Heart Disease Risk Prediction

Objective

The goal of this project is to build a machine learning model that predicts the likelihood of heart disease based on patient health metrics.

Importing required libraries for the Machine Learning Workflow

```
import  pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Loading the Dataset

```
df = pd.read_csv('heart_data.csv')
df.head(5)
```

```
   age  sex  chest pain type  resting bp s  cholesterol  fasting blood
sugar  \
0   40    1                2           140          289
0
1   49    0                3           160          180
0
2   37    1                2           130          283
0
3   48    0                4           138          214
0
4   54    1                3           150          195
0

   resting ecg  max heart rate  exercise angina  oldpeak  ST slope
target
0            0             172                0      0.0         1
0
1            0             156                0      1.0         2
1
2            1              98                0      0.0         1
0
3            0             108                1      1.5         2
1
4            0             122                0      0.0         1
0
```

```
df.tail(5)
```

```
      age  sex  chest pain type  resting bp s  cholesterol  \
1185   45    1                1           110          264
1186   68    1                4           144          193
1187   57    1                4           130          131
1188   57    0                2           130          236
1189   38    1                3           138          175

      fasting blood sugar  resting ecg  max heart rate  exercise
angina  \
1185                    0            0             132
0
1186                    1            0             141
0
1187                    0            0             115
1
1188                    0            2             174
0
1189                    0            0             173
0

      oldpeak  ST slope  target
1185      1.2         2       1
1186      3.4         2       1
1187      1.2         2       1
1188      0.0         2       1
1189      0.0         1       0
```

Checking numbers of rows and columns in data set

```
df.shape
```

```
(1190, 12)
```

```
df.describe()
```

```
               age          sex  chest pain type  resting bp s
cholesterol  \
count  1190.000000  1190.000000      1190.000000   1190.000000
1190.000000
mean     53.720168     0.763866         3.232773    132.153782
210.363866
std       9.358203     0.424884         0.935480     18.368823
101.420489
min      28.000000     0.000000         1.000000      0.000000
0.000000
25%      47.000000     1.000000         3.000000    120.000000
188.000000
50%      54.000000     1.000000         4.000000    130.000000
```

```
229.000000
75%       60.000000     1.000000          4.000000    140.000000
269.750000
max       77.000000     1.000000          4.000000    200.000000
603.000000

       fasting blood sugar  resting ecg  max heart rate  exercise
angina  \
count          1190.000000  1190.000000     1190.000000
1190.000000
mean              0.213445     0.698319      139.732773
0.387395
std               0.409912     0.870359       25.517636
0.487360
min               0.000000     0.000000       60.000000
0.000000
25%               0.000000     0.000000      121.000000
0.000000
50%               0.000000     0.000000      140.500000
0.000000
75%               0.000000     2.000000      160.000000
1.000000
max               1.000000     2.000000      202.000000
1.000000

           oldpeak     ST slope       target
count  1190.000000  1190.000000  1190.000000
mean      0.922773     1.624370     0.528571
std       1.086337     0.610459     0.499393
min      -2.600000     0.000000     0.000000
25%       0.000000     1.000000     0.000000
50%       0.600000     2.000000     1.000000
75%       1.600000     2.000000     1.000000
max       6.200000     3.000000     1.000000
```

Checking for Missing or Zero Values

```
(df == 0.0).sum()
```

```
age                      0
sex                    281
chest pain type          0
resting bp s             1
cholesterol            172
fasting blood sugar    936
resting ecg            684
max heart rate           0
exercise angina        729
oldpeak                455
ST slope                 1
```

```
target                      561
dtype: int64
```

Exploring Data Types and Target Distribution

```
print(df.dtypes)
```

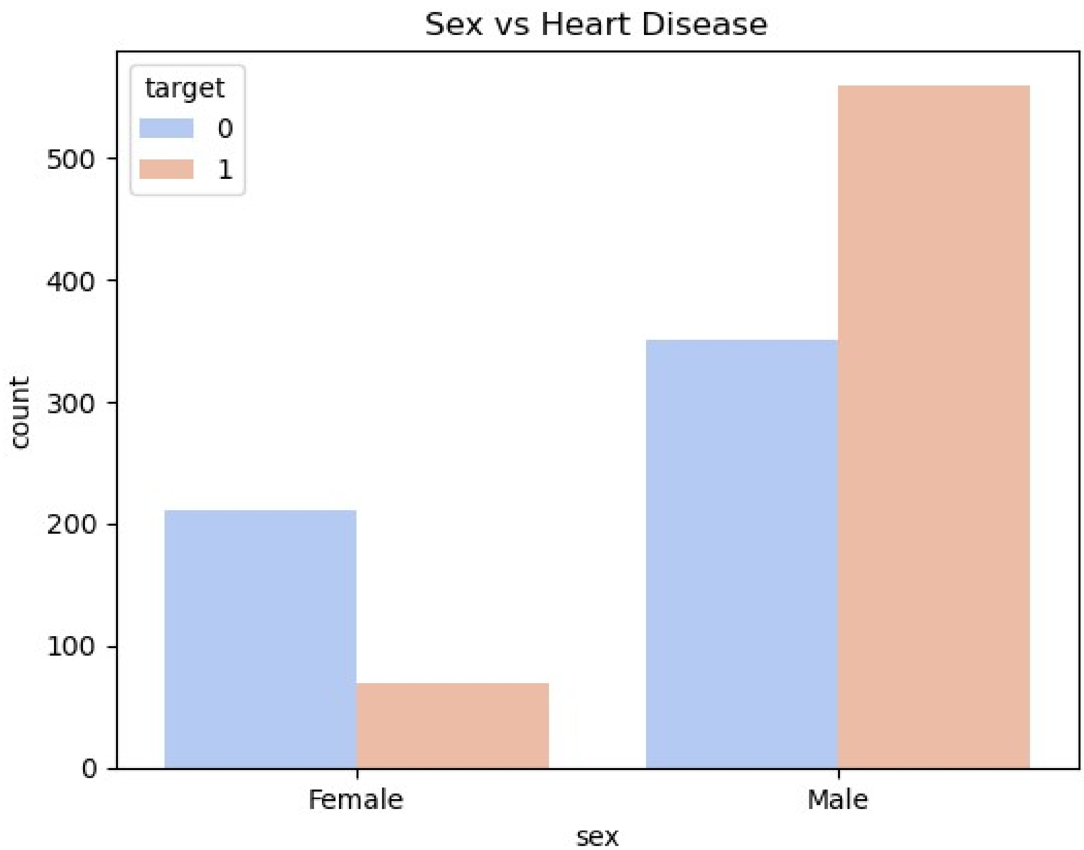
```
age                            int64
sex                            int64
chest pain type                int64
resting bp s                   int64
cholesterol                    int64
fasting blood sugar            int64
resting ecg                    int64
max heart rate                 int64
exercise angina                int64
oldpeak                      float64
ST slope                       int64
target                         int64
dtype: object
```

```
print(df['target'].value_counts())
```

```
target
1    629
0    561
Name: count, dtype: int64
```

Visualizes how categorical features relate to heart disease. For example, the sex countplot shows the number of males and females with or without heart disease, helping identify patterns and important features for prediction.

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

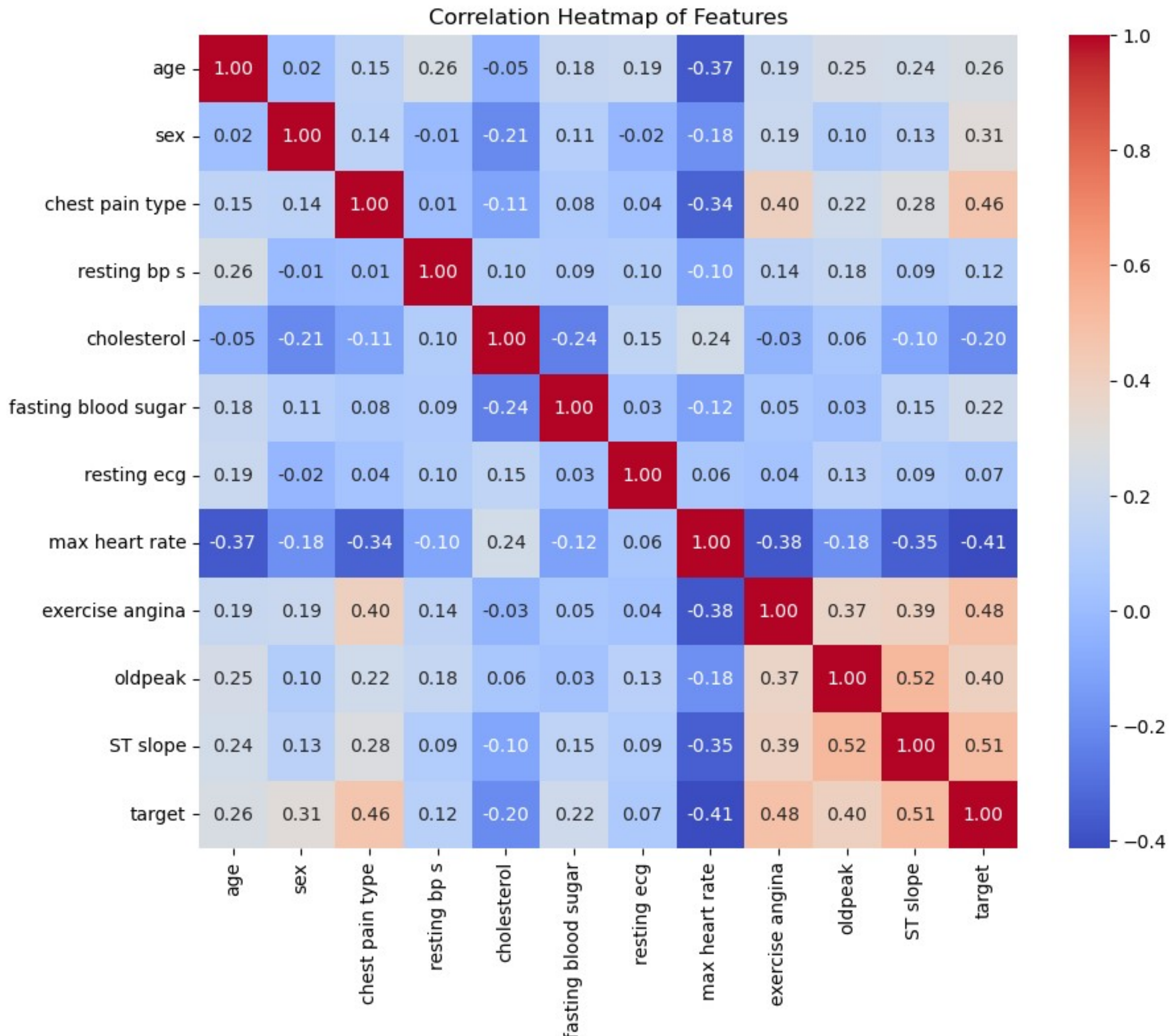


Correlation Heatmap

Shows how features are correlated with each other and with the target.

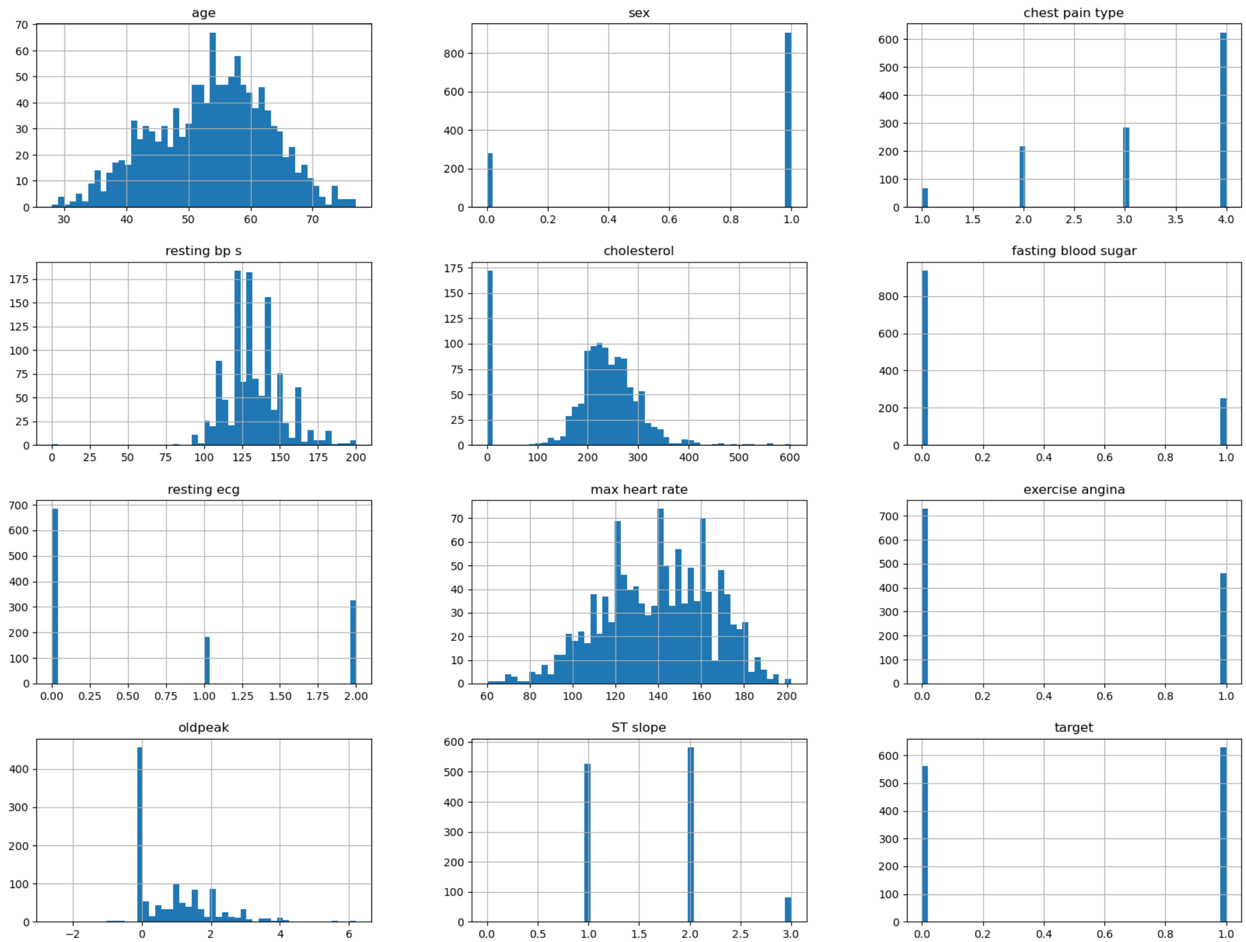
Helps in understanding which features may be more important for prediction.

```
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap of Features")
plt.show()
```




```
df.hist(bins = 50, figsize = (20,15))
```

```
array([[<Axes: title={'center': 'age'}>, <Axes: title={'center':
'sex'}>,
        <Axes: title={'center': 'chest pain type'}>],
       [<Axes: title={'center': 'resting bp s'}>,
        <Axes: title={'center': 'cholesterol'}>,
        <Axes: title={'center': 'fasting blood sugar'}>],
       [<Axes: title={'center': 'resting ecg'}>,
        <Axes: title={'center': 'max heart rate'}>,
        <Axes: title={'center': 'exercise angina'}>],
       [<Axes: title={'center': 'oldpeak'}>,
        <Axes: title={'center': 'ST slope'}>,
        <Axes: title={'center': 'target'}>]], dtype=object)
```




```
(df == 0.0).sum()
```

```
age                      0
sex                    281
chest pain type          0
resting bp s             1
cholesterol            172
fasting blood sugar    936
resting ecg            684
max heart rate           0
exercise angina        729
oldpeak                455
ST slope                 1
target                 561
dtype: int64
```

Handling Missing/Zero Values

Replaces 0 values in cholesterol with the median of non-zero cholesterol values.

This avoids biasing the model with invalid zeros.

```
median_cholesterol = df[df['cholesterol'] > 0]
['cholesterol'].median()
print(median_cholesterol)
```

```
240.0
```

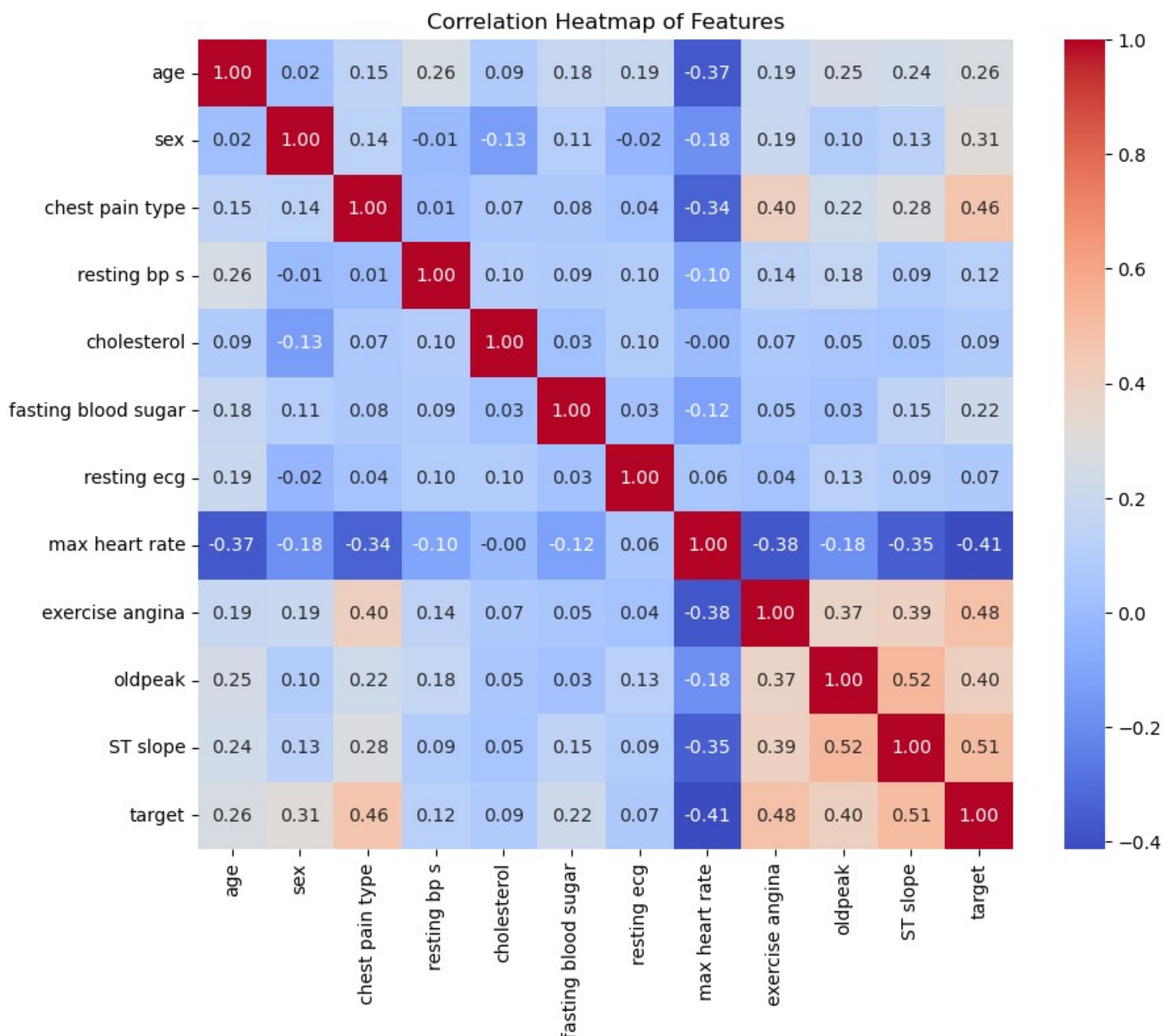
```
df['cholesterol'] = df['cholesterol'].replace(0, median_cholesterol)
```

finding data where their values is 0.0

```
(df == 0.0).sum()
```

```
age                      0
sex                    281
chest pain type          0
resting bp s             1
cholesterol              0
fasting blood sugar    936
resting ecg            684
max heart rate           0
exercise angina        729
oldpeak                455
ST slope                 1
target                 561
dtype: int64
```

```
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap of Features")
plt.show()
```



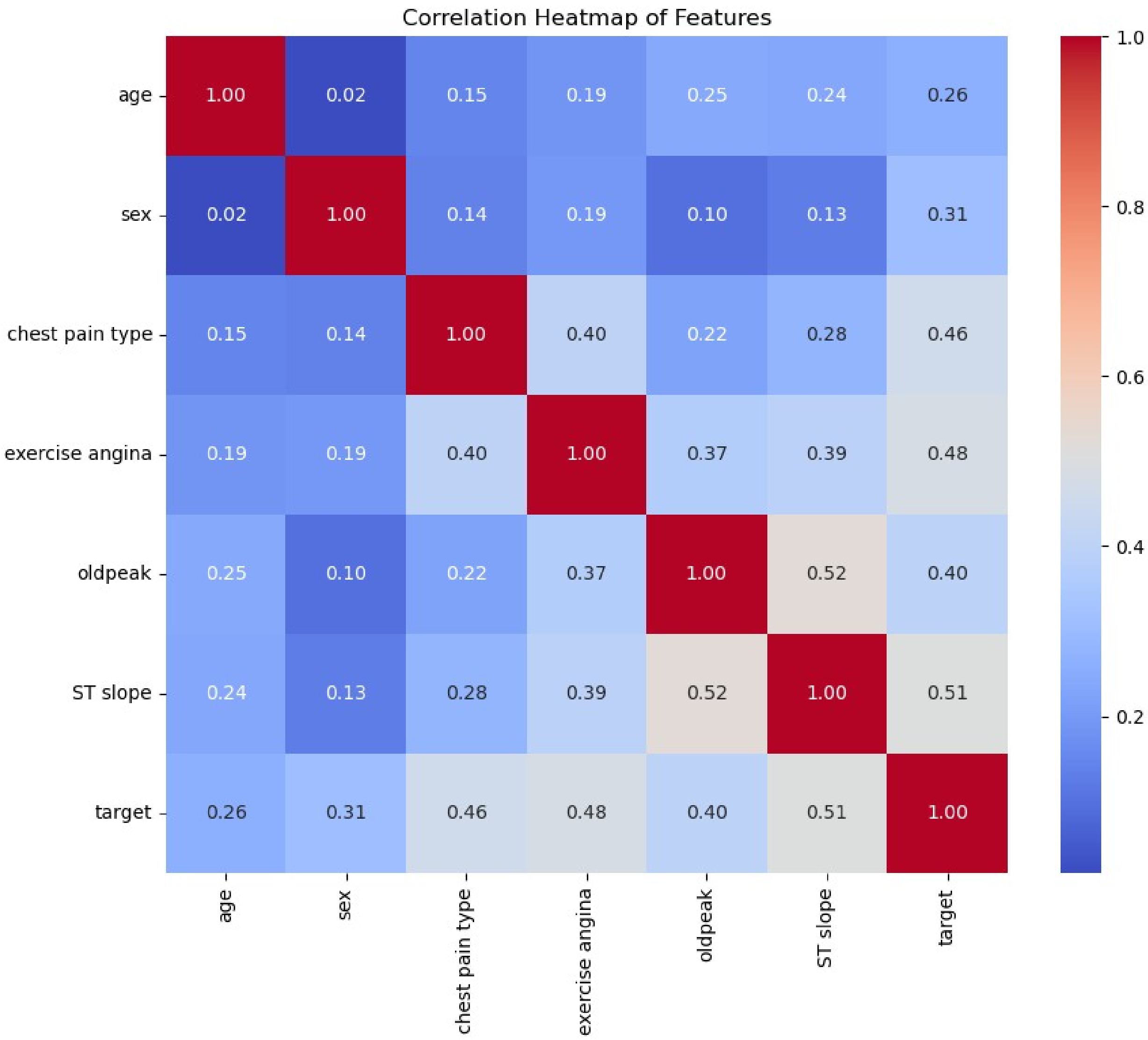
Dropping Less Useful Features ie, negative correlated columns

Keeps the dataset clean and reduces noise.

```
df1 = df.drop([ 'resting bp s', 'cholesterol',
               'fasting blood sugar', 'resting ecg', 'max heart
rate'], axis=1)

df1

      age  sex  chest pain type  exercise angina  oldpeak  ST slope
target
0      40    1                2                0      0.0         1
0
1      49    0                3                0      1.0         2
1
2      37    1                2                0      0.0         1
```

```
0
3       48    0                 4                 1      1.5          2
1
4       54    1                 3                 0      0.0          1
0
...    ...  ...               ...               ...      ...        ...
...
1185    45    1                 1                 0      1.2          2
1
1186    68    1                 4                 0      3.4          2
1
1187    57    1                 4                 1      1.2          2
1
1188    57    0                 2                 0      0.0          2
1
1189    38    1                 3                 0      0.0          1
0

[1190 rows x 7 columns]
```

```
plt.figure(figsize=(10,8))
sns.heatmap(df1.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap of Features")
plt.show()
```



Checking Data Distribution

Prints the distribution of values for each column.

Helps understand categorical feature balance.

```
for col in df1.columns:
    print(f"\nColumn: {col}")
    print(df1[col].value_counts())


Column: age
age
54    67
58    58
57    50
52    47
```

```
55    47
59    47
56    47
51    47
62    46
60    44
53    40
48    38
61    38
63    37
41    33
50    32
64    31
43    31
46    31
44    29
65    29
49    27
42    26
45    25
67    23
47    23
66    19
39    18
38    17
69    16
40    16
35    14
37    13
68    13
70    11
34     9
74     8
71     8
36     6
32     5
72     4
29     4
77     3
75     3
76     3
33     2
31     2
30     1
28     1
73     1
Name: count, dtype: int64

Column: sex
```

```
sex
1    909
0    281
Name: count, dtype: int64

Column: chest pain type
chest pain type
4    625
3    283
2    216
1     66
Name: count, dtype: int64

Column: exercise angina
exercise angina
0    729
1    461
Name: count, dtype: int64

Column: oldpeak
oldpeak
 0.0    455
 1.0     98
 2.0     84
 1.5     58
 1.2     40
 0.2     33
 3.0     32
 1.4     31
 1.6     27
 1.8     27
 0.8     27
 0.6     26
 0.5     24
 0.1     20
 0.4     19
 2.5     18
 0.3     14
 2.6     13
 1.9     12
 2.8     11
 4.0     10
 2.2      9
 1.1      9
 3.6      8
 0.7      8
 1.3      8
 0.9      7
 2.4      7
 1.7      6
```

```
 3.4      5
 4.2      4
 2.3      4
 3.2      4
 2.1      3
 3.5      3
-0.5      2
 6.2      2
 3.8      2
 2.9      2
 5.6      2
-1.0      2
-0.1      2
 3.1      2
-1.5      1
-2.0      1
 3.7      1
-0.8      1
-0.7      1
-1.1      1
-2.6      1
-0.9      1
 5.0      1
 4.4      1
Name: count, dtype: int64

Column: ST slope
ST slope
2    582
1    526
3     81
0      1
Name: count, dtype: int64

Column: target
target
1    629
0    561
Name: count, dtype: int64
```

```
print(df.dtypes)
```

```
age                          int64
sex                          int64
chest pain type              int64
resting bp s                 int64
cholesterol                  int64
fasting blood sugar          int64
resting ecg                  int64
max heart rate               int64
```

```
exercise angina          int64
oldpeak                float64
ST slope                 int64
target                   int64
dtype: object
```

Train-Test Split

Splits the data into training set (80%) and testing set (20%)

```python
from sklearn.model_selection import train_test_split

X = df1.drop('target', axis=1)
y = df1['target']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=45, stratify=y  # stratify keeps 
balance
)

print("Train target distribution:\n", y_train.value_counts())
print("Test target distribution:\n", y_test.value_counts())
```

```
Train target distribution:
 target
1    503
0    449
Name: count, dtype: int64
Test target distribution:
 target
1    126
0    112
Name: count, dtype: int64
```

```python
for col in ['sex', 'chest pain type', 'exercise angina', 'ST 
slope','oldpeak']:
    print(f"\n{col} - Train:")
    print(X_train[col].value_counts(normalize=True))
    print(f"{col} - Test:")
    print(X_test[col].value_counts(normalize=True))
```

```

sex - Train:
sex
1    0.77521
0    0.22479
Name: proportion, dtype: float64
sex - Test:
sex
1    0.718487
```

```
0    0.281513
Name: proportion, dtype: float64

chest pain type - Train:
chest pain type
4    0.526261
3    0.243697
2    0.175420
1    0.054622
Name: proportion, dtype: float64
chest pain type - Test:
chest pain type
4    0.521008
3    0.214286
2    0.205882
1    0.058824
Name: proportion, dtype: float64

exercise angina - Train:
exercise angina
0    0.617647
1    0.382353
Name: proportion, dtype: float64
exercise angina - Test:
exercise angina
0    0.592437
1    0.407563
Name: proportion, dtype: float64

ST slope - Train:
ST slope
2    0.489496
1    0.445378
3    0.064076
0    0.001050
Name: proportion, dtype: float64
ST slope - Test:
ST slope
2    0.487395
1    0.428571
3    0.084034
Name: proportion, dtype: float64

oldpeak - Train:
oldpeak
 0.0    0.383403
 1.0    0.084034
 2.0    0.069328
 1.5    0.047269
 1.2    0.036765
```

```
 0.2    0.029412
 1.4    0.027311
 3.0    0.026261
 0.8    0.025210
 1.6    0.022059
 1.8    0.021008
 0.5    0.021008
 0.6    0.018908
 0.4    0.018908
 2.5    0.016807
 0.1    0.014706
 0.3    0.011555
 1.9    0.011555
 2.8    0.009454
 2.6    0.008403
 0.7    0.007353
 4.0    0.007353
 2.4    0.007353
 1.3    0.006303
 2.2    0.006303
 1.1    0.006303
 0.9    0.005252
 3.4    0.005252
 1.7    0.004202
 3.6    0.004202
 3.2    0.003151
 2.3    0.003151
 2.1    0.003151
 3.1    0.002101
 3.5    0.002101
 4.2    0.002101
 6.2    0.002101
 3.8    0.002101
 5.6    0.002101
-0.1    0.002101
 5.0    0.001050
-1.5    0.001050
 2.9    0.001050
-0.7    0.001050
-2.0    0.001050
 4.4    0.001050
-2.6    0.001050
 3.7    0.001050
-0.9    0.001050
-1.0    0.001050
-1.1    0.001050
-0.5    0.001050
Name: proportion, dtype: float64
oldpeak - Test:
```

```
oldpeak
 0.0    0.378151
 2.0    0.075630
 1.0    0.075630
 1.5    0.054622
 0.6    0.033613
 1.8    0.029412
 3.0    0.029412
 0.1    0.025210
 1.6    0.025210
 1.2    0.021008
 2.6    0.021008
 1.4    0.021008
 0.2    0.021008
 3.6    0.016807
 0.5    0.016807
 4.0    0.012605
 2.2    0.012605
 0.3    0.012605
 1.1    0.012605
 0.8    0.012605
 4.2    0.008403
 1.7    0.008403
 1.3    0.008403
 0.9    0.008403
 2.8    0.008403
 2.5    0.008403
-1.0    0.004202
 2.9    0.004202
-0.5    0.004202
 0.4    0.004202
 1.9    0.004202
-0.8    0.004202
 3.2    0.004202
 2.3    0.004202
 3.5    0.004202
 0.7    0.004202
Name: proportion, dtype: float64
```

Handling Negative Values

Replaces negative values in oldpeak with 0.

Negative values are invalid in this context.

```
X['oldpeak'] = X['oldpeak'].apply(lambda x: 0 if x < 0 else x)
X_train['oldpeak'] = X_train['oldpeak'].apply(lambda x: 0 if x < 0
else x)
```

```python
X_test['oldpeak']  = X_test['oldpeak'].apply(lambda x: 0 if x < 0 else
x)
```

```python
print(df1['oldpeak'])
```

```
0       0.0
1       1.0
2       0.0
3       1.5
4       0.0
       ...
1185    1.2
1186    3.4
1187    1.2
1188    0.0
1189    0.0
Name: oldpeak, Length: 1190, dtype: float64
```

```python
for col in ['oldpeak']:
    print(f"\n{col} - Train:")
    print(X_train[col].value_counts(normalize=True))
    print(f"{col} - Test:")
    print(X_test[col].value_counts(normalize=True))
```

```
oldpeak - Train:
oldpeak
0.0    0.393908
1.0    0.084034
2.0    0.069328
1.5    0.047269
1.2    0.036765
0.2    0.029412
1.4    0.027311
3.0    0.026261
0.8    0.025210
1.6    0.022059
1.8    0.021008
0.5    0.021008
0.4    0.018908
0.6    0.018908
2.5    0.016807
0.1    0.014706
0.3    0.011555
1.9    0.011555
2.8    0.009454
2.6    0.008403
4.0    0.007353
0.7    0.007353
2.4    0.007353
```

```
1.3    0.006303
1.1    0.006303
2.2    0.006303
0.9    0.005252
3.4    0.005252
1.7    0.004202
3.6    0.004202
2.1    0.003151
2.3    0.003151
3.2    0.003151
5.6    0.002101
3.1    0.002101
6.2    0.002101
4.2    0.002101
3.8    0.002101
3.5    0.002101
4.4    0.001050
5.0    0.001050
2.9    0.001050
3.7    0.001050
Name: proportion, dtype: float64
oldpeak - Test:
oldpeak
0.0    0.390756
1.0    0.075630
2.0    0.075630
1.5    0.054622
0.6    0.033613
3.0    0.029412
1.8    0.029412
0.1    0.025210
1.6    0.025210
0.2    0.021008
1.2    0.021008
1.4    0.021008
2.6    0.021008
0.5    0.016807
3.6    0.016807
4.0    0.012605
2.2    0.012605
0.3    0.012605
1.1    0.012605
0.8    0.012605
2.5    0.008403
4.2    0.008403
1.3    0.008403
1.7    0.008403
0.9    0.008403
2.8    0.008403
```

```
2.9    0.004202
3.5    0.004202
1.9    0.004202
3.2    0.004202
2.3    0.004202
0.4    0.004202
0.7    0.004202
Name: proportion, dtype: float64
```

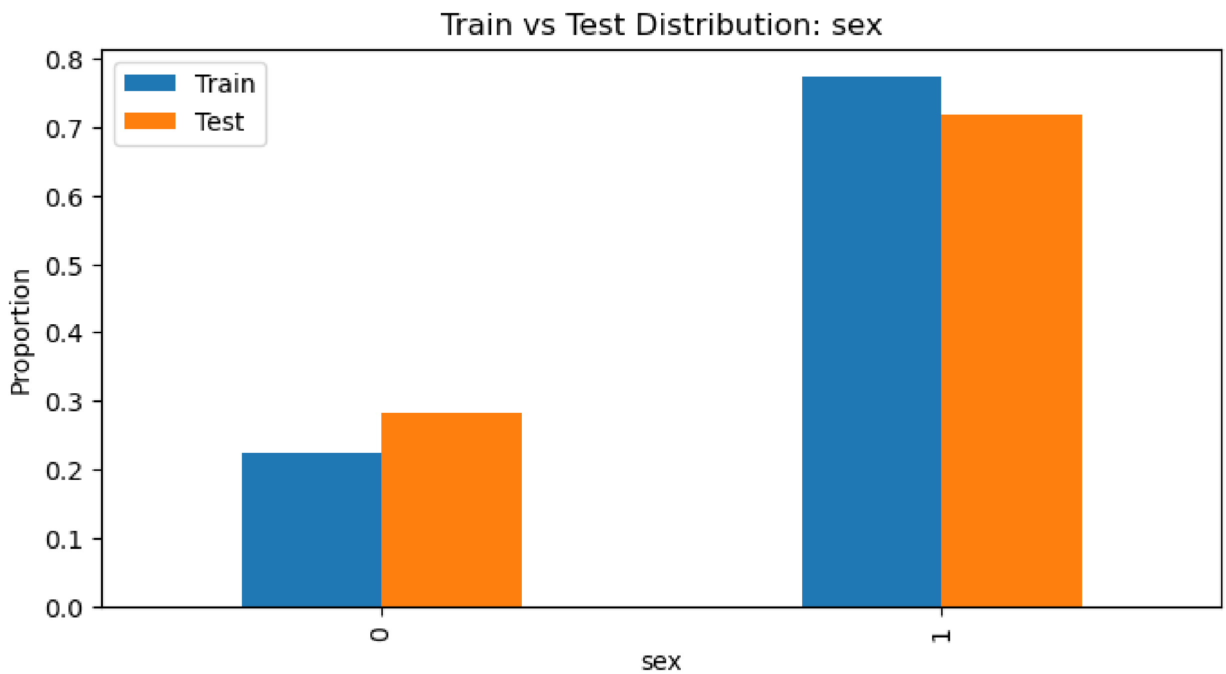
```
df1_train = X_train.copy()
df1_train['target'] = y_train
df1_test = X_test.copy()
df1_test['target'] = y_test
```

Comparing Feature Distribution in Train vs Test

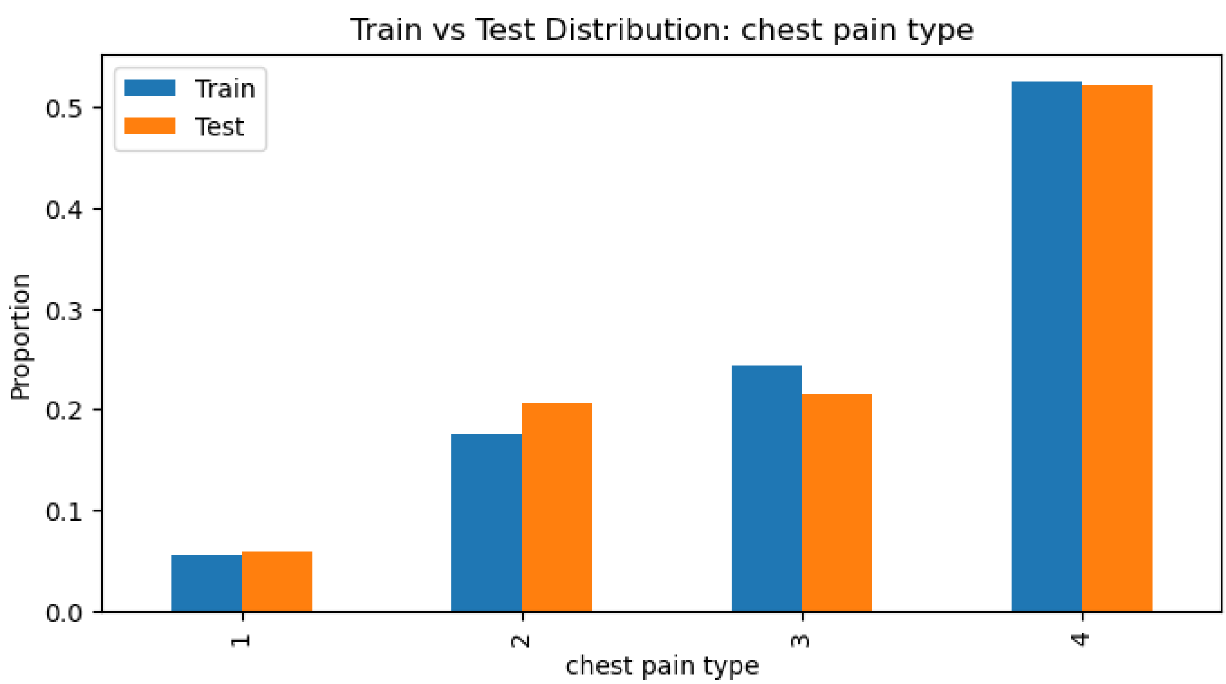
Plots bar charts for selected categorical features (sex, chest pain type, exercise angina, ST slope) to verify that train and test distributions are similar.

```
cols = ['sex', 'chest pain type', 'exercise angina', 'ST slope']

for col in cols:
    plt.figure(figsize=(8,4))
    train_counts = 
df1_train[col].value_counts(normalize=True).sort_index()
    test_counts  = 
df1_test[col].value_counts(normalize=True).sort_index()
    df_plot = pd.DataFrame({'Train': train_counts, 'Test': 
test_counts})
    df_plot.plot(kind='bar', figsize=(8,4))
    plt.title(f'Train vs Test Distribution: {col}')
    plt.ylabel('Proportion')
    plt.xlabel(col)
    plt.show()
```

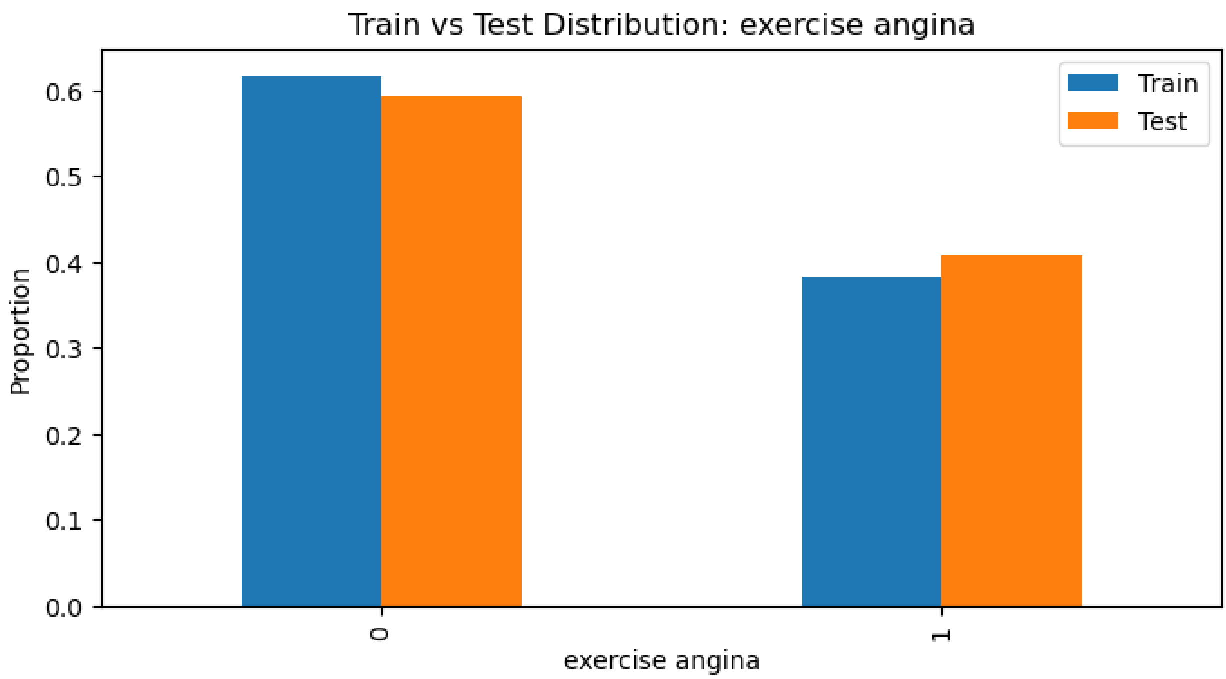
```
<Figure size 800x400 with 0 Axes>
```



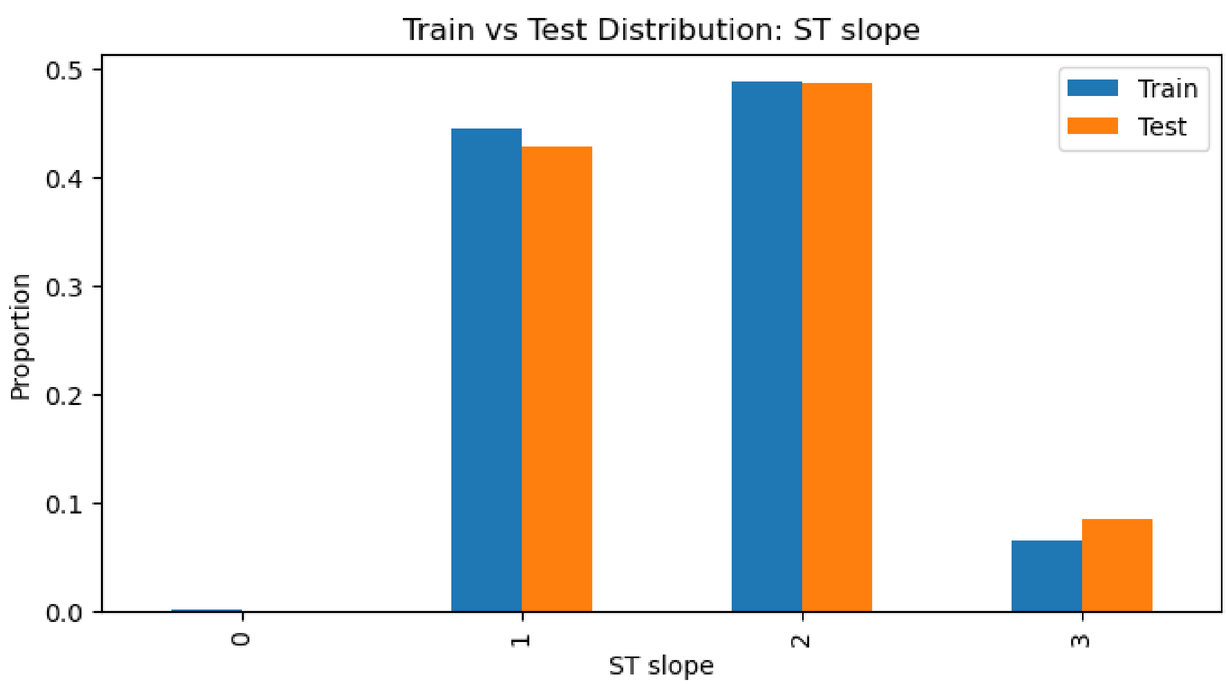

```
&lt;Figure size 800x400 with 0 Axes&gt;
```




```
&lt;Figure size 800x400 with 0 Axes&gt;
```




```
<Figure size 800x400 with 0 Axes>
```




```
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
```

```
from sklearn.metrics import accuracy_score, confusion_matrix


pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('model', LogisticRegression())
])

# Train
pipeline.fit(X_train, y_train)

# Predict
y_pred = pipeline.predict(X_test)

# Evaluate
print("Accuracy:", accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.8529411764705882
```

```
from sklearn.tree import DecisionTreeClassifier

# Pipeline
pipe_dt = Pipeline([
    ('scaler', StandardScaler()),          # optional for DT but keeps
uniformity
    ('dt', DecisionTreeClassifier(random_state=45))
])

# Fit
pipe_dt.fit(X_train[cols], y_train)

# Predict
y_pred_dt = pipe_dt.predict(X_test[cols])

# Evaluate
print("Decision Tree Accuracy:", accuracy_score(y_test, y_pred_dt))
```

```
Decision Tree Accuracy: 0.8529411764705882
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report

# Random Forest pipeline
pipe_rf = Pipeline([
    ('scaler', StandardScaler()),  # optional for tree-based models
    ('rf', RandomForestClassifier(n_estimators=100, random_state=45))
])

# Train
pipe_rf.fit(X_train, y_train)
```

```python
# Predict
y_pred_rf = pipe_rf.predict(X_test)

# Evaluate
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))

print("\nClassification Report:\n", classification_report(y_test,
y_pred_rf))
```

```
Random Forest Accuracy: 0.8571428571428571

Classification Report:
               precision    recall  f1-score   support

           0       0.88      0.81      0.84       112
           1       0.84      0.90      0.87       126

    accuracy                           0.86       238
   macro avg       0.86      0.85      0.86       238
weighted avg       0.86      0.86      0.86       238
```

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Linear Regression pipeline
pipe_lr_model = Pipeline([
    ('scaler', StandardScaler()),
    ('lr', LinearRegression())
])

# Train
pipe_lr_model.fit(X_train, y_train)

# Predict
y_pred_lr = pipe_lr_model.predict(X_test)

# Evaluate

print("MSE:", mean_squared_error(y_test, y_pred_lr))
print("R2 Score:", r2_score(y_test, y_pred_lr))

y_pred_lr_bin = (y_pred_lr >= 0.5).astype(int)
from sklearn.metrics import accuracy_score
print("Linear Regression Accuracy (binary):", accuracy_score(y_test,
y_pred_lr_bin))
```

```
MSE: 0.13756887436408036
R2 Score: 0.44781382373306633
Linear Regression Accuracy (binary): 0.8529411764705882
```

```
from sklearn.neighbors import KNeighborsClassifier

# KNN pipeline
pipe_knn = Pipeline([
    ('scaler', StandardScaler()),  # scaling is important for KNN
    ('knn', KNeighborsClassifier(n_neighbors=5))  # you can tune
n_neighbors
])

# Train
pipe_knn.fit(X_train, y_train)

# Predict
y_pred_knn = pipe_knn.predict(X_test)

# Evaluate
print("KNN Accuracy:", accuracy_score(y_test, y_pred_knn))
```

```
KNN Accuracy: 0.8235294117647058
```

```
from sklearn.ensemble import GradientBoostingClassifier

# Initialize the Gradient Boosting model
gb_model = GradientBoostingClassifier(
    n_estimators=200,    # number of trees
    learning_rate=0.1,   # step size shrinkage
    max_depth=3,         # depth of each tree
    random_state=45
)

# Train the model
gb_model.fit(X_train, y_train)

# Make predictions
y_pred_gb = gb_model.predict(X_test)

# Evaluate performance
print("Gradient Boosting Accuracy:", accuracy_score(y_test,
y_pred_gb))
print("\nClassification Report:\n", classification_report(y_test,
y_pred_gb))
```

```
Gradient Boosting Accuracy: 0.8403361344537815

Classification Report:
               precision    recall  f1-score   support

           0       0.82      0.85      0.83       112
           1       0.86      0.83      0.85       126

    accuracy                           0.84       238
```

```
   macro avg       0.84      0.84      0.84       238
weighted avg       0.84      0.84      0.84       238
```

```python
import pandas as pd
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, roc_auc_score

# Create a dictionary to store your models and predictions
models_preds = {
    'Logistic Regression': y_pred,
    'Decision Tree': y_pred_dt,
    'Random Forest': y_pred_rf,
    'Linear Regression (binary)': y_pred_lr_bin,
    'K-Nearest Neighbors': y_pred_knn,
    'Gradient Boosting': y_pred_gb
}

# Initialize a list to store metrics
metrics_list = []

# Calculate metrics for each model
for model_name, preds in models_preds.items():
    accuracy = accuracy_score(y_test, preds)
    precision = precision_score(y_test, preds)
    recall = recall_score(y_test, preds)
    f1 = f1_score(y_test, preds)



    metrics_list.append({
        'Model': model_name,
        'Accuracy': round(accuracy, 3),
        'Precision': round(precision, 3),
        'Recall': round(recall, 3),
        'F1-score': round(f1, 3),

    })

# Convert to DataFrame
metrics_df = pd.DataFrame(metrics_list)
metrics_df = metrics_df.sort_values(by='Accuracy',
ascending=False).reset_index(drop=True)

print(metrics_df)
```

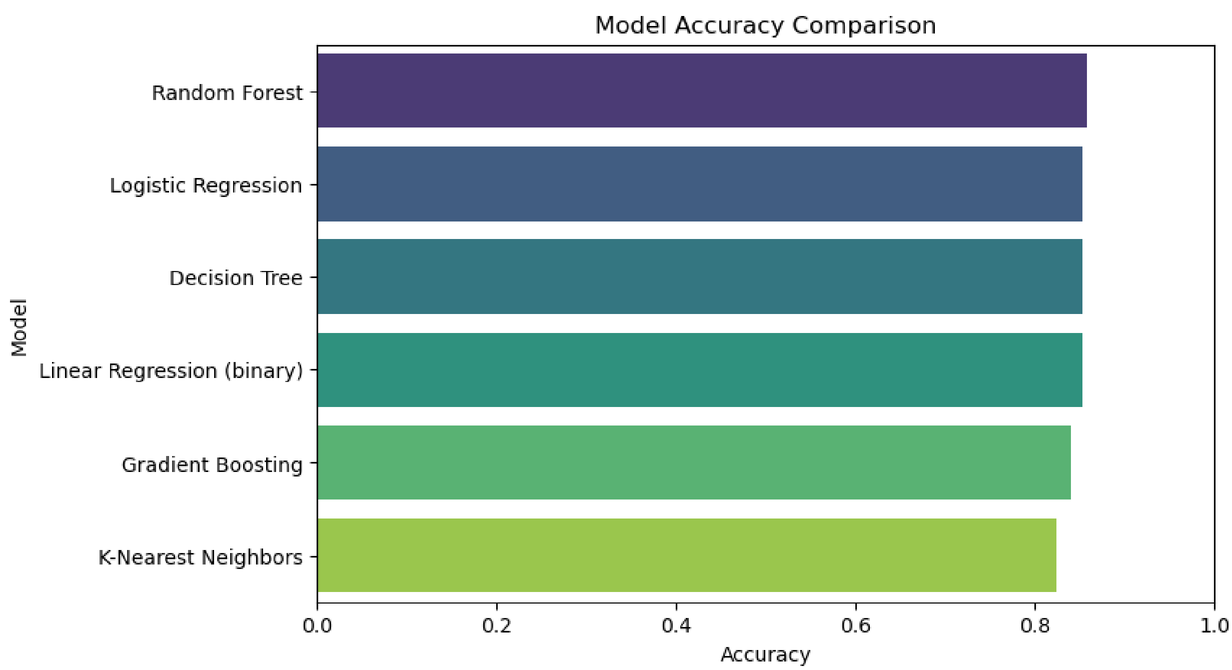
```
                        Model  Accuracy  Precision  Recall  F1-score
0               Random Forest     0.857      0.843   0.897     0.869
1         Logistic Regression     0.853      0.858   0.865     0.862
2               Decision Tree     0.853      0.858   0.865     0.862
```

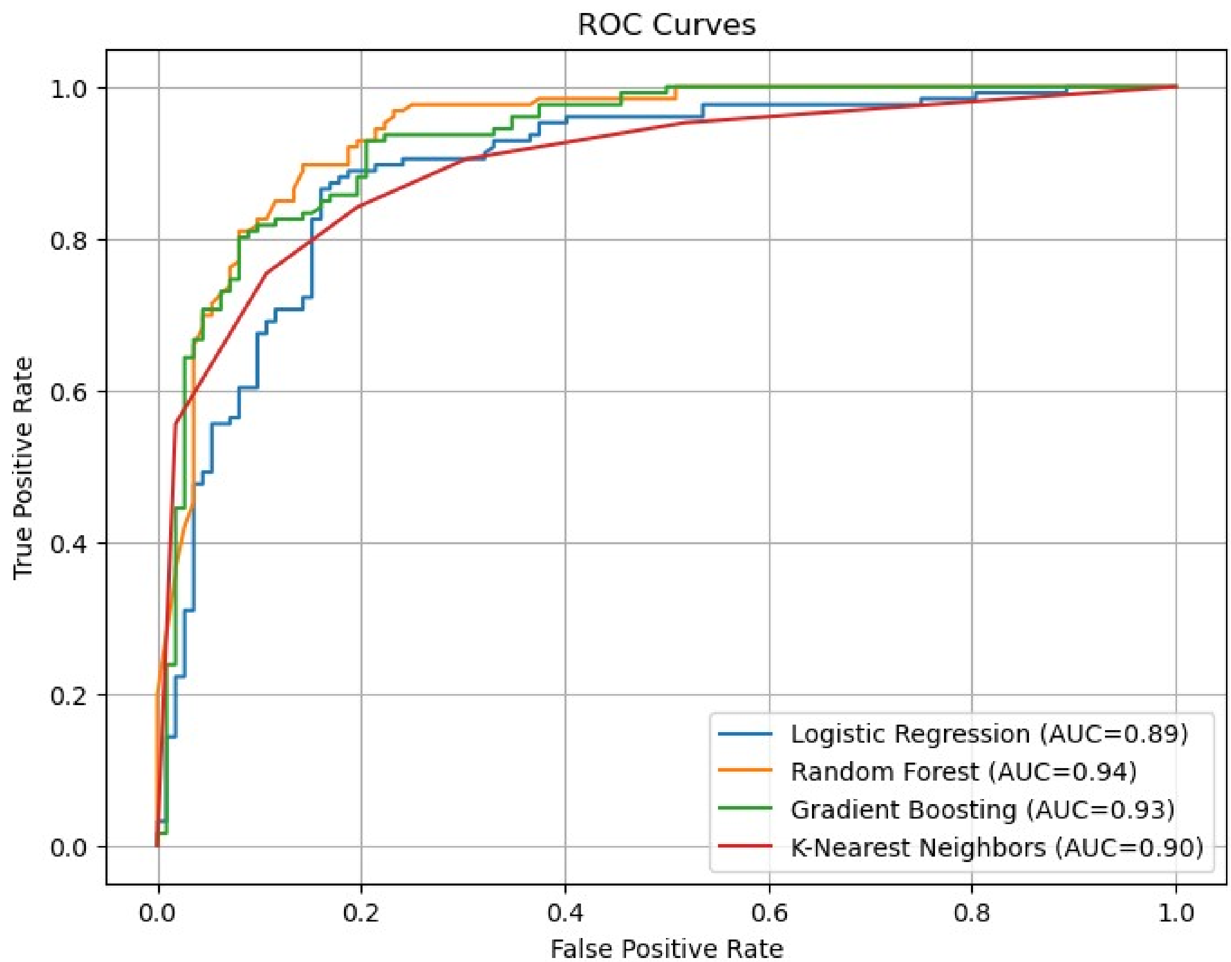
```
3  Linear Regression (binary)     0.853      0.858   0.865     0.862
4           Gradient Boosting     0.840      0.861   0.833     0.847
5         K-Nearest Neighbors     0.824      0.828   0.841     0.835
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import roc_curve, auc, confusion_matrix,
classification_report, accuracy_score

# --- 1. Accuracy Table and Bar Plot ---
accuracy_dict = {
    'Logistic Regression': accuracy_score(y_test, y_pred),
    'Decision Tree': accuracy_score(y_test, y_pred_dt),
    'Random Forest': accuracy_score(y_test, y_pred_rf),
    'Linear Regression (binary)': accuracy_score(y_test,
y_pred_lr_bin),
    'K-Nearest Neighbors': accuracy_score(y_test, y_pred_knn),
    'Gradient Boosting': accuracy_score(y_test, y_pred_gb)
}

accuracy_table = pd.DataFrame(list(accuracy_dict.items()),
columns=['Model', 'Accuracy']).sort_values(by='Accuracy',
ascending=False)
print(accuracy_table)

# Bar plot
plt.figure(figsize=(8,5))
sns.barplot(x='Accuracy', y='Model', data=accuracy_table,
palette='viridis')
plt.title('Model Accuracy Comparison')
plt.xlim(0,1)
plt.show()

# --- 3. ROC Curves ---
models_proba = {
    'Logistic Regression': pipeline,
    'Random Forest': pipe_rf,
    'Gradient Boosting': gb_model,
    'K-Nearest Neighbors': pipe_knn
}

plt.figure(figsize=(8,6))
for name, model in models_proba.items():
    try:
        y_proba = model.predict_proba(X_test)[:,1]
        fpr, tpr, _ = roc_curve(y_test, y_proba)
        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f'{name} (AUC={roc_auc:.2f})')
    except:
        print(f'{name} skipped (no predict_proba)')
```

```python
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves')
plt.legend()
plt.grid(True)
plt.show()
```

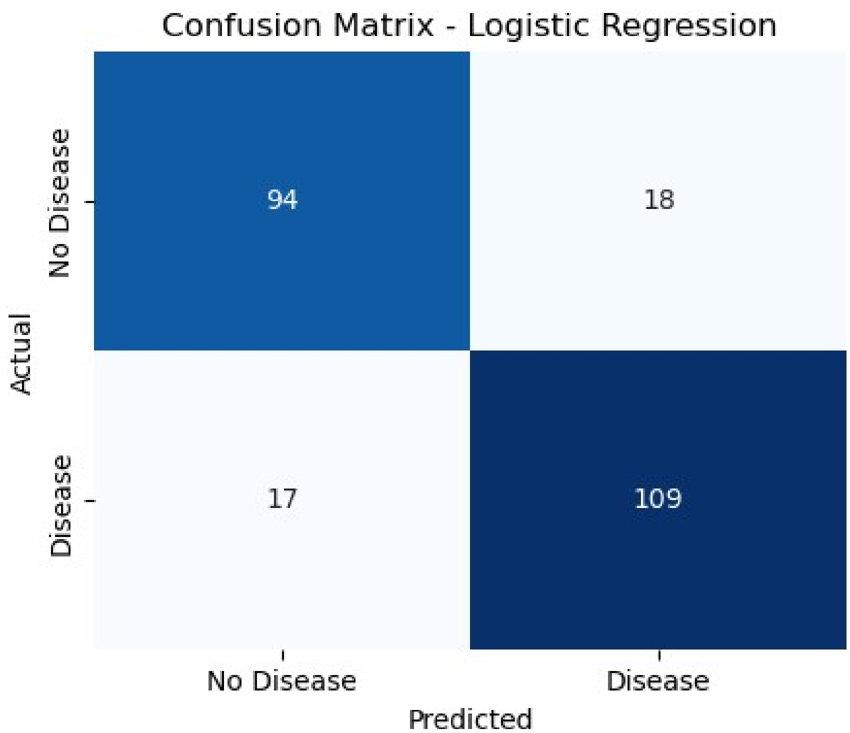
```
                         Model  Accuracy
2                Random Forest  0.857143
0          Logistic Regression  0.852941
1                Decision Tree  0.852941
3  Linear Regression (binary)  0.852941
5            Gradient Boosting  0.840336
4          K-Nearest Neighbors  0.823529

/var/folders/d6/jbdgpdts2dlc2370hmzb47k00000gn/T/
ipykernel_90722/1170332741.py:20: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='Accuracy', y='Model', data=accuracy_table,
palette='viridis')
```

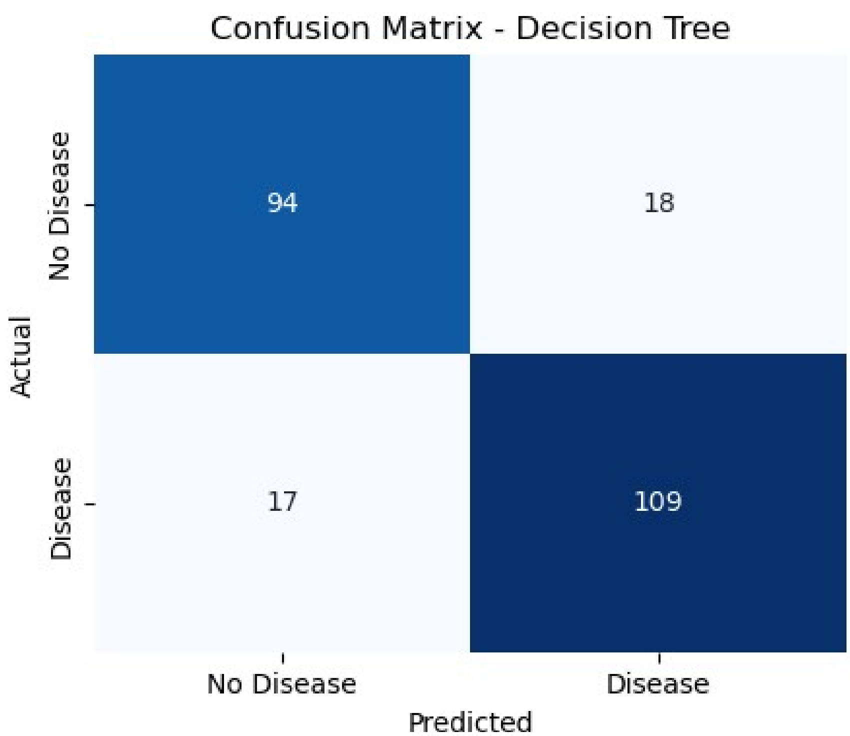


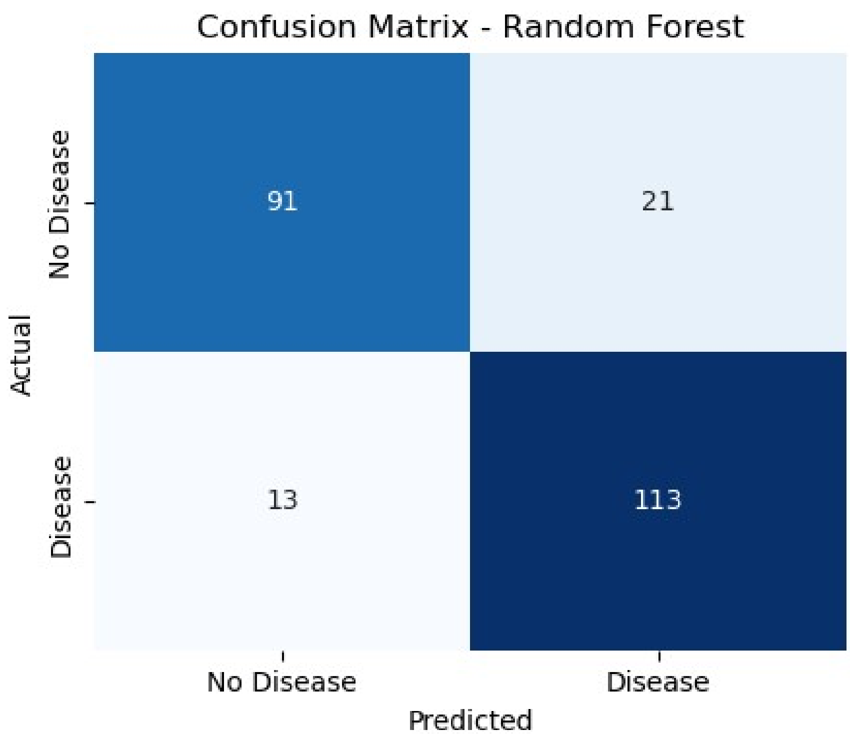


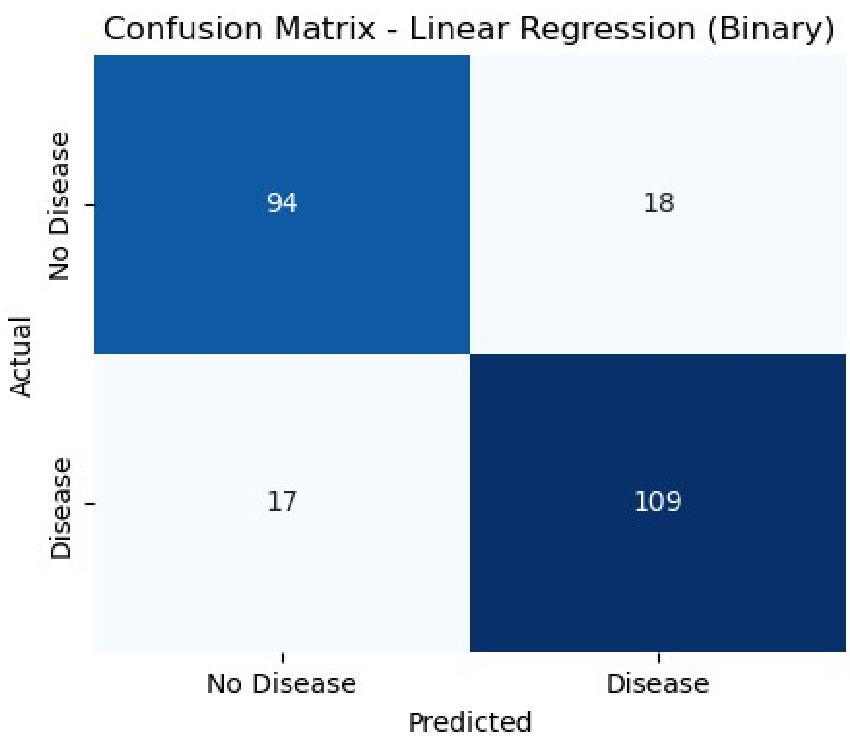

```
from sklearn.metrics import confusion_matrix

# Function to plot confusion matrix
def plot_conf_matrix(y_true, y_pred, model_name):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(5,4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
                xticklabels=['No Disease', 'Disease'],
                yticklabels=['No Disease', 'Disease'])
    plt.title(f'Confusion Matrix - {model_name}')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

# Example usage for your models:
plot_conf_matrix(y_test, y_pred, "Logistic Regression")
plot_conf_matrix(y_test, y_pred_dt, "Decision Tree")
plot_conf_matrix(y_test, y_pred_rf, "Random Forest")
plot_conf_matrix(y_test, y_pred_lr_bin, "Linear Regression (Binary)")
```

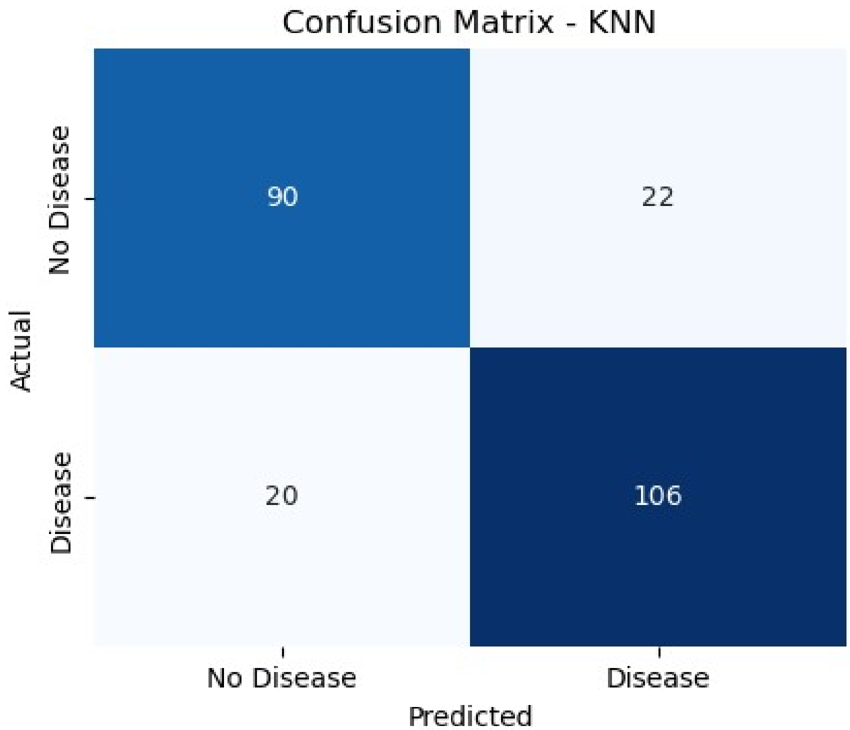
```
plot_conf_matrix(y_test, y_pred_knn, "KNN")
plot_conf_matrix(y_test, y_pred_gb, "Gradient Boosting")
```

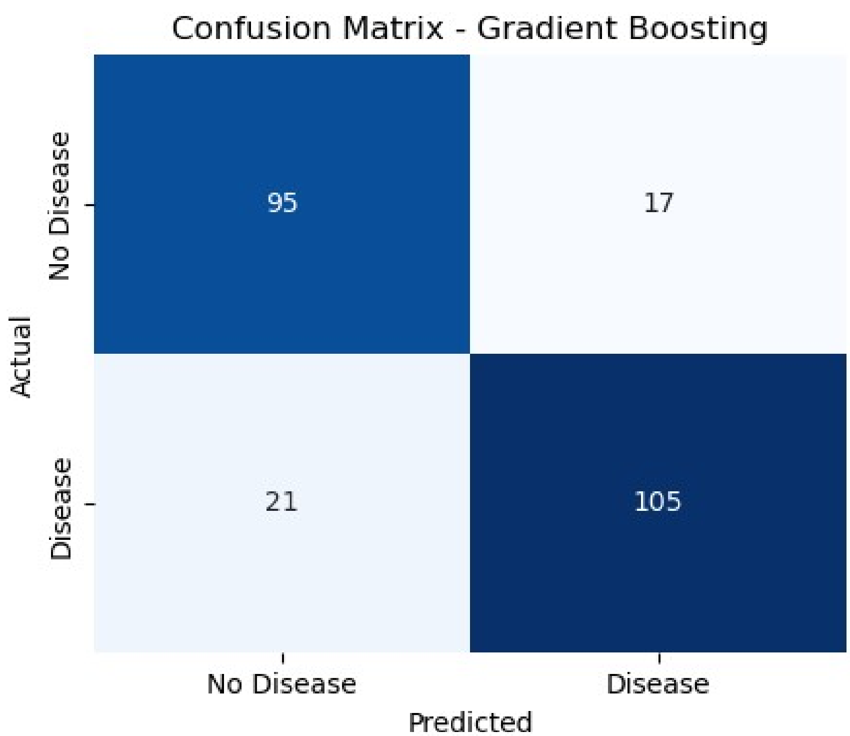





Confusion Matrix - Random Forest
Actual
No Disease
Disease
91
21
13
113
No Disease
Disease
Predicted


Confusion Matrix - Linear Regression (Binary)
Actual
No Disease
Disease
94
18
17
109
No Disease
Disease
Predicted


Confusion Matrix - KNN
No Disease
Disease
Actual
90
22
20
106
No Disease
Disease
Predicted


Confusion Matrix - Gradient Boosting
No Disease
Disease
Actual
95
17
21
105
No Disease
Disease
Predicted