Time Series Analysis with Crypto currency

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```
import requests
import pandas as pd
import numpy as np
from datetime import datetime, timedelta

# API Keys and Endpoints
COINGECKO_API_URL =
'https://api.coingecko.com/api/v3/coins/bitcoin/market_chart'
ALPHA_VANTAGE_API_URL = 'https://www.alphavantage.co/query'
YAHOO_FINANCE_URL =
'https://query1.finance.yahoo.com/v7/finance/download/'
BINANCE_API_URL = 'https://api.binance.com/api/v3/klines'

# Example: Collecting Binance data
def fetch_binance_data(symbol='BTCUSDT', interval='1d', limit=100):
    params = {
        'symbol': symbol,
        'interval': interval,
        'limit': limit
    }
    response = requests.get(BINANCE_API_URL, params=params)
    data = response.json()
    # Create DataFrame
    df = pd.DataFrame(data, columns=['Open Time', 'Open', 'High',
'Low', 'Close', 'Volume', 'Close Time', 'Quote Asset Volume', 'Number
of Trades', 'Taker Buy Base Volume', 'Taker Buy Quote Volume',
'Ignore'])
    df['Open Time'] = pd.to_datetime(df['Open Time'], unit='ms')
    df['Close Time'] = pd.to_datetime(df['Close Time'], unit='ms')
    df[['Open', 'High', 'Low', 'Close', 'Volume']] = df[['Open',
'High', 'Low', 'Close', 'Volume']].astype(float)
    return df[['Open Time', 'Open', 'High', 'Low', 'Close', 'Volume']]

# Example: Collecting CoinGecko data
def fetch_coingecko_data(days=30):
    params = {'vs_currency': 'usd', 'days': days}
    response = requests.get(COINGECKO_API_URL, params=params)
    data = response.json()
    prices = data['prices']
    df = pd.DataFrame(prices, columns=['timestamp', 'price'])
    df['timestamp'] = pd.to_datetime(df['timestamp'], unit='ms')
```

```python
    return df

# Data Preprocessing
def preprocess_data(df):
    # Handling Missing Values
    df = df.dropna()
    # Normalization
    df['price_normalized'] = (df['price'] - df['price'].min()) /
(df['price'].max() - df['price'].min())
    # Feature Engineering
    df['moving_average'] = df['price'].rolling(window=5).mean()
    df['volatility'] = df['price'].rolling(window=5).std()
    return df

# Save Data to CSV
def save_data_to_csv(df, filename):
    df.to_csv(filename, index=False)
    print(f"Data saved to {filename}")

# Sample Usage
if __name__ == "__main__":
    # Fetch Binance Data
    binance_data = fetch_binance_data()
    print("Binance Data:\n", binance_data.head())

    # Fetch CoinGecko Data
    coingecko_data = fetch_coingecko_data()
    print("CoinGecko Data:\n", coingecko_data.head())

    # Preprocess Data
    processed_data = preprocess_data(coingecko_data)
    print("Processed Data:\n", processed_data.head())

    # Save Data to CSV
    save_data_to_csv(processed_data, "crypto_data.csv")
```

```
Binance Data:
    Open Time      Open      High       Low     Close       Volume
0 2025-02-10  96462.75  98345.00  95256.00  97430.82  20572.87537
1 2025-02-11  97430.82  98478.42  94876.88  95778.20  18647.76379
2 2025-02-12  95778.21  98119.99  94088.23  97869.99  29151.16625
3 2025-02-13  97870.00  98083.91  95217.36  96608.14  19921.77616
4 2025-02-14  96608.13  98826.00  96252.82  97500.48  18173.02646
CoinGecko Data:
                 timestamp         price
0 2025-04-20 05:01:40.936  85195.672595
1 2025-04-20 06:01:18.578  85100.822792
2 2025-04-20 07:04:37.355  84950.900731
3 2025-04-20 08:04:51.704  84777.376134
4 2025-04-20 09:04:14.804  84631.436866
```

```
Processed Data:
                   timestamp         price  price_normalized
moving_average  \
0 2025-04-20 05:01:40.936  85195.672595          0.049135
NaN
1 2025-04-20 06:01:18.578  85100.822792          0.044906
NaN
2 2025-04-20 07:04:37.355  84950.900731          0.038220
NaN
3 2025-04-20 08:04:51.704  84777.376134          0.030482
NaN
4 2025-04-20 09:04:14.804  84631.436866          0.023974
84931.241824

   volatility
0         NaN
1         NaN
2         NaN
3         NaN
4  230.556649
Data saved to crypto_data.csv
```

Data Acquisition & Preprocessing for Cryptocurrency Analysis

1. Loading and Initial Inspection

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
df = pd.read_csv('crypto_data.csv', parse_dates=['timestamp'])

# Initial inspection
print(df.head(30))

                   timestamp         price  price_normalized
moving_average  \
0  2025-04-20 05:01:40.936  85195.672595          0.049135
NaN
1  2025-04-20 06:01:18.578  85100.822792          0.044906
NaN
2  2025-04-20 07:04:37.355  84950.900731          0.038220
NaN
3  2025-04-20 08:04:51.704  84777.376134          0.030482
NaN
4  2025-04-20 09:04:14.804  84631.436866          0.023974
84931.241824
5  2025-04-20 10:04:43.986  84530.865839          0.019489
```

```
84798.280472
6  2025-04-20 11:04:51.487  84160.544909           0.002975
84610.224896
7  2025-04-20 12:04:46.210  84093.833676           0.000000
84438.811485
8  2025-04-20 13:04:47.251  84347.364384           0.011306
84352.809135
9  2025-04-20 14:04:30.800  84327.789442           0.010433
84292.079650
10 2025-04-20 15:04:40.110  84612.566423           0.023132
84308.419767
11 2025-04-20 16:04:44.724  84357.124867           0.011741
84347.735758
12 2025-04-20 17:04:34.686  84598.168647           0.022490
84448.602753
13 2025-04-20 18:04:48.198  84563.859429           0.020960
84491.901762
14 2025-04-20 19:04:44.699  84561.238706           0.020843
84538.591615
15 2025-04-20 20:04:45.731  84633.096311           0.024048
84542.697592
16 2025-04-20 21:04:41.938  85074.930148           0.043751
84686.258648
17 2025-04-20 22:04:19.496  85006.658394           0.040707
84767.956597
18 2025-04-20 23:04:46.701  84832.447383           0.032938
84821.674188
19 2025-04-21 00:04:43.007  85140.019303           0.046654
84937.430308
20 2025-04-21 01:04:51.516  86714.027662           0.116845
85353.616578
21 2025-04-21 02:04:54.376  87278.346459           0.142010
85794.299840
22 2025-04-21 03:00:49.371  87325.359081           0.144107
86258.039978
23 2025-04-21 04:04:42.687  87228.601850           0.139792
86737.270871
24 2025-04-21 05:03:43.715  87323.940263           0.144043
87174.055063
25 2025-04-21 06:01:03.805  87542.225951           0.153778
87339.694721
26 2025-04-21 07:03:21.837  87506.676404           0.152192
87385.360709
27 2025-04-21 08:04:39.700  87446.144183           0.149493
87409.517730
28 2025-04-21 09:09:32.608  87636.206007           0.157969
87491.038561
29 2025-04-21 10:04:26.878  87491.963871           0.151536
87524.643283
```

```
      volatility
0            NaN
1            NaN
2            NaN
3            NaN
4     230.556649
5     231.629643
6     297.051957
7     298.599455
8     230.976768
9     171.721642
10    201.439333
11    183.771392
12    143.585609
13    137.956680
14    103.806585
15    107.793551
16    219.239123
17    251.886158
18    224.645307
19    205.171654
20    769.091274
21   1120.481577
22   1190.630571
23    926.251786
24    260.209404
25    119.976923
26    133.482404
27    130.811731
28    116.055617
29     71.253514
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 720 entries, 0 to 719
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   timestamp         720 non-null    datetime64[ns]
 1   price             720 non-null    float64
 2   price_normalized  720 non-null    float64
 3   moving_average    716 non-null    float64
 4   volatility        716 non-null    float64
dtypes: datetime64[ns](1), float64(4)
memory usage: 28.3 KB
None
```

```
print(df.describe())
```

```
                              timestamp          price  price_normalized  \
count                               720     720.000000        720.000000

mean   2025-05-05 04:57:43.756737536   97630.358880          0.603648

min       2025-04-20 05:01:40.936000   84093.833676          0.000000

25%    2025-04-27 16:49:56.128999936   94274.065735          0.453978

50%    2025-05-05 04:36:06.088499968   96333.903128          0.545834

75%    2025-05-12 17:19:43.298000128  103237.451618          0.853691

max              2025-05-20 05:06:05  106518.358867          1.000000

std                              NaN    5366.576857          0.239317


       moving_average   volatility
count      716.000000   716.000000
mean     97642.037292   290.196577
min      84292.079650    18.514953
25%      94286.101856   148.126028
50%      96322.947857   240.287178
75%     103264.977970   348.269655
max     106076.924744  1190.630571
std       5312.651036   200.722118
```

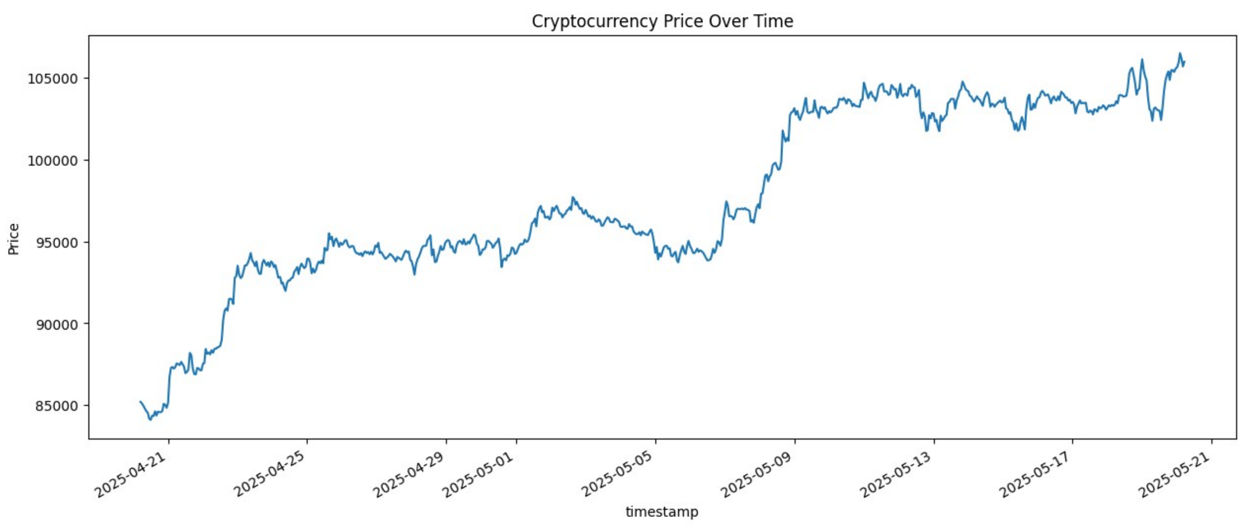
1. Handling Missing Values

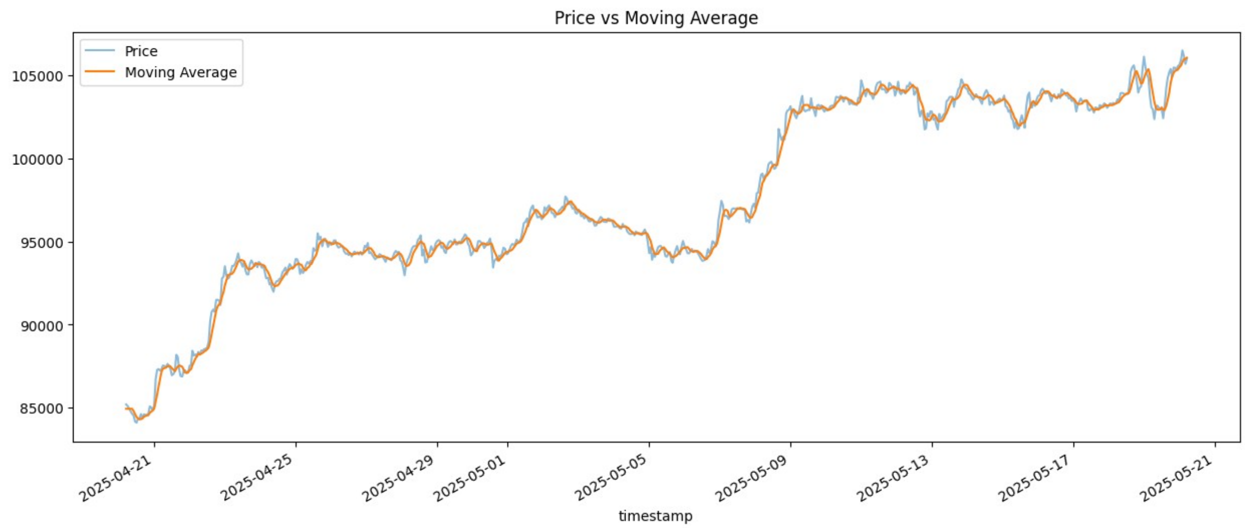
```
# Check for missing values
print(df.isnull().sum())

# Handle missing values
# Forward fill for price-related metrics
price_cols = ['price', 'price_normalized', 'moving_average',
'volatility']
df[price_cols] = df[price_cols].ffill().bfill()

# Verify no more missing values
print(df.isnull().sum())

timestamp           0
price               0
price_normalized    0
moving_average      4
volatility          4
dtype: int64
timestamp           0
price               0
```

```
price_normalized    0
moving_average      0
volatility          0
dtype: int64
```

1. Time Series Analysis

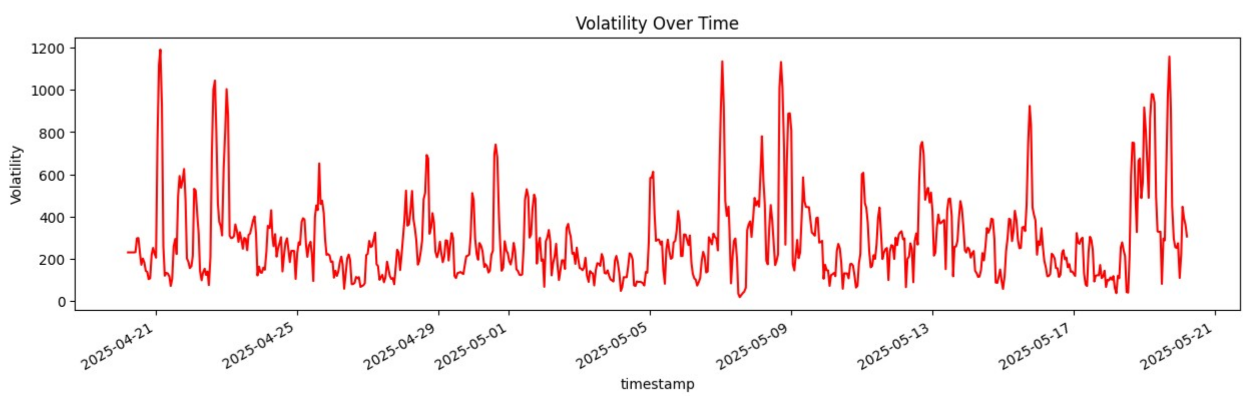
```
# Set timestamp as index
df.set_index('timestamp', inplace=True)

# Plot price trends
plt.figure(figsize=(15, 6))
df['price'].plot(title='Cryptocurrency Price Over Time')
plt.ylabel('Price')
plt.show()

# Plot moving average vs price
plt.figure(figsize=(15, 6))
df['price'].plot(label='Price', alpha=0.5)
df['moving_average'].plot(label='Moving Average')
plt.title('Price vs Moving Average')
plt.legend()
plt.show()
```

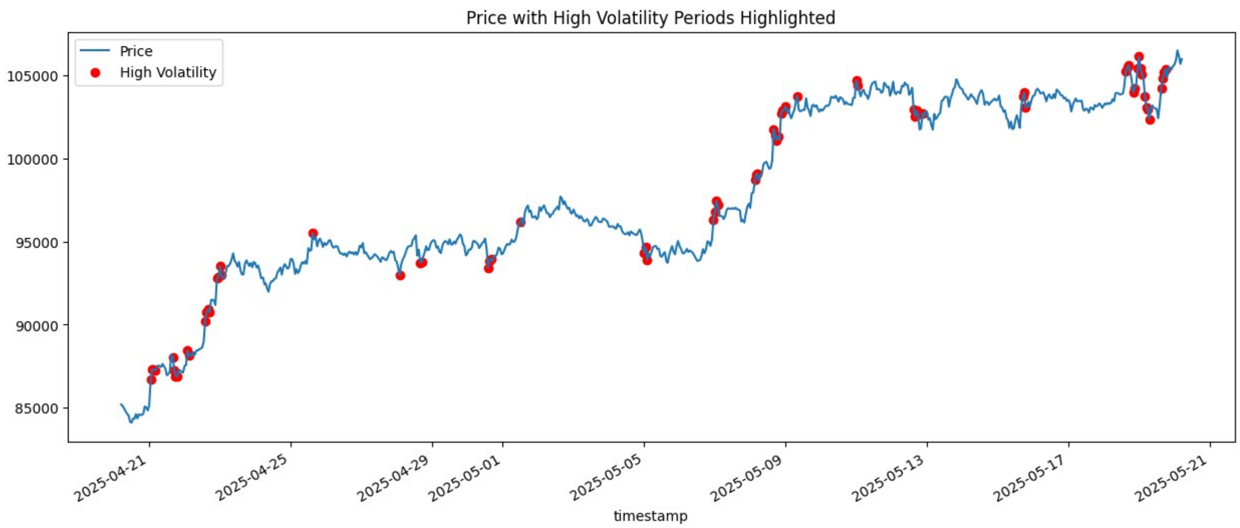




1. Volatility Analysis

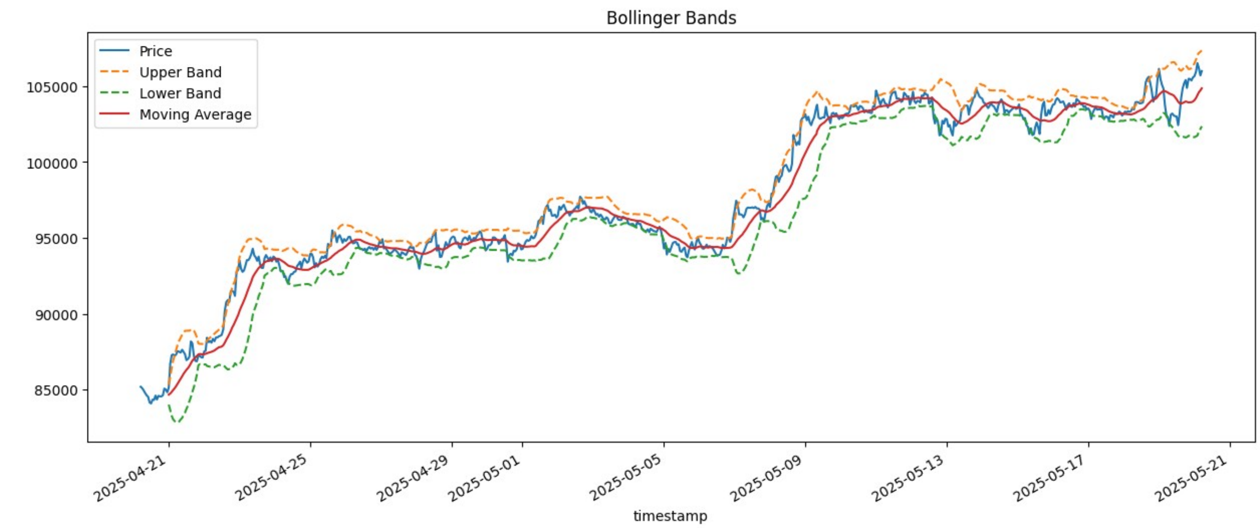
```
# Plot volatility
plt.figure(figsize=(15, 4))
df['volatility'].plot(title='Volatility Over Time', color='red')
plt.ylabel('Volatility')
plt.show()

# Identify high volatility periods
high_vol = df[df['volatility'] > df['volatility'].quantile(0.9)]
plt.figure(figsize=(15, 6))
df['price'].plot(label='Price')
plt.scatter(high_vol.index, high_vol['price'], color='red',
label='High Volatility')
plt.title('Price with High Volatility Periods Highlighted')
plt.legend()
plt.show()
```





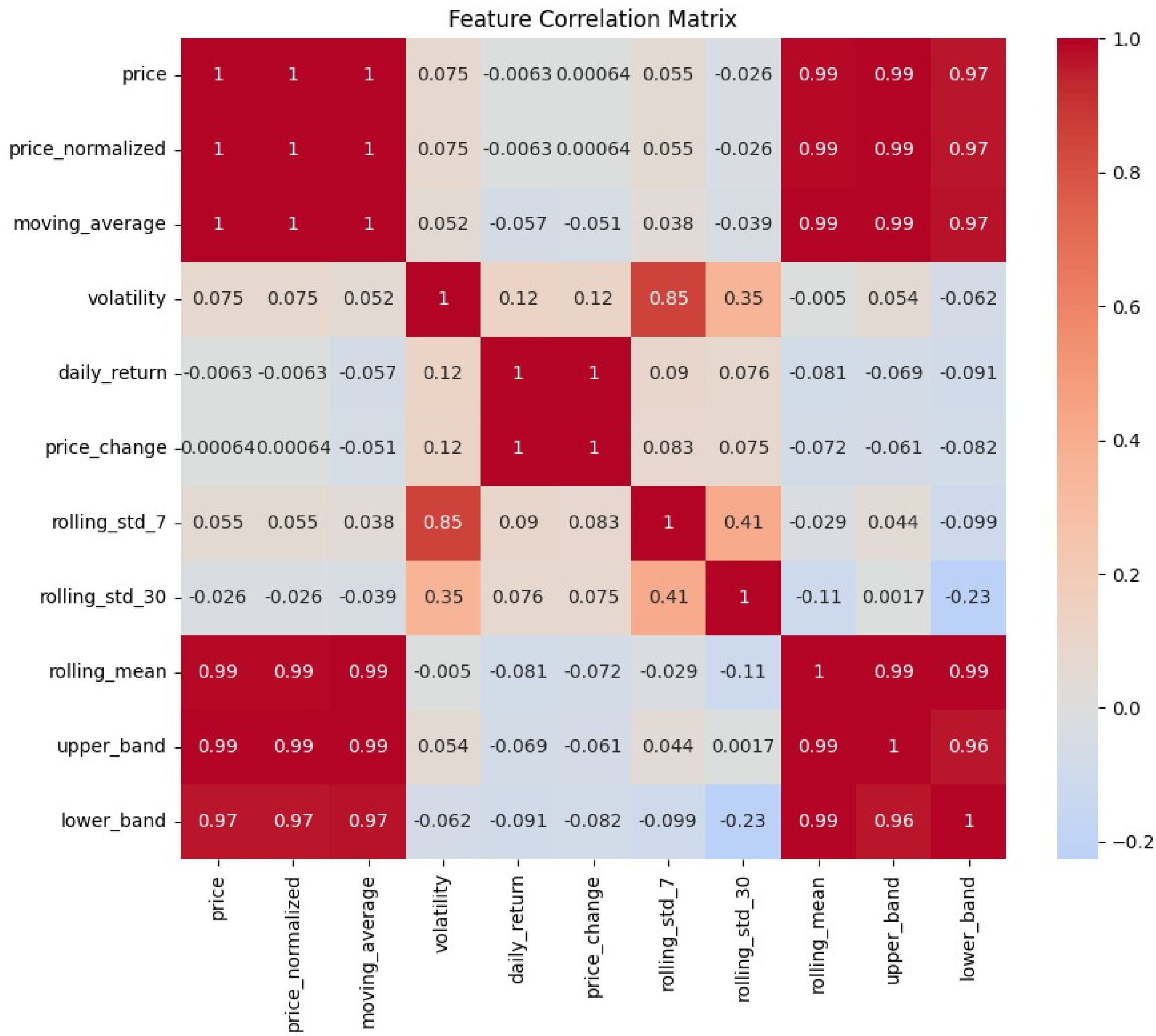
1. Feature Engineering

```
# Calculate additional features
df['daily_return'] = df['price'].pct_change() * 100
df['price_change'] = df['price'].diff()
df['rolling_std_7'] = df['price'].rolling(window=7).std()
df['rolling_std_30'] = df['price'].rolling(window=30).std()

# Bollinger Bands
df['rolling_mean'] = df['price'].rolling(window=20).mean()
df['upper_band'] = df['rolling_mean'] +
(df['price'].rolling(window=20).std() * 2)
df['lower_band'] = df['rolling_mean'] -
(df['price'].rolling(window=20).std() * 2)

# Plot Bollinger Bands
plt.figure(figsize=(15, 6))
df['price'].plot(label='Price')
df['upper_band'].plot(label='Upper Band', linestyle='--')
df['lower_band'].plot(label='Lower Band', linestyle='--')
df['rolling_mean'].plot(label='Moving Average')
plt.title('Bollinger Bands')
plt.legend()
plt.show()
```



1. Correlation Analysis

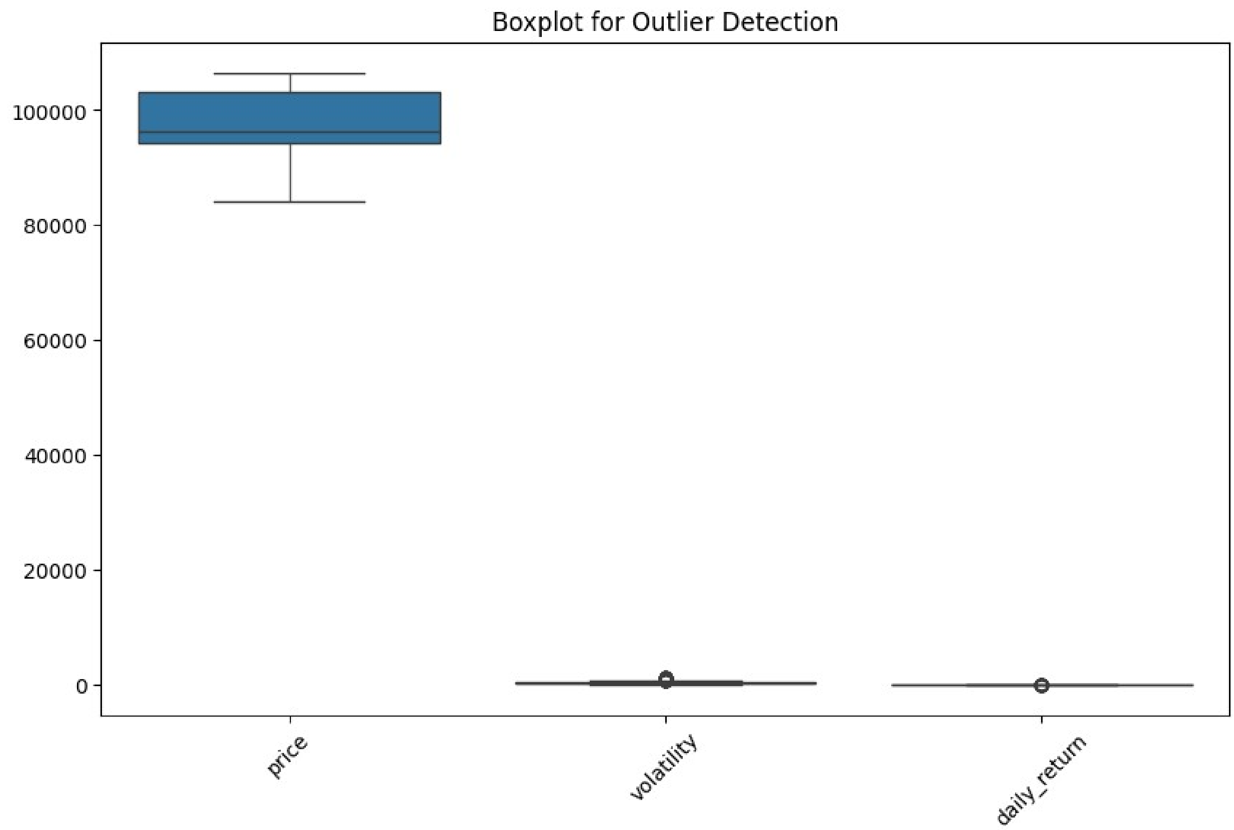
```
# Calculate correlations
corr_matrix = df.corr()

# Plot heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', center=0)
plt.title('Feature Correlation Matrix')
plt.show()
```



1. Outlier Detection

```
# Boxplot for outlier detection
plt.figure(figsize=(10, 6))
sns.boxplot(data=df[['price', 'volatility', 'daily_return']])
plt.title('Boxplot for Outlier Detection')
plt.xticks(rotation=45)
plt.show()

# Handle outliers (example using IQR)
def handle_outliers(series):
    Q1 = series.quantile(0.25)
    Q3 = series.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return series.clip(lower_bound, upper_bound)
```

```
df['price'] = handle_outliers(df['price'])
df['volatility'] = handle_outliers(df['volatility'])
```



1. Data Normalization

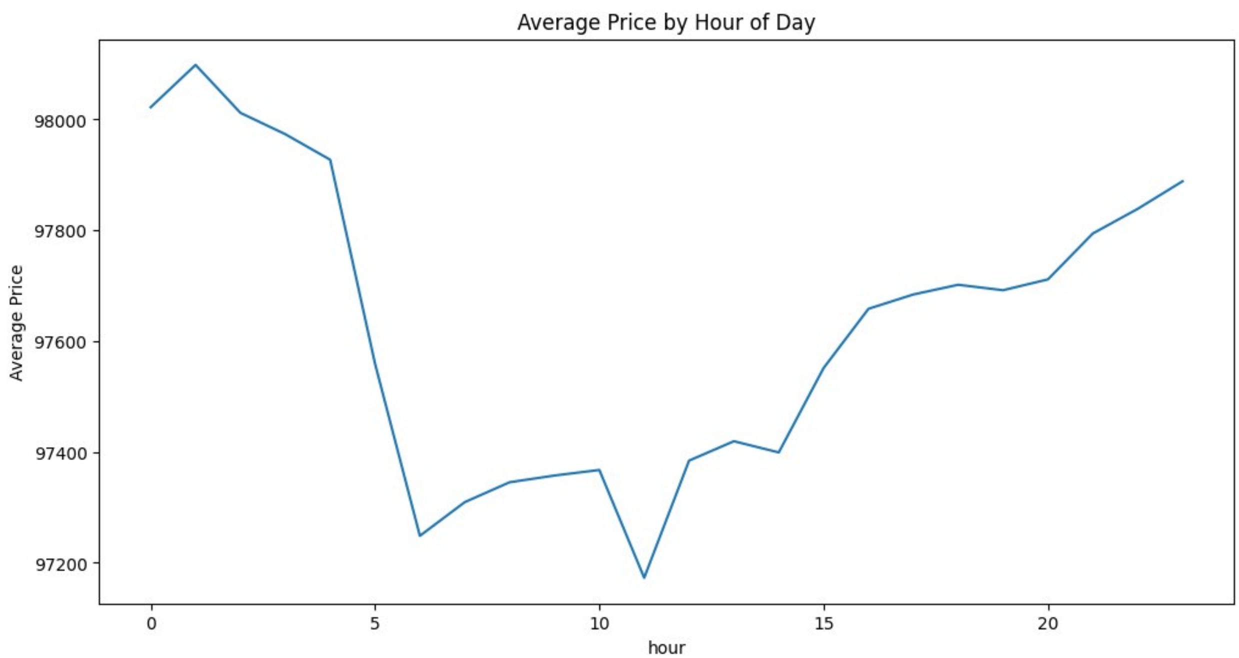
```
from sklearn.preprocessing import MinMaxScaler

# Initialize scaler
scaler = MinMaxScaler()

# Normalize features (if not already normalized)
if 'price_normalized' not in df.columns:
    df['price_normalized'] = scaler.fit_transform(df[['price']])

# Verify normalization
print(df[['price', 'price_normalized']].describe())
```

```
              price  price_normalized
count    720.000000        720.000000
mean   97630.358880          0.603648
std     5366.576857          0.239317
min    84093.833676          0.000000
25%    94274.065735          0.453978
50%    96333.903128          0.545834
```

```
75%    103237.451618          0.853691
max    106518.358867          1.000000
```

1. Time-Based Features

```
# Extract time-based features
df['hour'] = df.index.hour
df['day_of_week'] = df.index.dayofweek
df['month'] = df.index.month

# Analyze price by time periods
plt.figure(figsize=(12, 6))
df.groupby('hour')['price'].mean().plot(title='Average Price by Hour
of Day')
plt.ylabel('Average Price')
plt.show()
```



1. Final Data Preparation

```
# Ensure chronological order
df = df.sort_index()

# Save processed data
df.to_csv('processed_crypto_data.csv')

# Display final dataframe info
print(df.info())

<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 720 entries, 2025-04-20 05:01:40.936000 to 2025-05-20
```

```
05:06:05
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   price             720 non-null    float64
 1   price_normalized  720 non-null    float64
 2   moving_average    720 non-null    float64
 3   volatility        720 non-null    float64
 4   daily_return      719 non-null    float64
 5   price_change      719 non-null    float64
 6   rolling_std_7     714 non-null    float64
 7   rolling_std_30    691 non-null    float64
 8   rolling_mean      701 non-null    float64
 9   upper_band        701 non-null    float64
 10  lower_band        701 non-null    float64
 11  hour              720 non-null    int32
 12  day_of_week       720 non-null    int32
 13  month             720 non-null    int32
dtypes: float64(11), int32(3)
memory usage: 75.9 KB
None
```

Time Series Forecasting for Cryptocurrency Prices

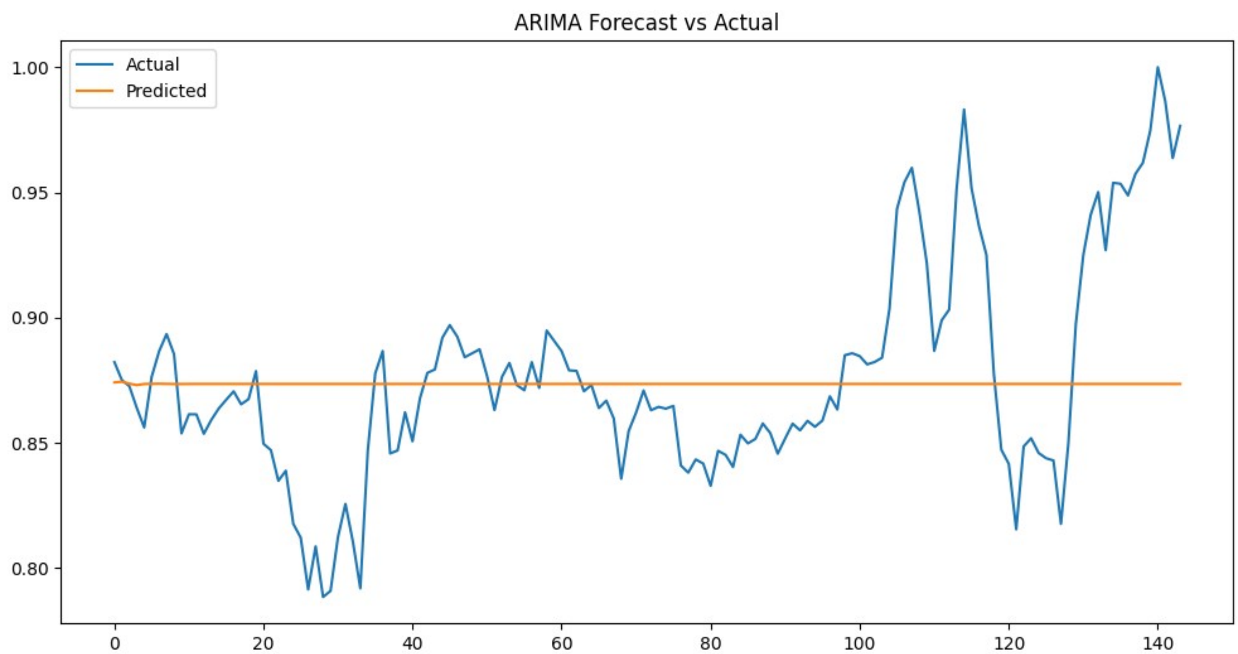
1. Data Preparation

```python
import pandas as pd
import numpy as np
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt

# Load preprocessed data
df = pd.read_csv('processed_crypto_data.csv',
parse_dates=['timestamp'], index_col='timestamp')

# Use the normalized price for modeling
series = df['price_normalized'].values.reshape(-1, 1)

# Train-test split (80-20)
train_size = int(len(series) * 0.8)
train, test = series[:train_size], series[train_size:]

# Function to evaluate models
def evaluate_model(y_true, y_pred, model_name):
    mse = mean_squared_error(y_true, y_pred)
    mae = mean_absolute_error(y_true, y_pred)
```

```python
    print(f'{model_name} - MSE: {mse:.6f}, MAE: {mae:.6f}')
    plt.figure(figsize=(12, 6))
    plt.plot(y_true, label='Actual')
    plt.plot(y_pred, label='Predicted')
    plt.title(f'{model_name} Forecast vs Actual')
    plt.legend()
    plt.show()
    return mse, mae
```

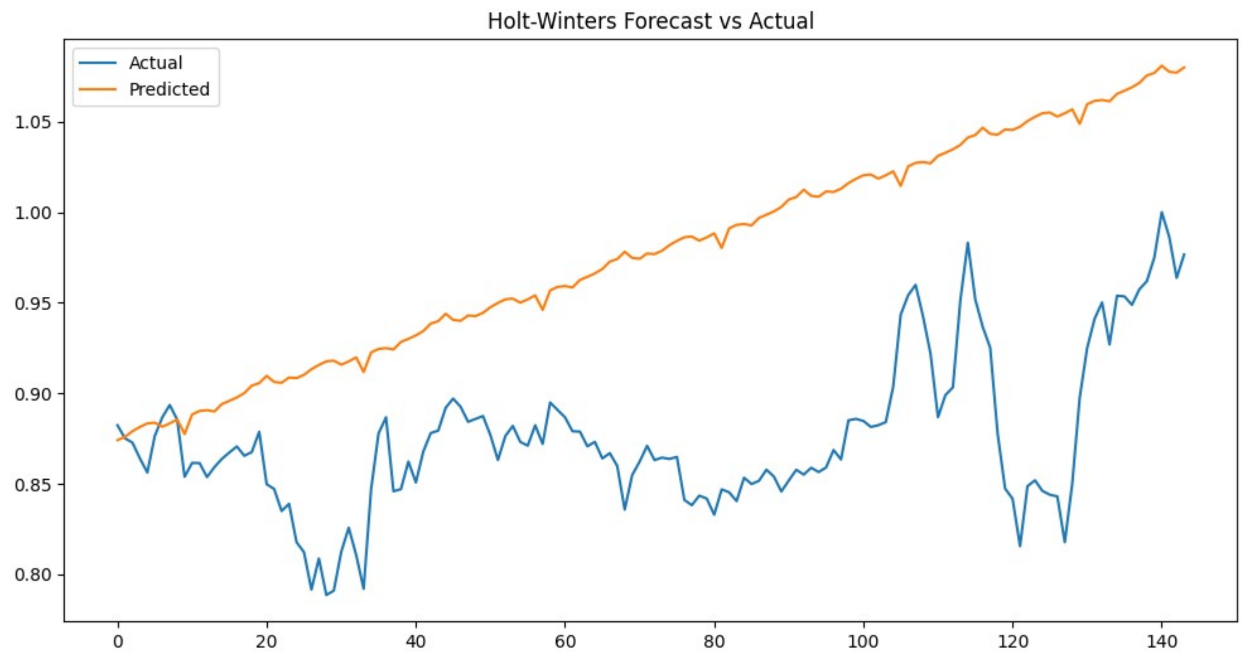
1. Statistical Models

```python
# ARIMA (AutoRegressive Integrated Moving Average)

from statsmodels.tsa.arima.model import ARIMA

# Fit ARIMA model
arima_model = ARIMA(train, order=(5,1,0))  # (p,d,q) parameters
arima_fit = arima_model.fit()

# Forecast
arima_forecast = arima_fit.forecast(steps=len(test))

# Evaluate
arima_mse, arima_mae = evaluate_model(test, arima_forecast, 'ARIMA')

ARIMA - MSE: 0.001786, MAE: 0.030876
```



Exponential Smoothing (Holt-Winters)

```
from statsmodels.tsa.holtwinters import ExponentialSmoothing

# Fit Holt-Winters model
hw_model = ExponentialSmoothing(train, trend='add', seasonal='add',
seasonal_periods=24)
hw_fit = hw_model.fit()

# Forecast
hw_forecast = hw_fit.forecast(len(test))

# Evaluate
hw_mse, hw_mae = evaluate_model(test, hw_forecast, 'Holt-Winters')

Holt-Winters - MSE: 0.012944, MAE: 0.101491
```



1. Machine Learning Models

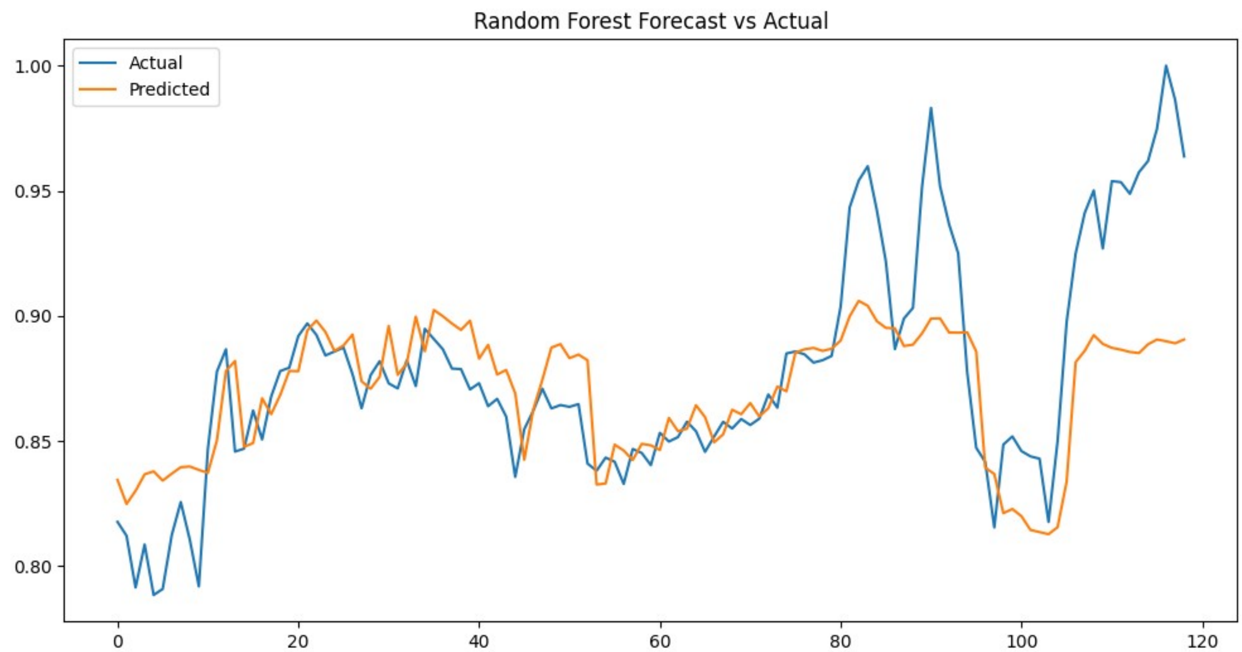
Firstly, creating the features for ML models:

```
def create_features(data, window_size=24):
    X, y = [], []
    for i in range(len(data) - window_size - 1):
        X.append(data[i:(i + window_size), 0])
        y.append(data[i + window_size, 0])
    return np.array(X), np.array(y)

window_size = 24  # Using 24 pe riods as historical context
X_train, y_train = create_features(train, window_size)
X_test, y_test = create_features(test, window_size)
```

Random Forest Regression

```
from sklearn.ensemble import RandomForestRegressor

# Train Random Forest
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Predict
rf_forecast = rf_model.predict(X_test)

# Evaluate
rf_mse, rf_mae = evaluate_model(y_test, rf_forecast, 'Random Forest')
```

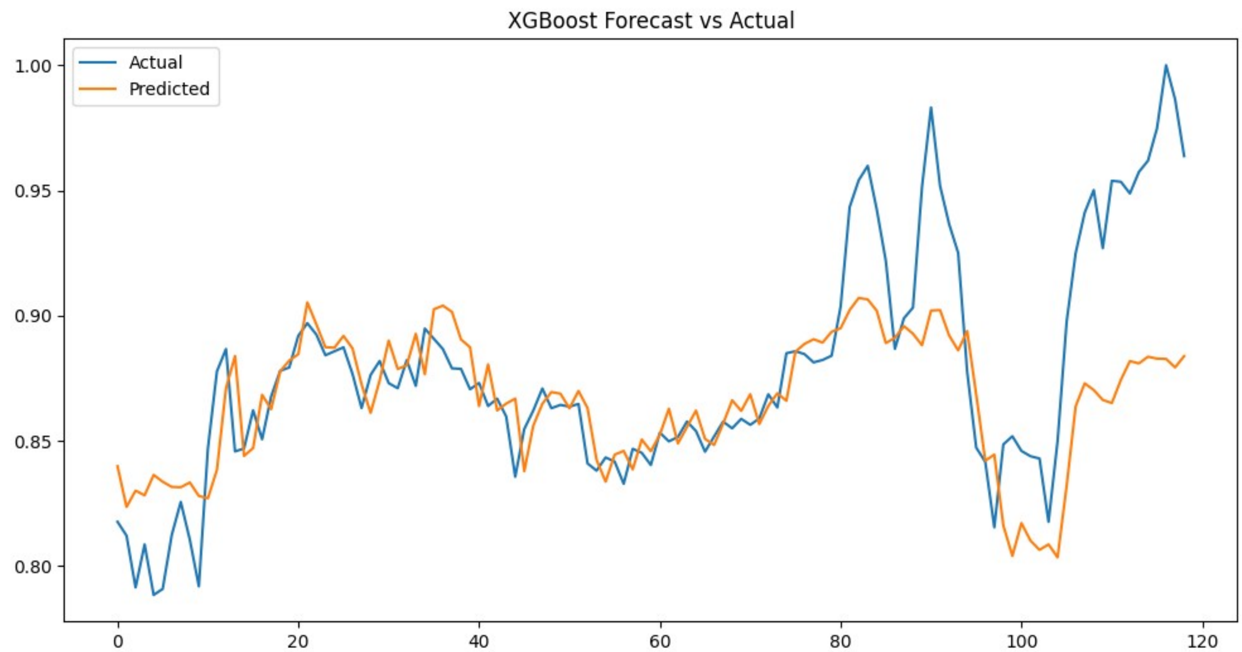
```
Random Forest - MSE: 0.001096, MAE: 0.023748
```



XGBoost

```
from xgboost import XGBRegressor

# Train XGBoost
xgb_model = XGBRegressor(n_estimators=100, learning_rate=0.1,
random_state=42)
xgb_model.fit(X_train, y_train)

# Predict
xgb_forecast = xgb_model.predict(X_test)

# Evaluate
xgb_mse, xgb_mae = evaluate_model(y_test, xgb_forecast, 'XGBoost')
```

```
XGBoost - MSE: 0.001262, MAE: 0.024281
```



1. Deep Learning Models

LSTM

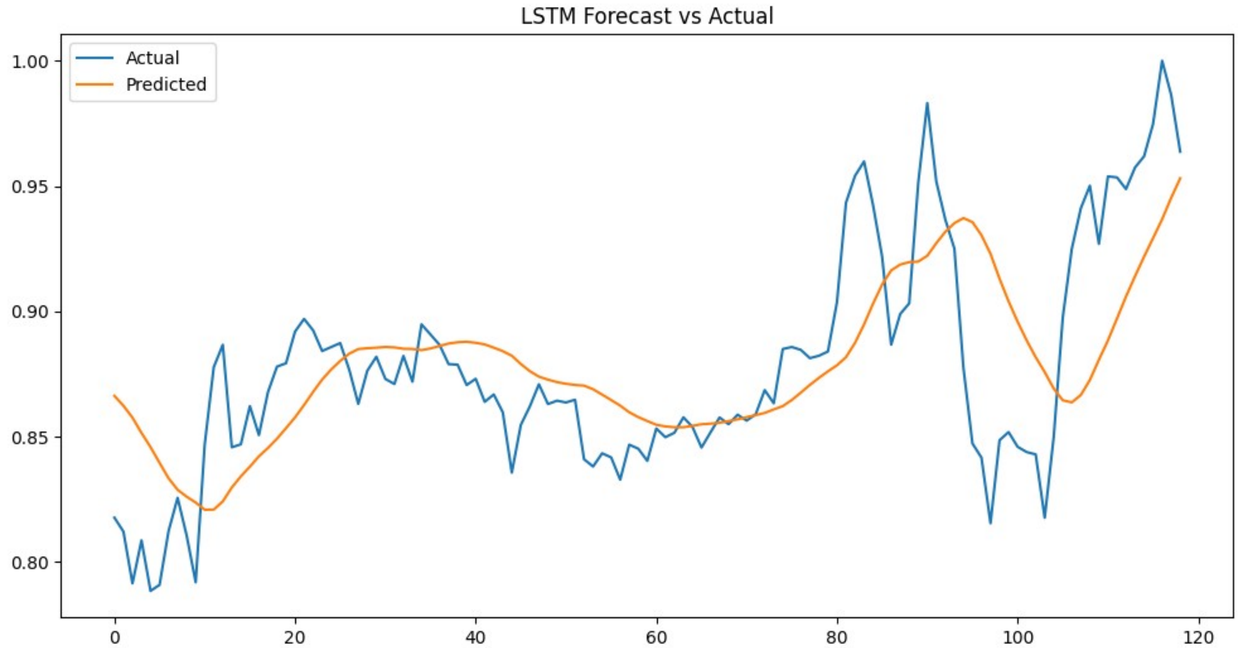
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout

# Reshape data for LSTM [samples, time steps, features]
X_train_lstm = X_train.reshape((X_train.shape[0], X_train.shape[1],
1))
X_test_lstm = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Build LSTM model
lstm_model = Sequential()
lstm_model.add(LSTM(50, return_sequences=True,
input_shape=(window_size, 1)))
lstm_model.add(LSTM(50))
lstm_model.add(Dense(1))
lstm_model.compile(optimizer='adam', loss='mse')

# Train
lstm_model.fit(X_train_lstm, y_train, epochs=20, batch_size=32,
verbose=1)

# Predict
lstm_forecast = lstm_model.predict(X_test_lstm)
```

```python
# Evaluate
lstm_mse, lstm_mae = evaluate_model(y_test, lstm_forecast, 'LSTM')
```

```
/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 the model instead.
  super().__init__(**kwargs)
```

```
Epoch 1/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 5s 32ms/step - loss: 0.1972
Epoch 2/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - loss: 0.0114
Epoch 3/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step - loss: 0.0032
Epoch 4/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 21ms/step - loss: 0.0018
Epoch 5/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 0.0014
Epoch 6/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 0.0012
Epoch 7/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 0.0012
Epoch 8/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 21ms/step - loss: 0.0011
Epoch 9/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 0.0014
Epoch 10/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step - loss: 0.0011
Epoch 11/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 21ms/step - loss: 0.0012
Epoch 12/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 9.2672e-04
Epoch 13/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 0.0012
Epoch 14/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 0.0010
Epoch 15/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - loss: 0.0012
Epoch 16/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 9.7874e-04
Epoch 17/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 0.0012
Epoch 18/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step - loss: 0.0010
Epoch 19/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 21ms/step - loss: 0.0010
Epoch 20/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 9.3706e-04
```

```
4/4 ━━━━━━━━━━━━━━━━━━━━ 1s 108ms/step
LSTM - MSE: 0.001290, MAE: 0.027491
```

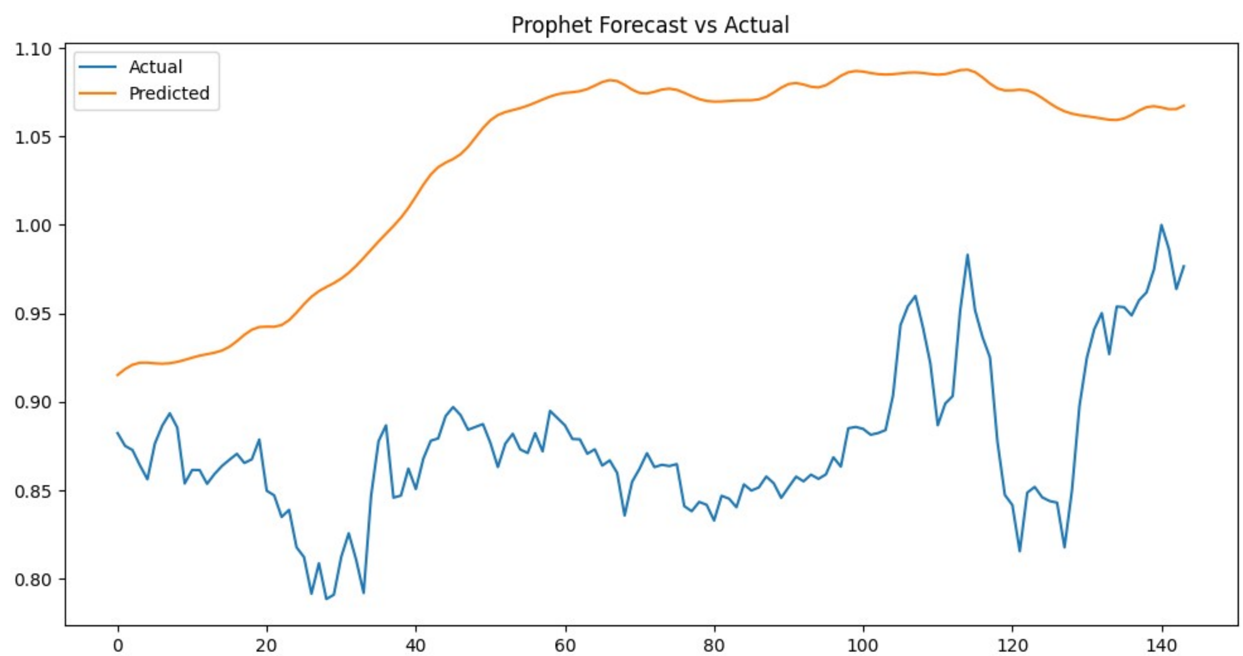


Facebook Prophet

```python
from prophet import Prophet

# Prepare data for Prophet
prophet_df = df.reset_index()[['timestamp',
'price_normalized']].rename(
    columns={'timestamp': 'ds', 'price_normalized': 'y'})

# Split train-test
prophet_train = prophet_df.iloc[:train_size]
prophet_test = prophet_df.iloc[train_size:]

# Fit model
prophet_model = Prophet(daily_seasonality=True)
prophet_model.fit(prophet_train)

# Create future dataframe
future = prophet_model.make_future_dataframe(periods=len(test),
freq='H')

# Forecast
prophet_forecast = prophet_model.predict(future)

# Evaluate on test period
prophet_preds = prophet_forecast.iloc[-len(test):]['yhat'].values
```

```
prophet_mse, prophet_mae = evaluate_model(test, prophet_preds,
'Prophet')
```

```
INFO:prophet:Disabling yearly seasonality. Run prophet with
yearly_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmphecu0jec/j68e33wk.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmphecu0jec/ai7bk7q0.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-
packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=9097',
'data', 'file=/tmp/tmphecu0jec/j68e33wk.json',
'init=/tmp/tmphecu0jec/ai7bk7q0.json', 'output',
'file=/tmp/tmphecu0jec/prophet_modelsgd15kv8/prophet_model-
20250520052758.csv', 'method=optimize', 'algorithm=lbfgs',
'iter=10000']
05:27:58 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
05:27:58 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
/usr/local/lib/python3.11/dist-packages/prophet/forecaster.py:1854:
FutureWarning: 'H' is deprecated and will be removed in a future
version, please use 'h' instead.
  dates = pd.date_range(

Prophet - MSE: 0.029458, MAE: 0.161068
```



Temporal Fusion Transformer (TFT)

```
!pip install pytorch-lightning pytorch-forecasting --quiet

import torch
import pytorch_lightning as pl
from pytorch_forecasting import TimeSeriesDataSet,
TemporalFusionTransformer
from pytorch_forecasting.metrics import QuantileLoss


# Prepare data for TFT
tft_data = df.reset_index()
tft_data['time_idx'] = tft_data.index
tft_data['group'] = 0  # single time series

# Create dataset
max_prediction_length = len(test)
max_encoder_length = window_size
training_cutoff = tft_data["time_idx"].max() - max_prediction_length

training = TimeSeriesDataSet(
    tft_data[lambda x: x.time_idx <= training_cutoff],
    time_idx="time_idx",
    target="price_normalized",
    group_ids=["group"],
    min_encoder_length=max_encoder_length // 2,
    max_encoder_length=max_encoder_length,
    min_prediction_length=1,
    max_prediction_length=max_prediction_length,
    time_varying_known_reals=["time_idx"],
    time_varying_unknown_reals=["price_normalized"],
)

# Create dataloaders
train_dataloader = training.to_dataloader(train=True, batch_size=32,
num_workers=0)

# Initialize TFT
tft = TemporalFusionTransformer.from_dataset(
    training,
    learning_rate=0.03,
    hidden_size=16,
    attention_head_size=1,
    dropout=0.1,
    hidden_continuous_size=8,
    output_size=7,
    loss=QuantileLoss(),
    reduce_on_plateau_patience=4,
)

trainer = pl.Trainer(
```

```python
    max_epochs=10,
    accelerator="cpu",  # or "gpu" if CUDA is available
    devices=1,
    enable_model_summary=True
)


# Predict (simplified for example)
# Note: Actual prediction would require more setup
```

```
/usr/local/lib/python3.11/dist-packages/lightning/pytorch/utilities/
parsing.py:209: Attribute 'loss' is an instance of `nn.Module` and is
already saved during checkpointing. It is recommended to ignore them
using `self.save_hyperparameters(ignore=['loss'])`.
/usr/local/lib/python3.11/dist-packages/lightning/pytorch/utilities/
parsing.py:209: Attribute 'logging_metrics' is an instance of
`nn.Module` and is already saved during checkpointing. It is
recommended to ignore them using
`self.save_hyperparameters(ignore=['logging_metrics'])`.
INFO:pytorch_lightning.utilities.rank_zero:Using default
`ModelCheckpoint`. Consider installing `litmodels` package to enable
`LitModelCheckpoint` for automatic upload to the Lightning model
registry.
INFO:pytorch_lightning.utilities.rank_zero:GPU available: False, used:
False
INFO:pytorch_lightning.utilities.rank_zero:TPU available: False,
using: 0 TPU cores
INFO:pytorch_lightning.utilities.rank_zero:HPU available: False,
using: 0 HPUs
```

1. Model Comparison

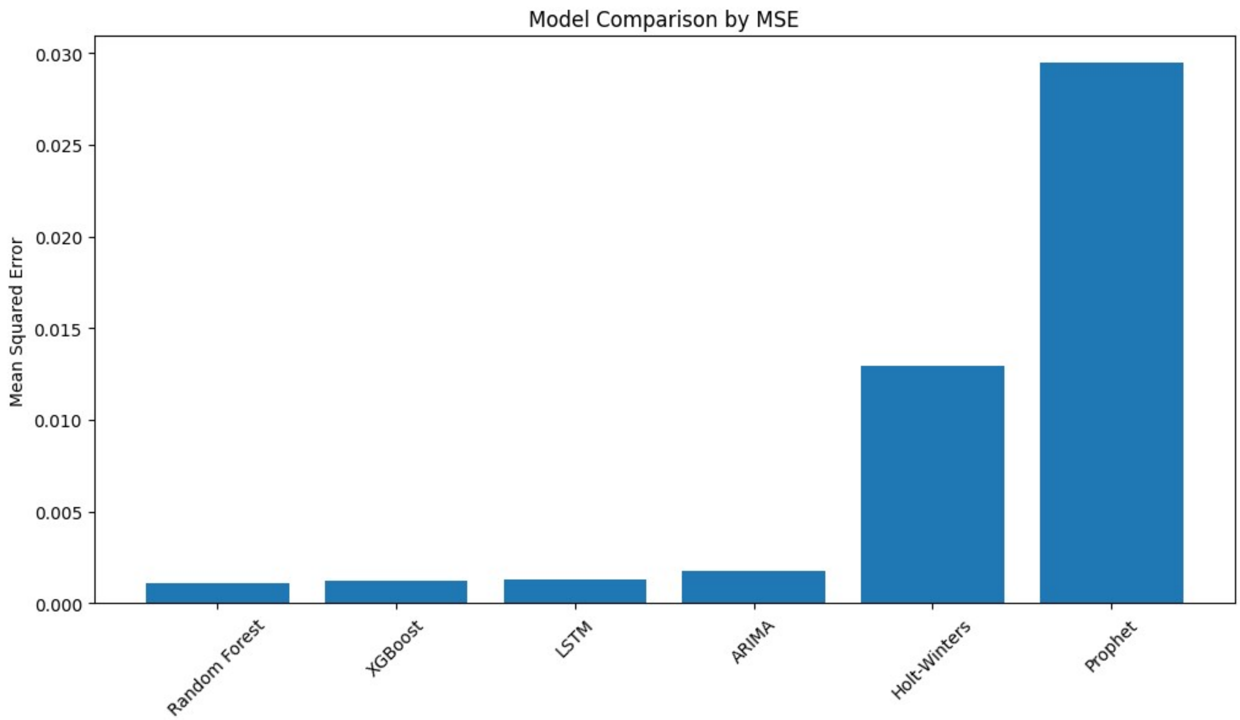
```python
# Compare all models
results = pd.DataFrame({
    'Model': ['ARIMA', 'Holt-Winters', 'Random Forest', 'XGBoost',
'LSTM', 'Prophet'],
    'MSE': [arima_mse, hw_mse, rf_mse, xgb_mse, lstm_mse,
prophet_mse],
    'MAE': [arima_mae, hw_mae, rf_mae, xgb_mae, lstm_mae, prophet_mae]
}).sort_values('MSE')

print(results)

# Plot comparison
plt.figure(figsize=(12, 6))
plt.bar(results['Model'], results['MSE'])
plt.title('Model Comparison by MSE')
plt.xticks(rotation=45)
```

```
plt.ylabel('Mean Squared Error')
plt.show()
```

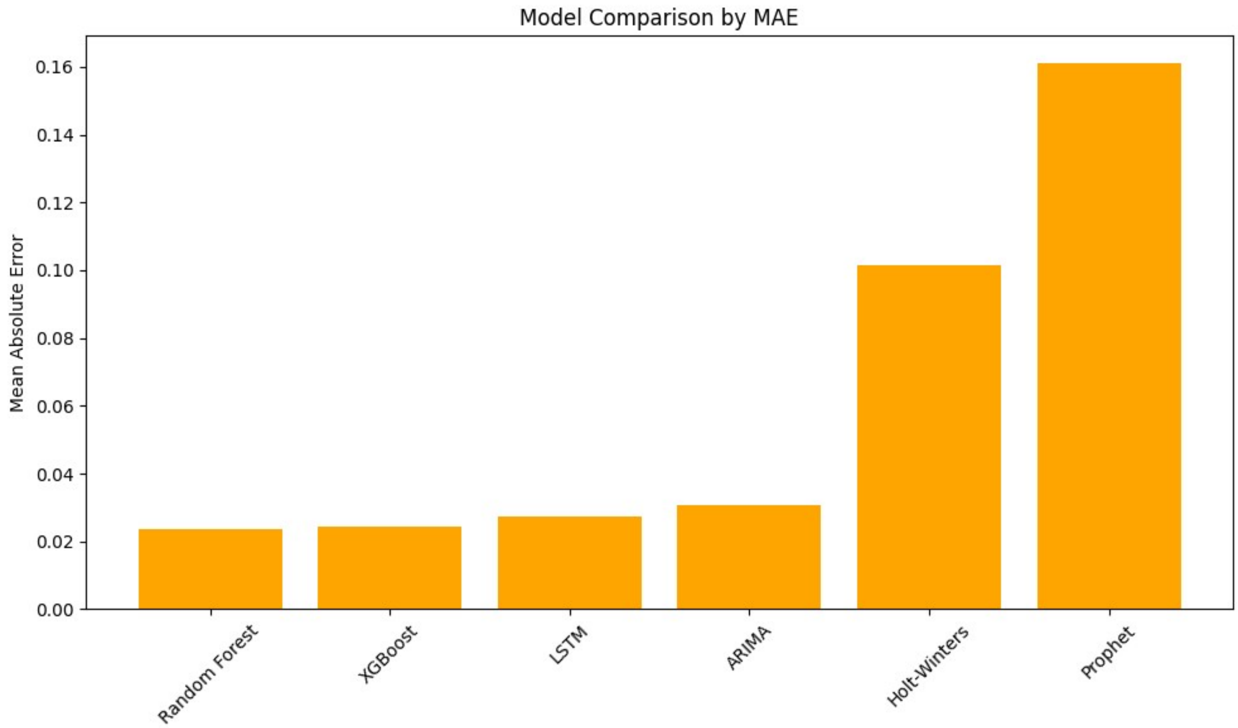
	Model	MSE	MAE
2	Random Forest	0.001096	0.023748
3	XGBoost	0.001262	0.024281
4	LSTM	0.001290	0.027491
0	ARIMA	0.001786	0.030876
1	Holt-Winters	0.012944	0.101491
5	Prophet	0.029458	0.161068




```
import matplotlib.pyplot as plt

models = ['Random Forest', 'XGBoost', 'LSTM', 'ARIMA', 'Holt-Winters',
'Prophet']
mae = [0.023748, 0.024291, 0.027491, 0.030876, 0.101491, 0.161068]

plt.figure(figsize=(10,6))
plt.bar(models, mae, color='orange')
plt.ylabel('Mean Absolute Error')
plt.title('Model Comparison by MAE')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Cryptocurrency Market Sentiment Analysis

1. Data Collection

```
import tweepy
import requests
import pandas as pd
from datetime import datetime, timedelta

# Twitter API setup (replace with your credentials)
twitter_auth = tweepy.OAuthHandler('KArmIMu5jTVkCPtFeAJWY8hJr',
'qTTbQRCQLBkdgdCkcu7n84kNLM27wm2ifgPeeRpcHp3etFEPxy')
twitter_auth.set_access_token('1924702325857464320-
6W79DecbnhKn2TNLU2FxDo8bfl0ZOZ',
'FNLFPInrU5aFt8yWaVwXie7SwsY1ltBv497WovIVQxhOr')
twitter_api = tweepy.API(twitter_auth)

# NewsAPI setup
NEWSAPI_KEY = '1c2df09c87a5441b83f4bd68cb37dda0'

def get_crypto_tweets(query='bitcoin OR crypto OR cryptocurrency',
count=1000):
    try:
        tweets = tweepy.Cursor(twitter_api.search_tweets,
                              q=query,
                              lang='en',
                              tweet_mode='extended').items(count)
```

```
        tweet_data = []
        for tweet in tweets:
            tweet_data.append({
                'text': tweet.full_text,
                'created_at': tweet.created_at,
                'source': 'twitter'
            })
        return pd.DataFrame(tweet_data)
    except Exception as e:
        print(f"Twitter error: {e}")
        return pd.DataFrame()

def get_crypto_news(query='crypto', days=7):
    try:
        from_date = (datetime.now() - 
timedelta(days=days)).strftime('%Y-%m-%d')
        url = f'https://newsapi.org/v2/everything?
q={query}&from={from_date}&sortBy=publishedAt&apiKey={NEWSAPI_KEY}'
        response = requests.get(url)
        news_data = []
        for article in response.json().get('articles', []):
            news_data.append({
                'text': f"{article['title']}. 
{article['description']}",
                'created_at': pd.to_datetime(article['publishedAt']),
                'source': article['source']['name']
            })
        return pd.DataFrame(news_data)
    except Exception as e:
        print(f"NewsAPI error: {e}")
        return pd.DataFrame()

# Get news data
news_df = get_crypto_news(query='crypto', days=7)

# Save news to CSV
news_df.to_csv('crypto_sentiment_raw.csv', index=False)
print("News data saved to 'crypto_sentiment_raw.csv'")

News data saved to 'crypto_sentiment_raw.csv'
```

1. Text Preprocessing

```
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import TreebankWordTokenizer

nltk.download('stopwords')
```

```
nltk.download('wordnet')

def preprocess_text(text):
    text = text.lower()
    text = re.sub(r'http\S+|www\S+|https\S+', '', text,
flags=re.MULTILINE)
    text = re.sub(r'\@\w+|\#', '', text)
    text = re.sub(r'[^\w\s]', '', text)

    tokenizer = TreebankWordTokenizer()
    tokens = tokenizer.tokenize(text)

    stop_words = set(stopwords.words('english'))
    tokens = [word for word in tokens if word not in stop_words]

    lemmatizer = WordNetLemmatizer()
    tokens = [lemmatizer.lemmatize(word) for word in tokens]

    return ' '.join(tokens)

# Then load your CSV and apply preprocessing
import pandas as pd
sentiment_df = pd.read_csv('crypto_sentiment_raw.csv',
parse_dates=['created_at'])
sentiment_df['processed_text'] =
sentiment_df['text'].apply(preprocess_text)
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

1. Sentiment Analysis with Multiple Approaches

VADER (Valence Aware Dictionary and sEntiment Reasoner)

```
from nltk.sentiment.vader import SentimentIntensityAnalyzer

nltk.download('vader_lexicon')

def vader_sentiment(text):
    analyzer = SentimentIntensityAnalyzer()
    scores = analyzer.polarity_scores(text)
    return scores['compound']

sentiment_df['vader_score'] =
sentiment_df['processed_text'].apply(vader_sentiment)
```

```
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

TextBlob

```
from textblob import TextBlob

def textblob_sentiment(text):
    analysis = TextBlob(text)
    return analysis.sentiment.polarity

sentiment_df['textblob_score'] =
sentiment_df['processed_text'].apply(textblob_sentiment)
```

BERT (Transformers)

```
from transformers import pipeline
import torch

# Initialize BERT sentiment analyzer
bert_sentiment = pipeline(
    "sentiment-analysis",
    model="finiteautomata/bertweet-base-sentiment-analysis",
    tokenizer="finiteautomata/bertweet-base-sentiment-analysis",
    device=0 if torch.cuda.is_available() else -1
)

def bert_sentiment(text):
    try:
        result = bert_sentiment(text[:512])  # Truncate to 512 tokens
        label = result[0]['label']
        score = result[0]['score']
        # Convert to numeric score: POSITIVE=1, NEUTRAL=0, NEGATIVE=-1
        if label == 'POS':
            return score
        elif label == 'NEG':
            return -score
        return 0
    except:
        return 0

# Apply BERT (this may take time for large datasets)
sentiment_df['bert_score'] =
sentiment_df['processed_text'].apply(bert_sentiment)
```

```
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/
_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your
settings tab (https://huggingface.co/settings/tokens), set it as
secret in your Google Colab and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to
```

```
access public models or datasets.
  warnings.warn(
```

{"model_id":"8bca3f85d3614392ae71b5245e149811","version_major":2,"version_minor":0}

```
Xet Storage is enabled for this repo, but the 'hf_xet' package is not
installed. Falling back to regular HTTP download. For better
performance, install the package with: `pip install
huggingface_hub[hf_xet]` or `pip install hf_xet`
WARNING:huggingface_hub.file_download:Xet Storage is enabled for this
repo, but the 'hf_xet' package is not installed. Falling back to
regular HTTP download. For better performance, install the package
with: `pip install huggingface_hub[hf_xet]` or `pip install hf_xet`
```

{"model_id":"d64d54f78eb94715870cb7389f815a07","version_major":2,"version_minor":0}

{"model_id":"72fdb8e448bd4be1b83329dbbca16db2","version_major":2,"version_minor":0}

{"model_id":"650d7c8775d6413a93561caa1bd2bbfb","version_major":2,"version_minor":0}

```
Xet Storage is enabled for this repo, but the 'hf_xet' package is not
installed. Falling back to regular HTTP download. For better
performance, install the package with: `pip install
huggingface_hub[hf_xet]` or `pip install hf_xet`
WARNING:huggingface_hub.file_download:Xet Storage is enabled for this
repo, but the 'hf_xet' package is not installed. Falling back to
regular HTTP download. For better performance, install the package
with: `pip install huggingface_hub[hf_xet]` or `pip install hf_xet`
```

{"model_id":"e818fe033cd24bae852c2fccfd31b0fa","version_major":2,"version_minor":0}

{"model_id":"c8079b81f4314a9db3fb5d794c6484ca","version_major":2,"version_minor":0}

{"model_id":"96fe6fa6a98f4e1ca9d8f6a777f03f92","version_major":2,"version_minor":0}

{"model_id":"89d48ef80547497b855ebb1f2d6d1930","version_major":2,"version_minor":0}

```
emoji is not installed, thus not converting emoticons or emojis into
text. Install emoji: pip3 install emoji==0.6.0
Device set to use cpu
```

1. Sentiment Aggregation and Time Series

```
# Use lowercase 'h' to avoid warning
sentiment_df['hour'] = sentiment_df['created_at'].dt.floor('h')

hourly_sentiment = sentiment_df.groupby('hour').agg({
    'vader_score': 'mean',
    'textblob_score': 'mean',
    'bert_score': 'mean',
    'source': 'count'
}).rename(columns={'source': 'volume'})

price_data.index = price_data.index.tz_localize(None) if
price_data.index.tz else price_data.index
hourly_sentiment.index = hourly_sentiment.index.tz_localize(None) if
hourly_sentiment.index.tz else hourly_sentiment.index

combined_data = price_data.join(hourly_sentiment, how='left')


# Forward fill missing sentiment scores
combined_data[['vader_score', 'textblob_score', 'bert_score']] = \
    combined_data[['vader_score', 'textblob_score',
'bert_score']].ffill()
```

1. Sentiment-Price Correlation Analysis

```
import seaborn as sns

# Calculate correlations
correlation_matrix = combined_data[['price_normalized', 'vader_score',
'textblob_score', 'bert_score']].corr()

# Plot correlation heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0)
plt.title('Sentiment-Price Correlation Matrix')
plt.show()

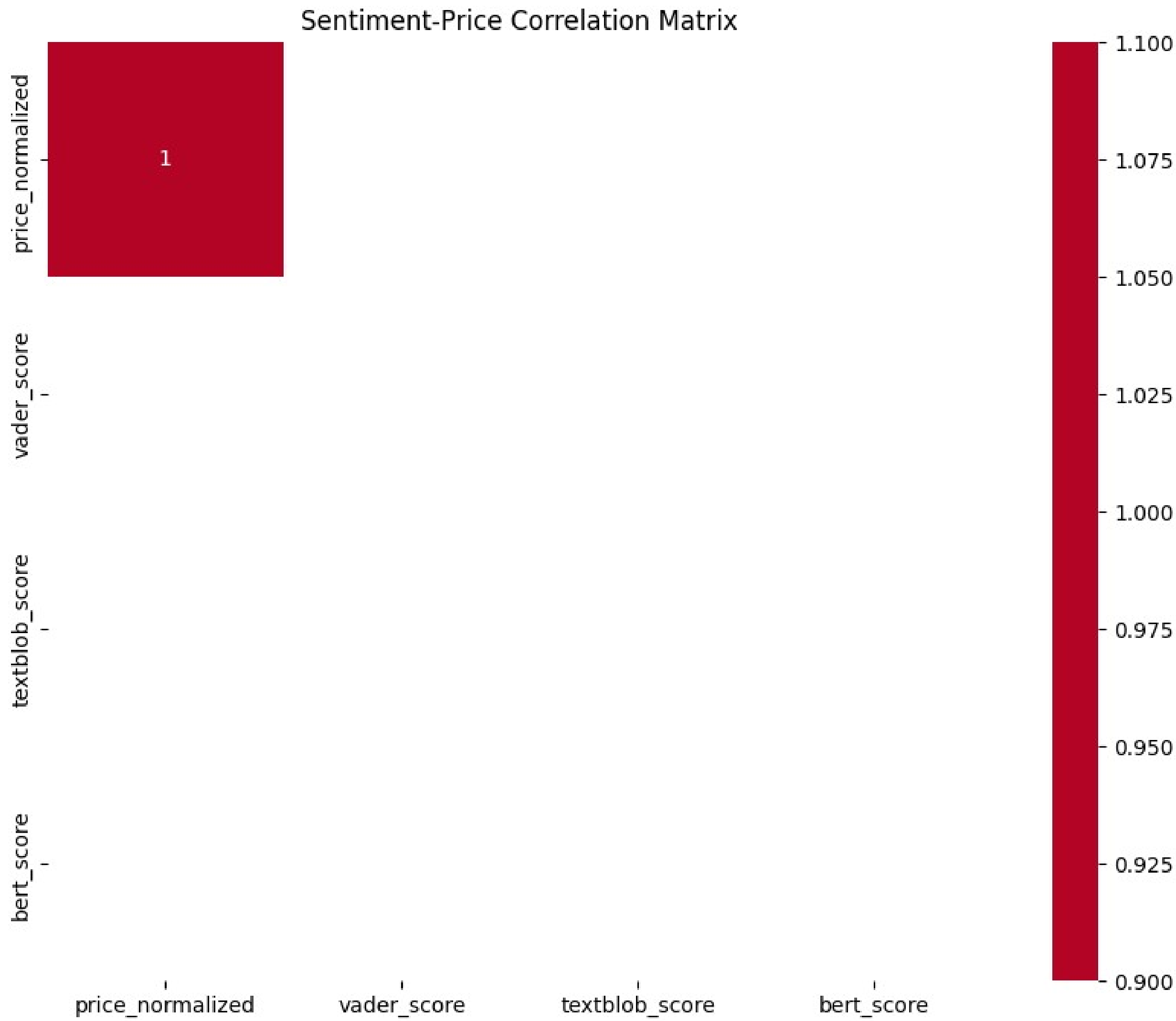
# Plot sentiment and price over time
fig, ax1 = plt.subplots(figsize=(15, 6))

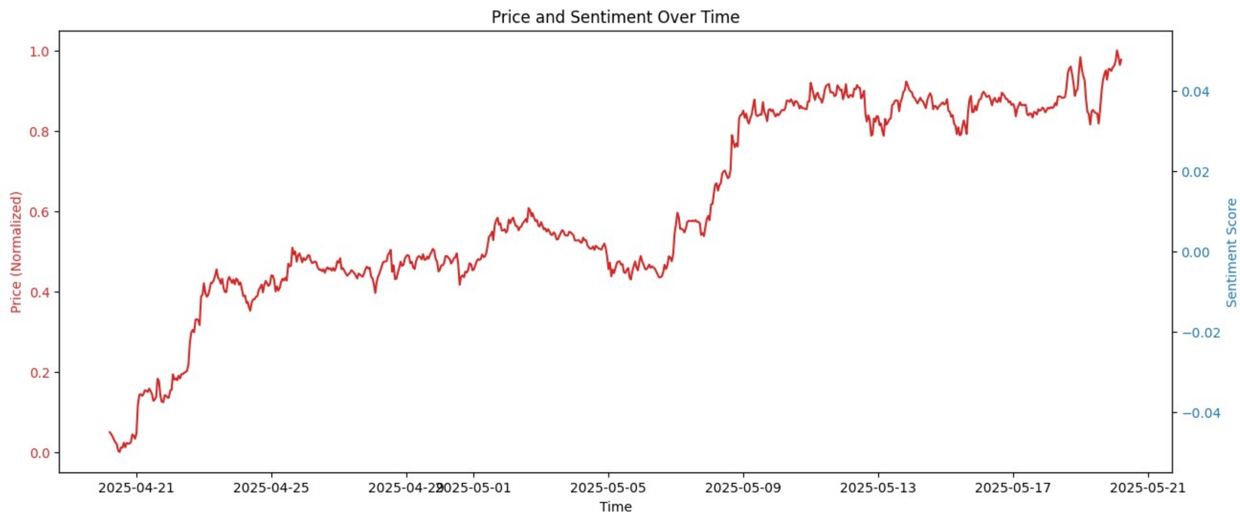
color = 'tab:red'
ax1.set_xlabel('Time')
ax1.set_ylabel('Price (Normalized)', color=color)
ax1.plot(combined_data.index, combined_data['price_normalized'],
color=color)
ax1.tick_params(axis='y', labelcolor=color)

ax2 = ax1.twinx()
color = 'tab:blue'
ax2.set_ylabel('Sentiment Score', color=color)
```

```
ax2.plot(combined_data.index, combined_data['bert_score'],
color=color, alpha=0.3)
ax2.tick_params(axis='y', labelcolor=color)

plt.title('Price and Sentiment Over Time')
plt.show()
```






```
# Install all requirements in one cell
!pip install numpy pandas matplotlib seaborn scipy scikit-learn
statsmodels xgboost nltk textblob
!pip install pmdarima tensorflow prophet pytorch-forecasting
!pip install tweepy vaderSentiment transformers torch sentencepiece
!pip install dash dash-bootstrap-components plotly

# NLTK downloads
import nltk
nltk.download(['punkt', 'stopwords', 'wordnet', 'vader_lexicon'])

print("All packages installed successfully!")
```

```
Requirement already satisfied: numpy in
/usr/local/lib/python3.11/dist-packages (2.0.2)
Requirement already satisfied: pandas in
/usr/local/lib/python3.11/dist-packages (2.2.2)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.11/dist-packages (3.10.0)
Requirement already satisfied: seaborn in
/usr/local/lib/python3.11/dist-packages (0.13.2)
Requirement already satisfied: scipy in
/usr/local/lib/python3.11/dist-packages (1.15.3)
Requirement already satisfied: scikit-learn in
/usr/local/lib/python3.11/dist-packages (1.6.1)
Requirement already satisfied: statsmodels in
/usr/local/lib/python3.11/dist-packages (0.14.4)
Requirement already satisfied: xgboost in
/usr/local/lib/python3.11/dist-packages (2.1.4)
Requirement already satisfied: nltk in /usr/local/lib/python3.11/dist-
packages (3.9.1)
Requirement already satisfied: textblob in
/usr/local/lib/python3.11/dist-packages (0.19.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
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/usr/local/lib/python3.11/dist-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.11/dist-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in
/usr/local/lib/python3.11/dist-packages (from pandas) (2025.2)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (4.58.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.4.8)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=8 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (3.2.3)
Requirement already satisfied: joblib>=1.2.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.5.0)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: patsy>=0.5.6 in
/usr/local/lib/python3.11/dist-packages (from statsmodels) (1.0.1)
Requirement already satisfied: nvidia-nccl-cu12 in
/usr/local/lib/python3.11/dist-packages (from xgboost) (2.21.5)
Requirement already satisfied: click in
/usr/local/lib/python3.11/dist-packages (from nltk) (8.2.0)
Requirement already satisfied: regex>=2021.8.3 in
/usr/local/lib/python3.11/dist-packages (from nltk) (2024.11.6)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-
packages (from nltk) (4.67.1)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2-
>pandas) (1.17.0)
Requirement already satisfied: pmdarima in
/usr/local/lib/python3.11/dist-packages (2.0.4)
Requirement already satisfied: tensorflow in
/usr/local/lib/python3.11/dist-packages (2.18.0)
Requirement already satisfied: prophet in
/usr/local/lib/python3.11/dist-packages (1.1.6)
Requirement already satisfied: pytorch-forecasting in
/usr/local/lib/python3.11/dist-packages (1.3.0)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (1.5.0)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (3.0.12)
Requirement already satisfied: numpy>=1.21.2 in
```

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/usr/local/lib/python3.11/dist-packages (from pmdarima) (2.0.2)
Requirement already satisfied: pandas>=0.19 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (2.2.2)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (1.6.1)
Requirement already satisfied: scipy>=1.3.2 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (1.15.3)
Requirement already satisfied: statsmodels>=0.13.2 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (0.14.4)
Requirement already satisfied: urllib3 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (2.4.0)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (75.2.0)
Requirement already satisfied: packaging>=17.1 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (24.2)
Requirement already satisfied: absl-py>=1.0.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (25.2.10)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1
in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.6.0)
Requirement already satisfied: google-pasta>=0.1.1 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.2.0)
Requirement already satisfied: libclang>=13.0.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (18.1.1)
Requirement already satisfied: opt-einsum>=2.3.2 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (3.4.0)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!
=4.21.3,!=4.21.4,!=4.21.5,<6.0.0dev,>=3.20.3 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (5.29.4)
Requirement already satisfied: requests<3,>=2.21.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (2.32.3)
Requirement already satisfied: six>=1.12.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (1.17.0)
Requirement already satisfied: termcolor>=1.1.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (3.1.0)
Requirement already satisfied: typing-extensions>=3.6.6 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (4.13.2)
Requirement already satisfied: wrapt>=1.11.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (1.17.2)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (1.71.0)
Requirement already satisfied: tensorboard<2.19,>=2.18 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (2.18.0)
Requirement already satisfied: keras>=3.5.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (3.8.0)
Requirement already satisfied: h5py>=3.11.0 in
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/usr/local/lib/python3.11/dist-packages (from tensorflow) (3.13.0)
Requirement already satisfied: ml-dtypes<0.5.0,>=0.4.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.4.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.37.1)
Requirement already satisfied: cmdstanpy>=1.0.4 in
/usr/local/lib/python3.11/dist-packages (from prophet) (1.2.5)
Requirement already satisfied: matplotlib>=2.0.0 in
/usr/local/lib/python3.11/dist-packages (from prophet) (3.10.0)
Requirement already satisfied: holidays<1,>=0.25 in
/usr/local/lib/python3.11/dist-packages (from prophet) (0.72)
Requirement already satisfied: tqdm>=4.36.1 in
/usr/local/lib/python3.11/dist-packages (from prophet) (4.67.1)
Requirement already satisfied: importlib-resources in
/usr/local/lib/python3.11/dist-packages (from prophet) (6.5.2)
Requirement already satisfied: torch!=2.0.1,<3.0.0,>=2.0.0 in
/usr/local/lib/python3.11/dist-packages (from pytorch-forecasting)
(2.6.0+cu124)
Requirement already satisfied: lightning<3.0.0,>=2.0.0 in
/usr/local/lib/python3.11/dist-packages (from pytorch-forecasting)
(2.5.1.post0)
Requirement already satisfied: wheel<1.0,>=0.23.0 in
/usr/local/lib/python3.11/dist-packages (from astunparse>=1.6.0-
>tensorflow) (0.45.1)
Requirement already satisfied: stanio<2.0.0,>=0.4.0 in
/usr/local/lib/python3.11/dist-packages (from cmdstanpy>=1.0.4-
>prophet) (0.5.1)
Requirement already satisfied: python-dateutil in
/usr/local/lib/python3.11/dist-packages (from holidays<1,>=0.25-
>prophet) (2.9.0.post0)
Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-
packages (from keras>=3.5.0->tensorflow) (13.9.4)
Requirement already satisfied: namex in
/usr/local/lib/python3.11/dist-packages (from keras>=3.5.0-
>tensorflow) (0.0.9)
Requirement already satisfied: optree in
/usr/local/lib/python3.11/dist-packages (from keras>=3.5.0-
>tensorflow) (0.15.0)
Requirement already satisfied: PyYAML<8.0,>=5.4 in
/usr/local/lib/python3.11/dist-packages (from lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (6.0.2)
Requirement already satisfied: fsspec<2026.0,>=2022.5.0 in
/usr/local/lib/python3.11/dist-packages (from
fsspec[http]<2026.0,>=2022.5.0->lightning<3.0.0,>=2.0.0->pytorch-
forecasting) (2025.3.2)
Requirement already satisfied: lightning-utilities<2.0,>=0.10.0 in
/usr/local/lib/python3.11/dist-packages (from lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (0.14.3)
Requirement already satisfied: torchmetrics<3.0,>=0.7.0 in
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/usr/local/lib/python3.11/dist-packages (from lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (1.7.1)
Requirement already satisfied: pytorch-lightning in
/usr/local/lib/python3.11/dist-packages (from lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (2.5.1.post0)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib>=2.0.0-
>prophet) (1.3.2)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.11/dist-packages (from matplotlib>=2.0.0-
>prophet) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib>=2.0.0-
>prophet) (4.58.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib>=2.0.0-
>prophet) (1.4.8)
Requirement already satisfied: pillow>=8 in
/usr/local/lib/python3.11/dist-packages (from matplotlib>=2.0.0-
>prophet) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib>=2.0.0-
>prophet) (3.2.3)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.11/dist-packages (from pandas>=0.19->pmdarima)
(2025.2)
Requirement already satisfied: tzdata>=2022.7 in
/usr/local/lib/python3.11/dist-packages (from pandas>=0.19->pmdarima)
(2025.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0-
>tensorflow) (3.4.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0-
>tensorflow) (3.10)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0-
>tensorflow) (2025.4.26)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn>=0.22-
>pmdarima) (3.6.0)
Requirement already satisfied: patsy>=0.5.6 in
/usr/local/lib/python3.11/dist-packages (from statsmodels>=0.13.2-
>pmdarima) (1.0.1)
Requirement already satisfied: markdown>=2.6.8 in
/usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>=2.18-
>tensorflow) (3.8)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0
in /usr/local/lib/python3.11/dist-packages (from
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tensorboard<2.19,>=2.18->tensorflow) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in
/usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>=2.18-
>tensorflow) (3.0.6)
Requirement already satisfied: filelock in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (3.18.0)
Requirement already satisfied: networkx in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (3.4.2)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (3.1.6)
Requirement already satisfied: nvidia-cuda-nvrtc-cu12==12.4.127 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (12.4.127)
Requirement already satisfied: nvidia-cuda-runtime-cu12==12.4.127
in /usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (12.4.127)
Requirement already satisfied: nvidia-cuda-cupti-cu12==12.4.127 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (12.4.127)
Requirement already satisfied: nvidia-cudnn-cu12==9.1.0.70 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (9.1.0.70)
Requirement already satisfied: nvidia-cublas-cu12==12.4.5.8 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (12.4.5.8)
Requirement already satisfied: nvidia-cufft-cu12==11.2.1.3 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (11.2.1.3)
Requirement already satisfied: nvidia-curand-cu12==10.3.5.147 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (10.3.5.147)
Requirement already satisfied: nvidia-cusolver-cu12==11.6.1.9 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (11.6.1.9)
Requirement already satisfied: nvidia-cusparse-cu12==12.3.1.170 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (12.3.1.170)
Requirement already satisfied: nvidia-cusparselt-cu12==0.6.2 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (0.6.2)
Requirement already satisfied: nvidia-nccl-cu12==2.21.5 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (2.21.5)
Requirement already satisfied: nvidia-nvtx-cu12==12.4.127 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (12.4.127)
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Requirement already satisfied: nvidia-nvjitlink-cu12==12.4.127 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (12.4.127)
Requirement already satisfied: triton==3.2.0 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (3.2.0)
Requirement already satisfied: sympy==1.13.1 in
/usr/local/lib/python3.11/dist-packages (from torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
/usr/local/lib/python3.11/dist-packages (from sympy==1.13.1->torch!
=2.0.1,<3.0.0,>=2.0.0->pytorch-forecasting) (1.3.0)
Requirement already satisfied: aiohttp!=4.0.0a0,!=4.0.0a1 in
/usr/local/lib/python3.11/dist-packages (from
fsspec[http]<2026.0,>=2022.5.0->lightning<3.0.0,>=2.0.0->pytorch-
forecasting) (3.11.15)
Requirement already satisfied: MarkupSafe>=2.1.1 in
/usr/local/lib/python3.11/dist-packages (from werkzeug>=1.0.1-
>tensorboard<2.19,>=2.18->tensorflow) (3.0.2)
Requirement already satisfied: markdown-it-py>=2.2.0 in
/usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0-
>tensorflow) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
/usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0-
>tensorflow) (2.19.1)
Requirement already satisfied: aiohappyeyeballs>=2.3.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp!=4.0.0a0,!
=4.0.0a1->fsspec[http]<2026.0,>=2022.5.0->lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (2.6.1)
Requirement already satisfied: aiosignal>=1.1.2 in
/usr/local/lib/python3.11/dist-packages (from aiohttp!=4.0.0a0,!
=4.0.0a1->fsspec[http]<2026.0,>=2022.5.0->lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (1.3.2)
Requirement already satisfied: attrs>=17.3.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp!=4.0.0a0,!
=4.0.0a1->fsspec[http]<2026.0,>=2022.5.0->lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (25.3.0)
Requirement already satisfied: frozenlist>=1.1.1 in
/usr/local/lib/python3.11/dist-packages (from aiohttp!=4.0.0a0,!
=4.0.0a1->fsspec[http]<2026.0,>=2022.5.0->lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (1.6.0)
Requirement already satisfied: multidict<7.0,>=4.5 in
/usr/local/lib/python3.11/dist-packages (from aiohttp!=4.0.0a0,!
=4.0.0a1->fsspec[http]<2026.0,>=2022.5.0->lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (6.4.3)
Requirement already satisfied: propcache>=0.2.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp!=4.0.0a0,!
=4.0.0a1->fsspec[http]<2026.0,>=2022.5.0->lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (0.3.1)
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Requirement already satisfied: yarl<2.0,>=1.17.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp!=4.0.0a0,!
=4.0.0a1->fsspec[http]<2026.0,>=2022.5.0->lightning<3.0.0,>=2.0.0-
>pytorch-forecasting) (1.20.0)
Requirement already satisfied: mdurl~=0.1 in
/usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0-
>rich->keras>=3.5.0->tensorflow) (0.1.2)
Requirement already satisfied: tweepy in
/usr/local/lib/python3.11/dist-packages (4.15.0)
Collecting vaderSentiment
  Downloading vaderSentiment-3.3.2-py2.py3-none-any.whl.metadata (572
bytes)
Requirement already satisfied: transformers in
/usr/local/lib/python3.11/dist-packages (4.51.3)
Requirement already satisfied: torch in
/usr/local/lib/python3.11/dist-packages (2.6.0+cu124)
Requirement already satisfied: sentencepiece in
/usr/local/lib/python3.11/dist-packages (0.2.0)
Requirement already satisfied: oauthlib<4,>=3.2.0 in
/usr/local/lib/python3.11/dist-packages (from tweepy) (3.2.2)
Requirement already satisfied: requests<3,>=2.27.0 in
/usr/local/lib/python3.11/dist-packages (from tweepy) (2.32.3)
Requirement already satisfied: requests-oauthlib<3,>=1.2.0 in
/usr/local/lib/python3.11/dist-packages (from tweepy) (2.0.0)
Requirement already satisfied: filelock in
/usr/local/lib/python3.11/dist-packages (from transformers) (3.18.0)
Requirement already satisfied: huggingface-hub<1.0,>=0.30.0 in
/usr/local/lib/python3.11/dist-packages (from transformers) (0.31.2)
Requirement already satisfied: numpy>=1.17 in
/usr/local/lib/python3.11/dist-packages (from transformers) (2.0.2)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.11/dist-packages (from transformers) (24.2)
Requirement already satisfied: pyyaml>=5.1 in
/usr/local/lib/python3.11/dist-packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.11/dist-packages (from transformers)
(2024.11.6)
Requirement already satisfied: tokenizers<0.22,>=0.21 in
/usr/local/lib/python3.11/dist-packages (from transformers) (0.21.1)
Requirement already satisfied: safetensors>=0.4.3 in
/usr/local/lib/python3.11/dist-packages (from transformers) (0.5.3)
Requirement already satisfied: tqdm>=4.27 in
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Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.11/dist-packages (from jinja2->torch) (3.0.2)
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[nltk_data] Downloading package wordnet to /root/nltk_data...
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[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

Interactive Cryptocurrency Dashboard

```
# Interactive Cryptocurrency Dashboard with Correct Column Names
import dash
from dash import dcc, html, Input, Output, callback
import dash_bootstrap_components as dbc
import plotly.graph_objects as go
import pandas as pd
import numpy as np
from datetime import datetime, timedelta

# Load your preprocessed data with correct column names
df = pd.read_csv('processed_crypto_data.csv',
parse_dates=['timestamp'])
sentiment_df = pd.read_csv('crypto_sentiment_raw.csv',
parse_dates=['created_at'])

# Process sentiment data to create hourly aggregates
sentiment_df['hour'] = sentiment_df['created_at'].dt.floor('H')
hourly_sentiment = sentiment_df.groupby('hour').agg({
```

```
    'text': 'count'
}).rename(columns={'text': 'volume'})

# Initialize Dash app
app = dash.Dash(__name__, external_stylesheets=[dbc.themes.DARKLY])
app.title = "Crypto Analytics Dashboard"

# Define layout
app.layout = dbc.Container([
    dbc.Row(html.H1("Cryptocurrency Analytics Dashboard",
className="text-center my-4")),

    # Timeframe selector
    dbc.Row([
        dbc.Col([
            dcc.Dropdown(
                id='timeframe-selector',
                options=[
                    {'label': '24 Hours', 'value': '24h'},
                    {'label': '1 Week', 'value': '1w'},
                    {'label': '1 Month', 'value': '1m'},
                    {'label': '3 Months', 'value': '3m'},
                    {'label': 'All Time', 'value': 'all'}
                ],
                value='1m',
                clearable=False
            )
        ], width=3)
    ], className="mb-4"),

    # Main charts row
    dbc.Row([
        # Price chart
        dbc.Col([
            dcc.Graph(id='price-chart', style={'height': '500px'})
        ], width=8),

        # Indicators and sentiment
        dbc.Col([
            dbc.Card([
                dbc.CardHeader("Market Indicators"),
                dbc.CardBody([
                    dcc.Graph(id='indicators-chart', style={'height':
'200px'}),
                    html.Hr(),
                    dcc.Graph(id='sentiment-volume-chart',
style={'height': '200px'})
                ])
            ])
        ], width=4)
```

```
    ]),

    # Predictive analytics row
    dbc.Row([
        dbc.Col([
            dbc.Card([
                dbc.CardHeader("Predictive Analytics"),
                dbc.CardBody([
                    dcc.Dropdown(
                        id='model-selector',
                        options=[
                            {'label': 'ARIMA', 'value': 'arima'},
                            {'label': 'LSTM', 'value': 'lstm'},
                            {'label': 'Prophet', 'value': 'prophet'}
                        ],
                        value='lstm',
                        clearable=False
                    ),
                    dcc.Graph(id='forecast-chart', style={'height':
'300px'})
                ])
            ])
        ], width=6),

        # Risk assessment
        dbc.Col([
            dbc.Card([
                dbc.CardHeader("Risk Assessment & Strategy"),
                dbc.CardBody([
                    html.Div(id='risk-metrics'),
                    html.Hr(),
                    html.Div(id='strategy-recommendation')
                ])
            ])
        ], width=6)
    ], className="mt-4"),

    # Update interval
    dcc.Interval(id='update-interval', interval=300*1000,
n_intervals=0)  # 5 minutes
], fluid=True)

# 1. Price Chart Callback
@app.callback(
    Output('price-chart', 'figure'),
    [Input('timeframe-selector', 'value'),
     Input('update-interval', 'n_intervals')]
)
def update_price_chart(timeframe, n):
    # Filter data based on timeframe
```

```
    now = datetime.now()
    if timeframe == '24h':
        filtered_df = df[df['timestamp'] >= now - timedelta(hours=24)]
    elif timeframe == '1w':
        filtered_df = df[df['timestamp'] >= now - timedelta(weeks=1)]
    elif timeframe == '1m':
        filtered_df = df[df['timestamp'] >= now - timedelta(days=30)]
    elif timeframe == '3m':
        filtered_df = df[df['timestamp'] >= now - timedelta(days=90)]
    else:
        filtered_df = df

    # Create candlestick chart (using price as close since we don't
have OHLC)
    fig = go.Figure()

    # Price line
    fig.add_trace(go.Scatter(
        x=filtered_df['timestamp'],
        y=filtered_df['price'],
        mode='lines',
        name='Price',
        line=dict(color='#00BFFF')
    ))

    # Add moving averages
    fig.add_trace(go.Scatter(
        x=filtered_df['timestamp'],
        y=filtered_df['moving_average'],
        line=dict(color='orange', width=1.5),
        name='Moving Average'
    ))

    # Add Bollinger Bands
    fig.add_trace(go.Scatter(
        x=filtered_df['timestamp'],
        y=filtered_df['upper_band'],
        line=dict(color='rgba(0,100,80,0.2)', width=1),
        name='Upper Band',
        fill=None
    ))
    fig.add_trace(go.Scatter(
        x=filtered_df['timestamp'],
        y=filtered_df['lower_band'],
        line=dict(color='rgba(0,100,80,0.2)', width=1),
        name='Lower Band',
        fill='tonexty'
    ))

    fig.update_layout(
```

```
        title='Price Chart with Technical Indicators',
        xaxis_rangeslider_visible=False,
        template='plotly_dark',
        hovermode='x unified',
        legend=dict(orientation="h", yanchor="bottom", y=1.02,
xanchor="right", x=1)
    )

    return fig

# 2. Indicators and Sentiment Volume Callbacks
@app.callback(
    [Output('indicators-chart', 'figure'),
     Output('sentiment-volume-chart', 'figure')],
    [Input('timeframe-selector', 'value'),
     Input('update-interval', 'n_intervals')]
)
def update_secondary_charts(timeframe, n):
    # Filter data based on timeframe
    now = datetime.now()
    if timeframe == '24h':
        filtered_df = df[df['timestamp'] >= now - timedelta(hours=24)]
        filtered_sentiment = hourly_sentiment[hourly_sentiment.index
>= now - timedelta(hours=24)]
    elif timeframe == '1w':
        filtered_df = df[df['timestamp'] >= now - timedelta(weeks=1)]
        filtered_sentiment = hourly_sentiment[hourly_sentiment.index
>= now - timedelta(weeks=1)]
    elif timeframe == '1m':
        filtered_df = df[df['timestamp'] >= now - timedelta(days=30)]
        filtered_sentiment = hourly_sentiment[hourly_sentiment.index
>= now - timedelta(days=30)]
    elif timeframe == '3m':
        filtered_df = df[df['timestamp'] >= now - timedelta(days=90)]
        filtered_sentiment = hourly_sentiment[hourly_sentiment.index
>= now - timedelta(days=90)]
    else:
        filtered_df = df
        filtered_sentiment = hourly_sentiment

    # Create indicators chart
    indicators_fig = go.Figure()

    # Add volatility
    indicators_fig.add_trace(go.Scatter(
        x=filtered_df['timestamp'],
        y=filtered_df['volatility'],
        mode='lines',
        name='Volatility',
        line=dict(color='purple')
```

```
    ))

    # Add daily returns
    indicators_fig.add_trace(go.Bar(
        x=filtered_df['timestamp'],
        y=filtered_df['daily_return'],
        name='Daily Returns',
        marker_color=np.where(filtered_df['daily_return'] > 0,
'green', 'red'),
        opacity=0.6
    ))

    indicators_fig.update_layout(
        title='Market Indicators',
        template='plotly_dark',
        showlegend=True
    )

    # Create sentiment volume chart
    sentiment_volume_fig = go.Figure()

    if not filtered_sentiment.empty:
        sentiment_volume_fig.add_trace(go.Bar(
            x=filtered_sentiment.index,
            y=filtered_sentiment['volume'],
            name='Sentiment Volume',
            marker_color='rgba(50, 200, 150, 0.6)'
        ))

    sentiment_volume_fig.update_layout(
        title='Sentiment Data Volume',
        template='plotly_dark'
    )

    return indicators_fig, sentiment_volume_fig

# 3. Predictive Analytics Callback
@app.callback(
    Output('forecast-chart', 'figure'),
    [Input('model-selector', 'value'),
     Input('timeframe-selector', 'value'),
     Input('update-interval', 'n_intervals')]
)
def update_forecast_chart(model, timeframe, n):
    # Get last 30 days of data regardless of timeframe selection
    forecast_df = df[df['timestamp'] >= datetime.now() -
timedelta(days=30)].copy()

    # Generate dummy forecasts (replace with actual model predictions)
    last_date = forecast_df['timestamp'].iloc[-1]
```

```
    future_dates = pd.date_range(start=last_date, periods=7, freq='D')
[1:]

    if model == 'arima':
        # Placeholder ARIMA forecast
        forecast_values = np.linspace(
            forecast_df['price'].iloc[-1],
            forecast_df['price'].iloc[-1] * 1.05,
            6
        )
    elif model == 'lstm':
        # Placeholder LSTM forecast
        forecast_values = np.linspace(
            forecast_df['price'].iloc[-1],
            forecast_df['price'].iloc[-1] * 1.03,
            6
        )
    else:  # prophet
        # Placeholder Prophet forecast
        forecast_values = np.linspace(
            forecast_df['price'].iloc[-1],
            forecast_df['price'].iloc[-1] * 0.98,
            6
        )

    # Create figure
    fig = go.Figure()

    # Historical data
    fig.add_trace(go.Scatter(
        x=forecast_df['timestamp'],
        y=forecast_df['price'],
        mode='lines',
        name='Historical Price',
        line=dict(color='#00BFFF')
    ))

    # Forecast
    fig.add_trace(go.Scatter(
        x=future_dates,
        y=forecast_values,
        mode='lines+markers',
        name=f'{model.upper()} Forecast',
        line=dict(dash='dot', color='orange')
    ))

    # Confidence interval (placeholder)
    fig.add_trace(go.Scatter(
        x=future_dates,
        y=forecast_values * 1.05,
```

```
        fill=None,
        mode='lines',
        line=dict(width=0),
        showlegend=False
    ))
    fig.add_trace(go.Scatter(
        x=future_dates,
        y=forecast_values * 0.95,
        fill='tonexty',
        mode='lines',
        line=dict(width=0),
        fillcolor='rgba(255, 165, 0, 0.2)',
        name='Confidence Interval'
    ))

    fig.update_layout(
        title=f'7-Day Price Forecast ({model.upper()})',
        template='plotly_dark',
        legend=dict(orientation="h", yanchor="bottom", y=1.02,
xanchor="right", x=1)
    )

    return fig

# 4. Risk Assessment Callback
@app.callback(
    [Output('risk-metrics', 'children'),
     Output('strategy-recommendation', 'children')],
    [Input('timeframe-selector', 'value'),
     Input('update-interval', 'n_intervals')]
)
def update_risk_assessment(timeframe, n):
    # Calculate risk metrics (using last 30 days of data)
    risk_df = df[df['timestamp'] >= datetime.now() -
timedelta(days=30)]

    # Basic risk metrics
    volatility = risk_df['volatility'].mean()
    max_drawdown = (risk_df['price'].max() - risk_df['price'].min()) /
risk_df['price'].max()
    sharpe_ratio = risk_df['daily_return'].mean() /
risk_df['daily_return'].std() if risk_df['daily_return'].std() != 0
else 0

    # Risk level classification
    if volatility > 0.05:
        risk_level = "High"
        risk_color = "danger"
    elif volatility > 0.02:
        risk_level = "Medium"
```

```
        risk_color = "warning"
    else:
        risk_level = "Low"
        risk_color = "success"

    # Generate recommendation based on technical indicators
    current_price = risk_df['price'].iloc[-1]
    ma_ratio = current_price / risk_df['moving_average'].iloc[-1]

    if ma_ratio > 1.05:
        ma_signal = "Price significantly above MA - potential
overbought"
    elif ma_ratio < 0.95:
        ma_signal = "Price significantly below MA - potential
oversold"
    else:
        ma_signal = "Price near MA - neutral signal"

    # Final recommendation
    if risk_level == "High":
        recommendation = [
            html.P("Consider reducing position size or hedging with
options due to high volatility.", className="mb-2"),
            html.P(ma_signal, className="mb-2")
        ]
    elif risk_level == "Medium":
        recommendation = [
            html.P("Moderate risk environment - dollar-cost averaging
may be appropriate.", className="mb-2"),
            html.P(ma_signal, className="mb-2")
        ]
    else:
        recommendation = [
            html.P("Low risk environment - good for establishing new
positions.", className="mb-2"),
            html.P(ma_signal, className="mb-2")
        ]

    # Format metrics display
    metrics = [
        dbc.Row([
            dbc.Col(html.H5("Risk Metrics", className="mb-3"),
width=12)
        ]),
        dbc.Row([
            dbc.Col([
                html.Div(f"Volatility: {volatility:.4f}",
className="mb-2"),
                html.Div(f"Max Drawdown: {max_drawdown:.2%}",
className="mb-2"),
```

```
                html.Div(f"Sharpe Ratio: {sharpe_ratio:.2f}",
className="mb-2")
            ], width=6),
            dbc.Col([
                html.Div("Risk Level:", className="mb-2"),
                dbc.Badge(risk_level, color=risk_color, className="mb-
2"),
                html.Div(f"Price/MA Ratio: {ma_ratio:.2f}",
className="mt-2")
            ], width=6)
        ])
    ]

    # Format strategy
    strategy = [
        html.H5("Investment Recommendation", className="mt-3"),
        *recommendation,
        html.Hr(),
        html.H6("Technical Indicators Status:", className="mt-2"),
        html.Ul([
            html.Li(f"Current Volatility:
{risk_df['volatility'].iloc[-1]:.4f}"),
            html.Li(f"Bollinger Band Position: {'Upper' if
current_price > risk_df['upper_band'].iloc[-1] else 'Lower' if
current_price < risk_df['lower_band'].iloc[-1] else 'Middle'}"),
            html.Li(f"7-day Std Dev: {risk_df['rolling_std_7'].iloc[-
1]:.2f}")
        ])
    ]

    return metrics, strategy
if __name__ == '__main__':
    app.run(debug=True, port=8050)
```

```
<ipython-input-80-81438c52c943>:15: FutureWarning:

'H' is deprecated and will be removed in a future version, please use
'h' instead.


<IPython.core.display.Javascript object>
```