TASK 1: REGRESSION ANALYSIS

In [50]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.datasets import load_diabetes
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

In [51]:
```
diabetes = load_diabetes()

df = pd.DataFrame(diabetes.data, columns=diabetes.feature_names)
df['target'] = diabetes.target

df.head()
```

Out[51]:

	age	sex	bmi	bp	s1	s2	s3	s4
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493
2	0.085299	0.050680	0.044451	-0.005670	-0.045599	-0.034194	-0.032356	-0.002592
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592

In [52]:
```
X = df.drop('target', axis=1)
y = df['target']
```

In [53]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

In [54]:
```
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[54]:

▾ LinearRegression

▶ Parameters

In [55]:
```
y_pred = model.predict(X_test)
```

In [56]:
```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

```
print("Mean Squared Error:", mse)
print("R² Score:", r2)
```

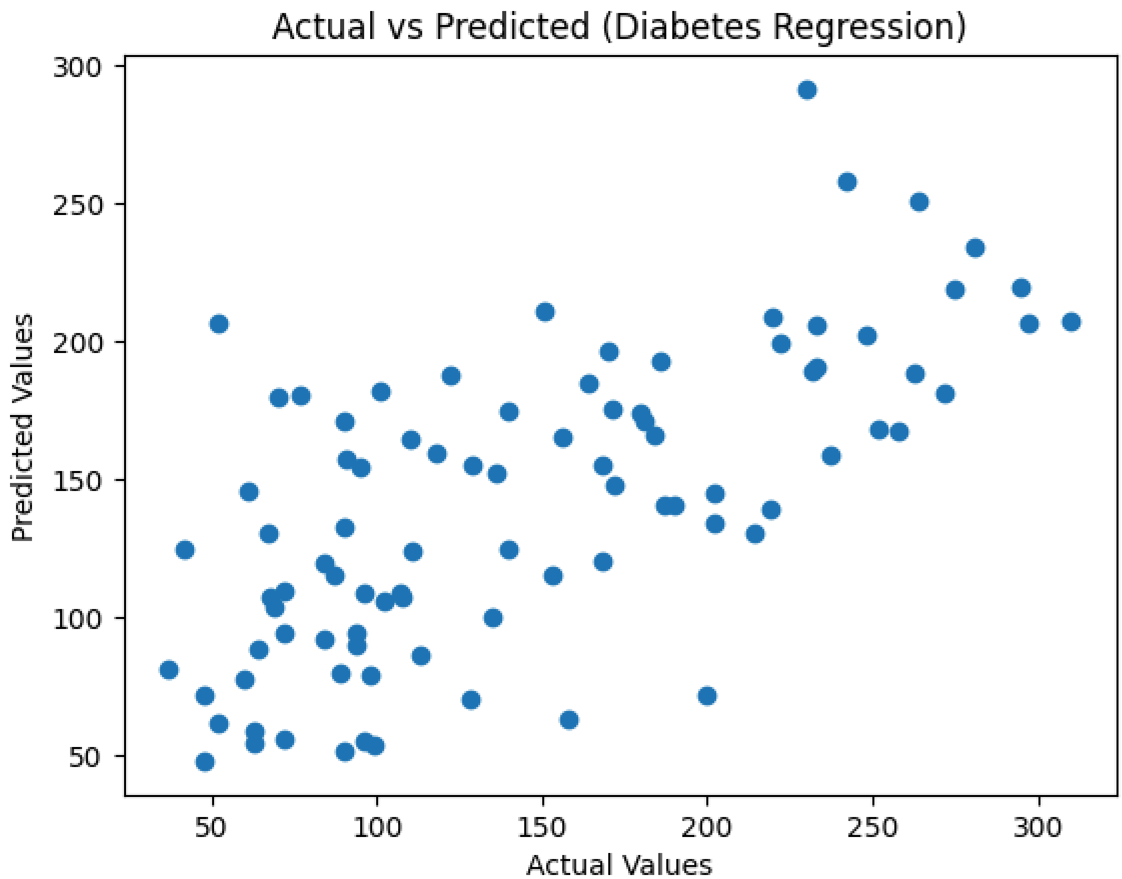
```
Mean Squared Error: 2900.19362849348
R² Score: 0.4526027629719197
```

In [57]:
```
coefficients = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': model.coef_
})

coefficients
```

Out[57]:

	Feature	Coefficient
0	age	37.904021
1	sex	-241.964362
2	bmi	542.428759
3	bp	347.703844
4	s1	-931.488846
5	s2	518.062277
6	s3	163.419983
7	s4	275.317902
8	s5	736.198859
9	s6	48.670657

In [58]:
```
plt.scatter(y_test, y_pred)
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title("Actual vs Predicted (Diabetes Regression)")
plt.show()
```



TIME SERIES ANALYSIS

In [59]:
```
import pandas as pd
import matplotlib.pyplot as plt

from statsmodels.tsa.seasonal import seasonal_decompose
```

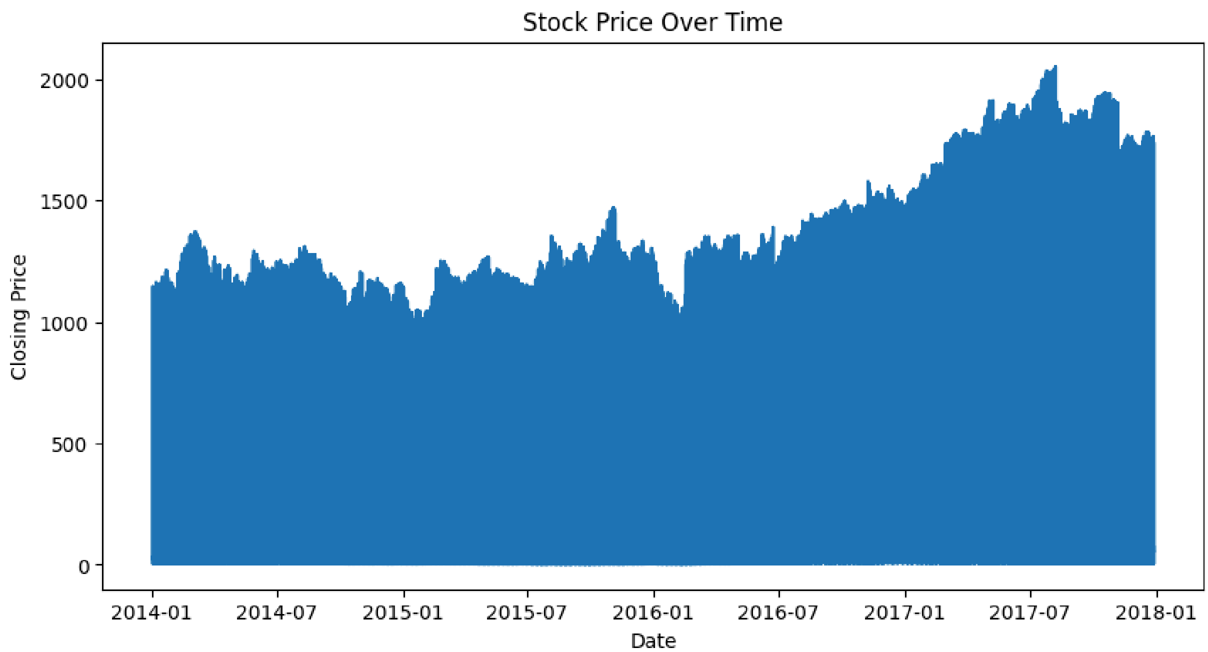
In [60]:
```
df = pd.read_csv("Stock Prices Data Set.csv")

df.head()
```

Out[60]:

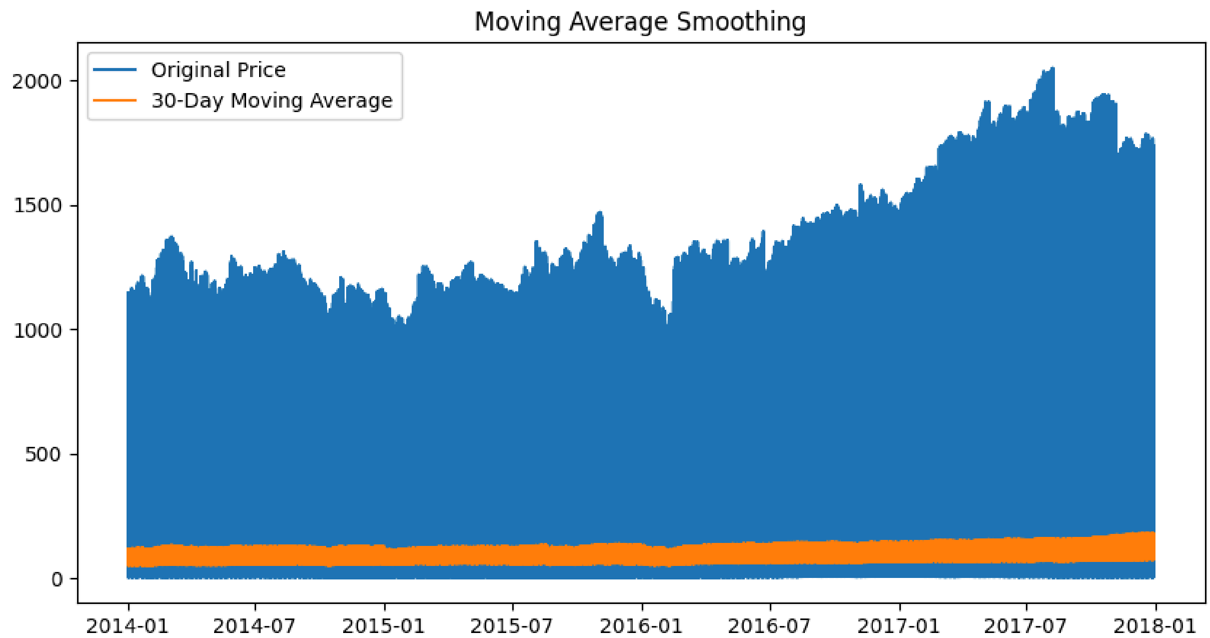
	symbol	date	open	high	low	close	volume
0	AAL	2014-01-02	25.0700	25.8200	25.0600	25.3600	8998943
1	AAPL	2014-01-02	79.3828	79.5756	78.8601	79.0185	58791957
2	AAP	2014-01-02	110.3600	111.8800	109.2900	109.7400	542711
3	ABBV	2014-01-02	52.1200	52.3300	51.5200	51.9800	4569061
4	ABC	2014-01-02	70.1100	70.2300	69.4800	69.8900	1148391

In [61]:
```
df['Date'] = pd.to_datetime(df['date'])
df.set_index('Date', inplace=True)
```

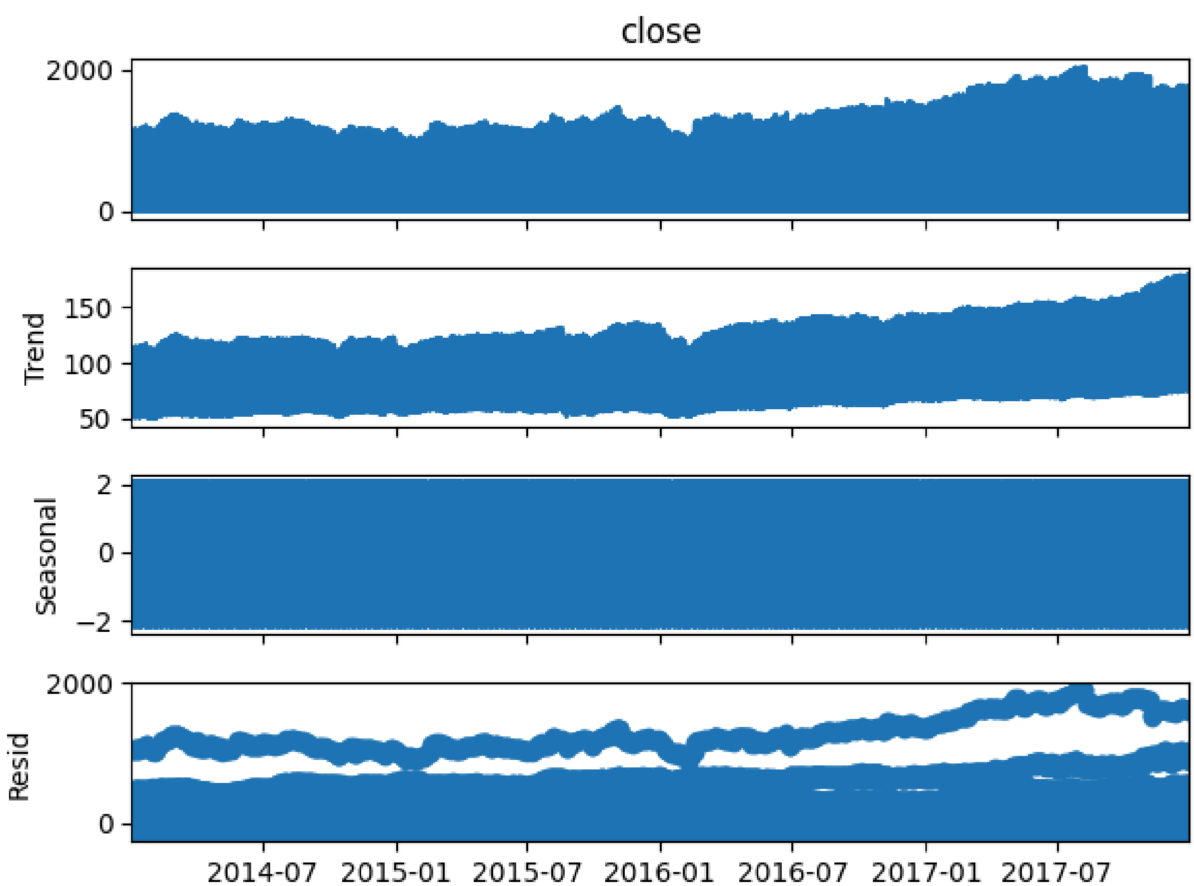
In [62]:
```
plt.figure(figsize=(10,5))
plt.plot(df['close'])
plt.title("Stock Price Over Time")
plt.xlabel("Date")
plt.ylabel("Closing Price")
plt.show()
```



In [63]:
```
df['MA_30'] = df['close'].rolling(window=30).mean()

plt.figure(figsize=(10,5))
plt.plot(df['close'], label="Original Price")
plt.plot(df['MA_30'], label="30-Day Moving Average")
plt.legend()
plt.title("Moving Average Smoothing")
plt.show()
```



In [64]:
```
decomposition = seasonal_decompose(df['close'], model='additive', period=30)

decomposition.plot()
plt.show()
```



In [65]:
```
print("Dataset Shape:", df.shape)
print("Missing Values:\n", df.isnull().sum())
```

```
Dataset Shape: (497472, 8)
Missing Values:
 symbol     0
date       0
open      11
high       8
low        8
close      0
volume     0
MA_30     29
dtype: int64
```

CLUSTERING ANALYSIS (K-MEANS)

In [66]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.datasets import load_iris
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

In [67]:
```
df1 = pd.read_csv("iris.csv")
df1.head()
```

Out[67]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

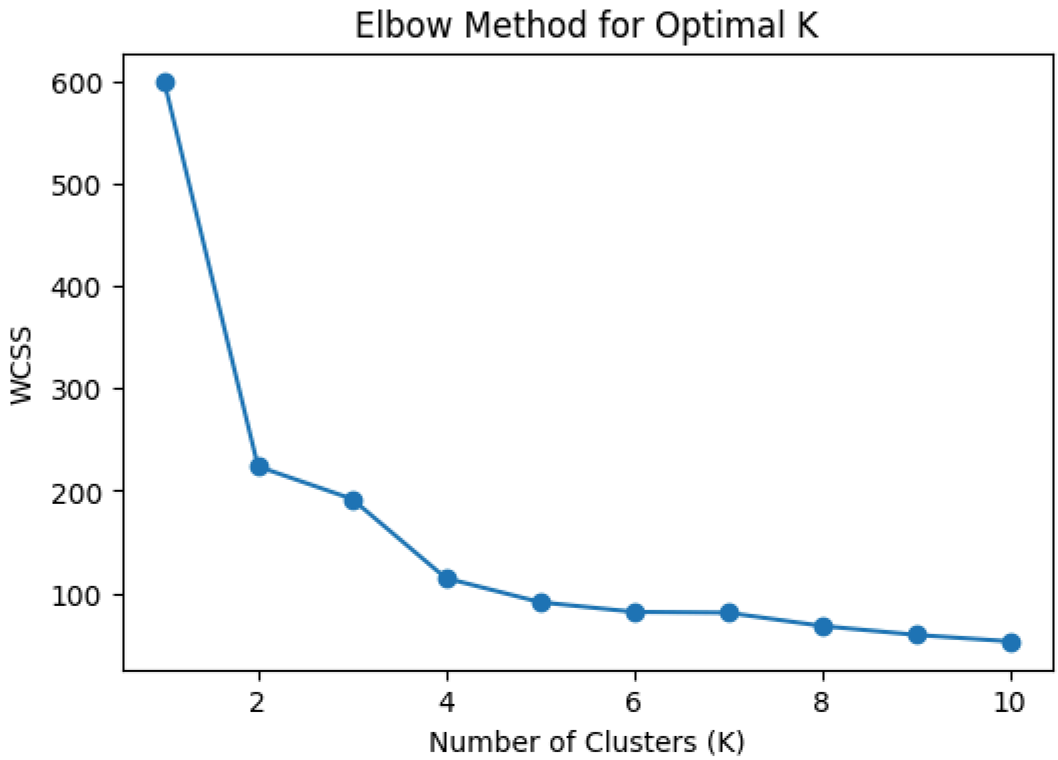
In [74]:
```
X = df1.drop(columns=['species'])
```

In [75]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [76]:
```
wcss = []

for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)
```

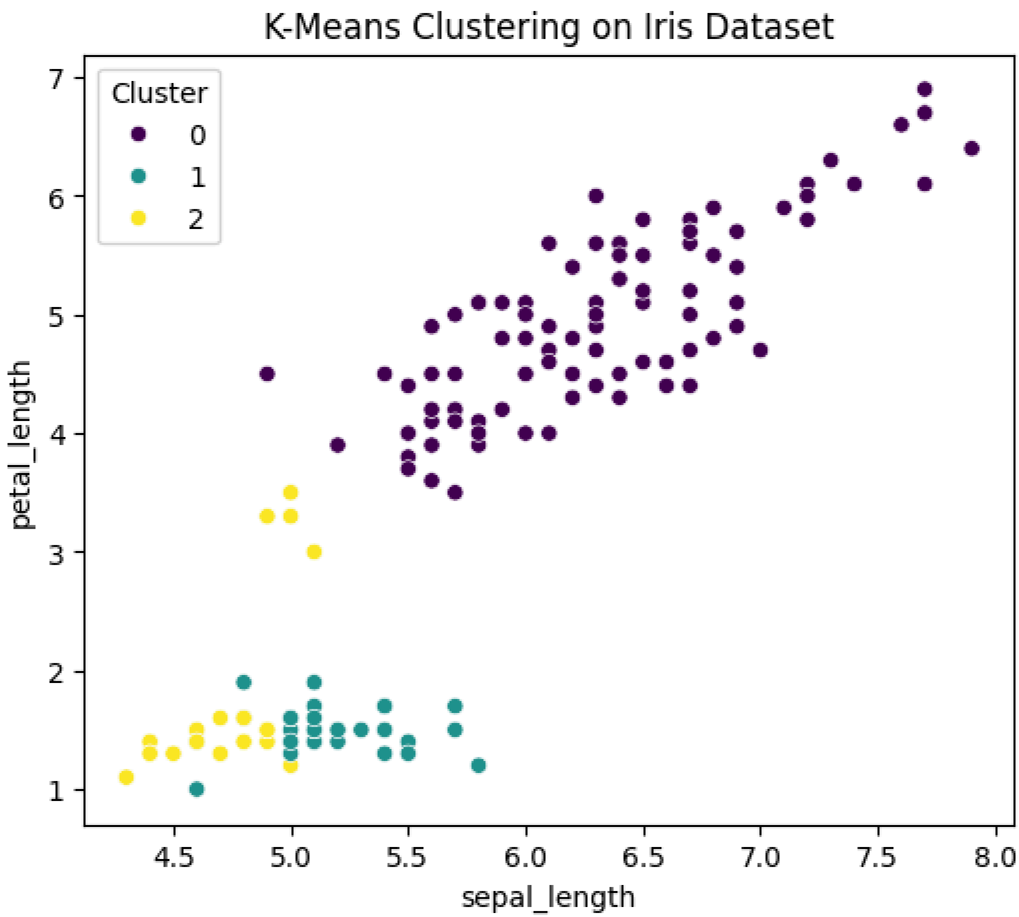
In [77]:
```
plt.figure(figsize=(6,4))
plt.plot(range(1,11), wcss, marker='o')
plt.xlabel("Number of Clusters (K)")
plt.ylabel("WCSS")
```

```
plt.title("Elbow Method for Optimal K")
plt.show()
```



In [79]:
```
kmeans = KMeans(n_clusters=3, random_state=42)
df1['Cluster'] = kmeans.fit_predict(X_scaled)
```

In [80]:
```
plt.figure(figsize=(6,5))
sns.scatterplot(
    x=df1['sepal_length'],
    y=df1['petal_length'],
    hue=df1['Cluster'],
    palette='viridis'
)
plt.title("K-Means Clustering on Iris Dataset")
plt.show()
```



In [81]:
```
pd.crosstab(df1['species'], df1['Cluster'])
```

Out[81]:

Cluster species	0	1	2
setosa	0	32	18
versicolor	46	0	4
virginica	50	0	0

In [ ]: