Step 1: Data Collection & Understanding 📊 🧠

In [18]:
```
# Importing pandas for data handling
import pandas as pd
# Pandas makes data cleaning and analysis faster and easier
# pandas can handle large datasets efficiently
class DataLoader:
    """
    This class is responsible for loading the dataset and providing an initial e

    Attributes:
        file_path (str): Path to the dataset file.
        df (DataFrame): Loaded dataset.
    """

    def __init__(self, file_path):
        """
        Initializes the DataLoader with the path to the dataset.

        Parameters:
            file_path (str): Path to the CSV dataset file.
        """
        self.file_path = file_path
        self.df = None

    def load_data(self):
        """
        Loads the dataset from the provided file path and prints important initi

        Returns:
            DataFrame: The loaded dataset.
        """
        print("\nDataset Loading...")
        print("-" * 100)

        # Load the dataset
        self.df = pd.read_csv(self.file_path)

        # Print shape of the dataset (rows, columns)
        print("\nDataset Loaded Successfully!")
        print("➡ Shape of Dataset:", self.df.shape)
        print("-" * 100)

        # Print the data types of each column
        print(" Data Types:\n")
        print(self.df.dtypes)
        print("-" * 100)

        # Display first 5 rows of the dataset
        print("First 5 Rows:\n")
        print(self.df.head())
        print("-" * 100)

        # Display missing values in the dataset
```

```
        print("Missing Values (Column-wise):\n")
        print(self.df.isnull().sum())
        print("-" * 100)

        # Show statistical summary of numeric features
        print("Statistical Summary (Numerical Columns):\n")
        print(self.df.describe().T)
        print("-" * 100)

        return self.df


loader = DataLoader("heart.csv")
df = loader.load_data()
```

```
Dataset Loading...
--------------------------------------------------------------------------------
-------------------

Dataset Loaded Successfully!
➞ Shape of Dataset: (918, 12)
--------------------------------------------------------------------------------
-------------------
 Data Types:

Age                int64
Sex               object
ChestPainType     object
RestingBP          int64
Cholesterol        int64
FastingBS          int64
RestingECG        object
MaxHR              int64
ExerciseAngina    object
Oldpeak          float64
ST_Slope          object
HeartDisease       int64
dtype: object
--------------------------------------------------------------------------------
-------------------
First 5 Rows:

   Age Sex ChestPainType  RestingBP  Cholesterol  FastingBS RestingECG  MaxHR  \
0   40   M           ATA        140          289          0     Normal    172
1   49   F           NAP        160          180          0     Normal    156
2   37   M           ATA        130          283          0         ST     98
3   48   F           ASY        138          214          0     Normal    108
4   54   M           NAP        150          195          0     Normal    122

  ExerciseAngina  Oldpeak ST_Slope  HeartDisease
0              N      0.0       Up             0
1              N      1.0     Flat             1
2              N      0.0       Up             0
3              Y      1.5     Flat             1
4              N      0.0       Up             0
--------------------------------------------------------------------------------
-------------------
Missing Values (Column-wise):

Age               0
Sex               0
ChestPainType     0
RestingBP         0
Cholesterol       0
FastingBS         0
RestingECG        0
MaxHR             0
ExerciseAngina    0
Oldpeak           0
ST_Slope          0
HeartDisease      0
dtype: int64
--------------------------------------------------------------------------------
-------------------
Statistical Summary (Numerical Columns):
```

```
              count        mean         std   min     25%    50%    75%    max
Age           918.0   53.510893    9.432617  28.0   47.00   54.0   60.0   77.0
RestingBP     918.0  132.396514   18.514154   0.0  120.00  130.0  140.0  200.0
Cholesterol   918.0  198.799564  109.384145   0.0  173.25  223.0  267.0  603.0
FastingBS     918.0    0.233115    0.423046   0.0    0.00    0.0    0.0    1.0
MaxHR         918.0  136.809368   25.460334  60.0  120.00  138.0  156.0  202.0
Oldpeak       918.0    0.887364    1.066570  -2.6    0.00    0.6    1.5    6.2
HeartDisease  918.0    0.553377    0.497414   0.0    0.00    1.0    1.0    1.0
-----------------------------------------------------------------------------------
-------------------
```

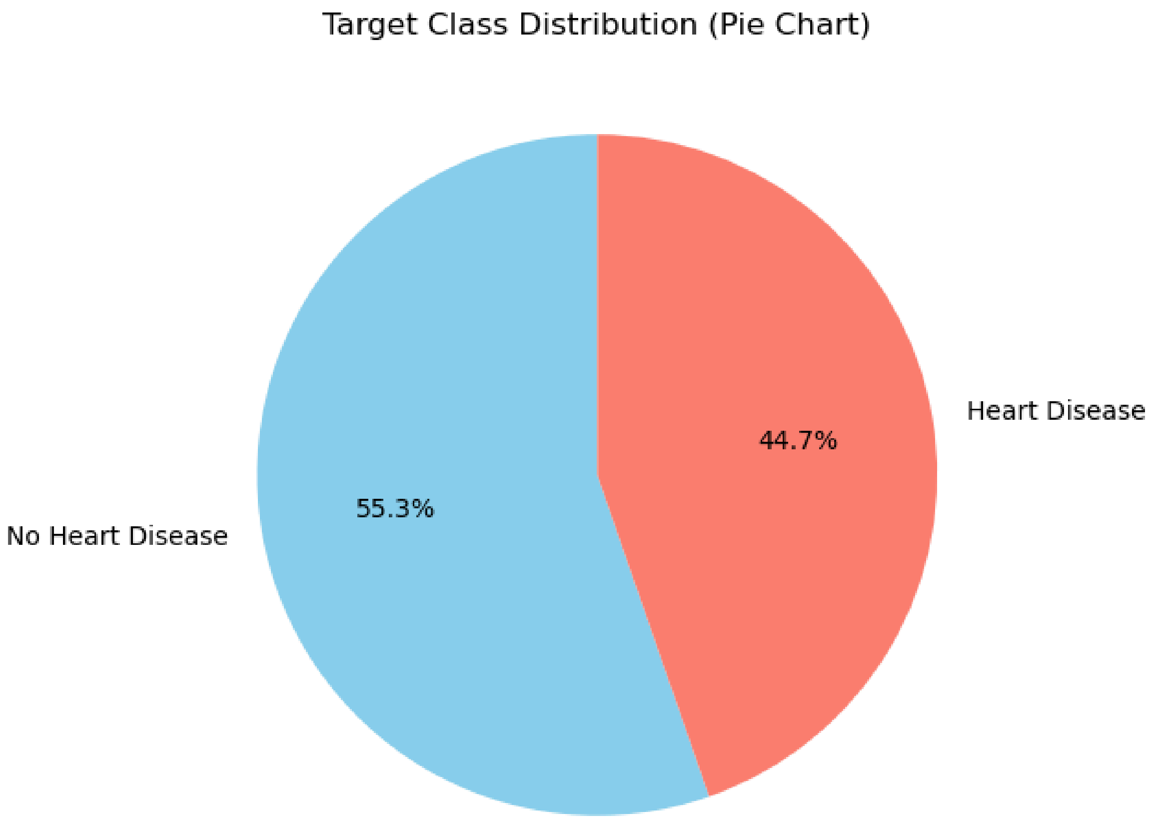
Step 2: Preprocessing, Univariate & Bivariate Analysis

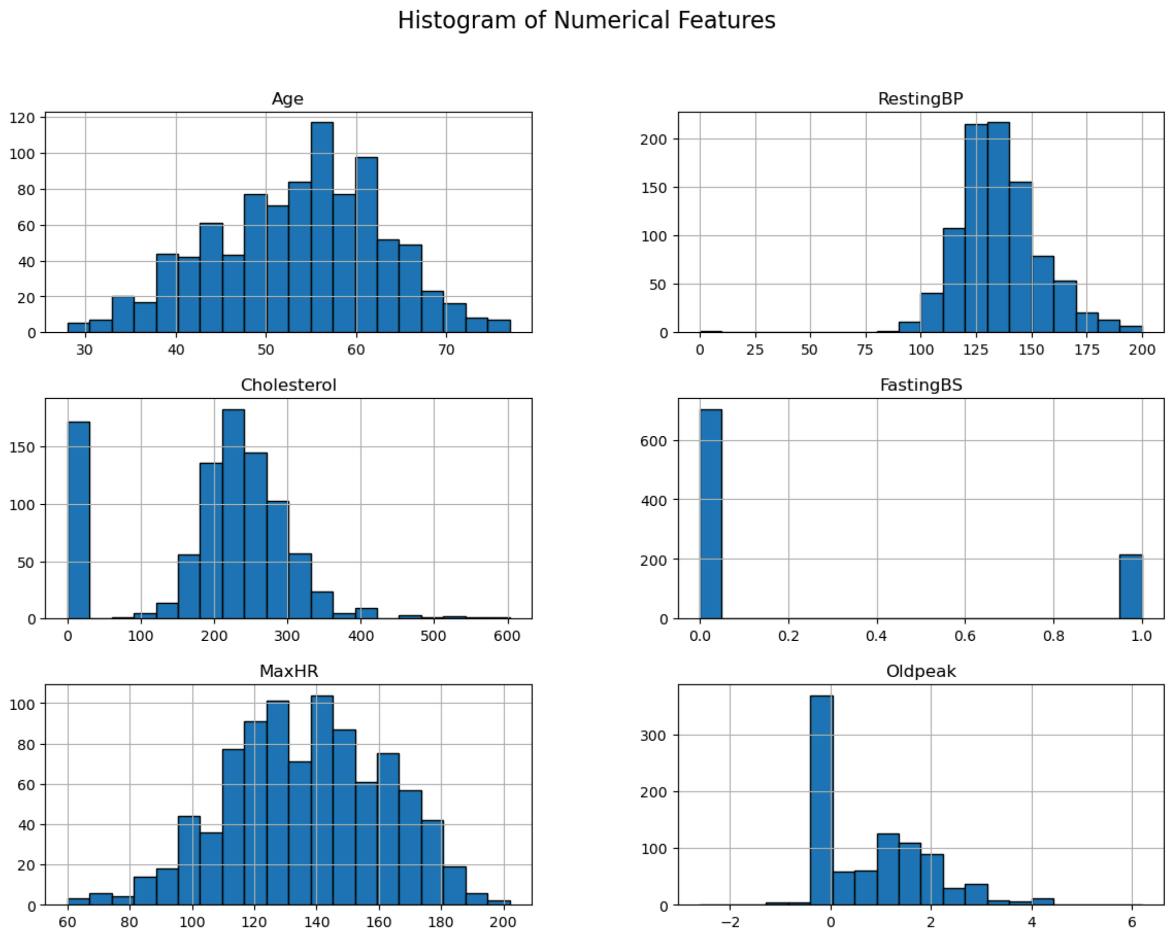
In [19]:

```python
import seaborn as sns # Built on top of matplotlib, seaborn makes it easy to cre
import matplotlib.pyplot as plt # Low-level plotting library for creating visual
import numpy as np      # Provides numerical operations and supports fast array 
from sklearn.preprocessing import StandardScaler # From Scikit-learn, this class
# Crucial for machine learning algorithms that rely on feature scaling.

class DataPreprocessor:
    """
    This class handles preprocessing, univariate analysis, and bivariate analysi
    """

    def __init__(self, df):
        self.df = df

    def preprocess(self):
        """
        Handles missing values, encodes categorical variables, and returns the p
        """
        print("Starting Data Preprocessing...")
        print("-" * 100)

        # Handling missing values (if any)
        if self.df.isnull().sum().sum() > 0:
            self.df = self.df.fillna(self.df.median(numeric_only=True))
            print("Missing values filled with median of respective columns.")

        # Encoding categorical features
        self.df = pd.get_dummies(self.df, drop_first=True)
        print("Categorical Variables Encoded.")
        print("-" * 100)

        print("Data Preprocessing Completed Successfully.")
        print("-" * 100)
        return self.df

    def univariate_analysis(self):
        """
        Performs univariate analysis including countplots, pie charts, and histo
        """
        print("Univariate Analysis Started...")
        print("-" * 100)
```

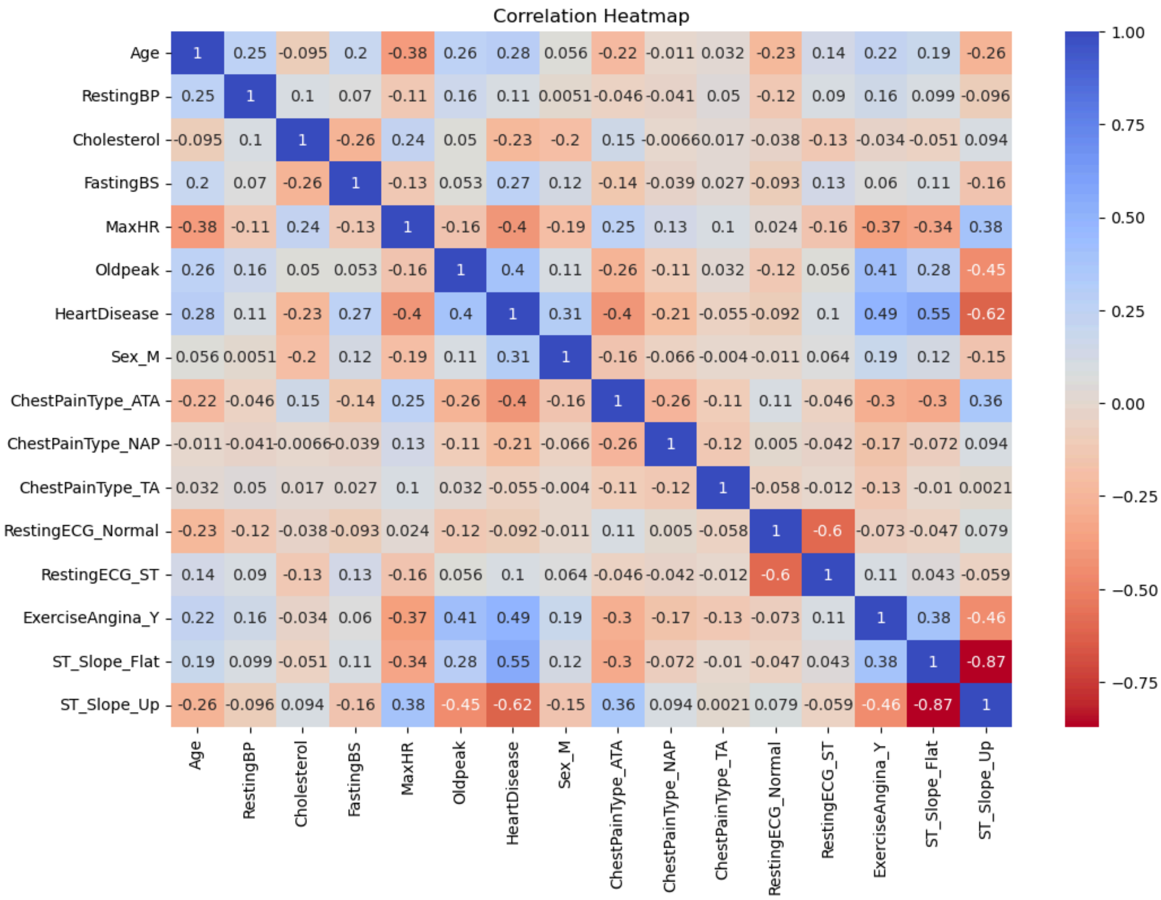
```
        # Countplot of Target Variable
        sns.countplot(x='HeartDisease', data=self.df)
        plt.title("Target Class Distribution (Countplot)")
        plt.show()

        # Pie Chart of Target Variable
        target_counts = self.df['HeartDisease'].value_counts()
        plt.figure(figsize=(6, 6))
        plt.pie(target_counts, labels=['No Heart Disease', 'Heart Disease'], aut
        plt.title("Target Class Distribution (Pie Chart)")
        plt.show()

        # Histograms of Numerical Features
        numeric_cols = self.df.select_dtypes(include=[np.number]).columns.drop('
        self.df[numeric_cols].hist(bins=20, figsize=(14, 10), edgecolor='black')
        plt.suptitle("Histogram of Numerical Features", fontsize=16)
        plt.show()

        print(self.df['HeartDisease'].value_counts())
        print("-" * 100)

    def bivariate_analysis(self):
        """
        Performs bivariate analysis including correlation heatmap and boxplots o
        """
        print("Bivariate Analysis Started...")
        print("-" * 100)

        # Correlation Heatmap
        plt.figure(figsize=(12, 8))
        sns.heatmap(self.df.corr(), annot=True, cmap='coolwarm_r')
        plt.title("Correlation Heatmap")
        plt.show()

        # Boxplots for Numerical Features vs Target
        numeric_cols = self.df.select_dtypes(include=[np.number]).columns.drop('
        for col in numeric_cols:
            plt.figure(figsize=(8, 5))
            sns.boxplot(x='HeartDisease', y=col, data=self.df)
            plt.title(f"{col} vs HeartDisease (Boxplot)")
            plt.show()

        # Optional Pairplot for smaller datasets (commented out)
        # sns.pairplot(self.df, hue='HeartDisease', diag_kind='hist')
        # plt.show()

        print("-" * 100)



preprocessor = DataPreprocessor(df)
df = preprocessor.preprocess()
preprocessor.univariate_analysis()
preprocessor.bivariate_analysis()
```

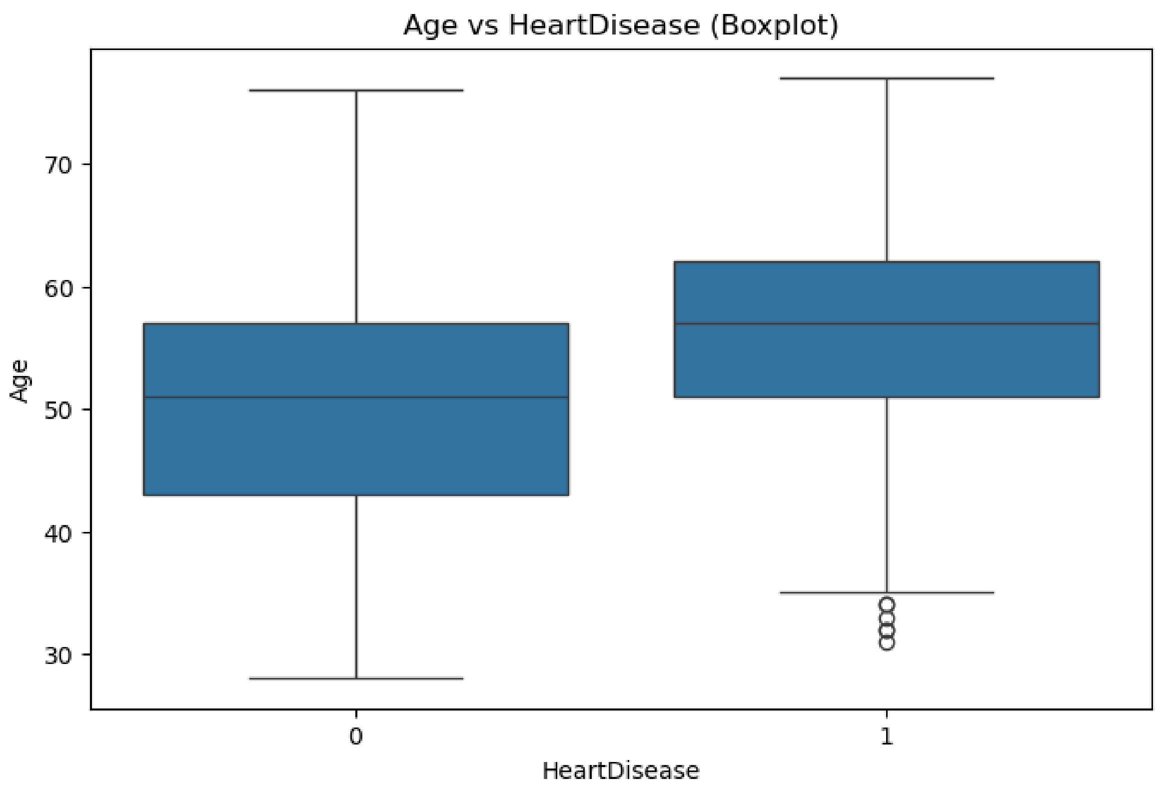
```
Starting Data Preprocessing...
--------------------------------------------------------------------------------
-------------------
Categorical Variables Encoded.
--------------------------------------------------------------------------------
-------------------
Data Preprocessing Completed Successfully.
--------------------------------------------------------------------------------
-------------------
Univariate Analysis Started...
--------------------------------------------------------------------------------
-------------------
```

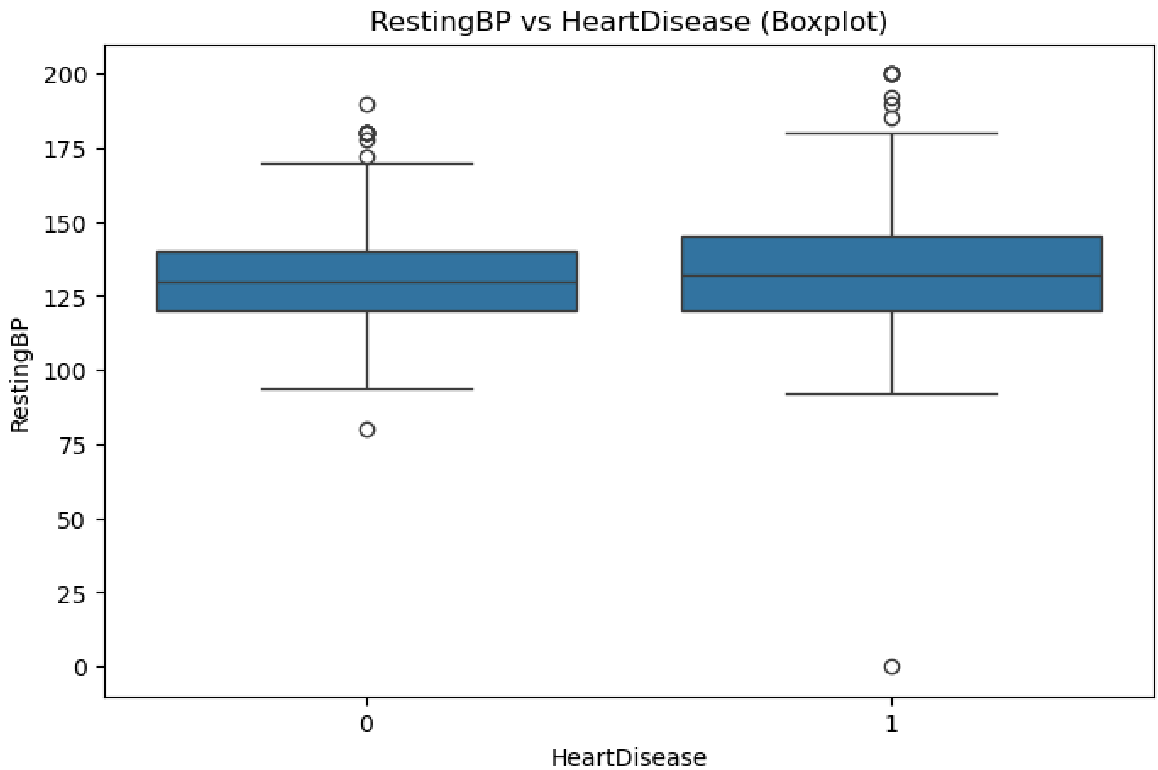

Target Class Distribution (Pie Chart)
Heart Disease
44.7%
55.3%
No Heart Disease

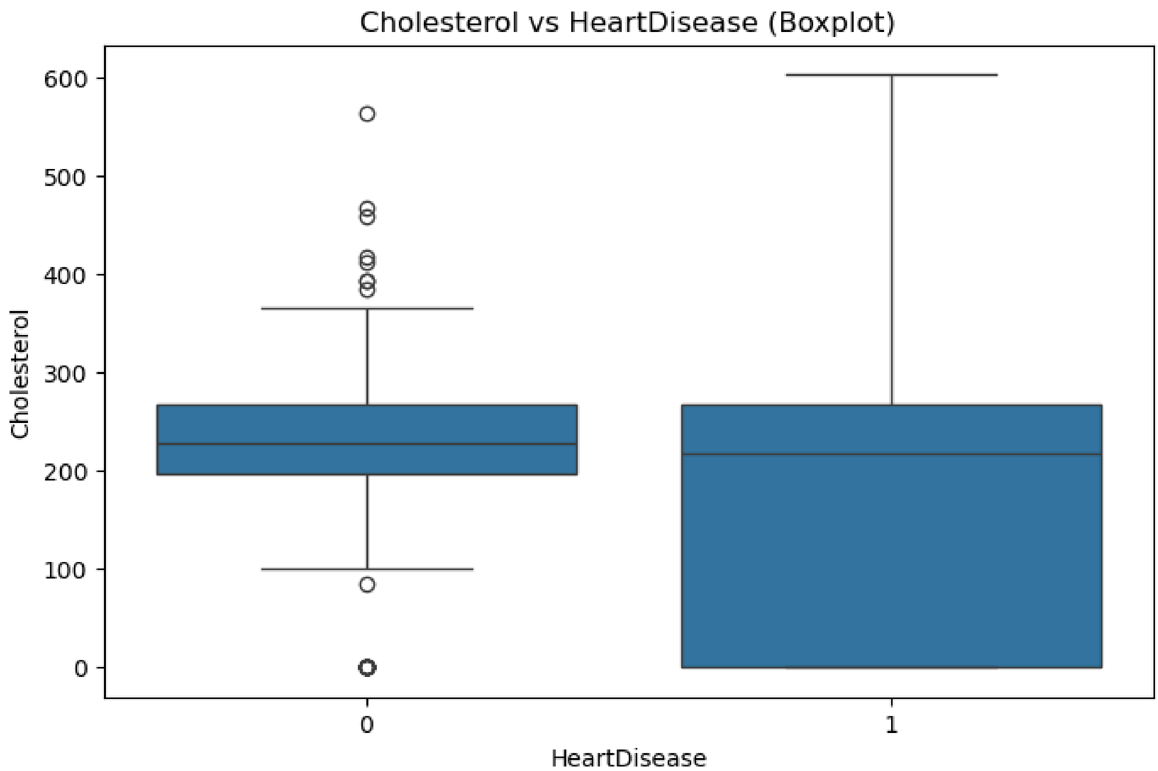

Histogram of Numerical Features
Age
RestingBP
Cholesterol
FastingBS
MaxHR
Oldpeak

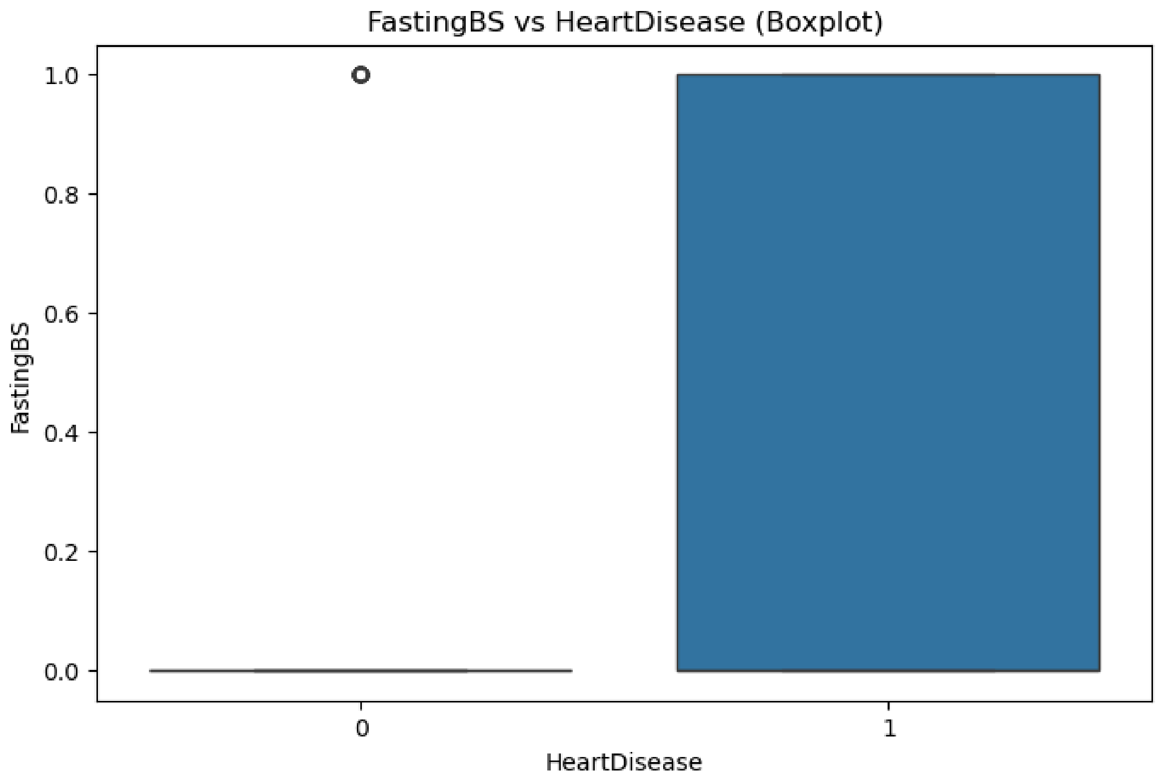
```
HeartDisease
1    508
0    410
Name: count, dtype: int64
--------------------------------------------------------------------------------------------------
Bivariate Analysis Started...
--------------------------------------------------------------------------------------------------
```

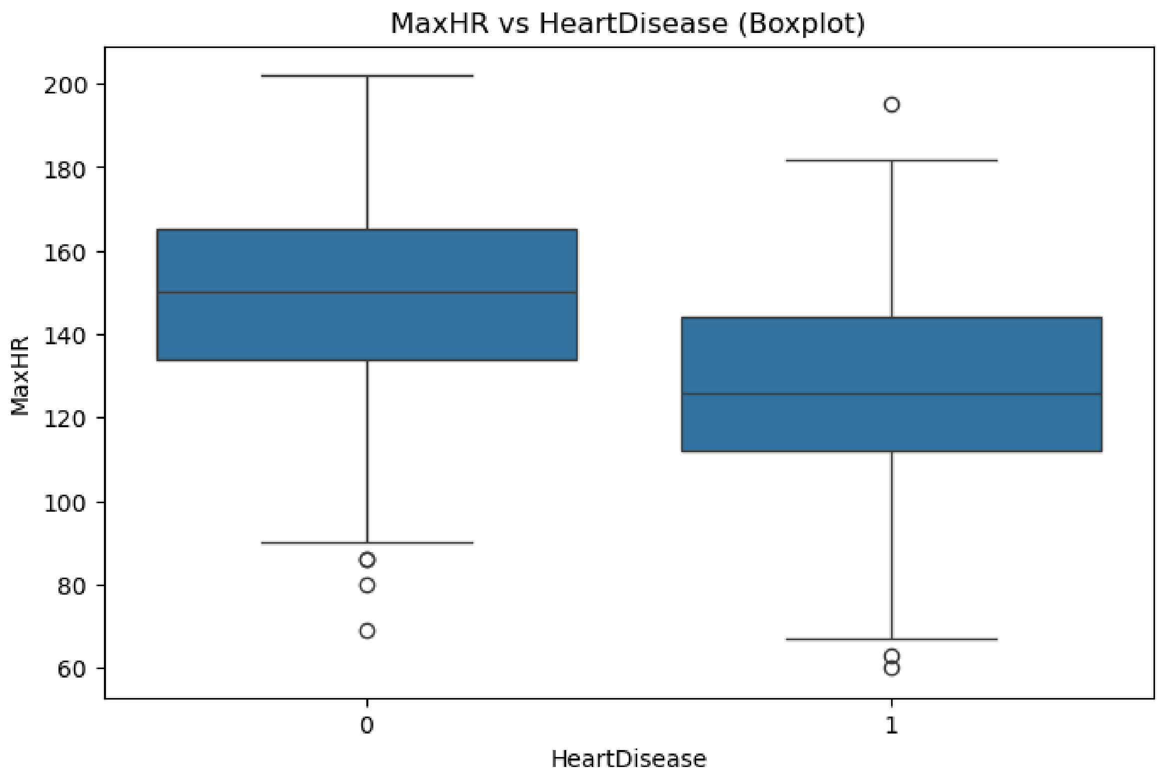


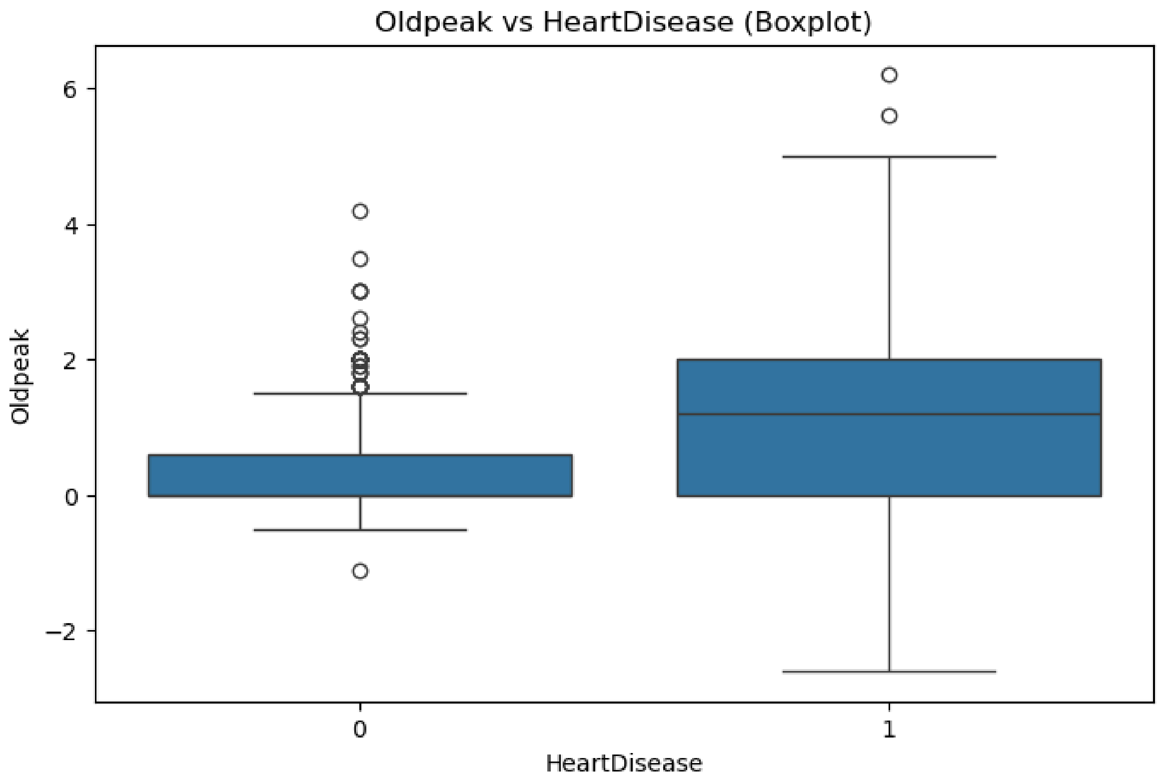



RestingBP vs HeartDisease (Boxplot)
RestingBP
0
25
50
75
100
125
150
175
200
0
1
HeartDisease


Cholesterol vs HeartDisease (Boxplot)
Cholesterol
0
100
200
300
400
500
600
0
1
HeartDisease


FastingBS vs HeartDisease (Boxplot)
FastingBS
1.0
0.8
0.6
0.4
0.2
0.0
0
1
HeartDisease


MaxHR vs HeartDisease (Boxplot)
MaxHR
200
180
160
140
120
100
80
60
0
1
HeartDisease



Step 3: Data Splitting ✂️

In [20]:
```
from sklearn.model_selection import train_test_split # Splits your dataset into
from sklearn.preprocessing import StandardScaler # Standardizes/Scales your nume

class DataSplitter:
    """
    Splits the dataset into training and testing sets and applies feature scalin
    """

    def __init__(self, df):
        self.df = df

    def split(self):
        # Step 1: Separate Features and Target Variable
        X = self.df.drop('HeartDisease', axis=1)
        y = self.df['HeartDisease']

        # Step 2: Train-Test Split (70% training, 30% testing)
        X_train, X_test, y_train, y_test = train_test_split(
            X, y, test_size=0.3, random_state=42
        )

        # Step 3: Apply Feature Scaling
        scaler = StandardScaler()
        X_train_scaled = scaler.fit_transform(X_train)
        X_test_scaled = scaler.transform(X_test)

        # Step 4: Display Shape of Data
        print("Data Split Completed:")
        print(f"Training Set Shape: {X_train.shape}")
```

```
        print(f"Testing Set Shape:  {X_test.shape}")
        print("Data Scaled Successfully.")
        print("-" * 100)

        return X_train_scaled, X_test_scaled, y_train, y_test, scaler

# Example Usage
splitter = DataSplitter(df)
X_train, X_test, y_train, y_test, scaler = splitter.split()
```

```
Data Split Completed:
Training Set Shape: (642, 15)
Testing Set Shape:  (276, 15)
Data Scaled Successfully.
----------------------------------------------------------------------------------
------------------
```

Step 4: Model Training (SVM) and Evaluation 🤖

In [21]:

```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report

class SVMTrainer:
    """
    Trains and evaluates a Support Vector Machine (SVM) classifier.
    """

    def __init__(self):
        self.model = None

    def train(self, X_train, y_train, kernel='linear'):
        """
        Train an SVM model on the provided training data.

        Parameters:
            X_train: Training features
            y_train: Training target labels
            kernel: Kernel type ('linear', 'rbf', 'poly', etc.)
        """
        self.model = SVC(kernel=kernel)
        self.model.fit(X_train, y_train)
        print("Model Training Completed.")
        print("-" * 100)
        return self.model

    def evaluate(self, model, X_test, y_test):
        """
        Evaluate the trained model on test data.

        Parameters:
            model: Trained model object
            X_test: Testing features
            y_test: Actual target labels for test data
        """
        print("Model Evaluation Results")
        print("-" * 100)
        y_pred = model.predict(X_test)
```

```
        print(f"Accuracy Score: {accuracy_score(y_test, y_pred):.4f}")
        print("\nClassification Report:\n")
        print(classification_report(y_test, y_pred))
        print("-" * 100)

# Example Usage
trainer = SVMTrainer()
model = trainer.train(X_train, y_train, kernel='linear')
trainer.evaluate(model, X_test, y_test)
```

```
Model Training Completed.
--------------------------------------------------------------------------------
--------------------
Model Evaluation Results
--------------------------------------------------------------------------------
--------------------
Accuracy Score: 0.8732

Classification Report:

              precision    recall  f1-score   support

           0       0.81      0.89      0.85       112
           1       0.92      0.86      0.89       164

    accuracy                           0.87       276
   macro avg       0.87      0.88      0.87       276
weighted avg       0.88      0.87      0.87       276

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```

Step 5: Model Saving and Loading using Pickle 📦

In [22]:

```
import pickle

class ModelManager:
    """
    Handles saving and loading of trained ML models using pickle.
    """

    def save_model(self, model, scaler, filename='heart_disease_svm_model.pkl'):
        """
        Saves the trained model and scaler to a file.

        Parameters:
            model: Trained machine learning model
            scaler: Scaler object used for data preprocessing
            filename: Name of the file to save
        """
        with open(filename, 'wb') as f:
            pickle.dump((model, scaler), f)
        print(f"Model Saved as '{filename}'")
        print("-" * 100)

    def load_model(self, filename='heart_disease_svm_model.pkl'):
        """
```

```
        Loads the trained model and scaler from a file.

        Returns:
            model: The trained machine learning model
            scaler: The scaler object used for preprocessing
        """
        with open(filename, 'rb') as f:
            model, scaler = pickle.load(f)
        print(f"Model Loaded from '{filename}'")
        return model, scaler

manager = ModelManager()
manager.save_model(model, scaler)                        # Saves model
loaded_model, loaded_scaler = manager.load_model()      # Loads model back
print("Testing Reloaded Model Accuracy:")
print("-" * 100)
print("Score:", loaded_model.score(X_test, y_test))
```

```
Model Saved as 'heart_disease_svm_model.pkl'
---------------------------------------------------------------------------------
-------------------
Model Loaded from 'heart_disease_svm_model.pkl'
Testing Reloaded Model Accuracy:
---------------------------------------------------------------------------------
-------------------
Score: 0.8731884057971014
```