Heart Disease Prediction

Introduction

Heart disease remains one of the leading causes of death worldwide. Early prediction based on clinical data can lead to better management and preventive measures. This project aims to predict the presence of heart disease using patient data containing features such as age, chest pain type, cholesterol, and maximum heart rate. The goal is to identify the key contributing factors and build an accurate predictive model.

Research Question

Can we accurately predict the presence of heart disease based on clinical attributes such as age, cholesterol level, chest pain type, and maximum heart rate?

In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, auc
import numpy as np

# Load dataset
df = pd.read_csv("heart.csv")
df.head()
```

Out[2]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	th
0	52	1	0	125	212	0	1	168	0	1.0	2	2	
1	53	1	0	140	203	1	0	155	1	3.1	0	0	
2	70	1	0	145	174	0	1	125	1	2.6	0	0	
3	61	1	0	148	203	0	1	161	0	0.0	2	1	
4	62	0	0	138	294	1	1	106	0	1.9	1	3	

Data Overview and Cleaning

In [4]:
```
df.info()
df.describe()
df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       1025 non-null   int64  
 1   sex       1025 non-null   int64  
 2   cp        1025 non-null   int64  
 3   trestbps  1025 non-null   int64  
 4   chol      1025 non-null   int64  
 5   fbs       1025 non-null   int64  
 6   restecg   1025 non-null   int64  
 7   thalach   1025 non-null   int64  
 8   exang     1025 non-null   int64  
 9   oldpeak   1025 non-null   float64
 10  slope     1025 non-null   int64  
 11  ca        1025 non-null   int64  
 12  thal      1025 non-null   int64  
 13  target    1025 non-null   int64  
dtypes: float64(1), int64(13)
memory usage: 112.2 KB
```

Out[4]:

```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

Exploratory Data Analysis

In [8]:

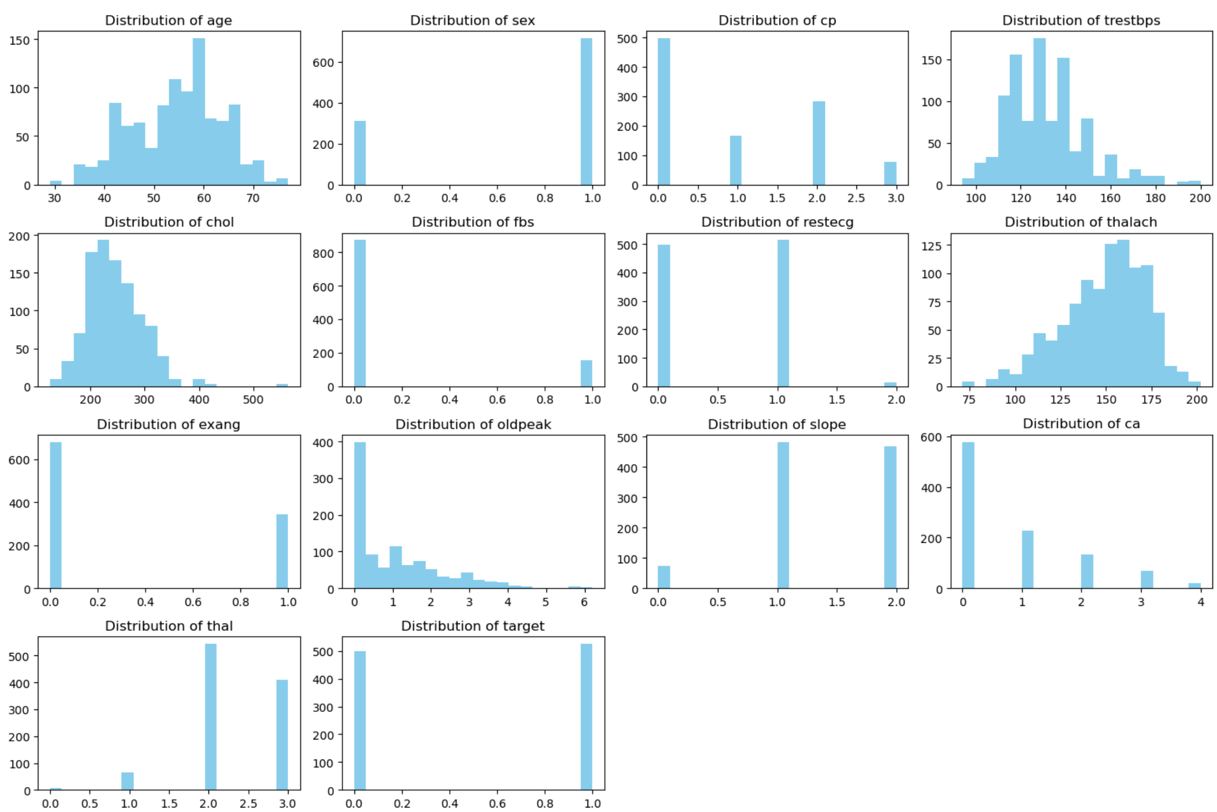
```
# Basic statistics
df.describe()
```

Out[8]:

	age	sex	cp	trestbps	chol	fbs
count	1025.000000	1025.000000	1025.000000	1025.000000	1025.00000	1025.00000
mean	54.434146	0.695610	0.942439	131.611707	246.00000	0.14926
std	9.072290	0.460373	1.029641	17.516718	51.59251	0.35652
min	29.000000	0.000000	0.000000	94.000000	126.00000	0.00000
25%	48.000000	0.000000	0.000000	120.000000	211.00000	0.00000
50%	56.000000	1.000000	1.000000	130.000000	240.00000	0.00000
75%	61.000000	1.000000	2.000000	140.000000	275.00000	0.00000
max	77.000000	1.000000	3.000000	200.000000	564.00000	1.00000

In [10]:

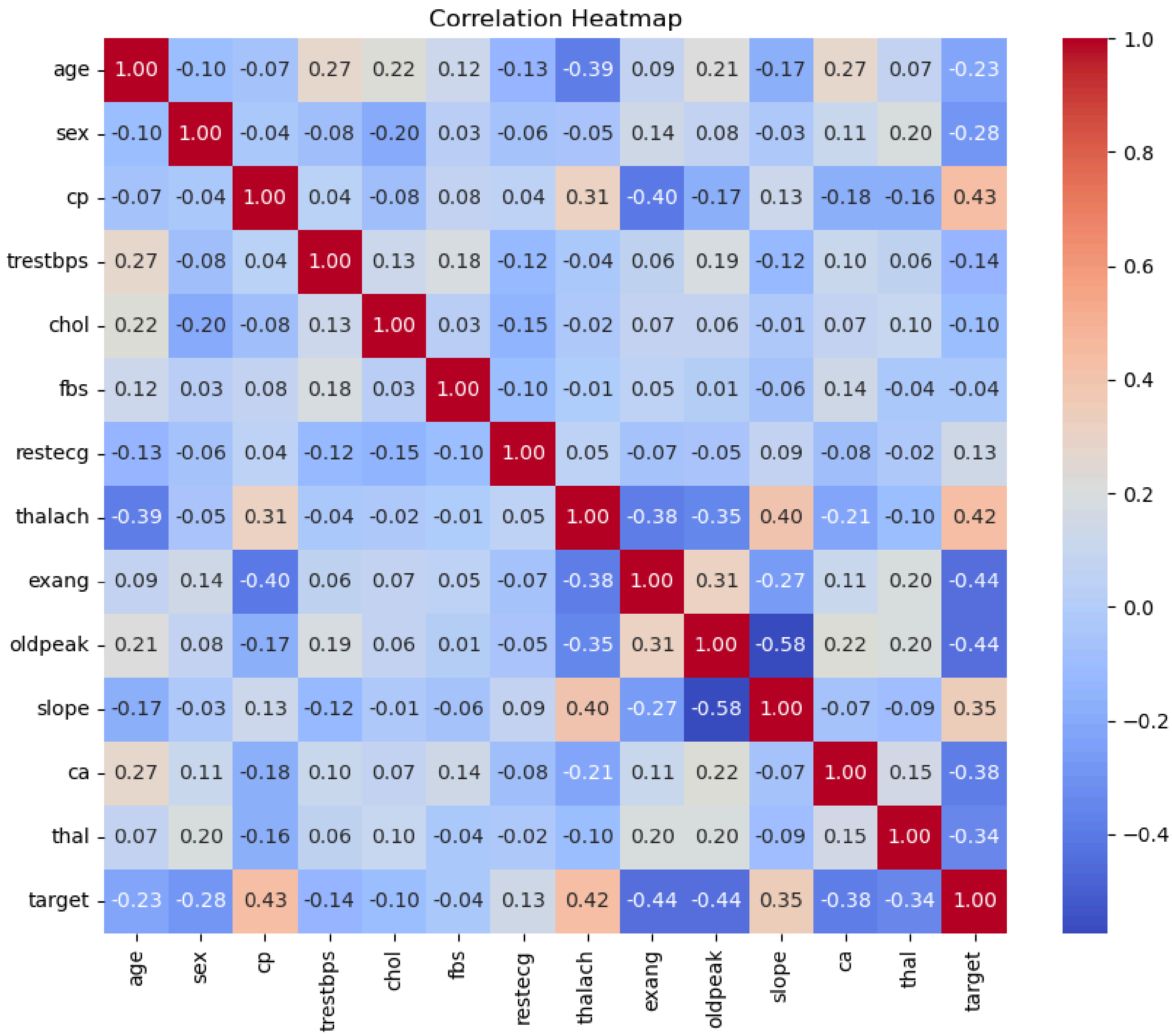
```
# Histogram of numeric features
numeric_cols = df.select_dtypes(include=[np.number]).columns

plt.figure(figsize=(15, 10))
for i, col in enumerate(numeric_cols, 1):
    plt.subplot(4, 4, i)
    plt.hist(df[col], bins=20, color='skyblue')
    plt.title(f'Distribution of {col}')
plt.tight_layout()
plt.show()
```



In [12]:

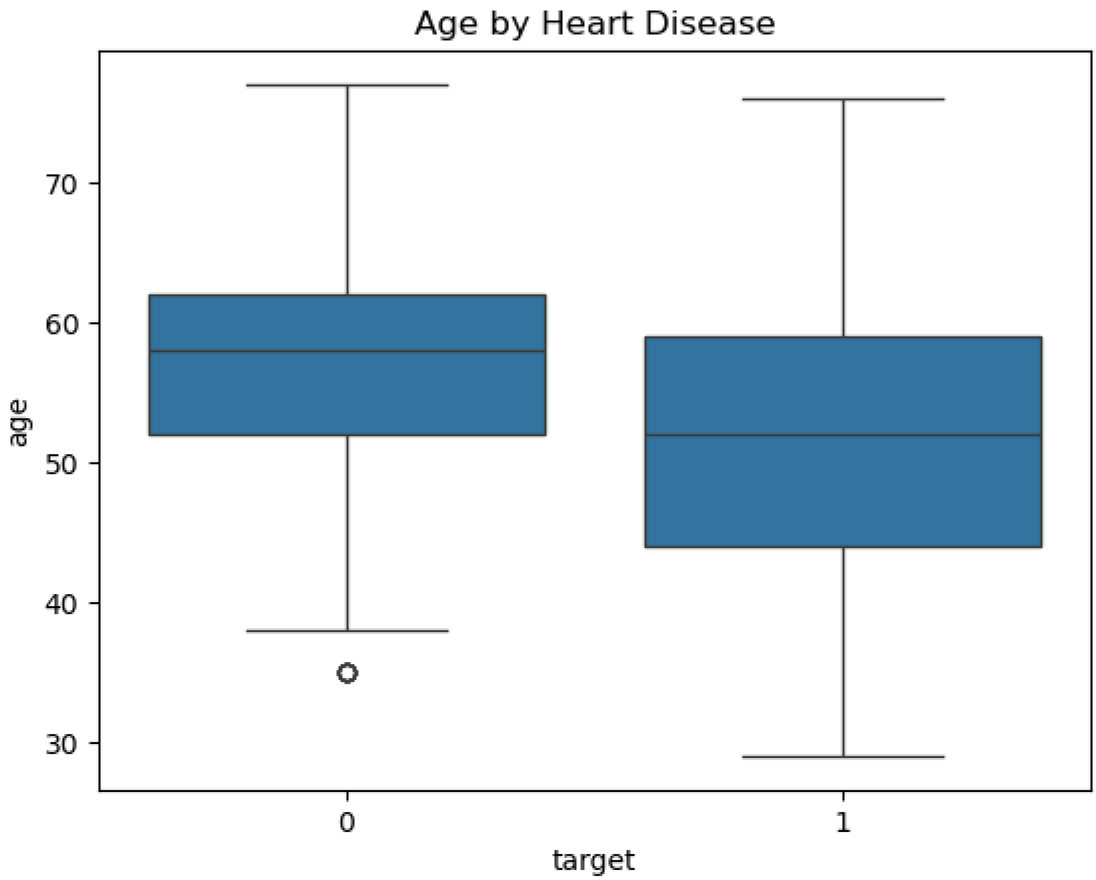
```
# Correlation Matrix
plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt=".2f")
```

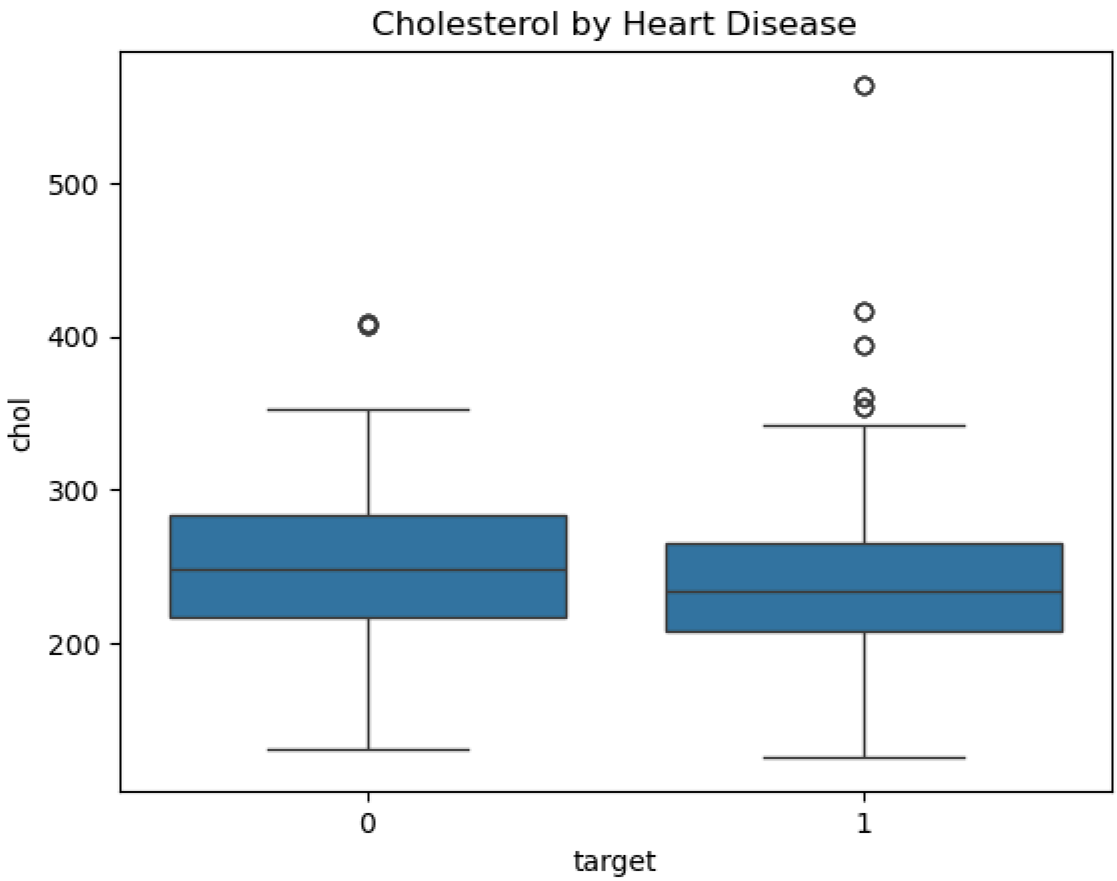
```
plt.title('Correlation Heatmap')
plt.show()
```

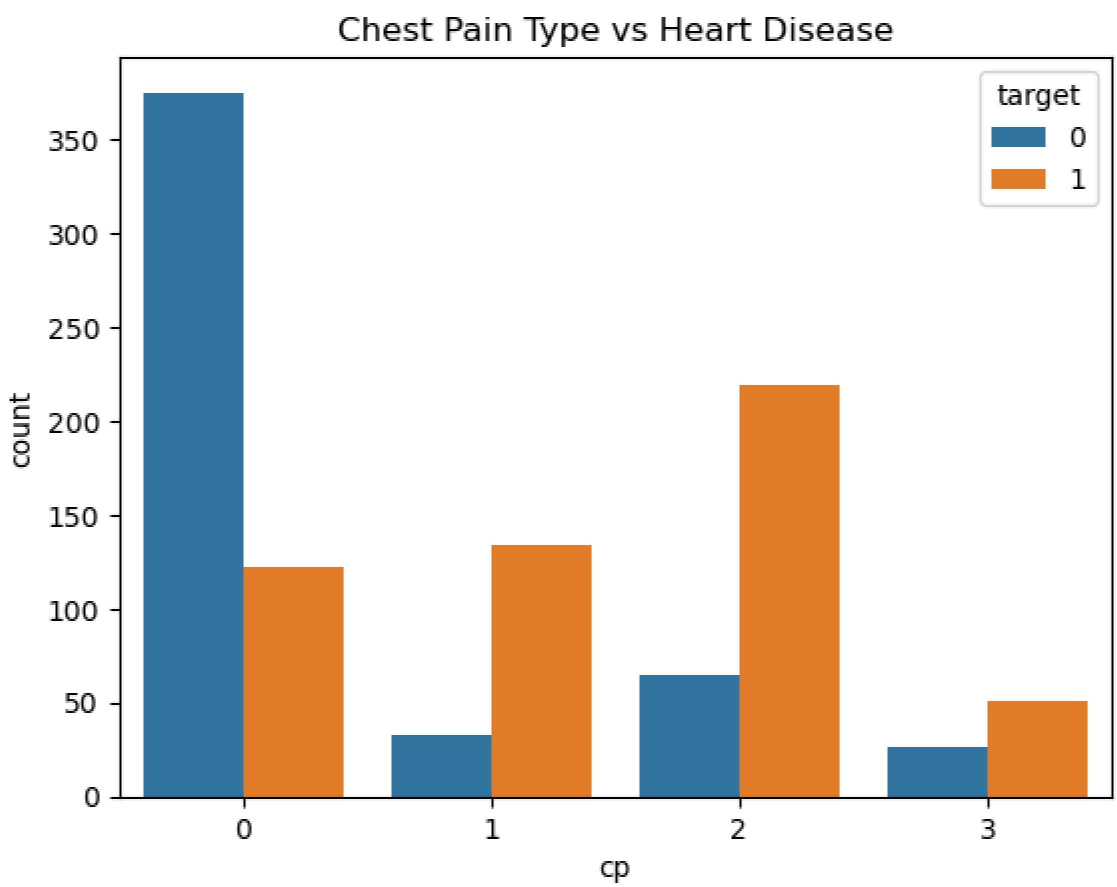


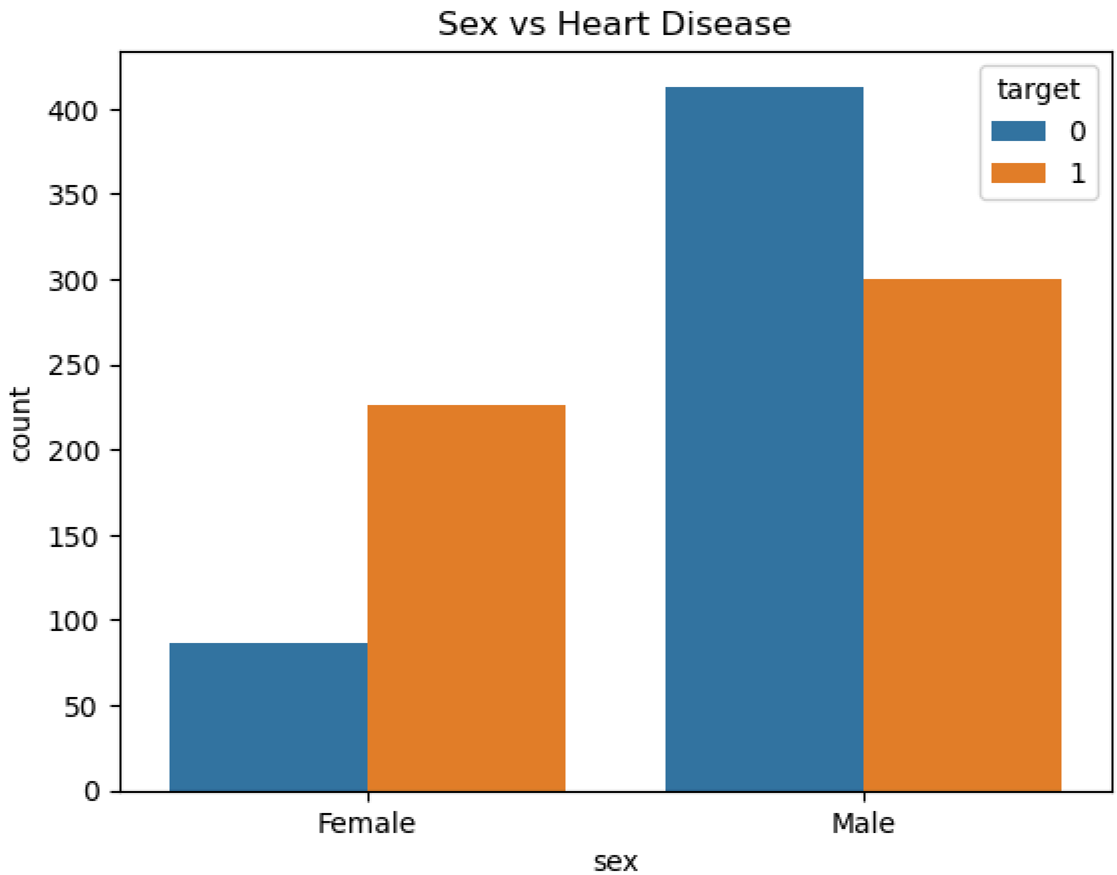
In [16]:
```
# Age by target
sns.boxplot(x='target', y='age', data=df)
plt.title('Age by Heart Disease')
plt.show()

# Cholesterol by target
sns.boxplot(x='target', y='chol', data=df)
plt.title('Cholesterol by Heart Disease')
plt.show()

# Chest pain type vs target
sns.countplot(x='cp', hue='target', data=df)
plt.title('Chest Pain Type vs Heart Disease')
plt.show()

# Sex vs target
sns.countplot(x='sex', hue='target', data=df)
plt.title('Sex vs Heart Disease')
plt.xticks([0,1], ['Female', 'Male'])
plt.show()
```

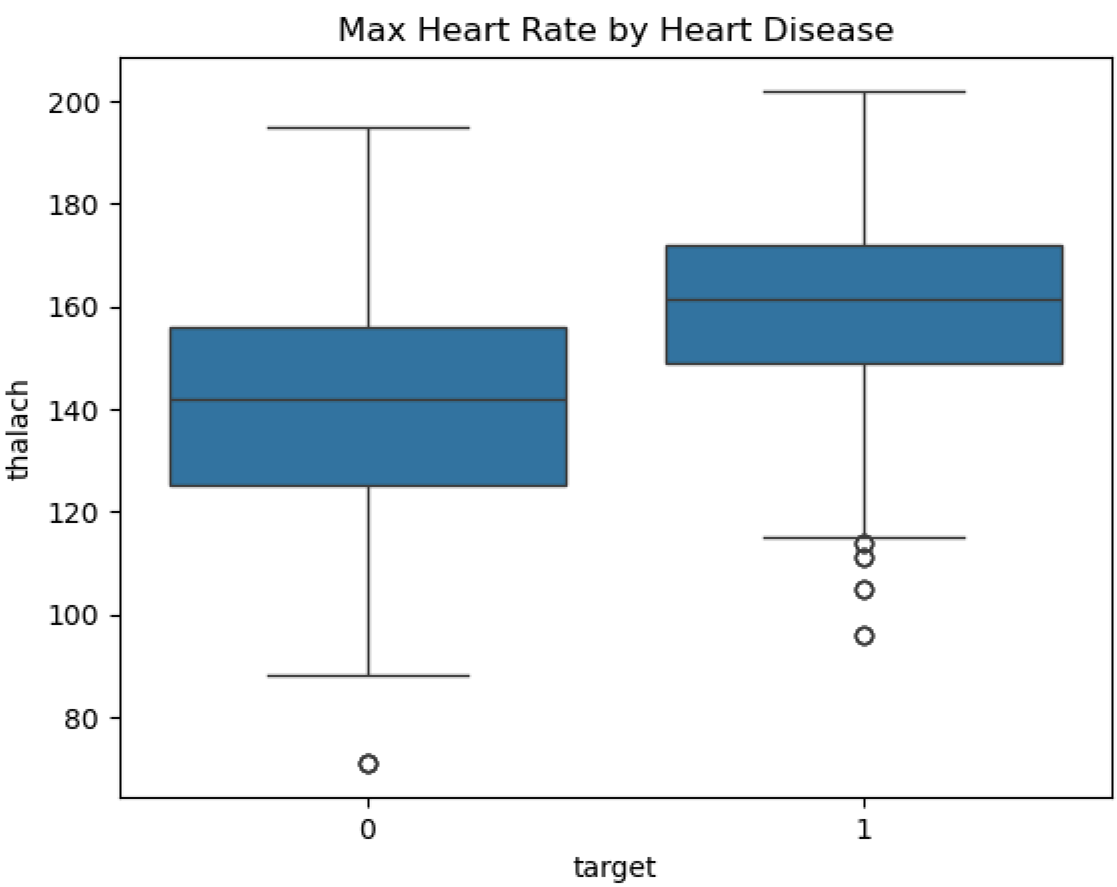
```
# Max heart rate
sns.boxplot(x='target', y='thalach', data=df)
plt.title('Max Heart Rate by Heart Disease')
plt.show()
```




Cholesterol by Heart Disease
500
400
300
200
chol
0
1
target


Chest Pain Type vs Heart Disease
target
0
1
350
300
250
200
150
100
50
0
count
0
1
2
3
cp


Sex vs Heart Disease
target
0
1
count
400
350
300
250
200
150
100
50
0
Female
Male
sex


Max Heart Rate by Heart Disease
thalach
200
180
160
140
120
100
80
0
1
target

EDA Summary

We observed the following from our analysis:

- **Chest pain type** shows a strong association with heart disease.
- **Maximum heart rate** tends to be higher in patients without heart disease.
- **Cholesterol** and **age** distributions vary across classes, although not drastically.
- The **correlation matrix** indicates some strong correlations among features such as chest pain type, thalach (max heart rate), and target (presence of disease).

Train-Test Split

In [49]:
```
X = df.drop('target', axis=1)
y = df['target']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

We split the dataset into training and testing sets using an **80-20 ratio**.
This means:

- **80%** of the data was used to train the model (`X_train` , `y_train`)
- **20%** was used to test the model's performance on unseen data (`X_test` , `y_test`)

Using this split helps ensure the model generalizes well and avoids overfitting, while still giving enough data for training. The `random_state=42` ensures the results are reproducible.

Logistic Regression Model

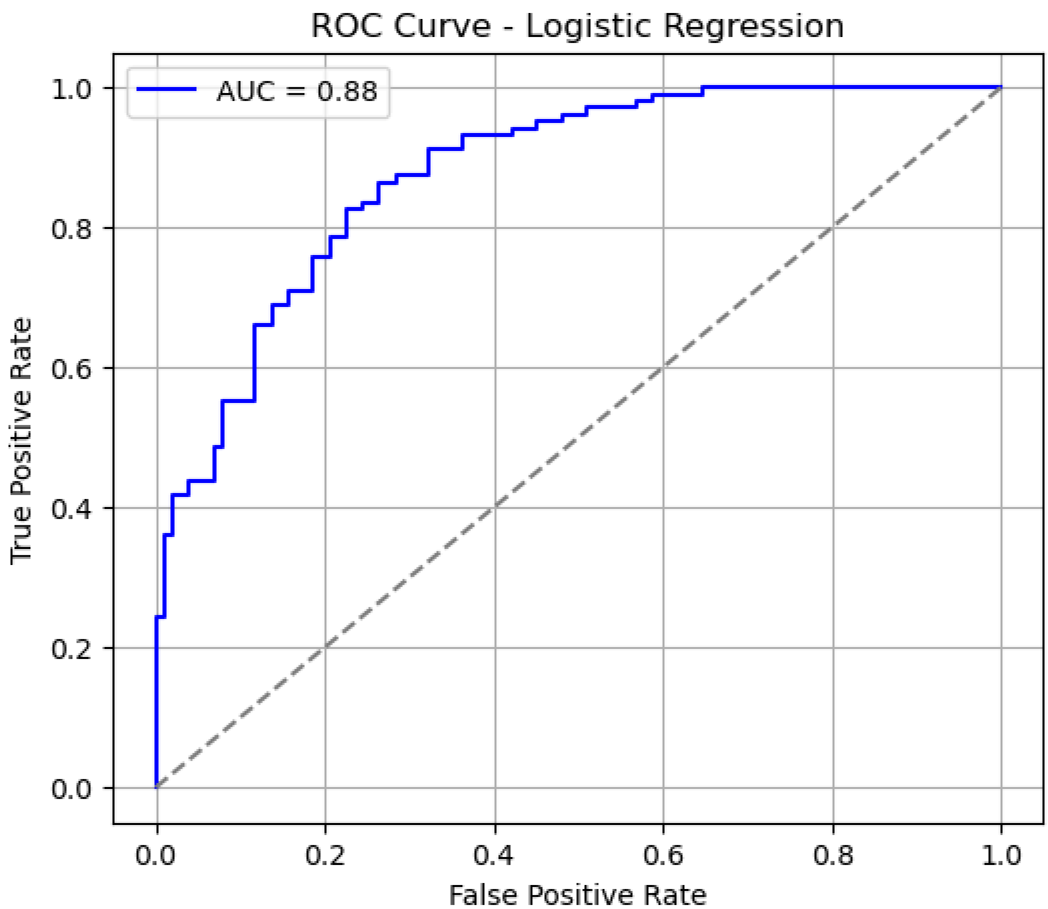
In [23]:
```
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)

# Predictions
y_probs = model.predict_proba(X_test)[:, 1]
y_pred = (y_probs > 0.5).astype(int)

# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Logistic Regression Accuracy: {round(accuracy*100, 2)}%")
```

```
Logistic Regression Accuracy: 79.51%
```

In [27]:
```
# Confusion Matrix
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_probs)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, color='blue', label=f'AUC = {roc_auc:.2f}')
plt.plot([0, 1], [0, 1], linestyle='--', color='grey')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Logistic Regression')
plt.legend()
plt.grid(True)
plt.show()
```

```
Confusion Matrix:
[[73 29]
 [13 90]]
```



Random Forest Model

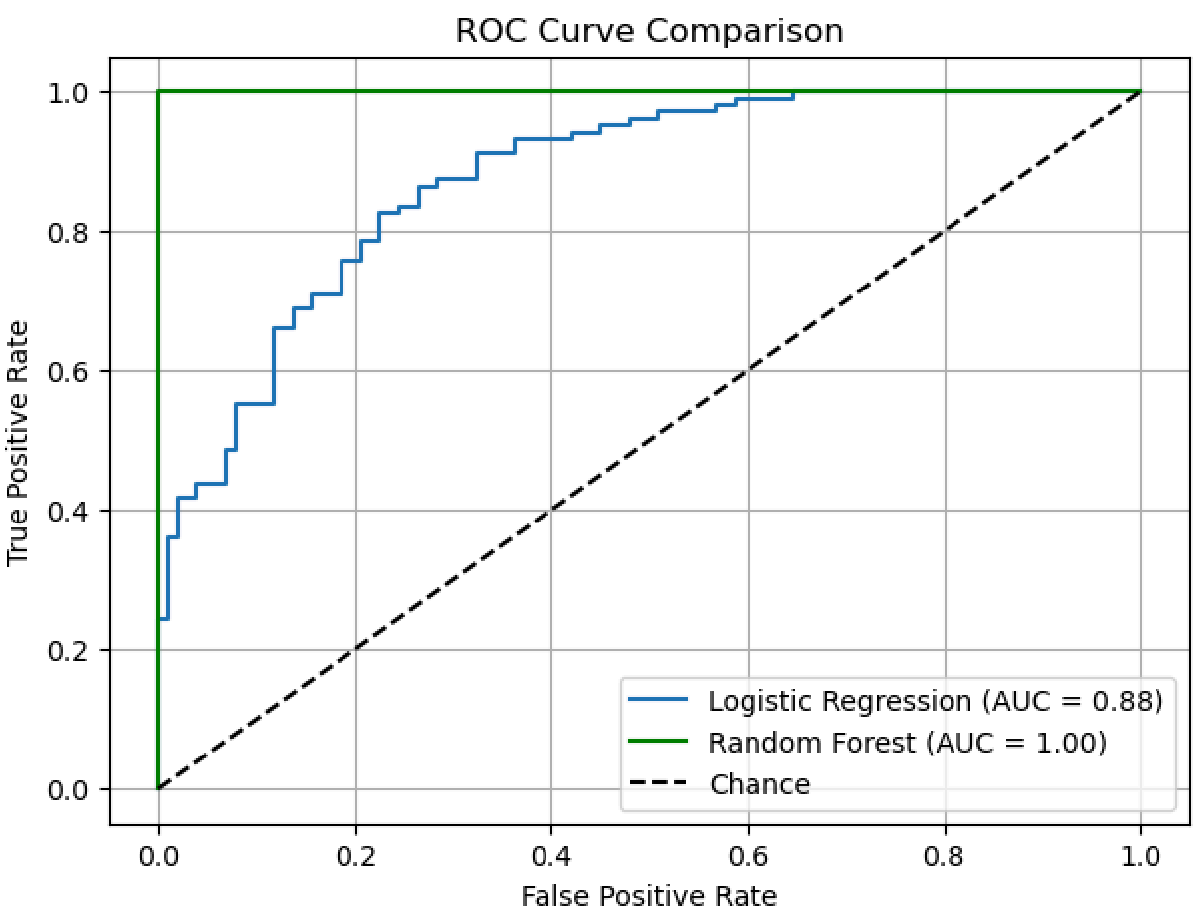
In [33]:
```
from sklearn.ensemble import RandomForestClassifier

# Train Random Forest
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)
rf_preds = rf_model.predict(X_test)
rf_probs = rf_model.predict_proba(X_test)[:, 1]
```

```
rf_acc = accuracy_score(y_test, rf_preds)
print(f"Random Forest Accuracy: {round(rf_acc * 100, 2)}%")
```

Random Forest Accuracy: 98.54%

ROC Curve Comparison

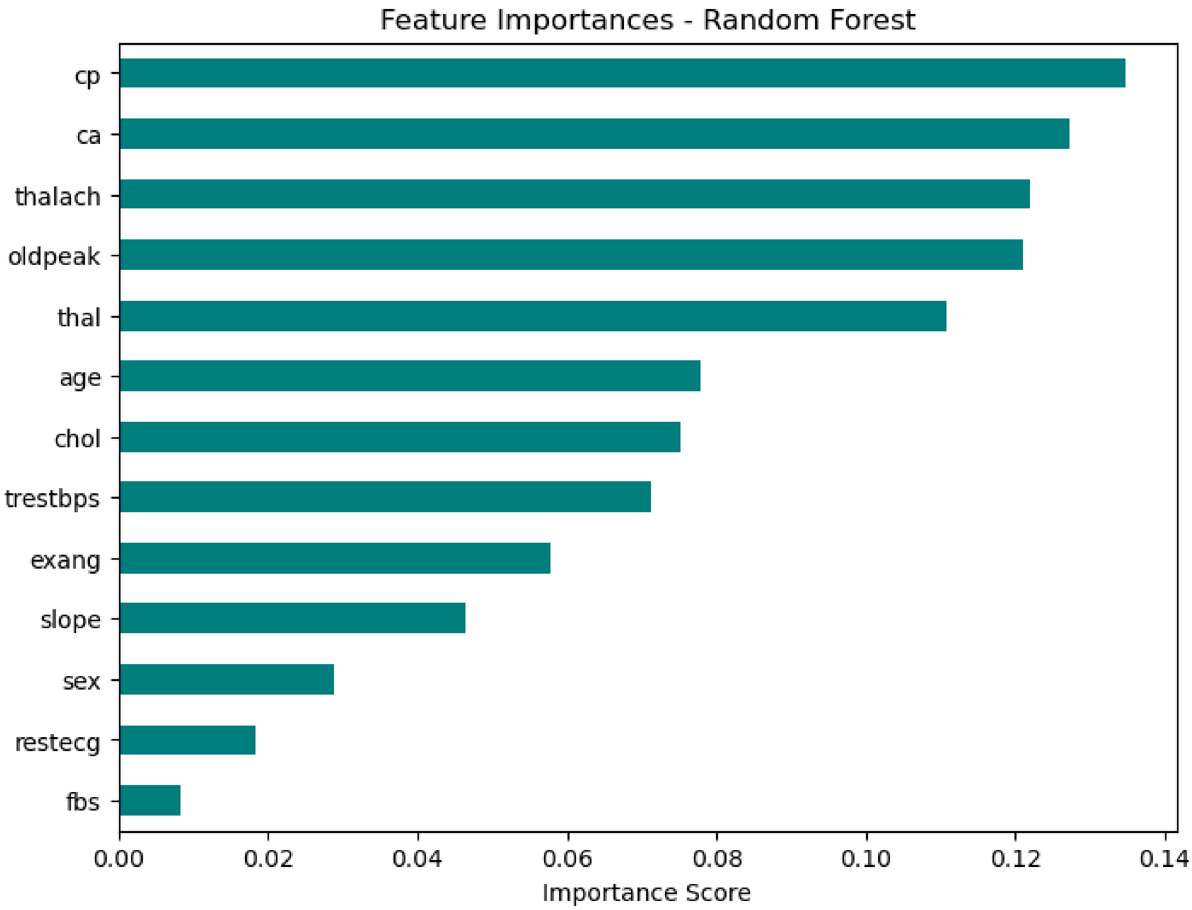
In [36]:
```
fpr_log, tpr_log, _ = roc_curve(y_test, log_probs)
fpr_rf, tpr_rf, _ = roc_curve(y_test, rf_probs)

plt.figure(figsize=(7, 5))
plt.plot(fpr_log, tpr_log, label='Logistic Regression (AUC = %.2f)' % auc(fp
plt.plot(fpr_rf, tpr_rf, label='Random Forest (AUC = %.2f)' % auc(fpr_rf, tp
plt.plot([0, 1], [0, 1], 'k--', label='Chance')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend()
plt.grid(True)
plt.show()
```



Feature Importance - Random Forest

In [39]:
```
feat_importances = pd.Series(rf_model.feature_importances_, index=X.columns)
feat_importances.sort_values().plot(kind='barh', figsize=(8,6), color='teal'
```

```
plt.title('Feature Importances - Random Forest')
plt.xlabel('Importance Score')
plt.show()
```



Model Summary

- **Logistic Regression Accuracy:** 79.51%
- **Random Forest Accuracy:** 98.54%

Random Forest outperforms Logistic Regression by a large margin. This is because it uses multiple decision trees to capture complex patterns and interactions between features, while Logistic Regression only learns linear relationships. This makes Random Forest much better for this kind of medical data, where feature effects are often non-linear.

Conclusion

Using clinical and demographic data, we built models to predict the presence of heart disease. After comparing Logistic Regression and Random Forest, we found that Random Forest achieved **98.54% accuracy**, making it the most effective model.

It also highlights the most important contributing factors, helping doctors focus on key indicators such as chest pain type, number of vessels colored, and maximum heart rate. This kind of analysis can support faster and more accurate risk assessment for patients.

Dataset Citation

No official citation provided.
Source: Heart Disease Dataset on Kaggle