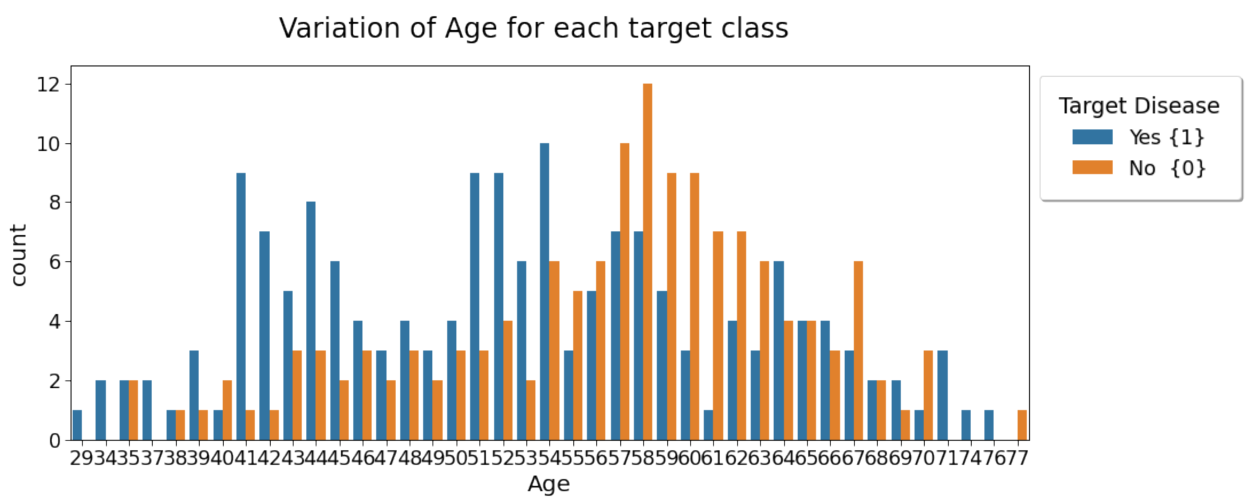
```
import pandas as pd
import numpy as np
# import warnings filter
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category = FutureWarning)
# import warnings filter
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category = FutureWarning)
import matplotlib.pyplot as plt
import seaborn as sb

import matplotlib.colors as colors
from sklearn.preprocessing import scale
from sklearn.decomposition import PCA

df = pd.read_csv('Heart-Prediction-Dataset.csv', header = None)

df.columns = ['Age', 'Sex', 'Chest_Pain_Type', 'Resting_BPs',
'Cholestrol',
              'Fasting_Blood_Sugar', 'Resting_ECG', 'Max_Heart_Rate',
'Exercise_Induced_Angina',
              'ST_depression_induced', 'Peak_ST',
'No_Of_Major_Vessels', 'Thal', 'Target_Disease']
#check the dataset having missing values or not
print(df.isnull().sum())
#add missing values in dataset
df['Target_Disease'] = df.Target_Disease.map({0: 0, 1: 1, 2: 1, 3: 1,
4: 1})
df['Sex'] = df.Sex.map({0: 'female', 1: 'male'})
df['Thal'] = df.Thal.fillna(df.Thal.mean())
df['No_Of_Major_Vessels'] =
df.No_Of_Major_Vessels.fillna(df.No_Of_Major_Vessels.mean())
df
```

```
Age                          0
Sex                          0
Chest_Pain_Type              0
Resting_BPs                  0
Cholestrol                   0
Fasting_Blood_Sugar          0
Resting_ECG                  0
Max_Heart_Rate               0
Exercise_Induced_Angina      0
ST_depression_induced        0
Peak_ST                      0
No_Of_Major_Vessels          4
Thal                         2
```

```
Target_Disease            0
dtype: int64

     Age     Sex  Chest_Pain_Type  Resting_BPs  Cholestrol  \
0     63    male                1          145         233
1     67    male                4          160         286
2     67    male                4          120         229
3     37    male                3          130         250
4     41  female                2          130         204
..   ...     ...              ...          ...         ...
298   45    male                1          110         264
299   68    male                4          144         193
300   57    male                4          130         131
301   57  female                2          130         236
302   38    male                3          138         175

     Fasting_Blood_Sugar  Resting_ECG  Max_Heart_Rate  \
0                      1            2             150
1                      0            2             108
2                      0            2             129
3                      0            0             187
4                      0            2             172
..                   ...          ...             ...
298                    0            0             132
299                    1            0             141
300                    0            0             115
301                    0            2             174
302                    0            0             173

     Exercise_Induced_Angina  ST_depression_induced  Peak_ST  \
0                          0                    2.3        3
1                          1                    1.5        2
2                          1                    2.6        2
3                          0                    3.5        3
4                          0                    1.4        1
..                       ...                    ...      ...
298                        0                    1.2        2
299                        0                    3.4        2
300                        1                    1.2        2
301                        0                    0.0        2
302                        0                    0.0        1

     No_Of_Major_Vessels  Thal  Target_Disease
0               0.000000   6.0               0
1               3.000000   3.0               1
2               2.000000   7.0               1
3               0.000000   3.0               0
4               0.000000   3.0               0
..                   ...   ...             ...
298             0.000000   7.0               1
```

```
299                2.000000   7.0                 1
300                1.000000   7.0                 1
301                1.000000   3.0                 1
302                0.672241   3.0                 0

[303 rows x 14 columns]
```

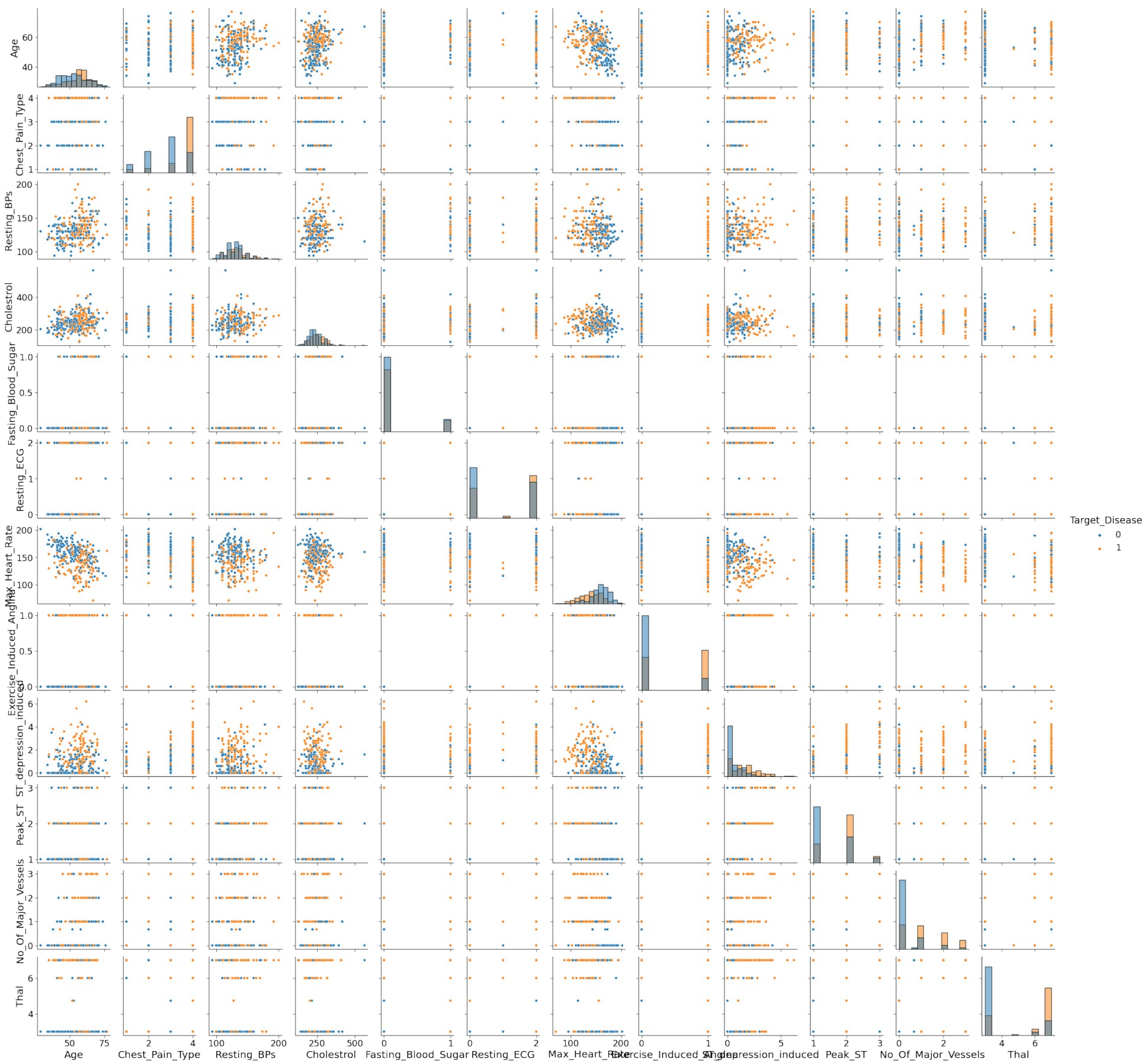
```
# distribution of age  with target Class
sb.set_context("paper", font_scale = 2, rc = {"font.size":
20,"axes.titlesize": 25,"axes.labelsize": 20})
fig, ax = plt.subplots(figsize=(15, 6))
a = sb.countplot(ax = ax, data = df, x = 'Age', hue =
'Target_Disease', order = df['Age'].sort_values().unique())
#sb.displot(data=df, x="Age", kde=True)
legend_labels, _= a.get_legend_handles_labels()
ax.legend(legend_labels, ['Yes {1}','No  {0}'],
bbox_to_anchor=(1,1),title="Target Disease",fancybox=True,
framealpha=1, shadow=True, borderpad=1)
fig.suptitle('Variation of Age for each target class')
plt.show()
```



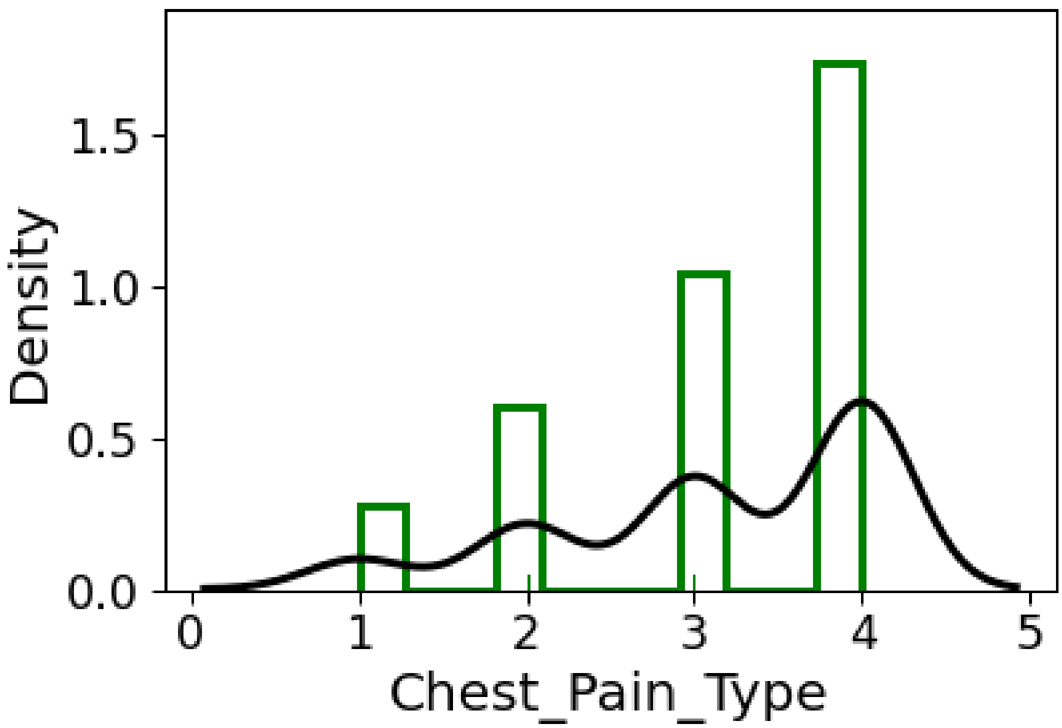

```
# distribution of sex vs age  with target
fig, axes = plt.subplots(1, 2, figsize=(15, 5), sharey=True)
fig.suptitle('Distribution of age vs sex with the target
class',fontsize=25)

sb.swarmplot(ax=axes[0],y = df['Age'], x = df['Sex'])

sb.violinplot(ax=axes[1],x="Sex", y= df['Age'], hue="Sex",
                    data=df, palette="Set2", split=True,
                    scale="count", inner="stick",
                    scale_hue=False, bw=.2)

<AxesSubplot:xlabel='Sex', ylabel='Age'>
```

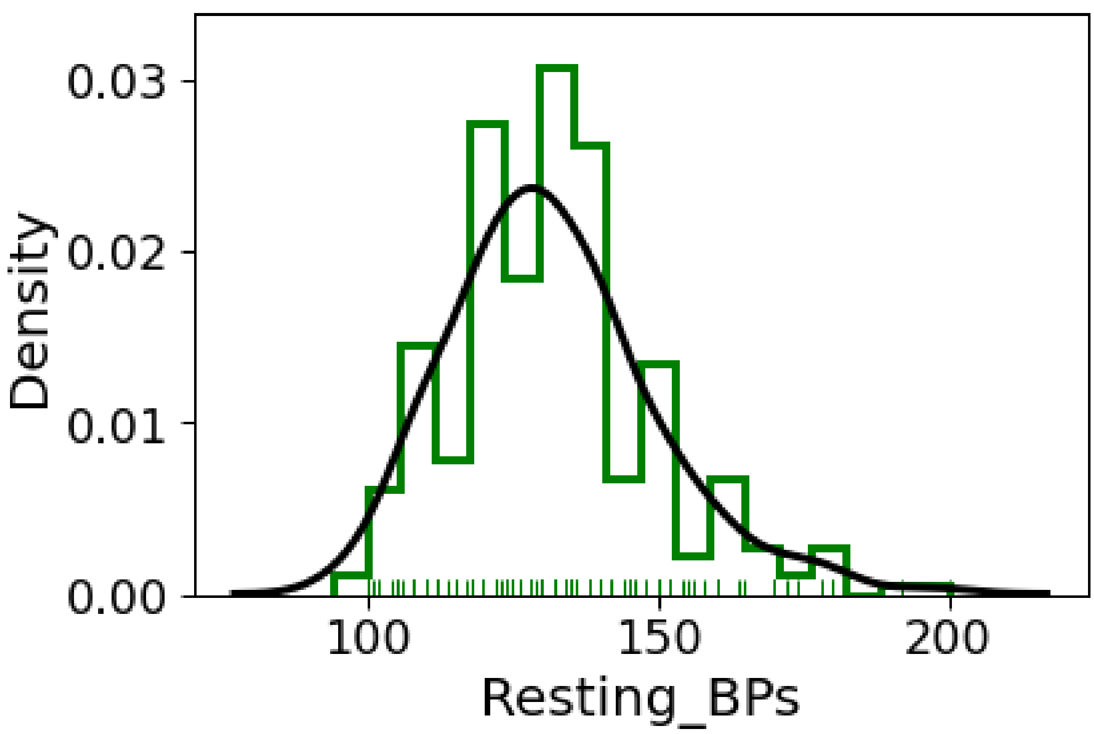

```
# Here we plot the pairplot of all the feature with respect to the others.
# Graph --
sb.pairplot(df, hue='Target_Disease',diag_kind = 'hist')
```

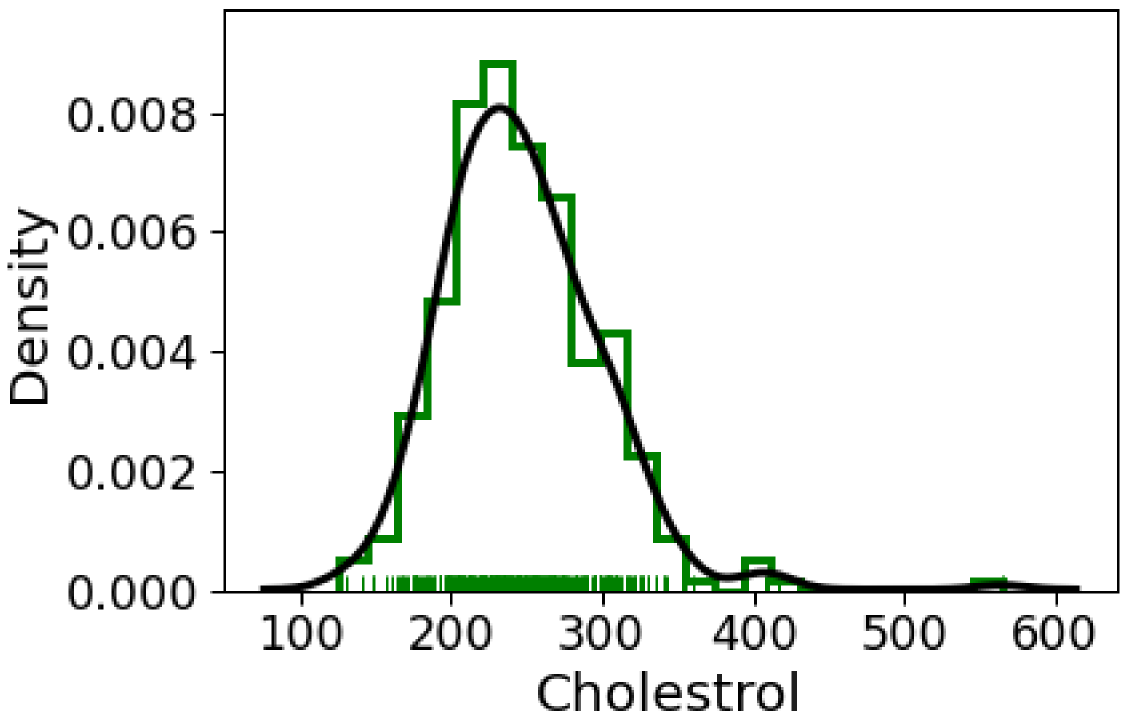
```
<seaborn.axisgrid.PairGrid at 0x1eaf2eae370>
```



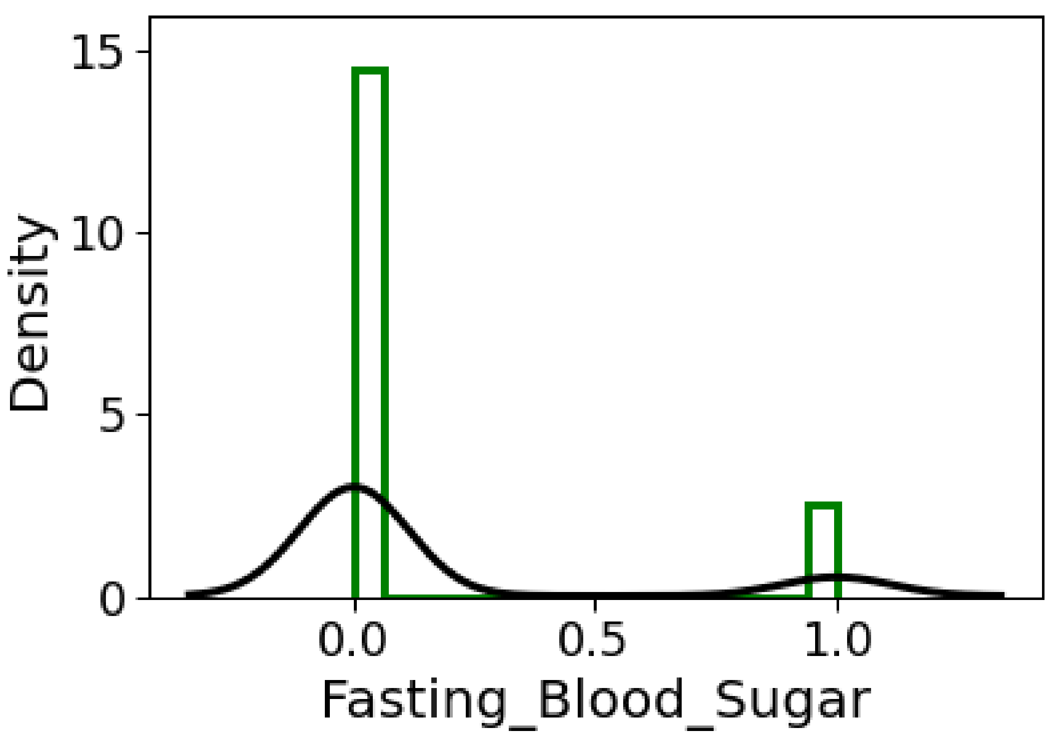

```
lables = np.array(df.columns[2:-1])

for i in (lables):
    plt.figure()
    sb.distplot(df[i], rug=True, rug_kws={"color": "g"},
                kde_kws={"color": "k", "lw": 3, "label": "KDE"},
                hist_kws={"histtype": "step", "linewidth": 3,
                          "alpha": 1, "color": "g"})
```


Density
0.0
0.5
1.0
1.5
0
1
2
3
4
5
Chest_Pain_Type

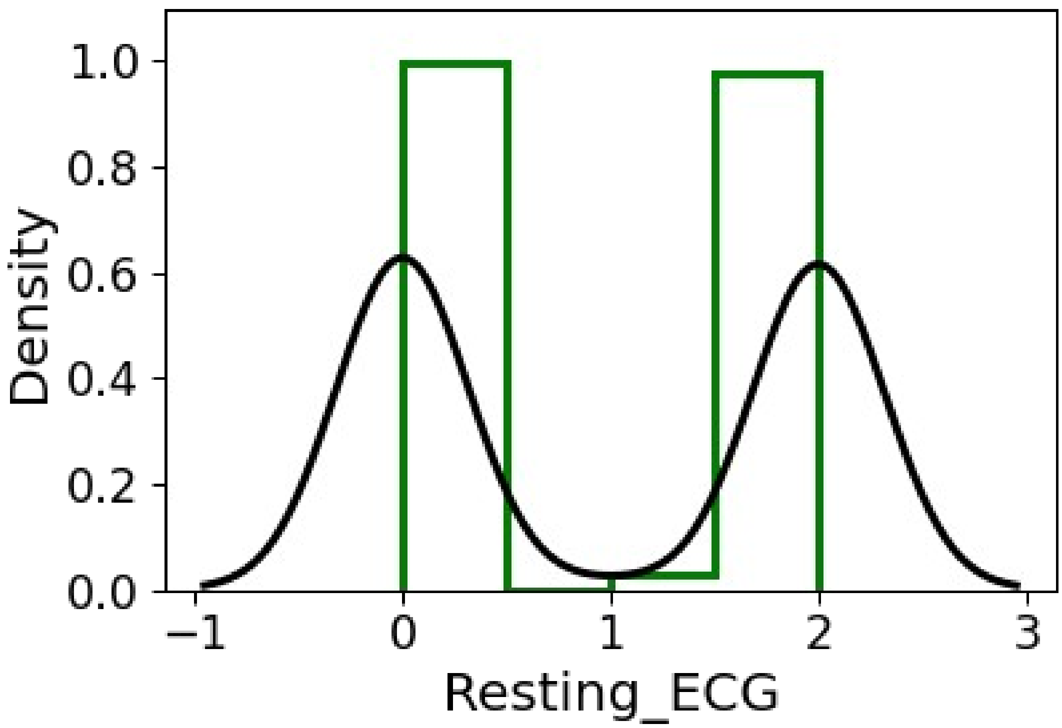

Density
0.00
0.01
0.02
0.03
100
150
200
Resting_BPs

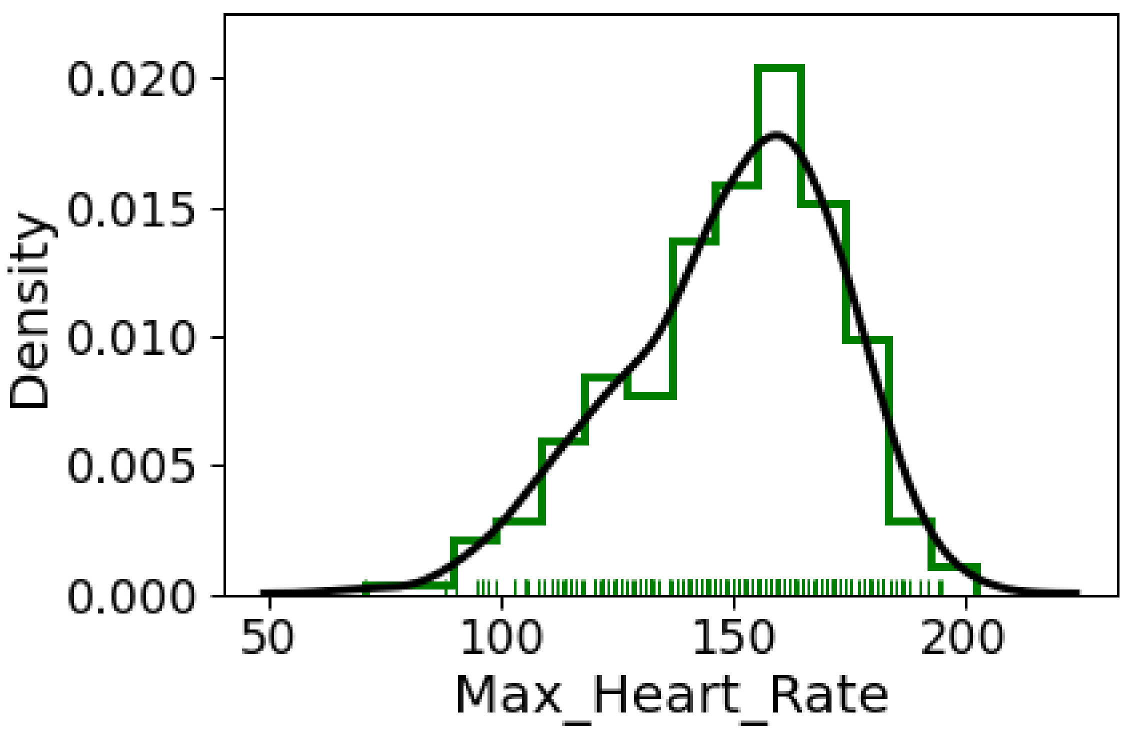


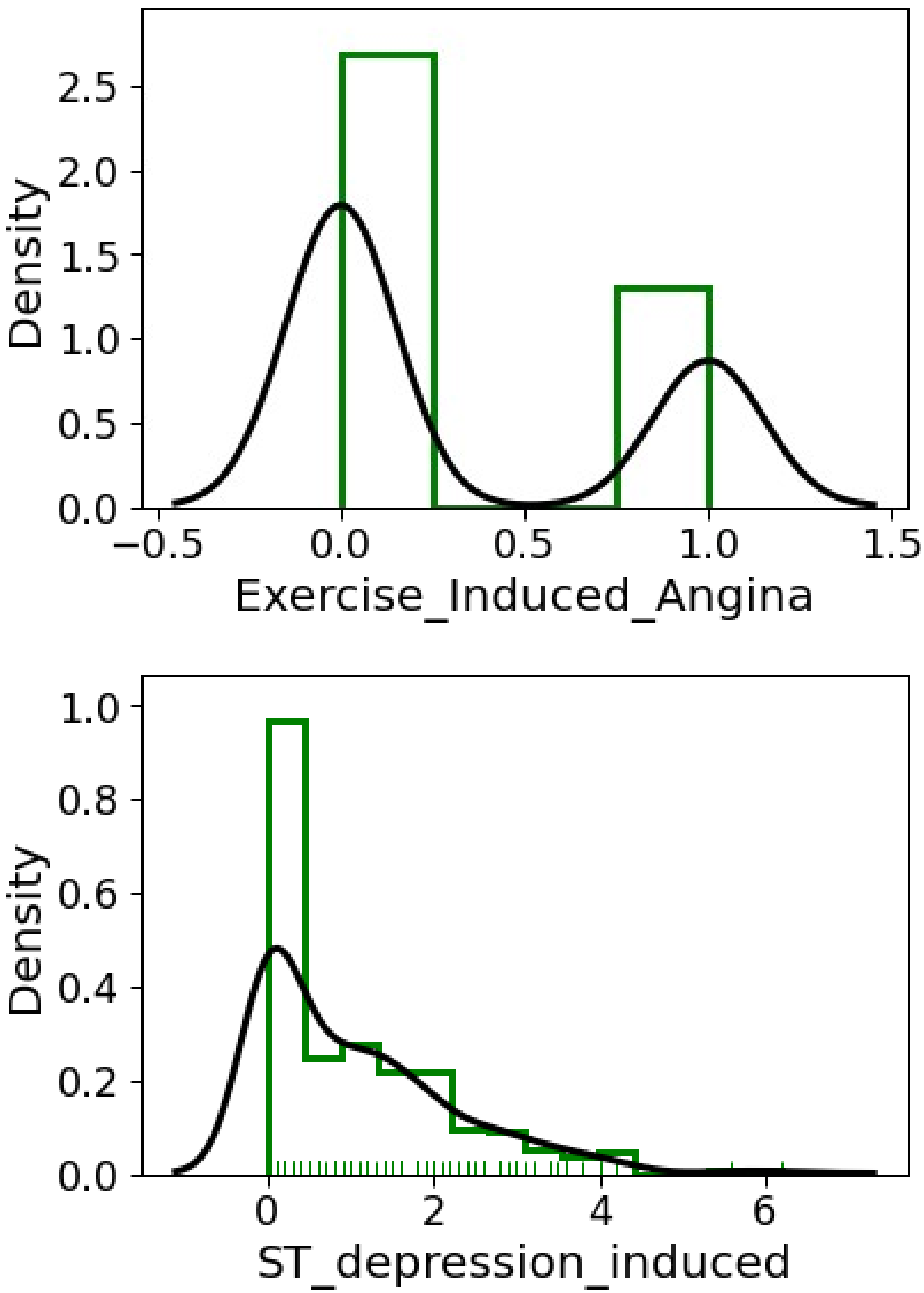
0.008
0.006
0.004
0.002
0.000
Density
100
200
300
400
500
600
Cholestrol



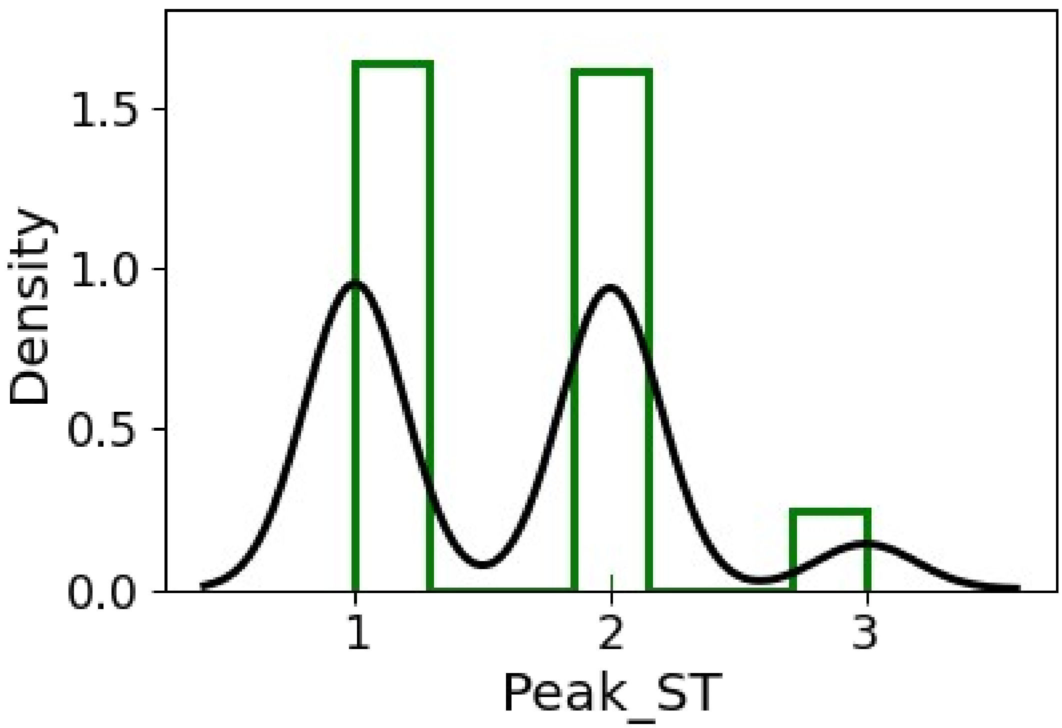
15
10
5
0
Density
0.0
0.5
1.0
Fasting_Blood_Sugar


Density
Resting_ECG
1.0
0.8
0.6
0.4
0.2
0.0
−1
0
1
2
3

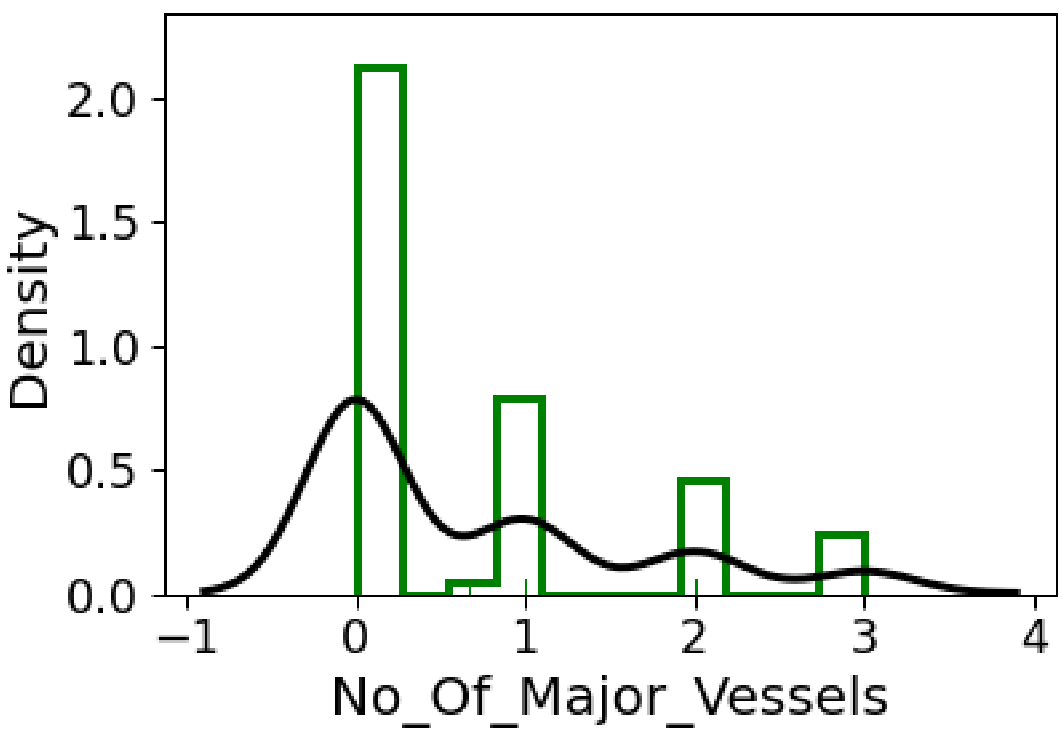

Density
Max_Heart_Rate
0.020
0.015
0.010
0.005
0.000
50
100
150
200



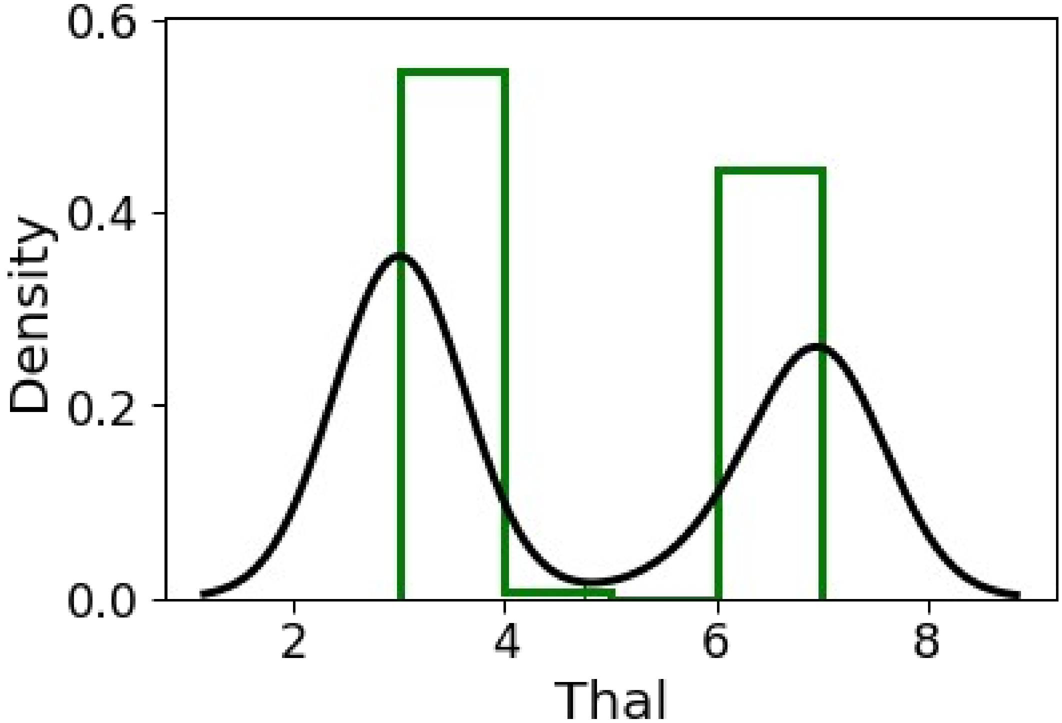
Density
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
0.0
0.5
1.0
1.5
Exercise_Induced_Angina
Density
1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
ST_depression_induced



Density
0.0
0.5
1.0
1.5
1
2
3
Peak_ST



Density
0.0
0.5
1.0
1.5
2.0
−1
0
1
2
3
4
No_Of_Major_Vessels




```
df['Sex'] = df.Sex.map({'female': 0, 'male': 1})

features = df.iloc[:, :-1].values
labels = df.iloc[:, -1].values
# Splits data 80/20
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features, labels,
test_size = 0.2, random_state = 0)

from sklearn.preprocessing import StandardScaler as ss
sc = ss()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
X_train
```

```
array([[-1.13185208,  0.67015058,  0.86665919, ..., -0.98667524,
         0.32127709, -0.97888213],
       [ 0.07286213,  0.67015058,  0.86665919, ...,  0.59461885,
         0.32127709,  1.08790769],
       [-0.03665734,  0.67015058,  0.86665919, ...,  0.59461885,
         0.32127709,  1.08790769],
       ...,
       [-2.11752735, -1.49220195,  0.86665919, ..., -0.98667524,
        -0.71560817, -0.97888213],
       [-0.47473524,  0.67015058,  0.86665919, ...,  0.59461885,
        -0.71560817,  1.08790769],
```

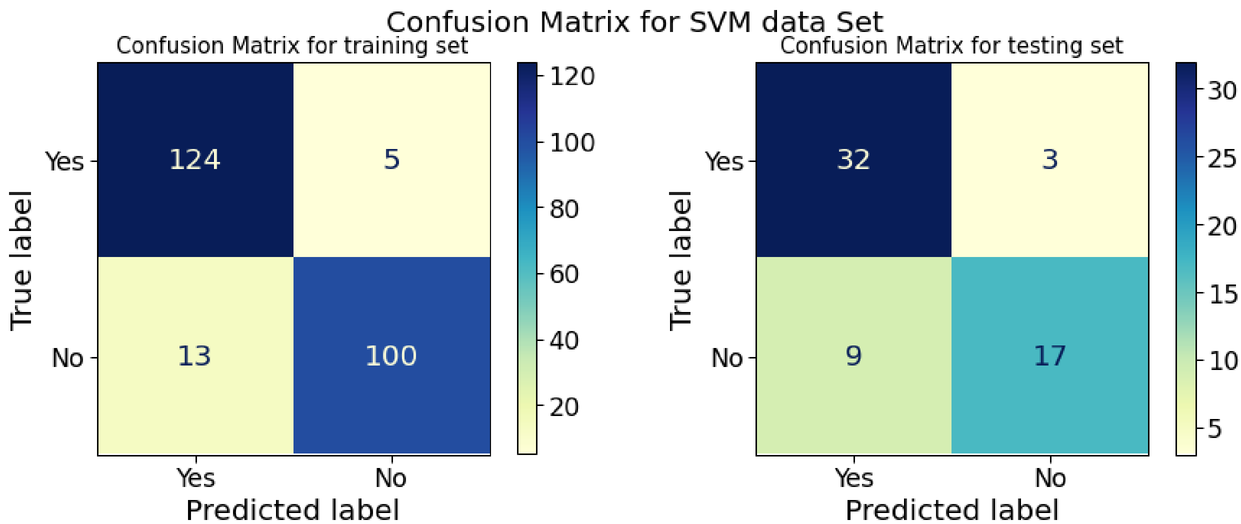
```
       [ 0.51094003, -1.49220195,  0.86665919, ...,  0.59461885,
        -0.71560817, -0.97888213]])

# Confusion Matrix visualization Function
def
plotConfusionMatrixFunction(ClassifierLabel,classifier,X_train,y_train
):
    fig, axes = plt.subplots(1, 2, figsize=(15, 5), sharex=True)
    fig.suptitle(ClassifierLabel,fontsize=20)
    print()
    disp = plot_confusion_matrix(classifier, X_train, y_train, ax =
axes[0], display_labels=["Yes", "No"],cmap=plt.cm.YlGnBu)
    disp.ax_.set_title('Confusion Matrix for training set',fontsize =
15)

    disp = plot_confusion_matrix(classifier, X_test, y_test, ax =
axes[1], display_labels=["Yes", "No"],cmap=plt.cm.YlGnBu)
    disp.ax_.set_title('Confusion Matrix for testing set',fontsize =
15)

def plotClassifierGraph(classifier, X_train, X_test):
    pca = PCA()
    X_train_scaled = scale(X_train)
    X_test_scaled = scale(X_test)
    X_train_pca = pca.fit_transform(X_train_scaled)

    pc1 = X_train_pca[:, 0]
    pc2 = X_train_pca[:, 1]

    # # pc1 contains the x-axis coordinates of the data after PCA
    # # pc2 contains the y-axis coordinates of the data after PCA

    # # Now we fitthe SVM to the x and y-axis coordinates
    # # of the data after PCA dimension reduction...

    classifier.fit(np.column_stack((pc1, pc2)), y_train)

    # # Now create a matrix of points that we can use to show
    # # the decision regions.
    # # The matrix will be a little bit larger than the
    # # transformed PCA points so that we can plot all of
    # # the PCA points on it without them being on the edge

    x_min = pc1.min() - 1
    x_max = pc1.max() + 1

    y_min = pc2.min() - 1
    y_max = pc2.max() + 1

    (xx, yy) = np.meshgrid(np.arange(start=x_min, stop=x_max,
                           step=0.1), np.arange(start=y_min,
```

```
                            stop=y_max, step=0.1))

    # # now we will classify every point in that
    # # matrix with the SVM. Points on one side of the
    # # classification boundary will get 0, and points on the other
    # # side will get 1.

    Z = classifier.predict(np.column_stack((xx.ravel(), yy.ravel())))

    # # Right now, Z is just a long array of lots of 0s and 1s, which
    # # reflect how each point in the mesh was classified.
    # # We use reshape() so that each classification (0 or 1)
corresponds
    # # to a specific point in the matrix.

    Z = Z.reshape(xx.shape)

    (fig, ax) = plt.subplots(figsize=(10, 10))

    # # now we will use contourf() to draw a filled contour plot
    # # using the matrix values and classifications.
    # # The contours will be filled according to the
    # # predicted classifications (0s and 1s) in Z

    ax.contourf(xx, yy, Z, cmap=plt.cm.winter, alpha=0.1)
    ax.xaxis.grid(True, zorder=0)
    ax.yaxis.grid(True, zorder=0)

    # # now create custom colors for the actual data points

    cmap = colors.ListedColormap(['#00796B', '#F44336'])

    # # now darw the actual data points - these will
    # # be colored by their known (not predcited) classifications
    # # NOTE: setting alpha=0.7 lets us see if we are covering up a
point

    scatter = ax.scatter(  # # 'k' = black
        pc1,
        pc2,
        c=y_train,
        cmap=cmap,
        s=120,
        edgecolors='k',
        alpha=0.5,
        )

    # # now create a legend

    legend = ax.legend(scatter.legend_elements()[0],
```

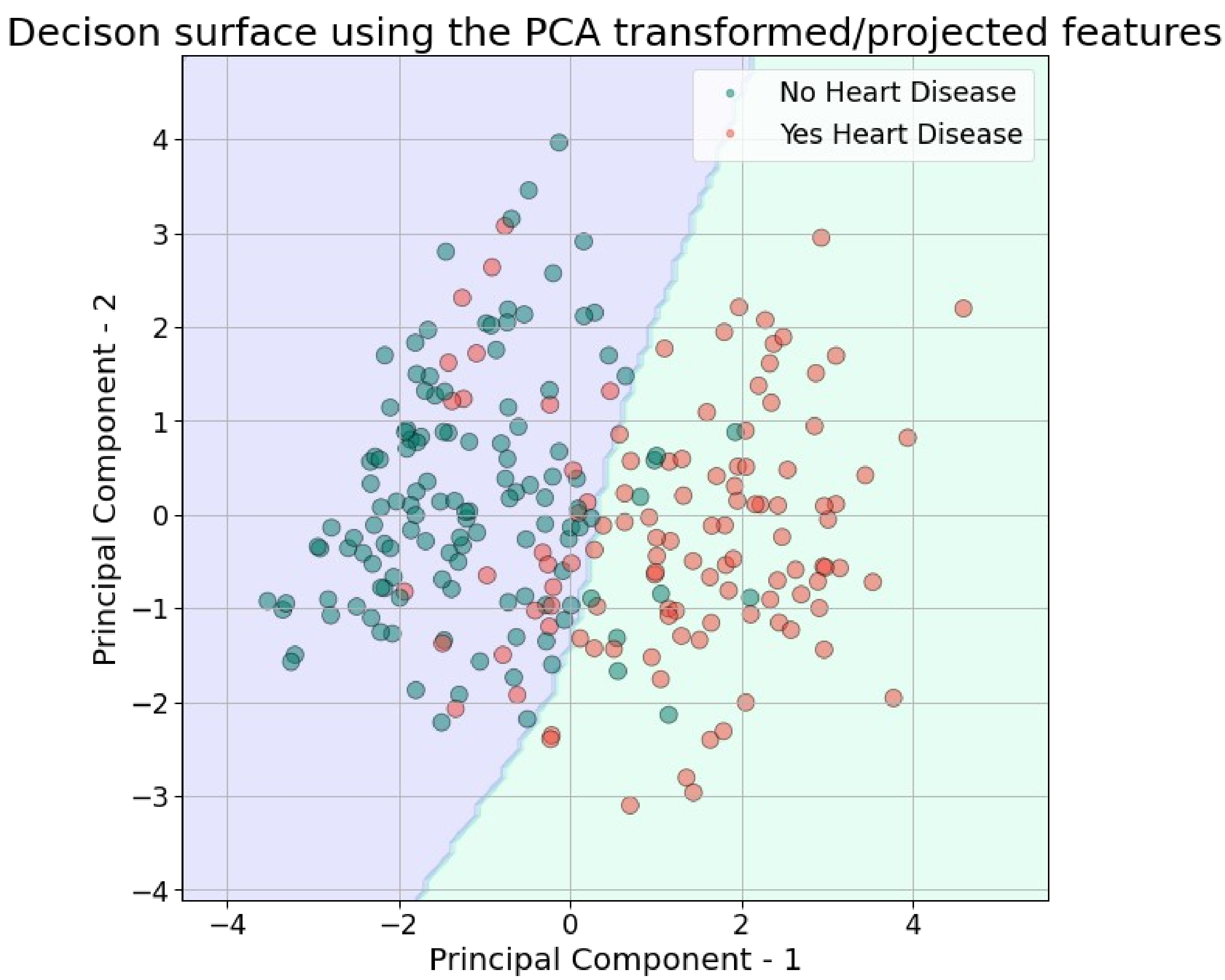
```
                       scatter.legend_elements()[1], loc='upper
right')
    legend.get_texts()[0].set_text('No Heart Disease')
    legend.get_texts()[1].set_text('Yes Heart Disease')

    # # now add axis labels and titles

    ax.set_ylabel('Principal Component - 2')
    ax.set_xlabel('Principal Component - 1')
    ax.set_title('Decison surface using the PCA transformed/projected
features'
                 )

    # plt.savefig('svm.png')

    plt.show()

#########################################   SVM
#############################################################
from sklearn.svm import SVC
classifier = SVC(kernel = 'rbf')
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
cm_test = confusion_matrix(y_pred, y_test)

y_pred_train = classifier.predict(X_train)
cm_train = confusion_matrix(y_pred_train, y_train)

print('Accuracy for training set for svm = {}'.format((cm_train[0][0]
+ cm_train[1][1])/len(y_train)))
print('Accuracy for test set for svm = {}'.format((cm_test[0][0] +
cm_test[1][1])/len(y_test)))
```

```
Accuracy for training set for svm = 0.9256198347107438
Accuracy for test set for svm = 0.8032786885245902
```

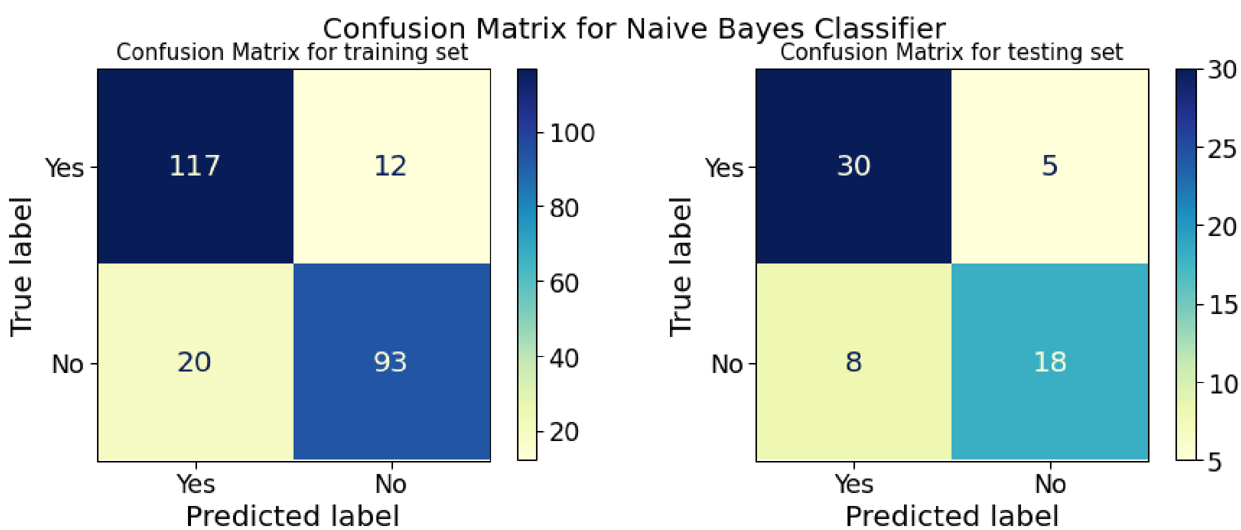
```
plotConfusionMatrixFunction('Confusion Matrix for SVM data
Set',classifier,X_train,y_train)
```



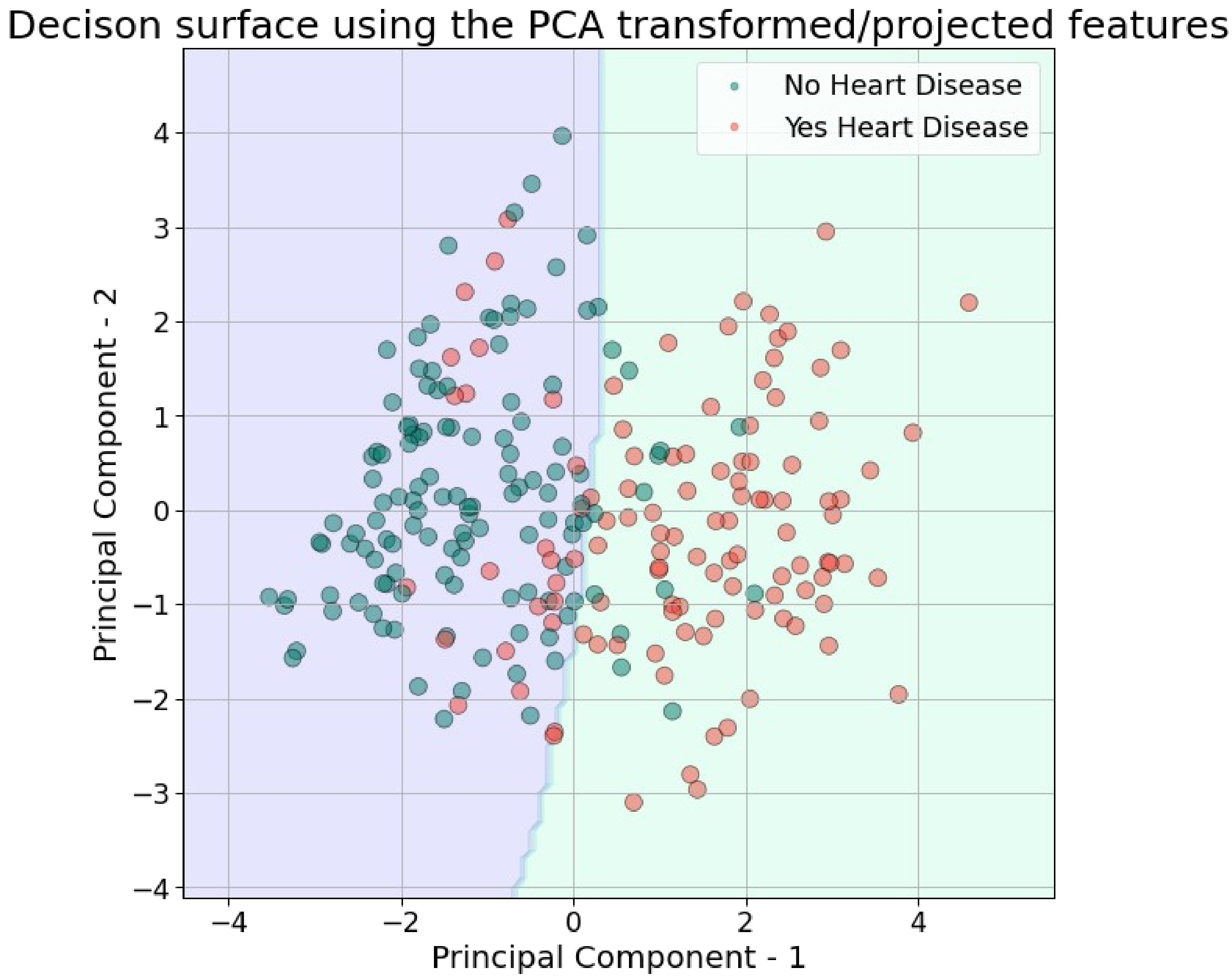

```
plotClassifierGraph(classifier,X_train,X_test)
```



```
########################################   Naive Bayes
############################################################
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 0)

from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

from sklearn.metrics import confusion_matrix
cm_test = confusion_matrix(y_pred, y_test)

y_pred_train = classifier.predict(X_train)
cm_train = confusion_matrix(y_pred_train, y_train)

print('Accuracy for training set for Naive Bayes =
{}'.format((cm_train[0][0] + cm_train[1][1])/len(y_train)))
print('Accuracy for test set for Naive Bayes = {}'.format((cm_test[0]
[0] + cm_test[1][1])/len(y_test)))

Accuracy for training set for Naive Bayes = 0.8677685950413223
Accuracy for test set for Naive Bayes = 0.7868852459016393

plotConfusionMatrixFunction('Confusion Matrix for Naive Bayes
Classifier',classifier,X_train,y_train)
```



```
plotClassifierGraph(classifier,X_train,X_test)
```

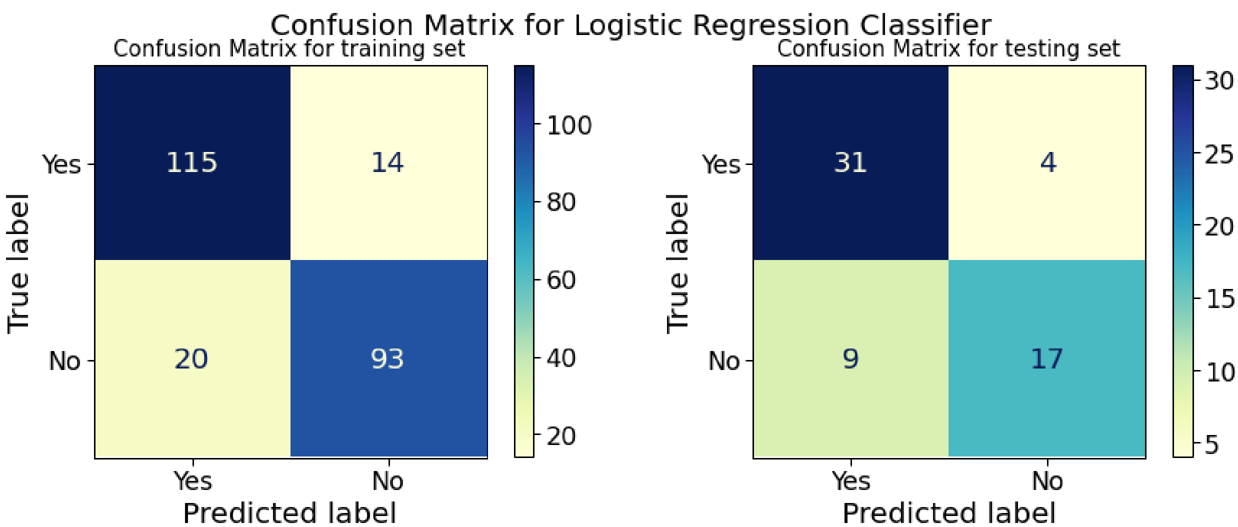



```
##########################################   Logistic Regression
##############################################################
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 0)

from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(max_iter=1000)
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

from sklearn.metrics import confusion_matrix
```

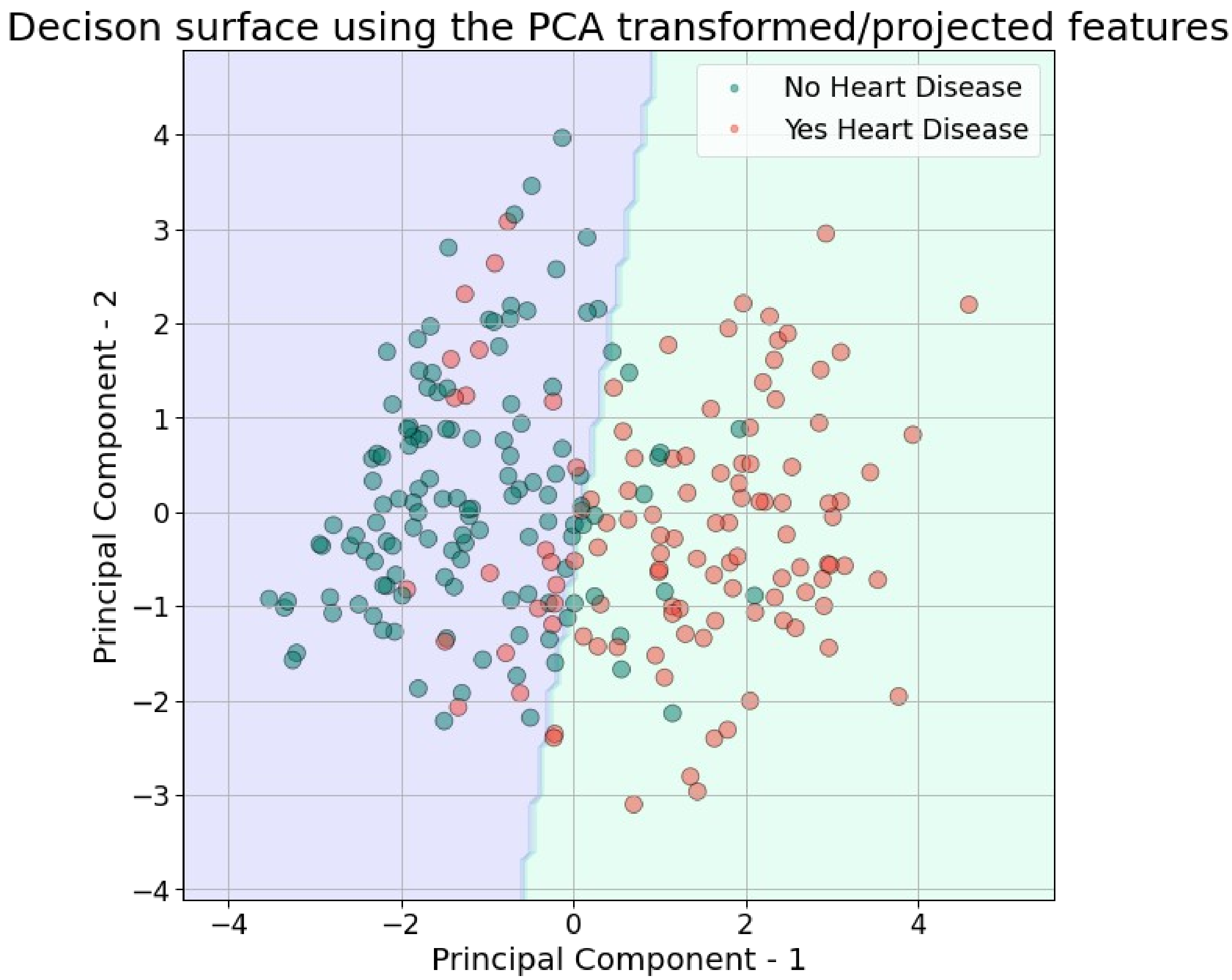
```
cm_test = confusion_matrix(y_pred, y_test)

y_pred_train = classifier.predict(X_train)
cm_train = confusion_matrix(y_pred_train, y_train)
print()
print('Accuracy for training set for Logistic Regression =
{}'.format((cm_train[0][0] + cm_train[1][1])/len(y_train)))
print('Accuracy for test set for Logistic Regression =
{}'.format((cm_test[0][0] + cm_test[1][1])/len(y_test)))
```

```
Accuracy for training set for Logistic Regression = 0.859504132231405
Accuracy for test set for Logistic Regression = 0.7868852459016393
```

```
plotConfusionMatrixFunction('Confusion Matrix for Logistic Regression
Classifier',classifier,X_train,y_train)
```




```
plotClassifierGraph(classifier,X_train,X_test)
```



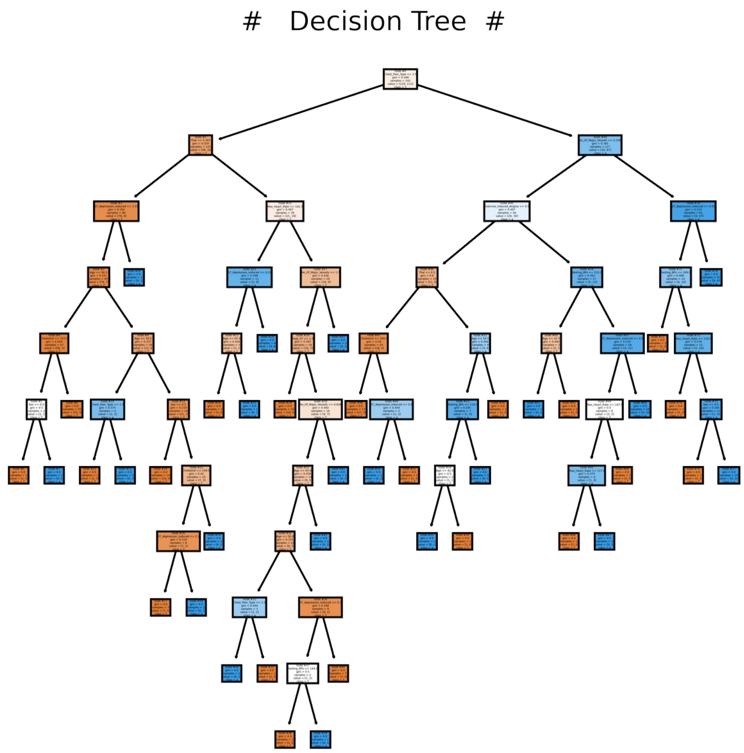

```
#########################################   Decision Tree
#############################################################
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 0)

from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier()
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

from sklearn.metrics import confusion_matrix
cm_test = confusion_matrix(y_pred, y_test)

y_pred_train = classifier.predict(X_train)
```

```
cm_train = confusion_matrix(y_pred_train, y_train)

print()

print('Accuracy for training set for Decision Tree = 
{}'.format((cm_train[0][0] + cm_train[1][1])/len(y_train)))
print('Accuracy for test set for Decision Tree = 
{}'.format((cm_test[0][0] + cm_test[1][1])/len(y_test)))
```

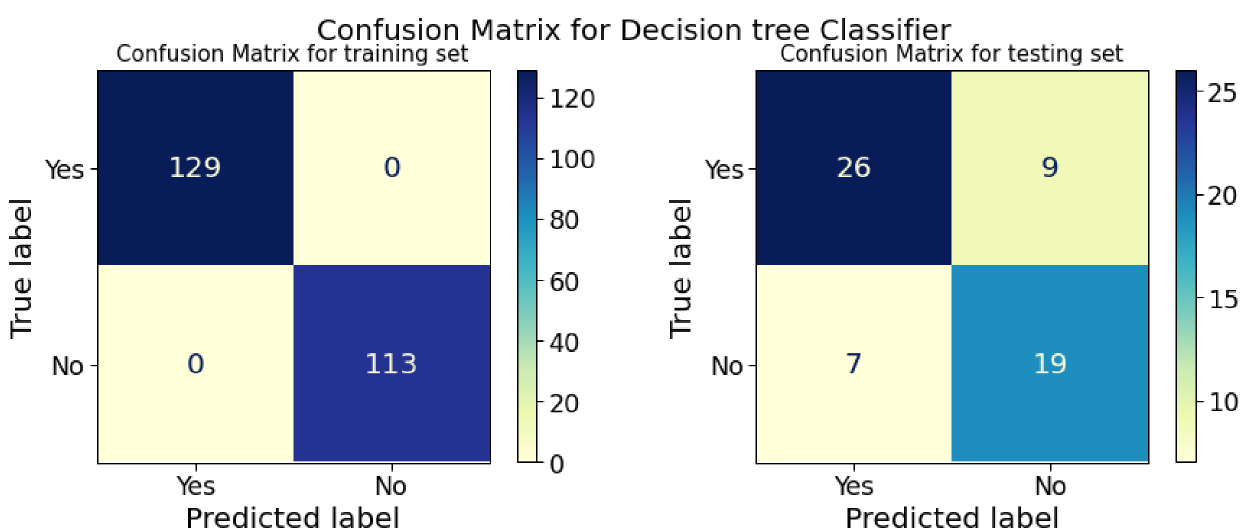
```
Accuracy for training set for Decision Tree = 1.0
Accuracy for test set for Decision Tree = 0.7704918032786885
```

```
# Plot Decision tree which are shown below,
from sklearn import tree
print()
fig, axes = plt.subplots(figsize = (5,5), dpi= 900)
fn=np.array(df.columns[:-1])
tn=df.columns[-1]
tree.plot_tree(classifier,
               feature_names = fn,
               class_names=tn,
               node_ids = True,
               filled = True,
               ax = axes);
axes.set_title('#   Decision Tree  #', fontsize=10)
#fig.savefig('DecisionTree.png')
```

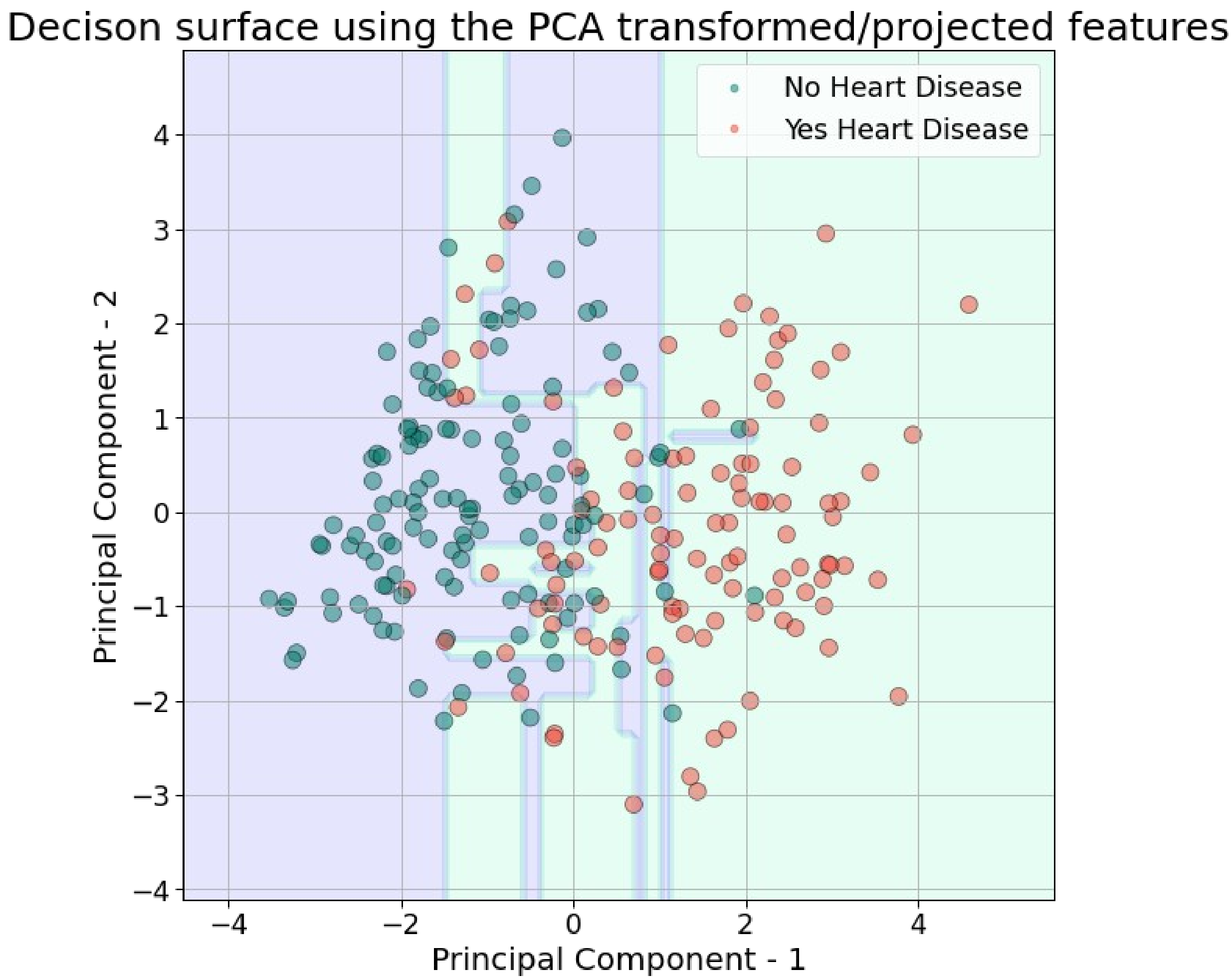
```
Text(0.5, 1.0, '#   Decision Tree  #')
```




```
plotConfusionMatrixFunction('Confusion Matrix for Decision tree
Classifier',classifier,X_train,y_train)
```




```
plotClassifierGraph(classifier,X_train,X_test)
```



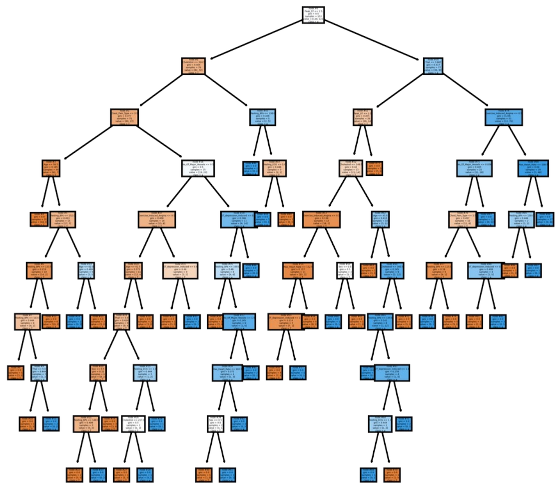

```
##########################################  Random Forest
###############################################################
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 0)

from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators = 10)
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

from sklearn.metrics import confusion_matrix
cm_test = confusion_matrix(y_pred, y_test)

y_pred_train = classifier.predict(X_train)
```

```python
cm_train = confusion_matrix(y_pred_train, y_train)

print('Accuracy for training set for Random Forest =
{}'.format((cm_train[0][0] + cm_train[1][1])/len(y_train)))
print('Accuracy for test set for Random Forest =
{}'.format((cm_test[0][0] + cm_test[1][1])/len(y_test)))
```

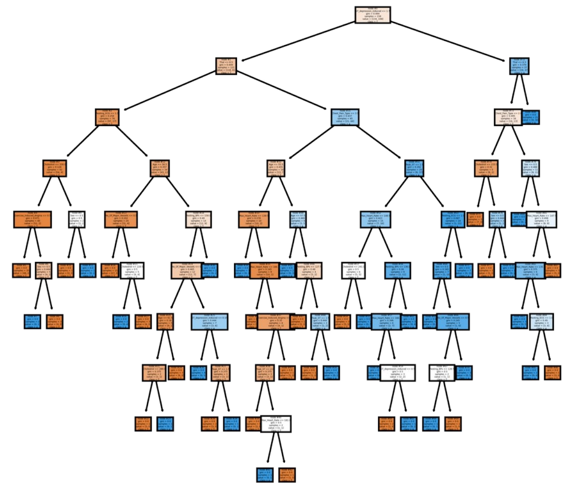
```
Accuracy for training set for Random Forest = 1.0
Accuracy for test set for Random Forest = 0.7213114754098361
```

```python
# All the Estimator trees are shown below,
from sklearn import tree
print()
fn=np.array(df.columns[:-1])
cn=df.columns[-1]
rows = 0
cols = 0
fig, axes = plt.subplots(nrows = 5,ncols = 2,figsize = (10,25),
dpi=900)
for index in range(0, 10):
    tree.plot_tree(classifier.estimators_[index],
                   feature_names = fn,
                   class_names=cn,
                   node_ids = True,
                   filled = True,
                   ax = axes[rows][cols]);
    axes[rows][cols].set_title('Estimator: ' + str(index+1), fontsize
= 11)
    cols += 1
    if(cols>=2):
        cols = 0
        rows += 1
#fig.savefig('RandomForests.png')
```

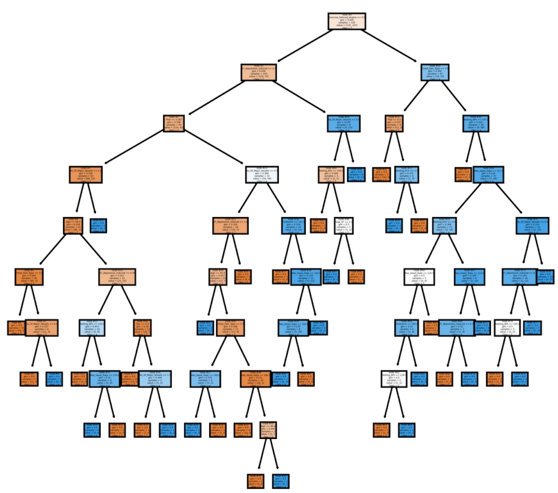
Estimator: 1



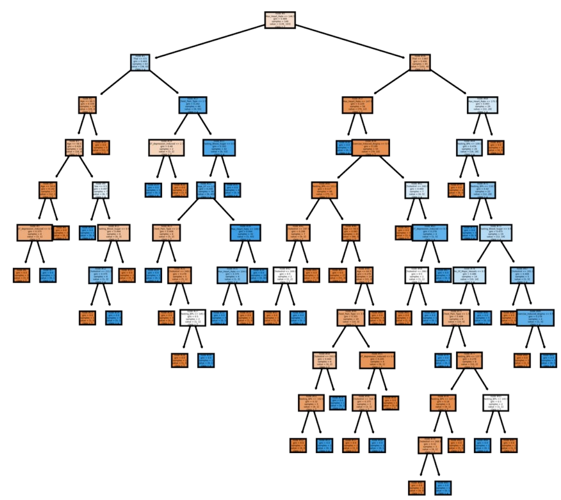
Estimator: 2



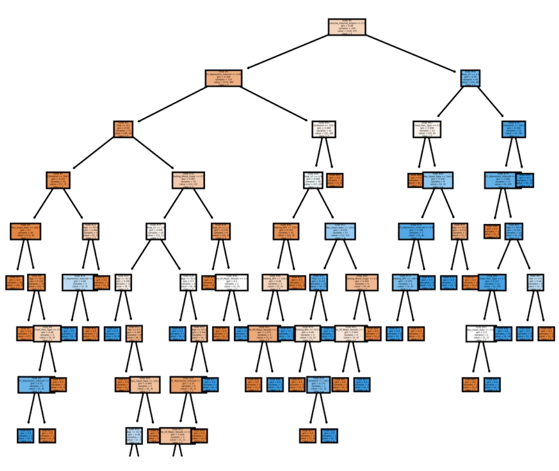
Estimator: 3



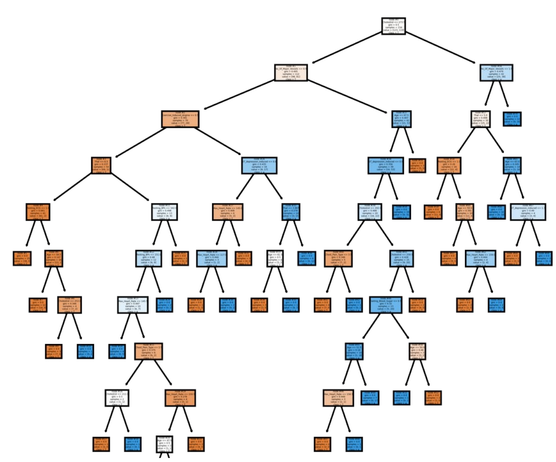
Estimator: 4



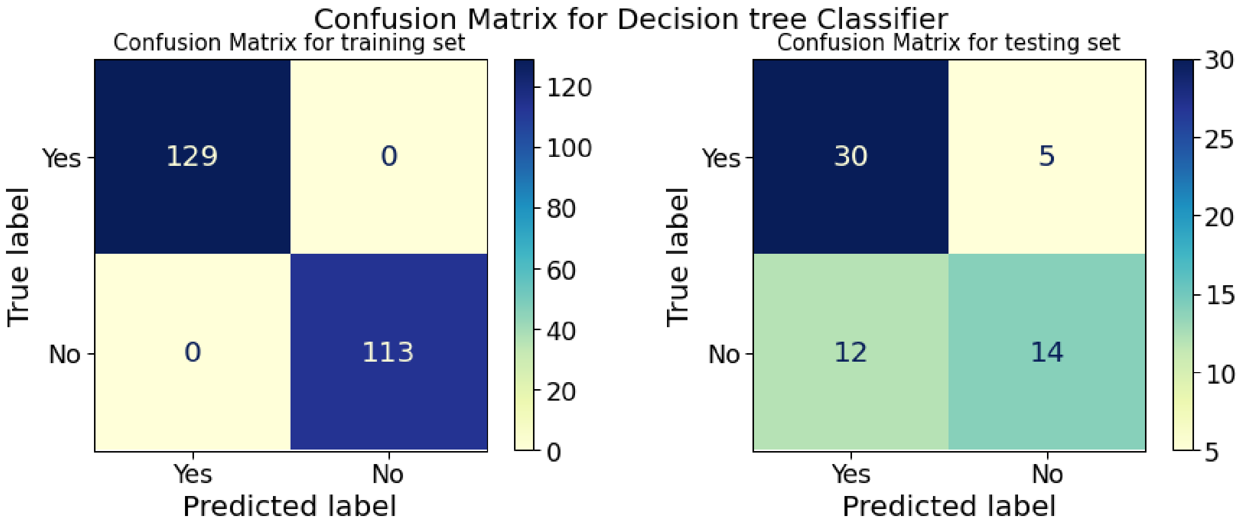
Estimator: 5



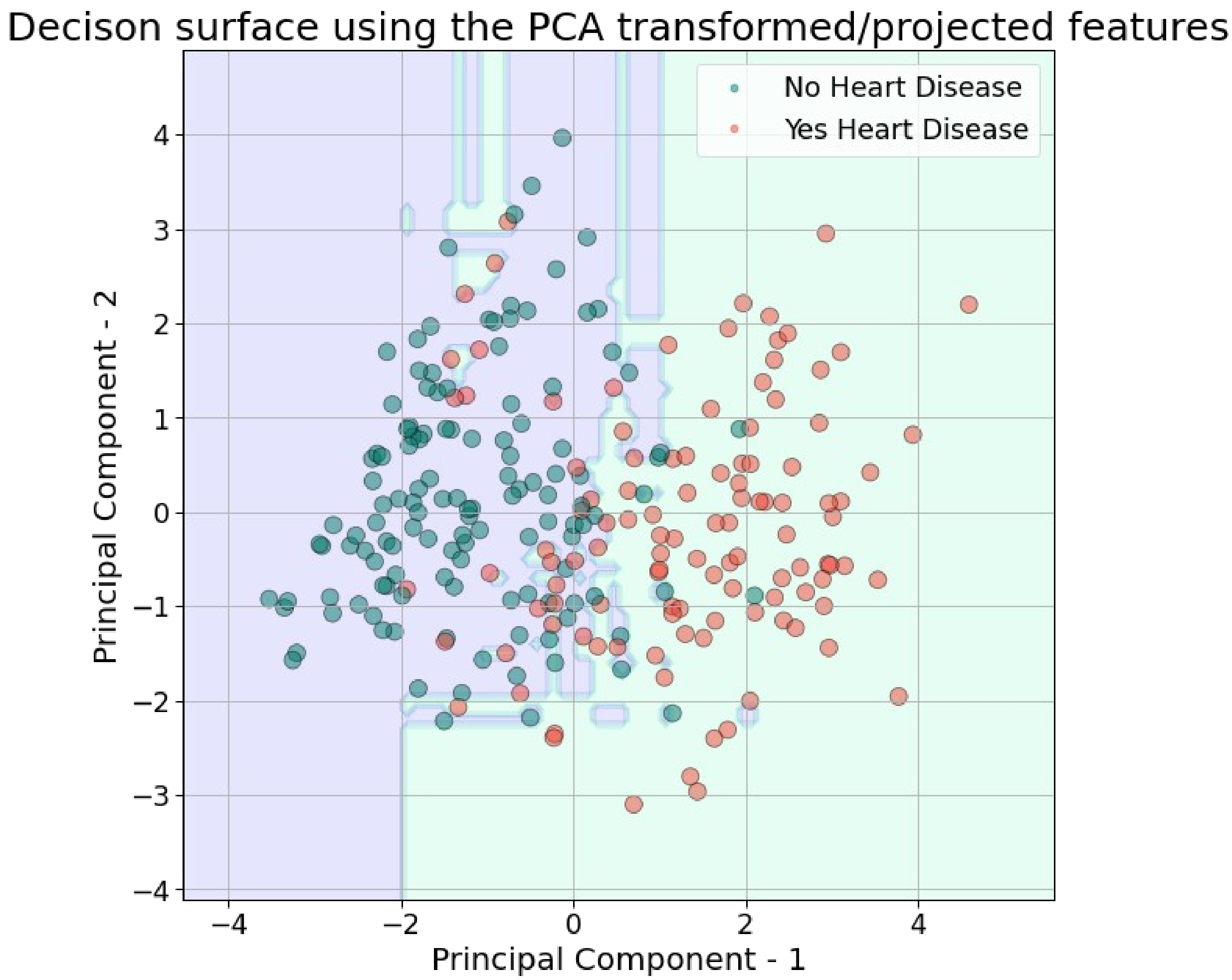
Estimator: 6



```
plotConfusionMatrixFunction('Confusion Matrix for Decision tree
Classifier',classifier,X_train,y_train)
```




```
plotClassifierGraph(classifier,X_train,X_test)
```


Decison surface using the PCA transformed/projected features
No Heart Disease
Yes Heart Disease
Principal Component - 2
Principal Component - 1
4
3
2
1
0
−1
−2
−3
−4
−4
−2
0
2
4