Import Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Read Data

In [6]:
```
df = pd.read_csv('dataset.csv')
```

Data Inspection

In [7]:
```
df.head()
```

Out[7]:

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

In [8]:
```
df.shape
```

Out[8]:
```
(1328, 14)
```

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1328 entries, 0 to 1327
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1328 non-null   int64
 1   sex       1328 non-null   int64
 2   cp        1328 non-null   int64
 3   trestbps  1328 non-null   int64
 4   chol      1328 non-null   int64
 5   fbs       1328 non-null   int64
 6   restecg   1328 non-null   int64
 7   thalach   1328 non-null   int64
 8   exang     1328 non-null   int64
```

```
 9   oldpeak   1328 non-null   float64
 10  slope     1328 non-null   int64
 11  ca        1328 non-null   int64
 12  thal      1328 non-null   int64
 13  target    1328 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 145.4 KB
```

In [10]:
```
df.describe().T
```

Out[10]:

	count	mean	std	min	25%	50%	75%	max
age	1328.0	54.418675	9.071150	29.0	48.0	56.0	61.0	77.0
sex	1328.0	0.692771	0.461519	0.0	0.0	1.0	1.0	1.0
cp	1328.0	0.948042	1.029854	0.0	0.0	1.0	2.0	3.0
trestbps	1328.0	131.614458	17.514997	94.0	120.0	130.0	140.0	200.0
chol	1328.0	246.060241	51.627522	126.0	211.0	240.0	275.0	564.0
fbs	1328.0	0.149096	0.356318	0.0	0.0	0.0	0.0	1.0
restecg	1328.0	0.529367	0.527220	0.0	0.0	1.0	1.0	2.0
thalach	1328.0	149.235693	22.975286	71.0	132.0	152.0	166.0	202.0
exang	1328.0	0.334337	0.471936	0.0	0.0	0.0	1.0	1.0
oldpeak	1328.0	1.064232	1.171519	0.0	0.0	0.8	1.8	6.2
slope	1328.0	1.388554	0.617203	0.0	1.0	1.0	2.0	2.0
ca	1328.0	0.748494	1.028603	0.0	0.0	0.0	1.0	4.0
thal	1328.0	2.321536	0.618543	0.0	2.0	2.0	3.0	3.0
target	1328.0	0.520331	0.499775	0.0	0.0	1.0	1.0	1.0

Checking missing values

In [11]:
```
df.isna().sum()
```

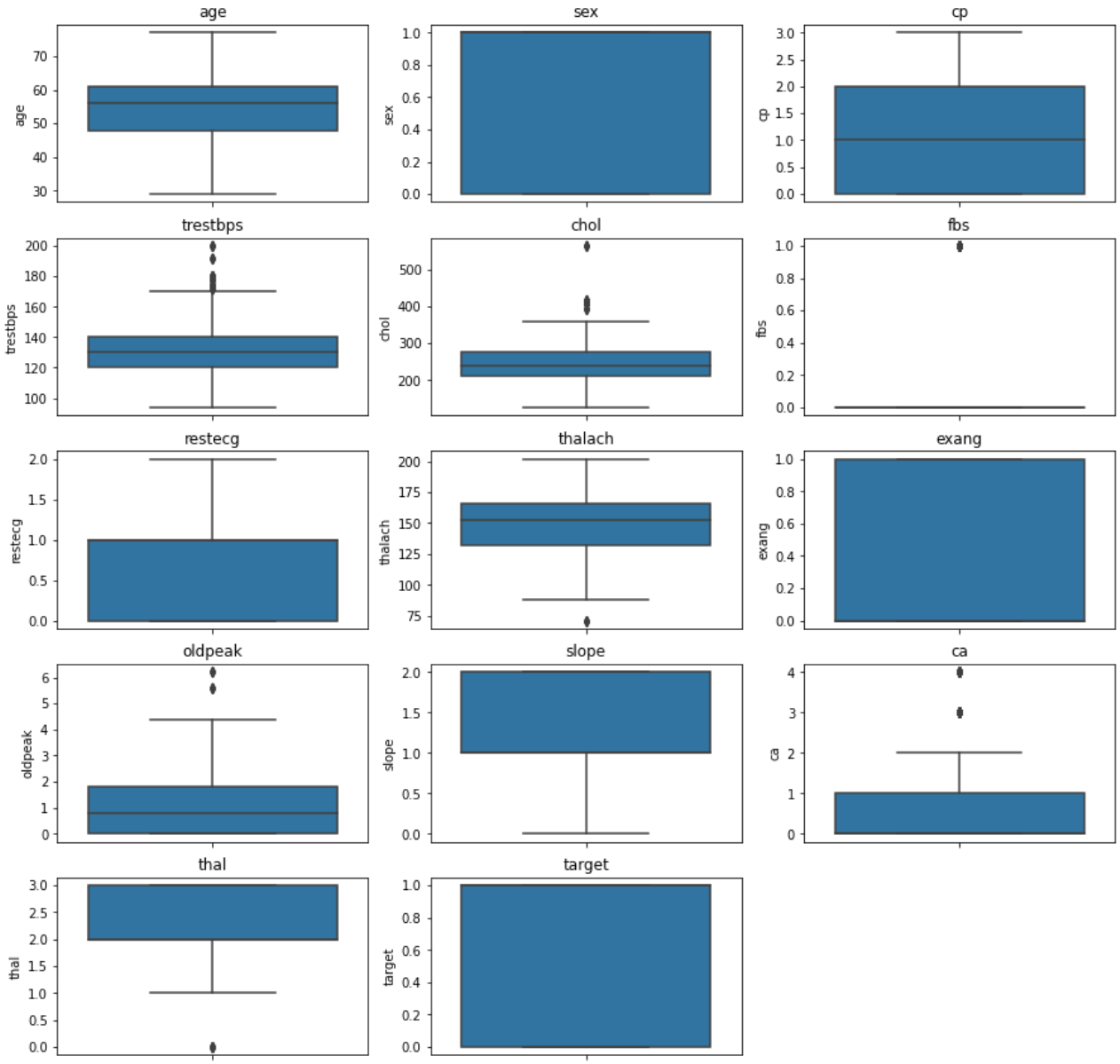
Out[11]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

Checking Outliers

In [12]:
```
df.shape
```

Out[12]:
```
(1328, 14)
```

In [13]:
```
i = 1
plt.figure(figsize=(15,15))
for x in df.columns:
    if i == 15:
        break
    else:
        plt.subplot(5,3,i)
        sns.boxplot(y=df[x])
        plt.title(x)
        #plt.show()
    i+=1
```



No Outliers, data points are in clusters, some higher data points are acceptable as it is true reading.

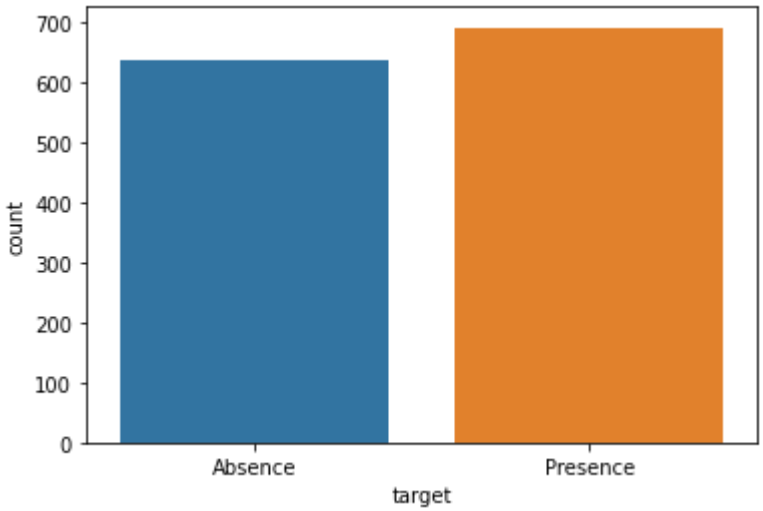
Visualization

In [14]:
```
data = df.copy()
```

In [15]:
```
data.target=data.target.map({0:'Absence',1:'Presence'})
```

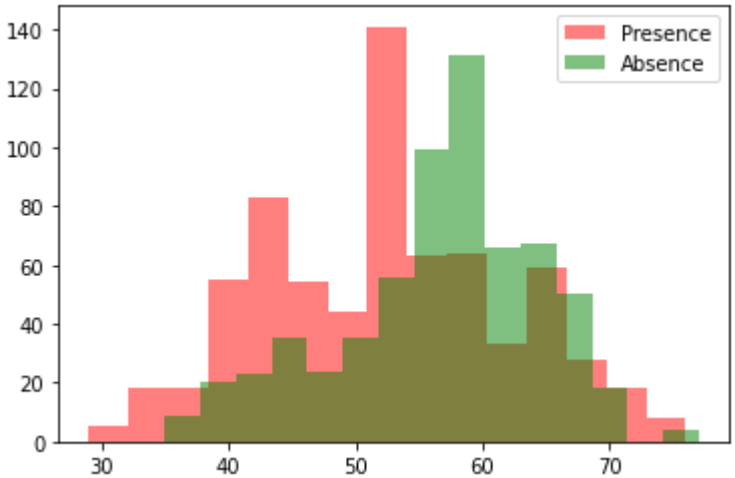
In [16]:
```
sns.countplot(data.target)
```

Out[16]:
```
<AxesSubplot:xlabel='target', ylabel='count'>
```



Disease present records are more than absent in this dataset

In [17]:
```
plt.hist(data[data.target=='Presence']['age'],color='r',alpha=0.5,bins=15,label='Presen
plt.hist(data[data.target=='Absence']['age'],color='g',alpha=0.5,bins=15,label='Absence
plt.legend()
plt.show()
```

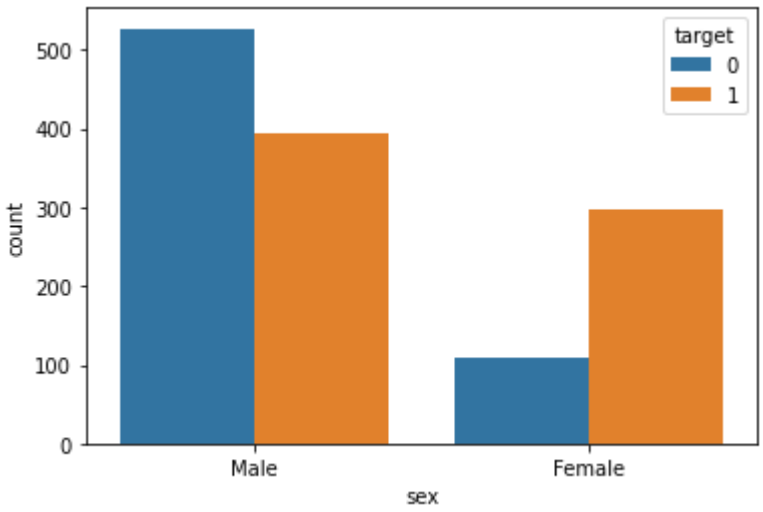


age range 40 to 60 have lot of risk of having disease

In [34]:
```
data = df.copy()
```

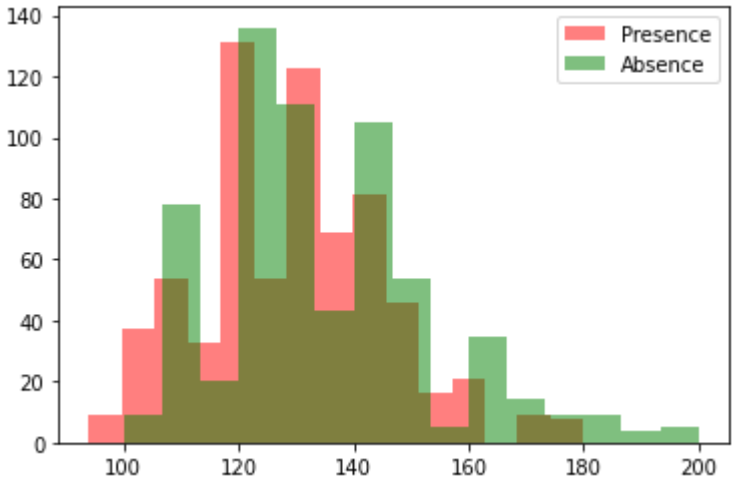
```
data.sex=data.sex.map({0:'Female',1:'Male'})
sns.countplot(data.sex,hue=data.target)
```

Out[34]:
```
<AxesSubplot:xlabel='sex', ylabel='count'>
```



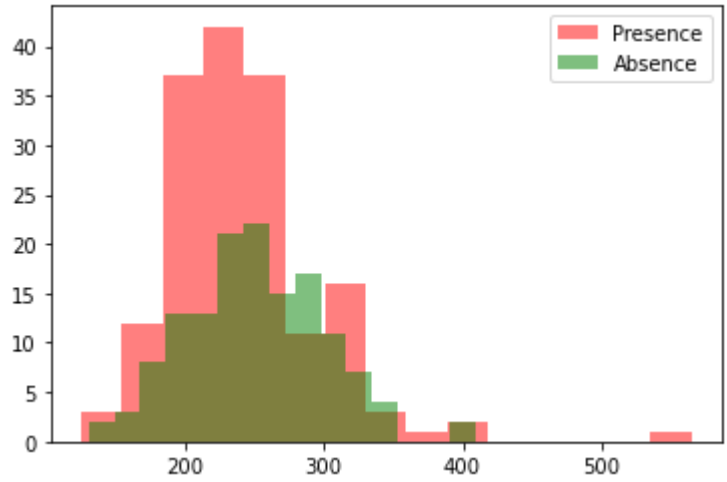
Comparing to Males, it seems more Females are having disease

In [22]:
```
plt.hist(data[data.target=='Presence']['trestbps'],color='r',alpha=0.5,bins=15,label='P
plt.hist(data[data.target=='Absence']['trestbps'],color='g',alpha=0.5,bins=15,label='Ab
plt.legend()
plt.show()
```



Resting Blood pressure looks similar for both disease presence and absence

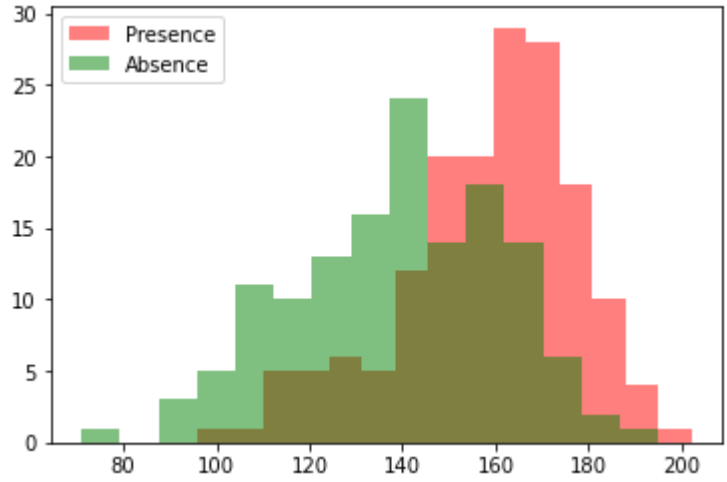
In [165…
```
plt.hist(data[data.target=='Presence']['chol'],color='r',alpha=0.5,bins=15,label='Prese
plt.hist(data[data.target=='Absence']['chol'],color='g',alpha=0.5,bins=15,label='Absenc
plt.legend()
plt.show()
```



Serum Cholestoral level between 200 to 380 mg/dl have high risk of disease

In [169…

```
plt.hist(data[data.target=='Presence']['thalach'],color='r',alpha=0.5,bins=15,label='Pr
plt.hist(data[data.target=='Absence']['thalach'],color='g',alpha=0.5,bins=15,label='Abs
plt.legend()
plt.show()
```



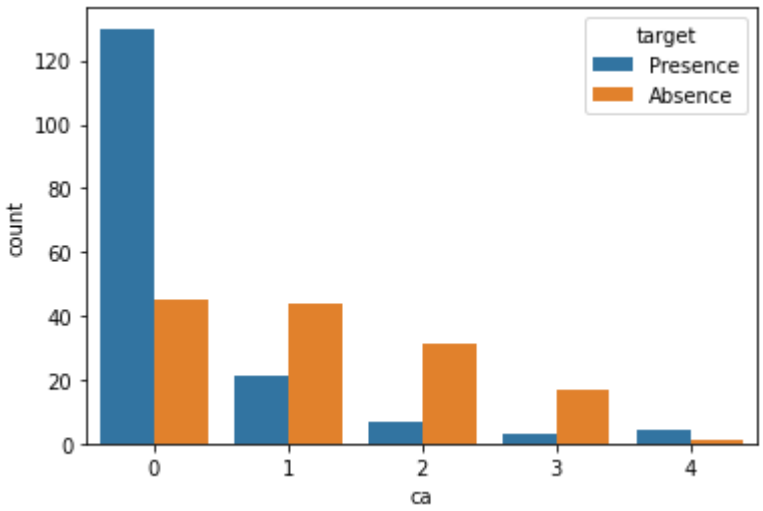
Maximun Heart Rate range between 150 to 180 have high risk of having the disease

In [174…

```
sns.countplot(data.ca,hue=data.target)
```

Out[174…

```
<AxesSubplot:xlabel='ca', ylabel='count'>
```



Less number of major vessels colored by flourosopy have risk of having the disease

Create X and Y

In [38]:
```
X = df.drop('target',axis=1)
X
```

Out[38]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
0	52	1	0	125	212	0	1	168	0	1.0	2	2	3
1	53	1	0	140	203	1	0	155	1	3.1	0	0	3
2	70	1	0	145	174	0	1	125	1	2.6	0	0	3
3	61	1	0	148	203	0	1	161	0	0.0	2	1	3
4	62	0	0	138	294	1	1	106	0	1.9	1	3	2
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1323	57	0	0	140	241	0	1	123	1	0.2	1	0	3
1324	45	1	3	110	264	0	1	132	0	1.2	1	0	3
1325	68	1	0	144	193	1	1	141	0	3.4	1	2	3
1326	57	1	0	130	131	0	1	115	1	1.2	1	1	3
1327	57	0	1	130	236	0	0	174	0	0.0	1	1	2

1328 rows × 13 columns

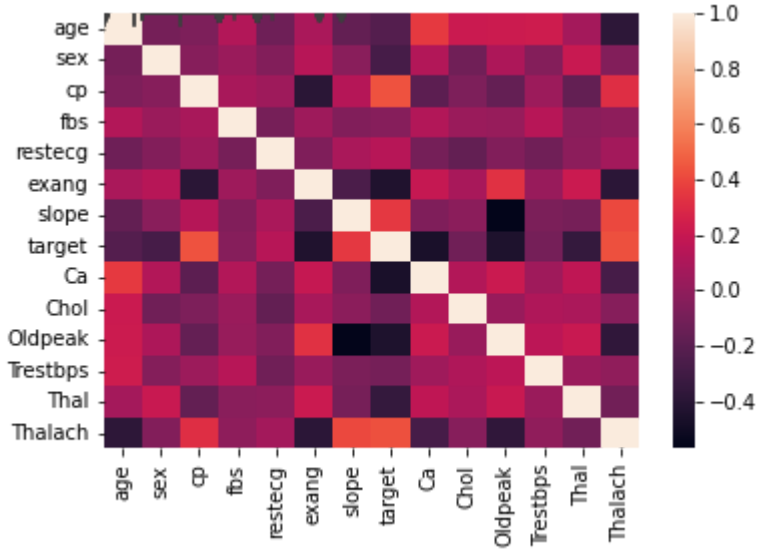
In [39]:
```
Y = df.target
```

In [37]:
```
df_m = df.copy()
import seaborn as sns
from scipy.stats.mstats import winsorize

sns.boxplot(x=df_m['ca'])
```

```
df_m['Ca']=winsorize(df_m['ca'],limits=[0.0,0.25])
df_m.drop("ca", axis=1, inplace=True)
sns.boxplot(x=df_m['Ca'])

sns.boxplot(x=df_m['chol'])

df_m['Chol']=winsorize(df_m['chol'],limits=[0.0,0.25])
sns.boxplot(x=df_m['Chol'])
df_m.drop("chol", axis=1, inplace=True)

sns.boxplot(x=df_m['oldpeak'])

df_m['Oldpeak']=winsorize(df_m['oldpeak'],limits=[0.03,0.05])
sns.boxplot(x=df_m['Oldpeak'])
df_m.drop("oldpeak", axis=1, inplace=True)

#Box Plot
sns.boxplot(x=df_m['trestbps'])

# Winsorization
df_m['Trestbps']=winsorize(df_m['trestbps'],limits=[0.0,0.25])
sns.boxplot(x=df_m['Trestbps'])
df_m.drop("trestbps", axis=1, inplace=True)

sns.boxplot(x=df_m['thal'])

df_m['Thal']=winsorize(df_m['thal'],limits=[0.03,0.05])
sns.boxplot(x=df_m['Thal'])
df_m.drop("thal", axis=1, inplace=True)


sns.boxplot(x=df_m['thalach'])

df_m['Thalach']=winsorize(df_m['thalach'],limits=[0.03,0.05])
sns.boxplot(x=df_m['Thalach'])
df_m.drop("thalach", axis=1, inplace=True)

import matplotlib.pyplot as plt

heat_map = sns.heatmap(df_m.corr())

plt.show()

#Decision Tree Classifier


from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn import metrics

feature_cols = ["age", "sex", "cp", "Trestbps", "Chol", "fbs", "restecg", "Thalach", "e
X = df_m[feature_cols]
y = df_m.target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1
clf = DecisionTreeClassifier()
clf = clf.fit(X_train,y_train)
```

```
print(df_m)

y_pred = clf.predict(X_test)
print("\n\n->Decision Tree Classifier<-")
print("\nAccuracy:",metrics.accuracy_score(y_test, y_pred))


# Logistic Regression


from sklearn.linear_model import LogisticRegression


feature_cols = ["age", "sex", "cp", "Trestbps", "Chol", "fbs", "restecg", "Thalach", "e
x = df_m[feature_cols]
y = df_m.target

from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(
        x, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc_x = StandardScaler()
xtrain = sc_x.fit_transform(xtrain)
xtest = sc_x.transform(xtest)




classifier = LogisticRegression(random_state = 0)
classifier.fit(xtrain, ytrain)

y_pred = classifier.predict(xtest)

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(ytest, y_pred)

print ("\nConfusion Matrix : \n", cm)

from sklearn.metrics import accuracy_score
print("\n\n->Logistic Regression<-")

print ("\nAccuracy : ", accuracy_score(ytest, y_pred))


#Random Forest


feature_cols = ["age", "sex", "cp", "Trestbps", "Chol", "fbs", "restecg", "Thalach", "e
X = df_m[feature_cols]
y = df_m.target

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

from sklearn.ensemble import RandomForestClassifier

#Create a Gaussian Classifier
clf=RandomForestClassifier(n_estimators=150)

#Train the model using the training sets y_pred=clf.predict(X_test)
```

```
clf.fit(X_train,y_train)

y_pred=clf.predict(X_test)

#Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics
# Model Accuracy, how often is the classifier correct?
print("\n\n->Random Forest<-")
print("\nAccuracy:",metrics.accuracy_score(y_test, y_pred))


#### Naive Bayes####
# Import LabelEncoder
from sklearn import preprocessing



feature_cols = ["age", "sex", "cp", "Trestbps", "Chol", "fbs", "restecg", "Thalach", "e
X = df_m[feature_cols]
y = df_m.target


# Import train_test_split function
from sklearn.model_selection import train_test_split

# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.3,random_state=109
#Import Gaussian Naive Bayes model


from sklearn.naive_bayes import GaussianNB

#Create a Gaussian Classifier
model = GaussianNB()

# Train the model using the training sets
model.fit(X_train,y_train)

#Predict Output
y_pred= model.predict(X_test) # 0:Overcast, 2:Mild
#print("Predicted Value:", y_pred)


#Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics

# Model Accuracy, how often is the classifier correct?
print("\n\n->Naive Bayes<-")
print("\nAccuracy:",metrics.accuracy_score(y_test, y_pred))
```



	age	sex	cp	fbs	restecg	exang	slope	target	Ca	Chol	Oldpeak	\
0	52	1	0	0	1	0	2	0	1	212	1.0	
1	53	1	0	1	0	1	0	0	0	203	3.1	
2	70	1	0	0	1	1	0	0	0	174	2.6	
3	61	1	0	0	1	0	2	0	1	203	0.0	
4	62	0	0	1	1	0	1	0	1	275	1.9	
...	...	...	..	...	...	...	...	...	..	...	...	
1323	57	0	0	0	1	1	1	0	0	241	0.2	
1324	45	1	3	0	1	0	1	0	0	264	1.2	
1325	68	1	0	1	1	0	1	0	1	193	3.4	
1326	57	1	0	0	1	1	1	0	1	131	1.2	
1327	57	0	1	0	0	0	1	0	1	236	0.0	

	Trestbps	Thal	Thalach
0	125	3	168
1	140	3	155
2	140	3	125
3	140	3	161
4	138	2	106
...	...	...	...
1323	140	3	123
1324	110	3	132
1325	140	3	141
1326	130	3	115
1327	130	2	174

[1328 rows x 14 columns]

->Decision Tree Classifier<-

Accuracy: 1.0

Confusion Matrix :
 [[129 31]
 [24 148]]

->Logistic Regression<-

Accuracy : 0.8343373493975904

```
->Random Forest<-

Accuracy: 1.0


->Naive Bayes<-

Accuracy: 0.8270676691729323
```