```
# Installing required libraries
!pip install cryptocmd
!pip install yfinance

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from cryptocmd import CmcScraper
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import TimeSeriesSplit
from sklearn.metrics import mean_squared_error
import yfinance as yf
import tensorflow as tf
from tensorflow import keras

!pip install keras-tuner
import keras_tuner
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Dropout, Bidirectional
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/cola
Collecting cryptocmd
  Downloading cryptocmd-0.6.1-py3-none-any.whl (8.5 kB)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-p
Collecting tablib
  Downloading tablib-3.4.0-py3-none-any.whl (45 kB)
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Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/pyth
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/di
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/
Installing collected packages: tablib, cryptocmd
Successfully installed cryptocmd-0.6.1 tablib-3.4.0
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/cola
Requirement already satisfied: yfinance in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: numpy>=1.16.5 in /usr/local/lib/python3.10/d
Requirement already satisfied: appdirs>=1.4.4 in /usr/local/lib/python3.10/
Requirement already satisfied: pandas>=1.3.0 in /usr/local/lib/python3.10/d
Requirement already satisfied: beautifulsoup4>=4.11.1 in /usr/local/lib/pyt
Requirement already satisfied: lxml>=4.9.1 in /usr/local/lib/python3.10/dis
Requirement already satisfied: frozendict>=2.3.4 in /usr/local/lib/python3.
Requirement already satisfied: requests>=2.26 in /usr/local/lib/python3.10/
Requirement already satisfied: cryptography>=3.3.2 in /usr/local/lib/python
Requirement already satisfied: html5lib>=1.1 in /usr/local/lib/python3.10/d
Requirement already satisfied: multitasking>=0.0.7 in /usr/local/lib/python
Requirement already satisfied: pytz>=2022.5 in /usr/local/lib/python3.10/di
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.10/d
Requirement already satisfied: cffi>=1.12 in /usr/local/lib/python3.10/dist
Requirement already satisfied: six>=1.9 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/di
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/pyt
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Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3
Requirement already satisfied: pycparser in /usr/local/lib/python3.10/dist-
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/cola
Collecting keras-tuner
  Downloading keras_tuner-1.3.5-py3-none-any.whl (176 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 176.1/176.1 kB 6.6 MB/s eta 0:
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
Collecting kt-legacy
  Downloading kt_legacy-1.0.5-py3-none-any.whl (9.6 kB)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/di
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/pyth
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3
Installing collected packages: kt-legacy, keras-tuner
Successfully installed keras-tuner-1.3.5 kt-legacy-1.0.5
<ipython-input-1-5712859aa970>:21: DeprecationWarning: `import kerastuner`
  from kerastuner.tuners import BayesianOptimization
```

```
# Scrape cryptocurrency data
scraper = CmcScraper("BTC", "01-01-2014", "31-03-2023")
bitcoin_df = scraper.get_dataframe()

# Scrape stock market data
stock_data = yf.download("SPY", start="2014-01-01", end="2023-03-31")
stock_df = stock_data["Adj Close"].to_frame().reset_index().rename(columns={"Adj

# Create a date range that includes all dates between start and end dates
date_range = pd.date_range(start="2014-01-01", end="2023-03-31")
date_range_df = pd.DataFrame(date_range, columns=["Date"])

# Merge stock_df with the date_range_df
stock_df = stock_df.merge(date_range_df, on="Date", how="outer")
stock_df.sort_values("Date", inplace=True)


# Fill missing values using ffill and bfill methods
stock_df["stock_price"].fillna(method="bfill", inplace=True)
stock_df["stock_price"].fillna(method="ffill", inplace=True)


# Merge the filled stock_df with bitcoin_df
merged_df = bitcoin_df.merge(stock_df, on="Date", how="inner")
merged_df.set_index("Date", inplace=True)
merged_df.index = pd.to_datetime(merged_df.index)
merged_df.interpolate(method="time", inplace=True)

# Add day, week, and month columns
merged_df["day"] = merged_df.index.day
merged_df["week"] = merged_df.index.week
merged_df["month"] = merged_df.index.month
merged_df = merged_df.sort_values(by = ['Date'])
```

```
[*********************100%***********************]  1 of 1 completed
<ipython-input-2-9ed5ca8e5600>:31: FutureWarning: weekofyear and week have
  merged_df["week"] = merged_df.index.week
```

```
# Normalize features separately
scaler_btc = MinMaxScaler()
merged_df["Close"] = scaler_btc.fit_transform(merged_df[["Close"]])
scaler_stock = MinMaxScaler()
merged_df["stock_price"] = scaler_stock.fit_transform(merged_df[["stock_price"]]
```

```
merged_df.head(7)
```

Date	Open	High	Low	Close	Volume	Market Cap	stock
2014-01-01	754.969971	775.349976	754.969971	0.008804	22489400.0	9.403308e+09	(
2014-01-02	773.440002	820.309998	767.210022	0.009264	38489500.0	9.781074e+09	(
2014-01-03	802.849976	834.150024	789.119995	0.009506	37810100.0	9.980135e+09	(
2014-01-04	823.270020	859.510010	801.669983	0.010112	38005000.0	1.047736e+10	(
2014-01-05	858.549988	952.400024	854.520020	0.011210	72898496.0	1.137966e+10	(

```
# Calculate the number of weeks since the start of the data
merged_df['week_number'] = (merged_df.index - merged_df.index[0]).days // 7

# Calculate weekly averages
weekly_avg = merged_df.groupby('week_number').mean()
weekly_avg.drop(['day', 'week', 'month'], axis=1, inplace=True)


# Calculate the number of months since the start of the data
merged_df['month_number'] = ((merged_df.index.year - merged_df.index[0].year) *

# Calculate monthly averages
monthly_avg = merged_df.groupby('month_number').mean()
monthly_avg.drop(['day', 'week', 'month', 'week_number'], axis=1, inplace=True)
```

```
weekly_avg.tail(7)
```

	Open	High	Low	Close	Volume	Mar
week_number						
476	24074.887644	24915.028665	23724.333755	0.359290	3.122549e+10	4.70
477	23718.815922	23922.283901	23224.945493	0.346592	2.334706e+10	4.54
478	22836.684136	23032.813324	22485.083911	0.334258	1.938761e+10	4.38
479	21639.657458	22640.759969	21151.922960	0.323839	3.657534e+10	4.24
480	26346.731502	27336.079353	25910.242125	0.395474	4.037439e+10	5.18
481	27699.229675	28198.604642	26986.916188	0.406564	2.097380e+10	5.32
482	27883.145311	28806.447363	27521.178593	0.417113	2.070721e+10	5.46

```
# Prepare data
def prepare_data(df, feature_columns, target_column, n_past, n_future):
    x_data, y_data = [], []
    for i in range(n_past, len(df) - n_future + 1):
        x_data.append(df[feature_columns].iloc[i - n_past:i].values)
        y_data.append(df[target_column].iloc[i:i + n_future].values)
    return np.array(x_data), np.array(y_data)
```

```
# Split into train and test sets
# Set the train_date index
train_week_index = 420
n_past_week = 40
n_future = 1
feature_columns = ["Close", "stock_price"]
target_column = "Close"
x_data2, y_data2 = prepare_data(weekly_avg, feature_columns, target_column, n_pa


# Calculate the train_size based on the index
train_size_week = train_week_index - n_past_week

x_train2, x_test2 = x_data2[:train_size_week], x_data2[train_size_week:]
y_train2, y_test2 = y_data2[:train_size_week], y_data2[train_size_week:]
```

```
print("x_train shape:", x_train2.shape)
print("y_train shape:", y_train2.shape)
print("x_test shape:", x_test2.shape)
print("y_test shape:", y_test2.shape)
```

```
x_train shape: (380, 40, 2)
y_train shape: (380, 1)
x_test shape: (63, 40, 2)
y_test shape: (63, 1)
```

```python
# LSTM & Hyperparameter tuning
from sklearn.model_selection import RandomizedSearchCV
from keras.wrappers.scikit_learn import KerasRegressor
import tensorflow as tf

def create_model(learning_rate=0.001, dropout_rate=0.2, neurons=50):
  model = Sequential()
  model.add(LSTM(neurons, activation="tanh", input_shape=(n_past_week, len(featu
  model.add(Dropout(dropout_rate))
  model.add(LSTM(neurons, activation="tanh", return_sequences=False))
  model.add(Dropout(dropout_rate))
  model.add(Dense(n_future))
  optimizer = tf.keras.optimizers.Adam(lr=learning_rate)
  model.compile(optimizer=optimizer, loss="mse")
  return model

model = KerasRegressor(build_fn=create_model, verbose=0)

param_dist = {
    'batch_size': [32, 64],
    'epochs': [10],
    'learning_rate': [0.01, 0.001],
    'dropout_rate': [0.2, 0.4],
    'neurons': [25, 50]
}

random_search = RandomizedSearchCV(estimator=model, param_distributions=param_di
random_search.fit(x_train2, y_train2)
```

```
<ipython-input-12-4dbbb2e3ef36>:17: DeprecationWarning: KerasRegressor is d
  model = KerasRegressor(build_fn=create_model, verbose=0)
Fitting 3 folds for each of 10 candidates, totalling 30 fits
/usr/local/lib/python3.10/dist-packages/joblib/externals/loky/process_execu
  warnings.warn(
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_ra
```

▸ **RandomizedSearchCV**

▸ **estimator: KerasRegressor**

▸ KerasRegressor

```
# Training the model
best_model = random_search.best_estimator_.model
best_model.fit(x_train2, y_train2, epochs=random_search.best_params_['epochs'],
```

```
Epoch 1/10
12/12 [==============================] - 1s 76ms/step - loss: 0.0054
Epoch 2/10
12/12 [==============================] - 1s 71ms/step - loss: 0.0044
Epoch 3/10
12/12 [==============================] - 1s 43ms/step - loss: 0.0041
Epoch 4/10
12/12 [==============================] - 1s 43ms/step - loss: 0.0036
Epoch 5/10
12/12 [==============================] - 1s 42ms/step - loss: 0.0038
Epoch 6/10
12/12 [==============================] - 1s 44ms/step - loss: 0.0040
Epoch 7/10
12/12 [==============================] - 1s 47ms/step - loss: 0.0030
Epoch 8/10
12/12 [==============================] - 1s 48ms/step - loss: 0.0029
Epoch 9/10
12/12 [==============================] - 1s 42ms/step - loss: 0.0036
Epoch 10/10
12/12 [==============================] - 1s 41ms/step - loss: 0.0036
<keras.callbacks.History at 0x7ff4da8b9120>
```

```
# Make predictions
y_pred = best_model.predict(x_test2)
```

```
2/2 [==============================] - 1s 19ms/step
```

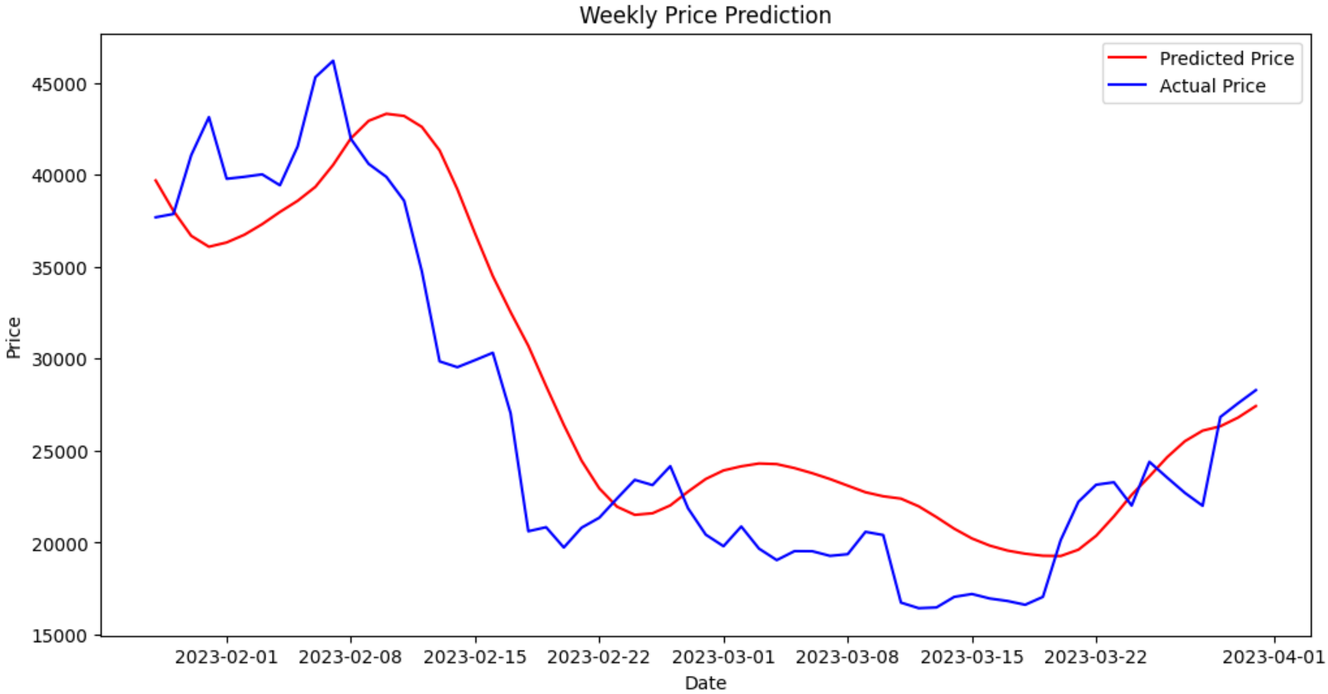
```
# Invert the scaling for predictions
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
y_pred_actual = scaler_btc.inverse_transform(y_pred)
y_test_actual = scaler_btc.inverse_transform(y_test2)
# Evaluate the model
mse = mean_squared_error(y_test_actual, y_pred_actual)
mae = mean_absolute_error(y_test_actual, y_pred_actual)
r2 = r2_score(y_test_actual, y_pred_actual)

print("Mean Squared Error: {:.2f}".format(mse))
print("Mean Absolute Error: {:.2f}".format(mae))
print("R2 Score: {:.2f}".format(r2))

# Visualize the results
plt.figure(figsize=(12, 6))
plt.plot(merged_df.index[-len(y_pred_actual):], y_pred_actual, label="Predicted
plt.plot(merged_df.index[-len(y_test_actual):], y_test_actual, label="Actual Pri
```

```
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend(loc="best")
plt.title("Weekly Price Prediction")
plt.show()
```

```
Mean Squared Error: 18772373.58
Mean Absolute Error: 3583.23
R2 Score: 0.76
```




```
# Create dataframes for actual prices with dates as their index
actual_price_df = pd.DataFrame(scaler_btc.inverse_transform(weekly_avg[["Close"]

# Forecast for the next 5 weeks
x_forecast = weekly_avg[feature_columns].values[-n_past_week:]
forecasted_prices = []
forecasted_weeks = []

for i in range(5):
```

```
    x_forecast = x_forecast.reshape((1, n_past_week, len(feature_columns)))
    y_forecast = best_model.predict(x_forecast)
    forecasted_price_actual = scaler_btc.inverse_transform(y_forecast)
    forecasted_prices.append(forecasted_price_actual[0][0])
    next_week = weekly_avg.index[-1] + pd.DateOffset(weeks=i+1)
    forecasted_weeks.append(next_week)
    new_row = np.array([y_forecast[0][0], x_forecast[0][-1][1]])
    x_forecast = np.append(x_forecast, new_row)
    x_forecast = x_forecast[-n_past_week * len(feature_columns):].reshape((n_pas

# Add the forecasted prices to a new dataframe
forecasted_price_df = pd.DataFrame(forecasted_prices, index=forecasted_weeks, co

# Limit the data to last three months
last_three_months = forecasted_price_df.index[-1] - pd.DateOffset(months=3)
actual_price_df_last_three_months = actual_price_df[last_three_months:]
forecasted_price_df_last_three_months = forecasted_price_df[last_three_months:]

# Visualize the last three months of actual vs forecasted data
plt.figure(figsize=(12, 6))
plt.plot(actual_price_df_last_three_months.index, actual_price_df_last_three_mon
plt.plot(forecasted_price_df_last_three_months.index, forecasted_price_df_last_t

# Joining the forecasted line with the actual prices
last_actual_price = actual_price_df_last_three_months["Actual Price"].iloc[-1]
first_forecasted_price = forecasted_price_df_last_three_months["Forecasted Price
plt.plot([actual_price_df_last_three_months.index[-1], forecasted_price_df_last_

plt.xlabel("Date")
plt.ylabel("Price")
plt.legend(loc="best")
plt.title("Forecasted Price for next 5 weeks")
plt.show()
```

```
1/1 [==============================] - 0s 96ms/step
1/1 [==============================] - 0s 42ms/step
1/1 [==============================] - 0s 45ms/step
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 78ms/step
```