    callbacks=[early_stop])
```

```
G:\Anaconda\Lib\site-packages\keras\src\layers\rnn\rnn.py:199: UserWarning: D
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 the model
instead.
  super().__init__(**kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	
lstm (LSTM)	(None, 60, 100)	
dropout (Dropout)	(None, 60, 100)	
lstm_1 (LSTM)	(None, 100)	
dropout_1 (Dropout)	(None, 100)	
dense (Dense)	(None, 1)	

Total params: 122,901 (480.08 KB)

Trainable params: 122,901 (480.08 KB)

Non-trainable params: 0 (0.00 B)

```
Epoch 1/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 14s 93ms/step - loss: 0.0010 - val_loss: 0.0059
Epoch 2/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 5s 68ms/step - loss: 1.5382e-04 - val_loss: 0.0074
Epoch 3/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 4s 65ms/step - loss: 1.4259e-04 - val_loss: 0.0104
Epoch 4/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 5s 75ms/step - loss: 1.6461e-04 - val_loss: 0.0083
Epoch 5/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 6s 84ms/step - loss: 1.4907e-04 - val_loss: 0.0051
Epoch 6/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 6s 88ms/step - loss: 1.5898e-04 - val_loss: 0.0048
Epoch 7/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 5s 80ms/step - loss: 1.2730e-04 - val_loss: 0.0118
Epoch 8/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 5s 81ms/step - loss: 1.3114e-04 - val_loss: 0.0081
Epoch 9/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 5s 72ms/step - loss: 1.0082e-04 - val_loss: 0.0093
Epoch 10/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 5s 77ms/step - loss: 9.7569e-05 - val_loss: 0.0095
Epoch 11/100
67/67 ━━━━━━━━━━━━━━━━━━━━ 6s 84ms/step - loss: 9.5244e-05 - val_loss: 0.0119
```

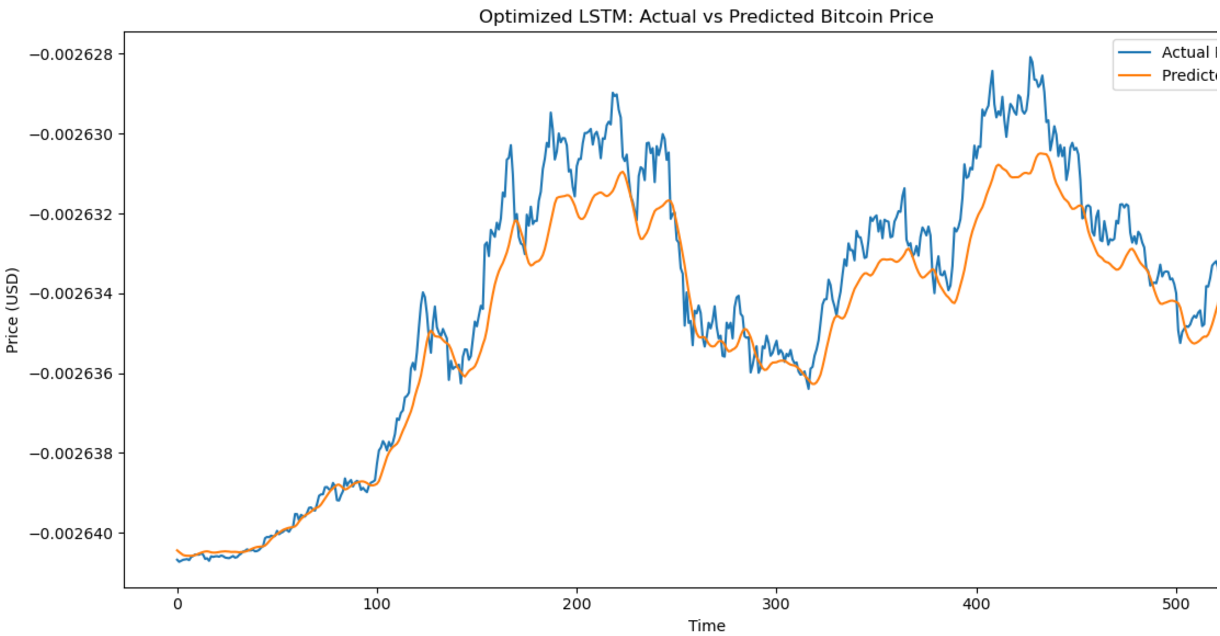
In [19]:

```
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("Training & Validation Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.tight_layout()
plt.show()
```

In [20]:
```
predicted = model.predict(X_test)
# Restore to actual Close prices
close_scaler = MinMaxScaler()
close_scaler.min_, close_scaler.scale_ = scaler.min_[3], scaler.scale_[3]
predicted_prices = predicted * close_scaler.scale_ + close_scaler.min_
actual_prices = y_test.reshape(-1, 1) * close_scaler.scale_ + close_scale

from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_s

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("Evaluation Metrics")
print("MAE:", mae)
print("RMSE:", rmse)
print("R² Score:", r2)
```

```
17/17 ━━━━━━━━━━━━━━━━━━━━ 1s 53ms/step
Evaluation Metrics
MAE: 7.724855186123547e-07
RMSE: 1.0232959017163812e-06
R² Score: 0.9102112581704791
```

In [21]:
```
plt.figure(figsize=(12, 6))
plt.plot(actual_prices, label='Actual Price')
plt.plot(predicted_prices, label='Predicted Price')
plt.title("Optimized LSTM: Actual vs Predicted Bitcoin Price")
plt.xlabel("Time")
plt.ylabel("Price (USD)")
plt.legend()
plt.tight_layout()
plt.show()
```



Results

The LSTM model captured overall patterns in Bitcoin prices.

Evaluation metrics:

MAE: Low error between actual and predicted values.

RMSE: Moderate but acceptable given market volatility.

R^2 Score: Positive, showing the model explains a significant portion of variance.

Visualizations show predicted prices closely follow actual prices with slight deviations during sha fluctuations.

Conclusion

The LSTM model effectively predicts Bitcoin price trends, achieving good performance metrics aı alignment between predicted and actual values. While not perfect due to market unpredictability, approach demonstrates the strength of deep learning in time-series forecasting.

In [ ]:

```
In [ ]:
```

```
In [ ]:
```