```
In [2]: # Import necessary libraries
    import pandas as pd
    import numpy as np
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import StandardScaler
    from sklearn.linear_model import LogisticRegression
    from sklearn.metrics import classification_report, accuracy_score, confusion_matrix, roc import matplotlib.pyplot as plt
    import seaborn as sns
```

Out[5]:

	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	са	thal	target
0	63.0	1.0	1.0	145.0	233.0	1.0	2.0	150.0	0.0	2.3	3.0	0.0	6.0	0
1	67.0	1.0	4.0	160.0	286.0	0.0	2.0	108.0	1.0	1.5	2.0	3.0	3.0	2
2	67.0	1.0	4.0	120.0	229.0	0.0	2.0	129.0	1.0	2.6	2.0	2.0	7.0	1
3	37.0	1.0	3.0	130.0	250.0	0.0	0.0	187.0	0.0	3.5	3.0	0.0	3.0	0
4	41.0	0.0	2.0	130.0	204.0	0.0	2.0	172.0	0.0	1.4	1.0	0.0	3.0	0
											•••			
298	45.0	1.0	1.0	110.0	264.0	0.0	0.0	132.0	0.0	1.2	2.0	0.0	7.0	1
299	68.0	1.0	4.0	144.0	193.0	1.0	0.0	141.0	0.0	3.4	2.0	2.0	7.0	2
300	57.0	1.0	4.0	130.0	131.0	0.0	0.0	115.0	1.0	1.2	2.0	1.0	7.0	3
301	57.0	0.0	2.0	130.0	236.0	0.0	2.0	174.0	0.0	0.0	2.0	1.0	3.0	1
302	38.0	1.0	3.0	138.0	175.0	0.0	0.0	173.0	0.0	0.0	1.0	?	3.0	0

303 rows × 14 columns

```
In [8]: # Preprocessing: Replace '?' with NaN and drop missing values for simplicity
    df.replace('?', np.nan, inplace=True)
    df.dropna(inplace=True)
```

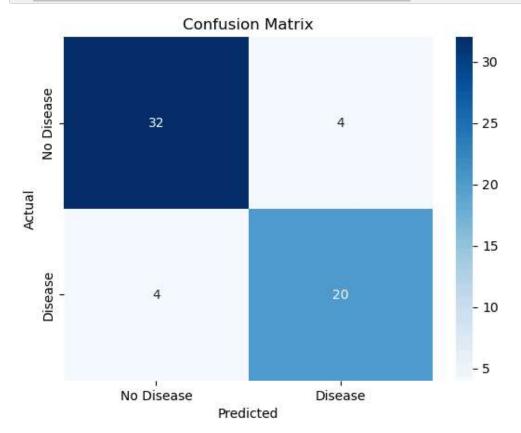
```
In [14]: # Convert categorical features to numeric
         df['ca'] = pd.to_numeric(df['ca'])
         df['thal'] = pd.to_numeric(df['thal'])
         print(df['ca'])
         print(df['thal'])
         0
                 0.0
         1
                 3.0
         2
                 2.0
          3
                 0.0
         4
                 0.0
                . . .
         297
                 0.0
          298
                 0.0
         299
                 2.0
         300
                 1.0
         301
                 1.0
         Name: ca, Length: 297, dtype: float64
         0
                 6.0
         1
                 3.0
         2
                 7.0
         3
                 3.0
         4
                 3.0
                . . .
         297
                 7.0
         298
                 7.0
         299
                 7.0
         300
                 7.0
         301
                 3.0
         Name: thal, Length: 297, dtype: float64
In [15]: # Convert target to binary classification (0: No Disease, 1: Disease)
         df['target'] = df['target'].apply(lambda x: 1 if x > 0 else 0)
         df['target']
Out[15]: 0
                 0
         1
                 1
         2
                 1
         3
                 0
         4
                 0
         297
                 1
         298
                 1
         299
                 1
          300
                 1
         301
         Name: target, Length: 297, dtype: int64
```

```
In [18]: # Features and Target
         X = df.drop('target', axis=1)
         y = df['target']
         print(X)
         print(y)
                                                      restecg thalach exang
                                                                                oldpeak \
                age
                    sex
                           ср
                               trestbps
                                           chol fbs
         0
               63.0
                     1.0
                          1.0
                                  145.0
                                          233.0
                                                 1.0
                                                          2.0
                                                                 150.0
                                                                           0.0
                                                                                    2.3
         1
               67.0
                     1.0 4.0
                                  160.0
                                         286.0
                                                 0.0
                                                          2.0
                                                                 108.0
                                                                           1.0
                                                                                    1.5
          2
                                  120.0 229.0
                                                 0.0
                                                          2.0
                                                                 129.0
                                                                           1.0
                                                                                    2.6
               67.0
                    1.0 4.0
          3
               37.0 1.0 3.0
                                  130.0 250.0
                                                 0.0
                                                          0.0
                                                                 187.0
                                                                           0.0
                                                                                    3.5
          4
               41.0 0.0 2.0
                                  130.0 204.0 0.0
                                                                 172.0
                                                                                    1.4
                                                          2.0
                                                                           0.0
                . . .
                     . . .
                          . . .
                                     . . .
                                            . . .
                                                 . . .
                                                          . . .
                                                                   . . .
                                                                           . . .
                                                                                    . . .
          . .
          297
              57.0
                    0.0 4.0
                                  140.0 241.0
                                                 0.0
                                                          0.0
                                                                 123.0
                                                                           1.0
                                                                                    0.2
          298
              45.0
                    1.0 1.0
                                  110.0 264.0
                                                 0.0
                                                          0.0
                                                                 132.0
                                                                           0.0
                                                                                    1.2
          299
              68.0
                    1.0 4.0
                                  144.0 193.0
                                                 1.0
                                                          0.0
                                                                 141.0
                                                                           0.0
                                                                                    3.4
          300
               57.0
                     1.0 4.0
                                  130.0 131.0
                                                 0.0
                                                          0.0
                                                                 115.0
                                                                           1.0
                                                                                    1.2
          301 57.0 0.0 2.0
                                  130.0 236.0 0.0
                                                                 174.0
                                                                                    0.0
                                                          2.0
                                                                           0.0
               slope
                          thal
                      ca
         0
                 3.0 0.0
                            6.0
         1
                 2.0 3.0
                            3.0
          2
                 2.0 2.0
                            7.0
          3
                 3.0 0.0
                            3.0
                 1.0 0.0
          4
                            3.0
          . .
                 . . .
                      . . .
                            . . .
          297
                 2.0 0.0
                            7.0
          298
                 2.0 0.0
                            7.0
          299
                 2.0 2.0
                            7.0
          300
                 2.0 1.0
                            7.0
          301
                 2.0 1.0
                            3.0
          [297 rows x 13 columns]
          0
                 0
         1
                 1
          2
                 1
                 0
          3
          4
                 0
          297
                 1
          298
                 1
          299
                 1
          300
                 1
          301
          Name: target, Length: 297, dtype: int64
In [20]: # Split the data into training and testing sets (80% train, 20% test)
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
```

```
In [22]: # Feature Scaling (Standardization)
         scaler = StandardScaler()
         X train scaled = scaler.fit transform(X train)
         X test scaled = scaler.transform(X test)
In [24]: # Logistic Regression Model
         log reg = LogisticRegression(random state=42)
         log_reg.fit(X_train_scaled, y_train)
Out[24]:
                   LogisticRegression
          LogisticRegression(random state=42)
In [27]:
        # Predictions
         y_pred = log_reg.predict(X_test_scaled)
         y_pred
Out[27]: array([0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,
                1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1,
                0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1], dtype=int64)
In [29]: # Performance Evaluation
         print("Accuracy:", accuracy_score(y_test, y_pred))
         print("\nClassification Report:\n", classification_report(y_test, y_pred))
         Accuracy: 0.866666666666667
         Classification Report:
```

	precision	recall	f1-score	support
0	0.89	0.89	0.89	36
1	0.83	0.83	0.83	24
accuracy			0.87	60
macro avg	0.86	0.86	0.86	60
weighted avg	0.87	0.87	0.87	60

```
In [33]: # Confusion Matrix
    conf_matrix = confusion_matrix(y_test, y_pred)
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No Disease', 'plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title('Confusion Matrix')
    plt.show()
```



```
In [34]: # Import necessary libraries
         import pandas as pd
         from sklearn.preprocessing import StandardScaler
         from sklearn.linear model import LogisticRegression
         # Assuming the dataset is already loaded and the model is trained as explained previousl
         # Pre-trained logistic regression model log reg and scaler scaler should be available
         # Function to collect user input dynamically and predict heart disease
         def predict heart disease():
             Predicts heart disease based on user input.
             # Collect user input
             print("Please enter the following information:")
             age = int(input("Age: "))
             sex = int(input("Sex (1 = Male, 0 = Female): "))
             cp = int(input("Chest pain type (0-3): "))
             trestbps = int(input("Resting blood pressure (in mm Hg): "))
             chol = int(input("Serum cholesterol (in mg/dl): "))
             fbs = int(input("Fasting blood sugar > 120 mg/dl (1 = True, 0 = False): "))
             restecg = int(input("Resting electrocardiographic results (0-2): "))
             thalach = int(input("Maximum heart rate achieved: "))
             exang = int(input("Exercise induced angina (1 = Yes, 0 = No): "))
             oldpeak = float(input("ST depression induced by exercise relative to rest: "))
             slope = int(input("The slope of the peak exercise ST segment (0-2): "))
             ca = int(input("Number of major vessels (0-3): "))
             thal = int(input("Thalassemia (1 = Normal, 2 = Fixed defect, 3 = Reversible defect):
             # Organize the input data into a dictionary
             user info = {
                  'age': age,
                 'sex': sex,
                 'cp': cp,
                 'trestbps': trestbps,
                 'chol': chol,
                 'fbs': fbs,
                 'restecg': restecg,
                 'thalach': thalach,
                 'exang': exang,
                 'oldpeak': oldpeak,
                 'slope': slope,
                 'ca': ca,
                 'thal': thal
             # Convert the input into a DataFrame
             user_data = pd.DataFrame([user_info])
             # Feature Scaling
             user_data_scaled = scaler.transform(user_data)
             # Prediction
             prediction = log_reg.predict(user_data_scaled)
             # Output the result
             if prediction[0] == 1:
                 print("The person is at risk of heart disease.")
             else:
                 print("The person is not at risk of heart disease.")
             return prediction[0]
         # Example of calling the function to predict heart disease based on user input
         predict heart disease()
```

```
Please enter the following information:

Age: 51

Sex (1 = Male, 0 = Female): 1

Chest pain type (0-3): 1

Resting blood pressure (in mm Hg): 122

Serum cholesterol (in mg/dl): 249

Fasting blood sugar > 120 mg/dl (1 = True, 0 = False): 1

Resting electrocardiographic results (0-2): 1

Maximum heart rate achieved: 120

Exercise induced angina (1 = Yes, 0 = No): 1

ST depression induced by exercise relative to rest: 1.5

The slope of the peak exercise ST segment (0-2): 2

Number of major vessels (0-3): 3

Thalassemia (1 = Normal, 2 = Fixed defect, 3 = Reversible defect): 3

The person is at risk of heart disease.
```

Out[34]: 1