Bitcoin Price Prediction

In [2]:
```
#yfinance is a popular Python library used for downloading historical market data from Yahoo Finance.
#It simplifies the process of accessing financial data for various securities, including stocks, commodities, cryptocurrencies, and more

pip install yfinance
```

```
Requirement already satisfied: yfinance in c:\users\jan saida\anaconda3\lib\site-packages (0.2.52)
Requirement already satisfied: pandas>=1.3.0 in c:\users\jan saida\anaconda3\lib\site-packages (from yfinance) (2.2.2)
Requirement already satisfied: numpy>=1.16.5 in c:\users\jan saida\anaconda3\lib\site-packages (from yfinance) (1.26.4)
Requirement already satisfied: requests>=2.31 in c:\users\jan saida\anaconda3\lib\site-packages (from yfinance) (2.32.2)
Requirement already satisfied: multitasking>=0.0.7 in c:\users\jan saida\anaconda3\lib\site-packages (from yfinance) (0.0.11)
Requirement already satisfied: lxml>=4.9.1 in c:\users\jan saida\anaconda3\lib\site-packages (from yfinance) (5.2.1)
Requirement already satisfied: platformdirs>=2.0.0 in c:\users\jan saida\appdata\roaming\python\python312\site-packages (from yfinance) (4.3.6)
Requirement already satisfied: pytz>=2022.5 in c:\users\jan saida\anaconda3\lib\site-packages (from yfinance) (2024.1)
Requirement already satisfied: frozendict>=2.3.4 in c:\users\jan saida\anaconda3\lib\site-packages (from yfinance) (2.4.2)
Requirement already satisfied: peewee>=3.16.2 in c:\users\jan saida\anaconda3\lib\site-packages (from yfinance) (3.17.8)
Requirement already satisfied: beautifulsoup4>=4.11.1 in c:\users\jan saida\anaconda3\lib\site-packages (from yfinance) (4.12.3)
Requirement already satisfied: html5lib>=1.1 in c:\users\jan saida\anaconda3\lib\site-packages (from yfinance) (1.1)
Requirement already satisfied: soupsieve>1.2 in c:\users\jan saida\anaconda3\lib\site-packages (from beautifulsoup4>=4.11.1->yfinance) (2.5)
Requirement already satisfied: six>=1.9 in c:\users\jan saida\appdata\roaming\python\python312\site-packages (from html5lib>=1.1->yfinance) (1.16.0)
Requirement already satisfied: webencodings in c:\users\jan saida\anaconda3\lib\site-packages (from html5lib>=1.1->yfinance) (0.5.1)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\jan saida\appdata\roaming\python\python312\site-packages (from pandas>=1.3.0->yfinance) (2.9.0.post0)
Requirement already satisfied: tzdata>=2022.7 in c:\users\jan saida\anaconda3\lib\site-packages (from pandas>=1.3.0->yfinance) (2023.3)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\users\jan saida\anaconda3\lib\site-packages (from requests>=2.31->yfinance) (2.0.4)
Requirement already satisfied: idna<4,>=2.5 in c:\users\jan saida\anaconda3\lib\site-packages (from requests>=2.31->yfinance) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in c:\users\jan saida\anaconda3\lib\site-packages (from requests>=2.31->yfinance) (2.2.2)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\jan saida\anaconda3\lib\site-packages (from requests>=2.31->yfinance) (2024.7.4)
Note: you may need to restart the kernel to use updated packages.
```

In [3]:
```python
import seaborn as sns
import yfinance as yf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
```

In [4]:
```python
#The code fetches historical price data for Bitcoin, Ethereum, Tether, and Binance Coin for the past 5 years and keeps only the Close and Volume columns for each of these cryptocurrencies.
#This cleaned data can then be used for further analysis or machine learning tasks, such as predicting future prices.

btc=yf.Ticker('BTC-USD')
prices1=btc.history(period='5y')
prices1.drop(columns=['Open','High','Dividends', 'Stock Splits'], axis = 1, inplace = True)

eth = yf.Ticker('ETH-USD')
prices2 = eth.history(period='5y')
prices2.drop(columns=['Open', 'High', 'Low', 'Dividends', 'Stock Splits'], axis = 1, inplace = True)

usdt = yf.Ticker('USDT-USD')
prices3 = usdt.history(period='5y')
prices3.drop(columns=['Open', 'High', 'Low', 'Dividends', 'Stock Splits'], axis = 1, inplace = True)

bnb = yf.Ticker('BNB-USD')
```

```python
prices4 = bnb.history(period='5y')
prices4.drop(columns=['Open', 'High', 'Low', 'Dividends', 'Stock Splits'], axis = 1, inplace = True)
```

In [5]:
```python
#The parameters lsuffix and rsuffix in the join method are used to add suffixes to overlapping column names when joining two DataFrames
# This is necessary to avoid column name conflicts when the two DataFrames have columns with the same name.

p1 = prices1.join(prices2, lsuffix = ' (BTC)', rsuffix = ' (ETH)')
p2 = prices3.join(prices4, lsuffix = ' (USDT)', rsuffix = ' (BNB)')
data = p1.join(p2, lsuffix = '_', rsuffix = '_')
```

In [6]:
```python
data.head()
```

Out[6]:

Date	Low	Close (BTC)	Volume (BTC)	Close (ETH)	Volume (ETH)	Close (USDT)	Volume (USDT)	Close (BNB)	Volume (BNB)
2020-02-04 00:00:00+00:00	9112.811523	9180.962891	29893183716	189.250595	11714191695	1.001745	36950713371	18.177366	213533737
2020-02-05 00:00:00+00:00	9163.704102	9613.423828	35222060874	204.230240	14865434435	1.002838	46504757742	19.215050	301486499
2020-02-06 00:00:00+00:00	9539.818359	9729.801758	37628823716	212.339081	16425589683	0.997216	46549174003	20.595263	394704716
2020-02-07 00:00:00+00:00	9726.002930	9795.943359	34522718159	222.726059	16673443564	0.997751	42966951015	22.062258	485529457
2020-02-08 00:00:00+00:00	9678.910156	9865.119141	35172043762	223.146515	16741203125	0.999534	44251729422	21.782419	376067881

In [7]:
```python
data.tail()
```

Out[7]:

Date	Low	Close (BTC)	Volume (BTC)	Close (ETH)	Volume (ETH)	Close (USDT)	Volume (USDT)	Close (BNB)	Volume (BNB)
2025-01-31 00:00:00+00:00	101543.882812	102405.023438	45732764360	3298.265137	30128115902	0.999771	96233410167	677.375366	1589542506
2025-02-01 00:00:00+00:00	100297.710938	100655.906250	27757944848	3118.328613	19917507079	0.999843	72792811129	653.432922	1544346912
2025-02-02 00:00:00+00:00	96216.078125	97688.976562	63091816853	2868.692871	42060930305	0.999760	147745588018	617.600647	2282982721
2025-02-03 00:00:00+00:00	91242.890625	101405.421875	115400897748	2884.566650	92453553253	1.001051	292831861639	617.120789	3960962742
2025-02-04 00:00:00+00:00	97963.304688	98712.531250	68290592768	2751.387939	46848655360	1.000552	150930571264	574.938049	2249767936

In [8]:
```python
data.shape
```

Out[8]: (1828, 9)

In [9]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1828 entries, 2020-02-04 00:00:00+00:00 to 2025-02-04 00:00:00+00:00
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Low            1828 non-null   float64
 1   Close (BTC)    1828 non-null   float64
 2   Volume (BTC)   1828 non-null   int64  
 3   Close (ETH)    1828 non-null   float64
 4   Volume (ETH)   1828 non-null   int64  
 5   Close (USDT)   1828 non-null   float64
 6   Volume (USDT)  1828 non-null   int64  
 7   Close (BNB)    1828 non-null   float64
 8   Volume (BNB)   1828 non-null   int64  
dtypes: float64(5), int64(4)
memory usage: 142.8 KB
```

In [10]:
```python
data.isna().sum()
```

Out[10]:
```
Low              0
Close (BTC)      0
Volume (BTC)     0
Close (ETH)      0
Volume (ETH)     0
Close (USDT)     0
Volume (USDT)    0
Close (BNB)      0
Volume (BNB)     0
dtype: int64
```

In [11]:
```python
data.describe()
```

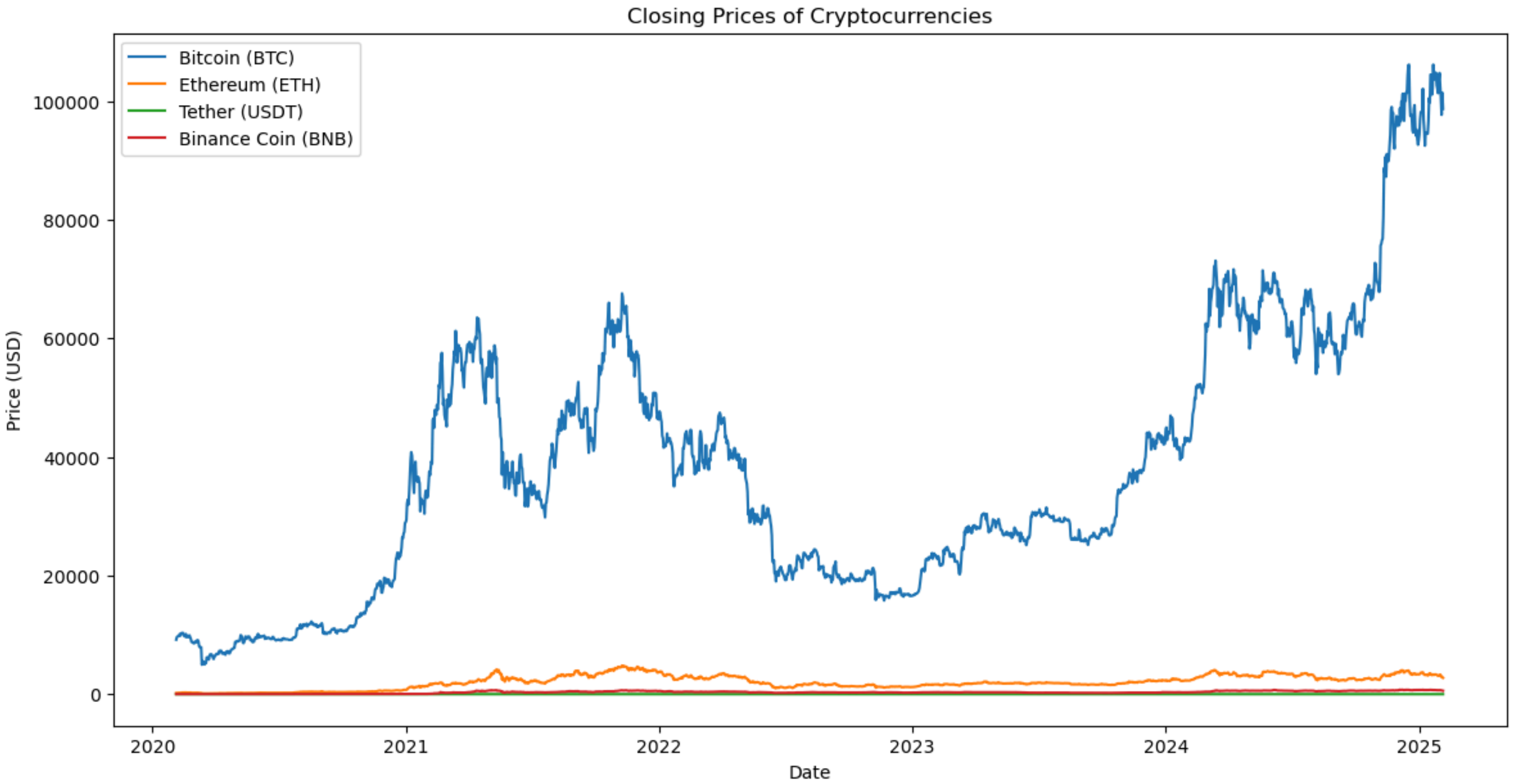
Out[11]:

	Low	Close (BTC)	Volume (BTC)	Close (ETH)	Volume (ETH)	Close (USDT)	Volume (USDT)	Close (BNB)	Volume (BNB)
count	1828.000000	1828.000000	1.828000e+03	1828.000000	1.828000e+03	1828.000000	1.828000e+03	1828.000000	1.828000e+03
mean	37141.454323	38053.590003	3.370915e+10	2041.098250	1.704349e+10	1.000366	6.083020e+10	319.393482	1.457044e+09
std	21963.516753	22498.661541	2.004917e+10	1132.951125	1.084360e+10	0.002095	3.966199e+10	198.762431	1.389998e+09
min	4106.980957	4970.788086	5.331173e+09	110.605873	2.081626e+09	0.974248	9.989859e+09	9.386050	1.365992e+08
25%	19934.478027	20356.477051	2.064499e+10	1299.825958	9.650473e+09	0.999912	3.591407e+10	219.296188	4.799710e+08
50%	33150.035156	34254.855469	3.021149e+10	1892.970093	1.488192e+10	1.000183	5.163867e+10	305.339066	1.144258e+09
75%	52501.022461	53999.031250	4.097135e+10	2971.376770	2.107294e+10	1.000553	7.278883e+10	481.755943	1.917543e+09
max	105291.734375	106146.265625	3.509679e+11	4812.087402	9.245355e+10	1.053585	3.006686e+11	750.272644	1.798295e+10

Exploratory Data Analysis

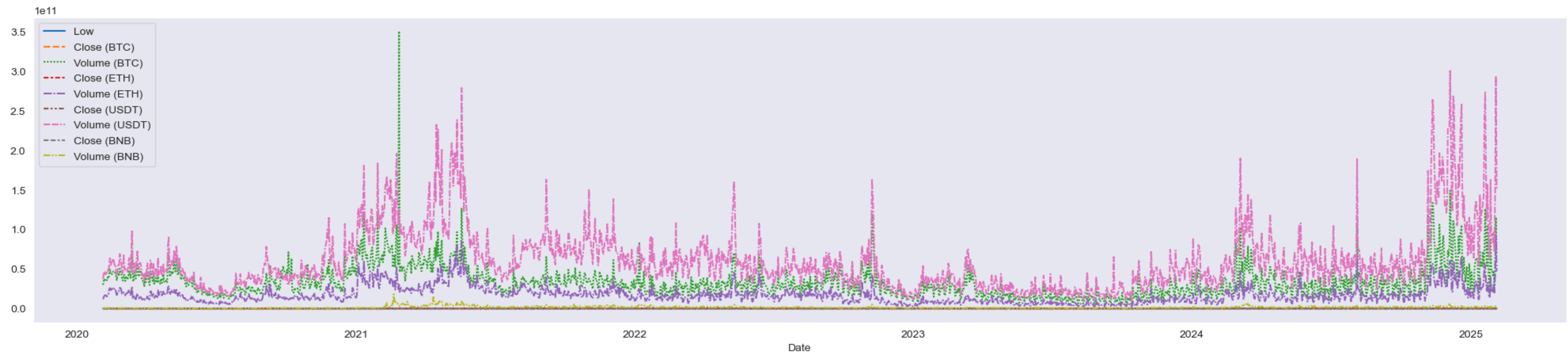
In [13]:
```python
#Visualize the Closing Prices
# create a line plot to visualize the closing prices of all four cryptocurrencies over time:

plt.figure(figsize=(14, 7))
plt.plot(data.index, data['Close (BTC)'], label='Bitcoin (BTC)')
```

```python
plt.plot(data.index, data['Close (ETH)'], label='Ethereum (ETH)')
plt.plot(data.index, data['Close (USDT)'], label='Tether (USDT)')
plt.plot(data.index, data['Close (BNB)'], label='Binance Coin (BNB)')
plt.title('Closing Prices of Cryptocurrencies')
plt.xlabel('Date')
plt.ylabel('Price (USD)')
plt.legend()
plt.show()
```



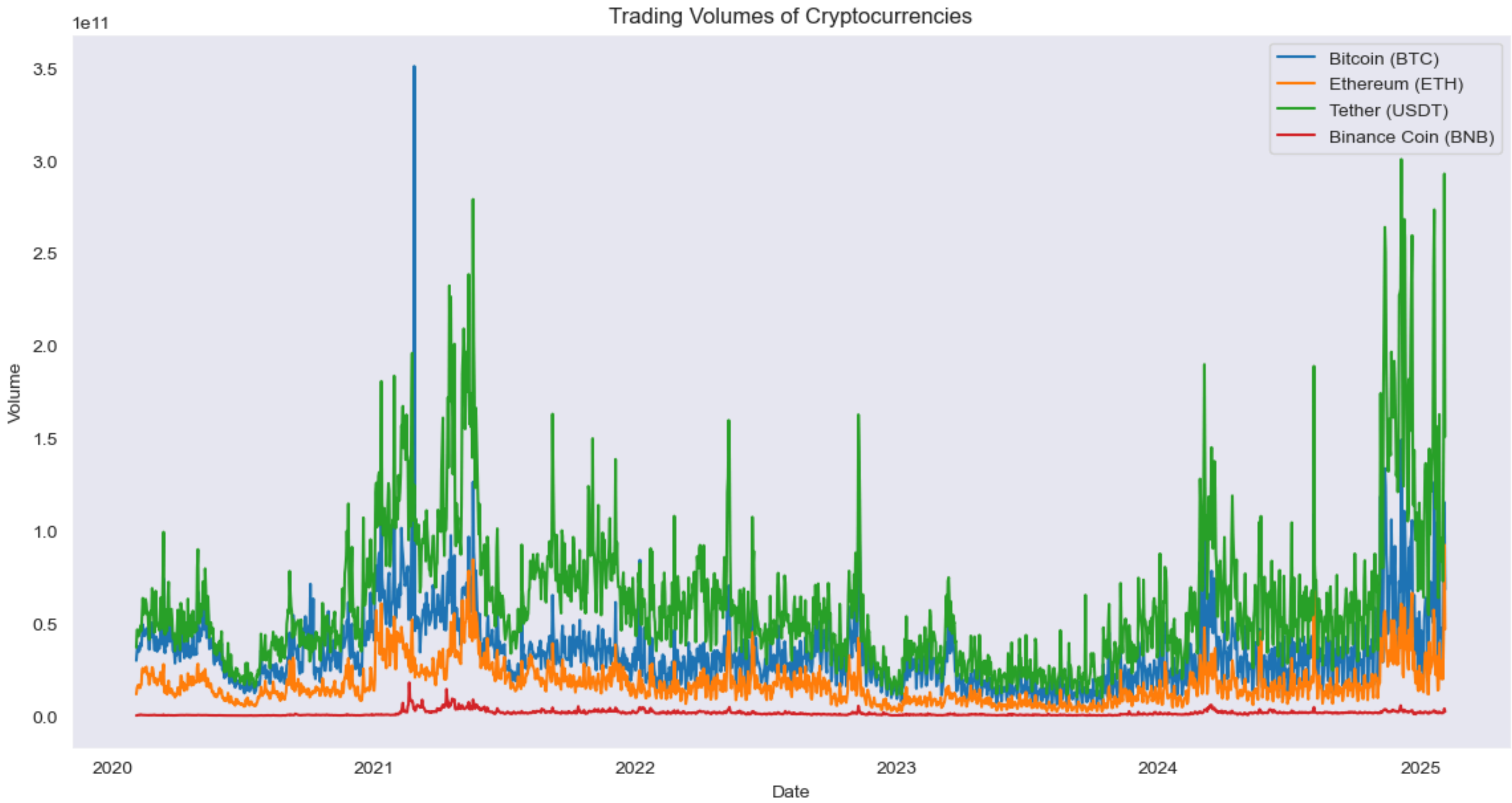
In [14]:
```python
plt.figure(figsize = (25, 5))
sns.set_style('dark')
sns.lineplot(data=data)
```

Out[14]: <Axes: xlabel='Date'>



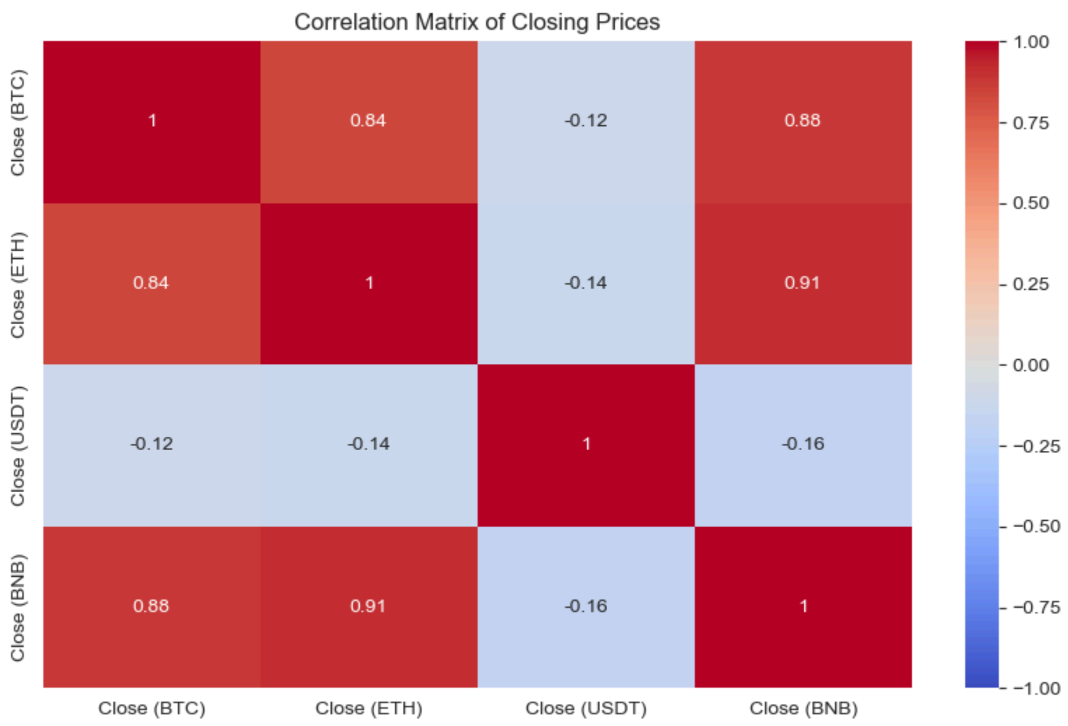
In [15]:

```
# Visualize the Trading Volumes
#Let's visualize the trading volumes of all four cryptocurrencies:

plt.figure(figsize=(14, 7))
plt.plot(data.index, data['Volume (BTC)'], label='Bitcoin (BTC)')
plt.plot(data.index, data['Volume (ETH)'], label='Ethereum (ETH)')
plt.plot(data.index, data['Volume (USDT)'], label='Tether (USDT)')
plt.plot(data.index, data['Volume (BNB)'], label='Binance Coin (BNB)')
plt.title('Trading Volumes of Cryptocurrencies')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.legend()
plt.show()
```



In [16]:

```
#Correlation Analysis
#We'll analyze the correlation between the closing prices of the cryptocurrencies:
# Calculate the correlation matrix

corr_matrix = data[['Close (BTC)', 'Close (ETH)', 'Close (USDT)', 'Close (BNB)']].corr()

# Plot the heatmap

plt.figure(figsize=(10, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Matrix of Closing Prices')
plt.show()
```



In [17]:

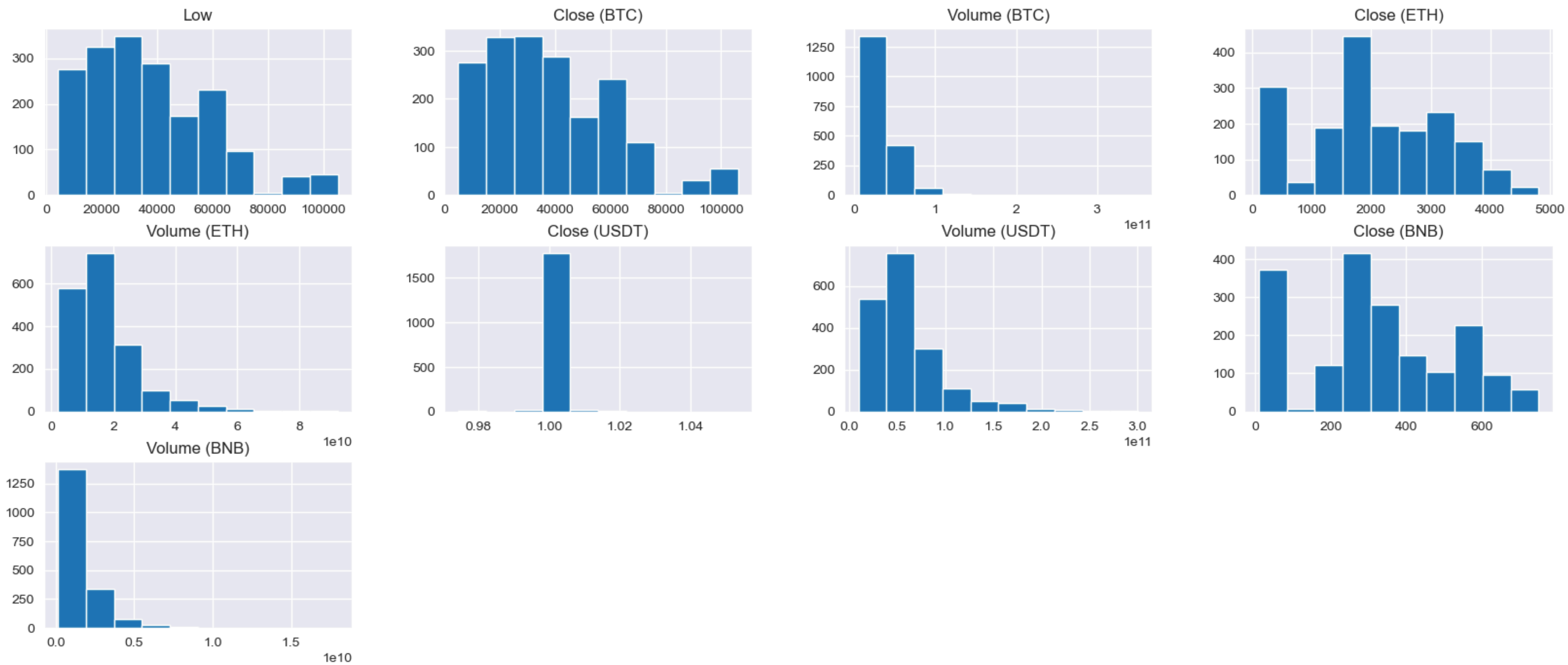
```
# Distribution of Closing Prices
#Let's plot the distribution of closing prices for each cryptocurrency:

plt.figure(figsize=(14, 7))

plt.subplot(2, 2, 1)
sns.histplot(data['Close (BTC)'], kde=True, color='blue')
plt.title('Distribution of Bitcoin (BTC) Closing Prices')

plt.subplot(2, 2, 2)
sns.histplot(data['Close (ETH)'], kde=True, color='orange')
plt.title('Distribution of Ethereum (ETH) Closing Prices')

plt.subplot(2, 2, 3)
sns.histplot(data['Close (USDT)'], kde=True, color='green')
plt.title('Distribution of Tether (USDT) Closing Prices')

plt.subplot(2, 2, 4)
sns.histplot(data['Close (BNB)'], kde=True, color='red')
plt.title('Distribution of Binance Coin (BNB) Closing Prices')

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

In [18]:

```
data.hist(figsize=(20, 8), layout=(3, 4))
```

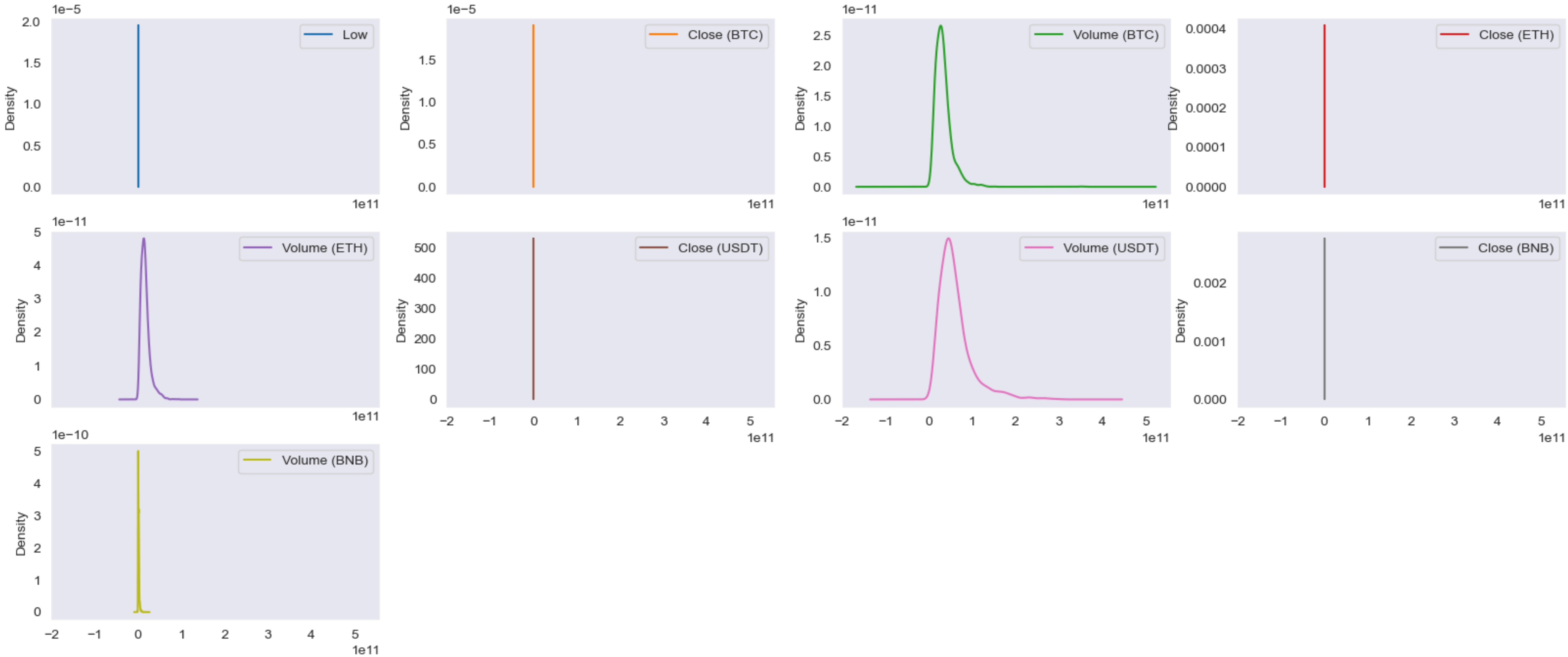
Out[18]:

```
array([[<Axes: title={'center': 'Low'}>,
        <Axes: title={'center': 'Close (BTC)'}>,
        <Axes: title={'center': 'Volume (BTC)'}>,
        <Axes: title={'center': 'Close (ETH)'}>],
       [<Axes: title={'center': 'Volume (ETH)'}>,
        <Axes: title={'center': 'Close (USDT)'}>,
        <Axes: title={'center': 'Volume (USDT)'}>,
        <Axes: title={'center': 'Close (BNB)'}>],
       [<Axes: title={'center': 'Volume (BNB)'}>, <Axes: >, <Axes: >,
        <Axes: >]], dtype=object)
```



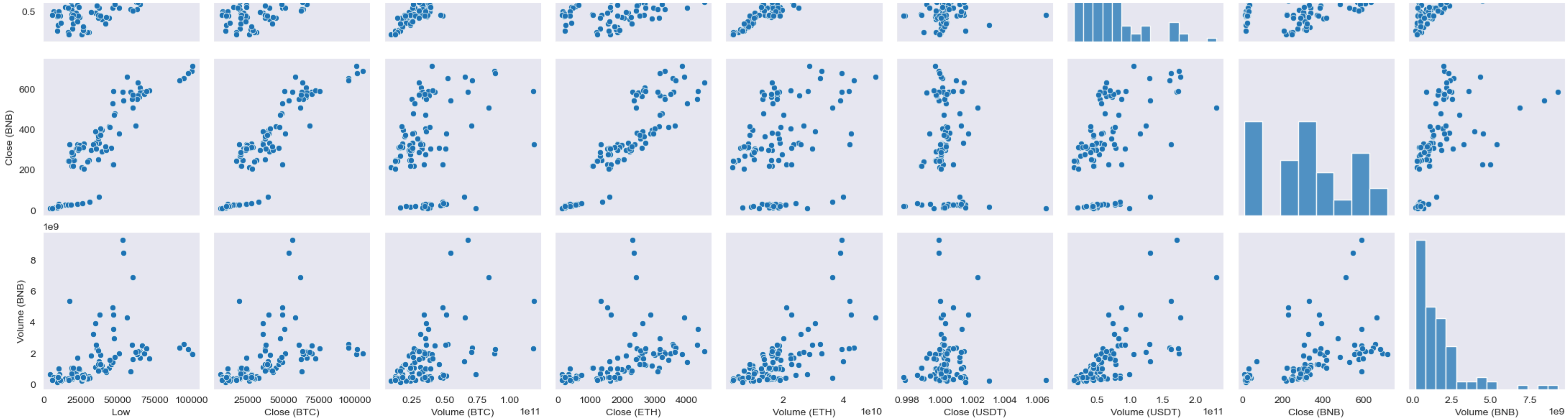
In [19]:
```python
data.plot(kind = "kde", subplots = True, layout = (3, 4), figsize = (20, 8))
```

Out[19]:
```
array([[<Axes: ylabel='Density'>, <Axes: ylabel='Density'>,
        <Axes: ylabel='Density'>, <Axes: ylabel='Density'>],
       [<Axes: ylabel='Density'>, <Axes: ylabel='Density'>,
        <Axes: ylabel='Density'>, <Axes: ylabel='Density'>],
       [<Axes: ylabel='Density'>, <Axes: ylabel='Density'>,
        <Axes: ylabel='Density'>, <Axes: ylabel='Density'>]], dtype=object)
```



In [20]:
```
sns.pairplot(data.sample(n=100));
```


Low
Close (BTC)
Volume (BTC)
Close (ETH)
Volume (ETH)
Close (USDT)
Volume (USDT)
1e11
1e10
1e11



Data Pre-processing

In [22]:
```
X = data.drop(columns = ['Close (BTC)'], axis = 1)
Y = data.loc[:, 'Close (BTC)']
```

In [23]:
```
X.head()
```

Out[23]:

Date	Low	Volume (BTC)	Close (ETH)	Volume (ETH)	Close (USDT)	Volume (USDT)	Close (BNB)	Volume (BNB)
2020-02-04 00:00:00+00:00	9112.811523	29893183716	189.250595	11714191695	1.001745	36950713371	18.177366	213533737
2020-02-05 00:00:00+00:00	9163.704102	35222060874	204.230240	14865434435	1.002838	46504757742	19.215050	301486499
2020-02-06 00:00:00+00:00	9539.818359	37628823716	212.339081	16425589683	0.997216	46549174003	20.595263	394704716
2020-02-07 00:00:00+00:00	9726.002930	34522718159	222.726059	16673443564	0.997751	42966951015	22.062258	485529457
2020-02-08 00:00:00+00:00	9678.910156	35172043762	223.146515	16741203125	0.999534	44251729422	21.782419	376067881

In [24]:
```
X.tail()
```

Out[24]:

Date	Low	Volume (BTC)	Close (ETH)	Volume (ETH)	Close (USDT)	Volume (USDT)	Close (BNB)	Volume (BNB)
2025-01-31 00:00:00+00:00	101543.882812	45732764360	3298.265137	30128115902	0.999771	96233410167	677.375366	1589542506
2025-02-01 00:00:00+00:00	100297.710938	27757944848	3118.328613	19917507079	0.999843	72792811129	653.432922	1544346912
2025-02-02 00:00:00+00:00	96216.078125	63091816853	2868.692871	42060930305	0.999760	147745588018	617.600647	2282982721
2025-02-03 00:00:00+00:00	91242.890625	115400897748	2884.566650	92453553253	1.001051	292831861639	617.120789	3960962742
2025-02-04 00:00:00+00:00	97963.304688	68290592768	2751.387939	46848655360	1.000552	150930571264	574.938049	2249767936

In [25]:
```
Y.head()
```

Out[25]:
```
Date
2020-02-04 00:00:00+00:00    9180.962891
2020-02-05 00:00:00+00:00    9613.423828
2020-02-06 00:00:00+00:00    9729.801758
2020-02-07 00:00:00+00:00    9795.943359
2020-02-08 00:00:00+00:00    9865.119141
Name: Close (BTC), dtype: float64
```

In [26]:
```
Y.tail()
```

Out[26]:
```
Date
2025-01-31 00:00:00+00:00    102405.023438
2025-02-01 00:00:00+00:00    100655.906250
2025-02-02 00:00:00+00:00     97688.976562
2025-02-03 00:00:00+00:00    101405.421875
2025-02-04 00:00:00+00:00     98712.531250
Name: Close (BTC), dtype: float64
```

In [27]:
```
# Split the data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=0)
```

In [28]:
```
# Print the shapes of the resulting datasets

print(f'X_train shape: {X_train.shape}')
print(f'X_test shape: {X_test.shape}')
print(f'y_train shape: {Y_train.shape}')
print(f'y_test shape: {Y_test.shape}')
```

```
X_train shape: (1462, 8)
X_test shape: (366, 8)
y_train shape: (1462,)
y_test shape: (366,)
```

In [29]:
```
#SelectKBest
#SelectKBest is a feature selection method provided by scikit-learn (sklearn) that selects the top k features based on a specified scoring function.
#This function evaluates each feature independently and selects those that have the strongest relationship with the target variable.

#Parameters
#k: Specifies the number of top features to select. In your case, k=4 indicates that you want to select the top 4 features

from sklearn.feature_selection import SelectKBest
```

```
fs = SelectKBest(k=4)
X_train = fs.fit_transform(X_train, Y_train)
X_test = fs.transform(X_test)
```

```
C:\Users\Jan Saida\anaconda3\Lib\site-packages\sklearn\feature_selection\_univariate_selection.py:109: RuntimeWarning: invalid value encountered in divide
  msw = sswn / float(dfwn)
```

In [30]:

```
mask = fs.get_support()
selected_features = X.columns[mask]
print("Selected Features:", selected_features)
```

```
Selected Features: Index(['Close (USDT)', 'Volume (USDT)', 'Close (BNB)', 'Volume (BNB)'], dtype='object')
```

In [31]:

```
X_train
```

Out[31]:

```
array([[1.00020003e+00, 4.25144241e+10, 2.84312153e+01, 3.60596998e+08],
       [9.99502003e-01, 4.72488257e+10, 2.73994808e+01, 4.82149967e+08],
       [1.00069594e+00, 7.57414313e+10, 4.13456207e+02, 1.47312139e+09],
       ...,
       [1.00029004e+00, 5.21447245e+10, 5.24015320e+02, 1.60440064e+09],
       [1.00043797e+00, 8.44380136e+10, 4.17470856e+02, 2.62057147e+09],
       [9.99988019e-01, 4.97521808e+10, 5.29972046e+02, 1.19958266e+09]])
```

In [32]:

```
#MinMaxScaler is a preprocessing method in scikit-learn that transforms features by scaling them to a specified range.
# It's often used when your data needs to be normalized within a specific range to ensure all features contribute equally to the analysis.

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [33]:

```
# implementation of 10 different regression algorithms using scikit-learn. Each algorithm is trained and evaluated on a sample dataset:

#Import Libraries and Generate Sample Data

from sklearn.datasets import make_regression
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_squared_error, r2_score
```

In [34]:

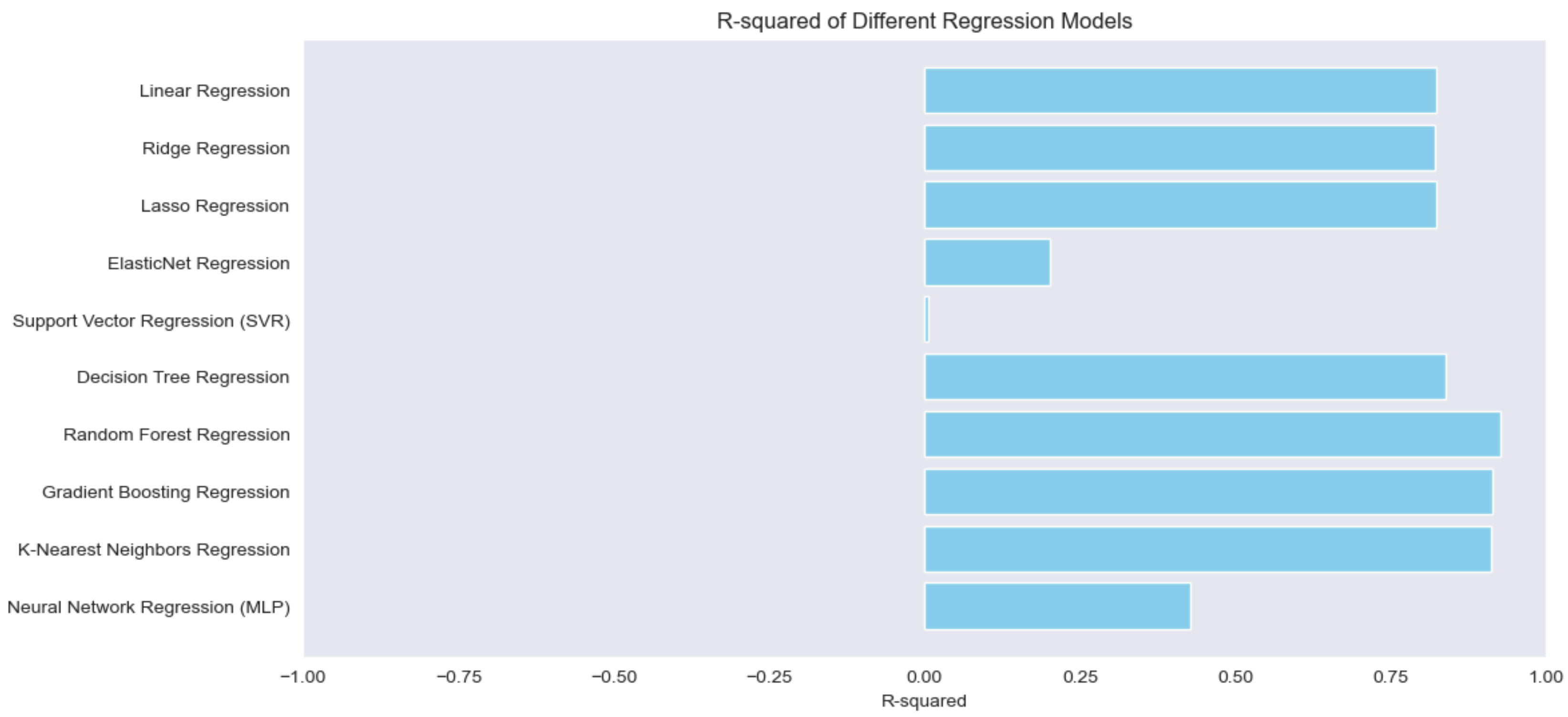
```
#Define Models and Perform Training and Evaluation

models = {
    'Linear Regression': LinearRegression(),
    'Ridge Regression': Ridge(alpha=1.0),
    'Lasso Regression': Lasso(alpha=1.0),
    'ElasticNet Regression': ElasticNet(alpha=1.0, l1_ratio=0.5),
    'Support Vector Regression (SVR)': SVR(kernel='rbf'),
    'Decision Tree Regression': DecisionTreeRegressor(),
    'Random Forest Regression': RandomForestRegressor(n_estimators=100),
    'Gradient Boosting Regression': GradientBoostingRegressor(n_estimators=100, learning_rate=0.1),
    'K-Nearest Neighbors Regression': KNeighborsRegressor(n_neighbors=5),
    'Neural Network Regression (MLP)': MLPRegressor(hidden_layer_sizes=(100, 50), activation='relu', solver='adam')
}
```

```python
# Train and evaluate each model

results = {'Model': [], 'MSE': [], 'R-squared': []}

for name, model in models.items():

    # Train the model

    model.fit(X_train, Y_train)

    # Predict on test set

    Y_pred = model.predict(X_test)

    # Evaluate model

    mse = mean_squared_error(Y_test, Y_pred)
    r2 = r2_score(Y_test, Y_pred)

    # Store results

    results['Model'].append(name)
    results['MSE'].append(mse)
    results['R-squared'].append(r2)

    # Print results

    print(f"----- {name} -----")
    print(f"Mean Squared Error (MSE): {mse}")
    print(f"R-squared: {r2}")
    print()

# Convert results to DataFrame for visualization

results_df = pd.DataFrame(results)
print(results_df)

# Plotting the results

plt.figure(figsize=(12, 6))
plt.barh(results_df['Model'], results_df['R-squared'], color='skyblue')
plt.xlabel('R-squared')
plt.title('R-squared of Different Regression Models')
plt.xlim(-1, 1)
plt.gca().invert_yaxis()
plt.show()
```

```
----- Linear Regression -----
Mean Squared Error (MSE): 91822989.40739869
R-squared: 0.8225492739048273

----- Ridge Regression -----
Mean Squared Error (MSE): 92917900.31610283
R-squared: 0.8204333251972871

----- Lasso Regression -----
Mean Squared Error (MSE): 91802706.85481039
R-squared: 0.8225884705559829

----- ElasticNet Regression -----
Mean Squared Error (MSE): 413553613.0595567
R-squared: 0.20079503629417517

----- Support Vector Regression (SVR) -----
Mean Squared Error (MSE): 514735030.3557013
R-squared: 0.005258863028476557

----- Decision Tree Regression -----
Mean Squared Error (MSE): 83536513.99177702
R-squared: 0.8385631402444195

----- Random Forest Regression -----
Mean Squared Error (MSE): 38421657.53465013
R-squared: 0.9257489755963623

----- Gradient Boosting Regression -----
Mean Squared Error (MSE): 44683115.05804003
R-squared: 0.913648518062684

----- K-Nearest Neighbors Regression -----
Mean Squared Error (MSE): 45737035.18400449
R-squared: 0.9116117852923213
```

```
C:\Users\Jan Saida\anaconda3\Lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
  warnings.warn(
```

```
----- Neural Network Regression (MLP) -----
Mean Squared Error (MSE): 296572607.20707595
R-squared: 0.4268643960681855

                           Model           MSE  R-squared
0              Linear Regression  9.182299e+07   0.822549
1               Ridge Regression  9.291790e+07   0.820433
2               Lasso Regression  9.180271e+07   0.822588
3          ElasticNet Regression  4.135536e+08   0.200795
4  Support Vector Regression (SVR)  5.147350e+08   0.005259
5       Decision Tree Regression  8.353651e+07   0.838563
6       Random Forest Regression  3.842166e+07   0.925749
7   Gradient Boosting Regression  4.468312e+07   0.913649
8  K-Nearest Neighbors Regression  4.573704e+07   0.911612
9  Neural Network Regression (MLP)  2.965726e+08   0.426864
```



Random Forest Regression is a powerful and versatile algorithm suitable for various regression tasks, offering robust performance and the ability to handle complex data relationships

Saving the model

In [37]:
```
import pickle
import numpy as np
from sklearn.datasets import make_regression
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score

# Generate sample data

X, Y = make_regression(n_samples=1000, n_features=10, noise=0.1, random_state=0)


# Scale the features (optional but recommended for some algorithms)
```

```python
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Initialize Random Forest Regressor

model_rf = RandomForestRegressor(n_estimators=100, random_state=0)

# Train the model

model_rf.fit(X_train, Y_train)

# Save the model to a file

filename = 'random_forest_model.pkl'
pickle.dump(model_rf, open(filename, 'wb'))

# Save scaler to a file

with open('scaler.pkl', 'wb') as f:
    pickle.dump(scaler, f)

# Load the model from the file

loaded_model = pickle.load(open(filename, 'rb'))

# Predict using the loaded model

Y_pred = loaded_model.predict(X_test)

# Evaluate the loaded model

mse = mean_squared_error(Y_test, Y_pred)
r2 = r2_score(Y_test, Y_pred)

print(f"Loaded Random Forest Regression - Mean Squared Error (MSE): {mse}")
print(f"Loaded Random Forest Regression - R-squared: {r2}")
```

```
Loaded Random Forest Regression - Mean Squared Error (MSE): 38086378.67246037
Loaded Random Forest Regression - R-squared: 0.9263969122179415
```

In [71]:

```python
import os
os.getcwd()
```

Out[71]:

```
'C:\\Users\\Jan Saida'
```

In [ ]: