Healthcare

December 6, 2022

0.1 Project : Health Care

0.1.1 Description:

Cardiovascular diseases are the leading cause of death globally. It is therefore necessary to identify the causes and develop a system to predict heart attacks in an effective manner. The data below has the information about the factors that might have an impact on cardiovascular health.

Dataset description:

Variable	Description
Age	Age in years
Sex	1 = male; 0 = female
cp	Chest pain type
trestbps	Resting blood pressure (in mm Hg on admission to the hospital)
chol	Serum cholesterol in mg/dl
fbs	Fasting blood sugar > 120 mg/dl (1 = true; 0 = false)
restecg	Resting electrocardiographic results
thalach	Maximum heart rate achieved
exang	Exercise induced angina (1 = yes; 0 = no)
oldpeak	ST depression induced by exercise relative to rest
slope	Slope of the peak exercise ST segment
ca	Number of major vessels (0-3) colored by fluoroscopy
thal	3 = normal; 6 = fixed defect; 7 = reversible defect
Target	1 or 0

Note:

Download CEP 1_ Dataset.xlsx using the link given in the Healthcare project problem statement

Task to be performed:

1. Preliminary analysis:

    a. Perform preliminary data inspection and report the findings on the structure of the data, missing values, duplicates, etc.

    b. Based on these findings, remove duplicates (if any) and treat missing values using an appropriate strategy

2. Prepare a report about the data explaining the distribution of the disease and the related factors using the steps listed below:

    a. Get a preliminary statistical summary of the data and explore the measures of central tendencies and spread of the data

    b. Identify the data variables which are categorical and describe and explore these variables using the appropriate tools, such as count plot

    c. Study the occurrence of CVD across the Age category

    d. Study the composition of all patients with respect to the Sex category

    e. Study if one can detect heart attacks based on anomalies in the resting blood pressure (trestbps) of a patient

    f. Describe the relationship between cholesterol levels and a target variable

    g. State what relationship exists between peak exercising and the occurrence of a heart attack

    h. Check if thalassemia is a major cause of CVD

    i. List how the other factors determine the occurrence of CVD

    j. Use a pair plot to understand the relationship between all the given variables

3. Build a baseline model to predict the risk of a heart attack using a logistic regression and random forest and explore the results while using correlation analysis and logistic regression (leveraging standard error and p-values from statsmodels) for feature selection

[1]:
```
## Importing required Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.ensemble import RandomForestClassifier

import warnings
warnings.filterwarnings('ignore')
```

0.1.2 Reading the dataset

[3]:
```
healthcare=pd.read_excel('1645792390_cep1_dataset.xlsx')
```

[4]:
```
healthcare.head()
```

[4]:
```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  \
0   63    1   3       145   233    1        0      150      0      2.3      0
1   37    1   2       130   250    0        1      187      0      3.5      0
2   41    0   1       130   204    0        0      172      0      1.4      2
3   56    1   1       120   236    0        1      178      0      0.8      2
4   57    0   0       120   354    0        1      163      1      0.6      2

   ca  thal  target
0   0     1       1
1   0     2       1
2   0     2       1
3   0     2       1
4   0     2       1
```

0.1.3 Preliminary Analysis

a. Perform preliminary data inspection and report the findings on the structure of the data, missing values, duplicates, etc.

[5]:
```
healthcare.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       303 non-null    int64
 1   sex       303 non-null    int64
 2   cp        303 non-null    int64
 3   trestbps  303 non-null    int64
 4   chol      303 non-null    int64
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    int64
 7   thalach   303 non-null    int64
 8   exang     303 non-null    int64
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64
 11  ca        303 non-null    int64
 12  thal      303 non-null    int64
 13  target    303 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

[6]:
```
healthcare.isna().sum()
```

[6]:
```
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
```

- *No Missing Values in Dataset*

[7]:
```
healthcare[healthcare.duplicated()]
```

[7]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
164   38    1   2       138   175    0        1      173      0      0.0

     slope  ca  thal  target
164      2   4     2       1
```

- *One Duplicate observation is present*

  b. Based on these findings, remove duplicates (if any) and treat missing values using an appropriate strategy

[8]:
```
# Removing the duplicates from the dataset
healthcare.drop_duplicates(inplace=True)
```

[9]:
```
healthcare.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 302 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       302 non-null    int64
 1   sex       302 non-null    int64
 2   cp        302 non-null    int64
 3   trestbps  302 non-null    int64
 4   chol      302 non-null    int64
 5   fbs       302 non-null    int64
 6   restecg   302 non-null    int64
 7   thalach   302 non-null    int64
```

```
 8   exang      302 non-null    int64  
 9   oldpeak    302 non-null    float64
 10  slope      302 non-null    int64  
 11  ca         302 non-null    int64  
 12  thal       302 non-null    int64  
 13  target     302 non-null    int64  
dtypes: float64(1), int64(13)
memory usage: 35.4 KB
```

0.1.4 Prepare a report about the data explaining the distribution of the disease and the related factors using the steps listed below:

a. Get a preliminary statistical summary of the data and explore the measures of central tendencies and spread of the data

[10]:
```
# Statistical Summary of the data
healthcare.describe().T
```

[10]:

	count	mean	std	min	25%	50%	75%	max
age	302.0	54.420530	9.047970	29.0	48.00	55.5	61.00	77.0
sex	302.0	0.682119	0.466426	0.0	0.00	1.0	1.00	1.0
cp	302.0	0.963576	1.032044	0.0	0.00	1.0	2.00	3.0
trestbps	302.0	131.602649	17.563394	94.0	120.00	130.0	140.00	200.0
chol	302.0	246.500000	51.753489	126.0	211.00	240.5	274.75	564.0
fbs	302.0	0.149007	0.356686	0.0	0.00	0.0	0.00	1.0
restecg	302.0	0.526490	0.526027	0.0	0.00	1.0	1.00	2.0
thalach	302.0	149.569536	22.903527	71.0	133.25	152.5	166.00	202.0
exang	302.0	0.327815	0.470196	0.0	0.00	0.0	1.00	1.0
oldpeak	302.0	1.043046	1.161452	0.0	0.00	0.8	1.60	6.2
slope	302.0	1.397351	0.616274	0.0	1.00	1.0	2.00	2.0
ca	302.0	0.718543	1.006748	0.0	0.00	0.0	1.00	4.0
thal	302.0	2.314570	0.613026	0.0	2.00	2.0	3.00	3.0
target	302.0	0.543046	0.498970	0.0	0.00	1.0	1.00	1.0

b. Identify the data variables which are categorical and describe and explore these variables using the appropriate tools, such as count plot

[11]:
```
# Selecting the categorical data
healthcare_category=healthcare[['sex','cp','fbs','restecg','exang','slope','ca','thal','target
healthcare_category.describe()
```

[11]:

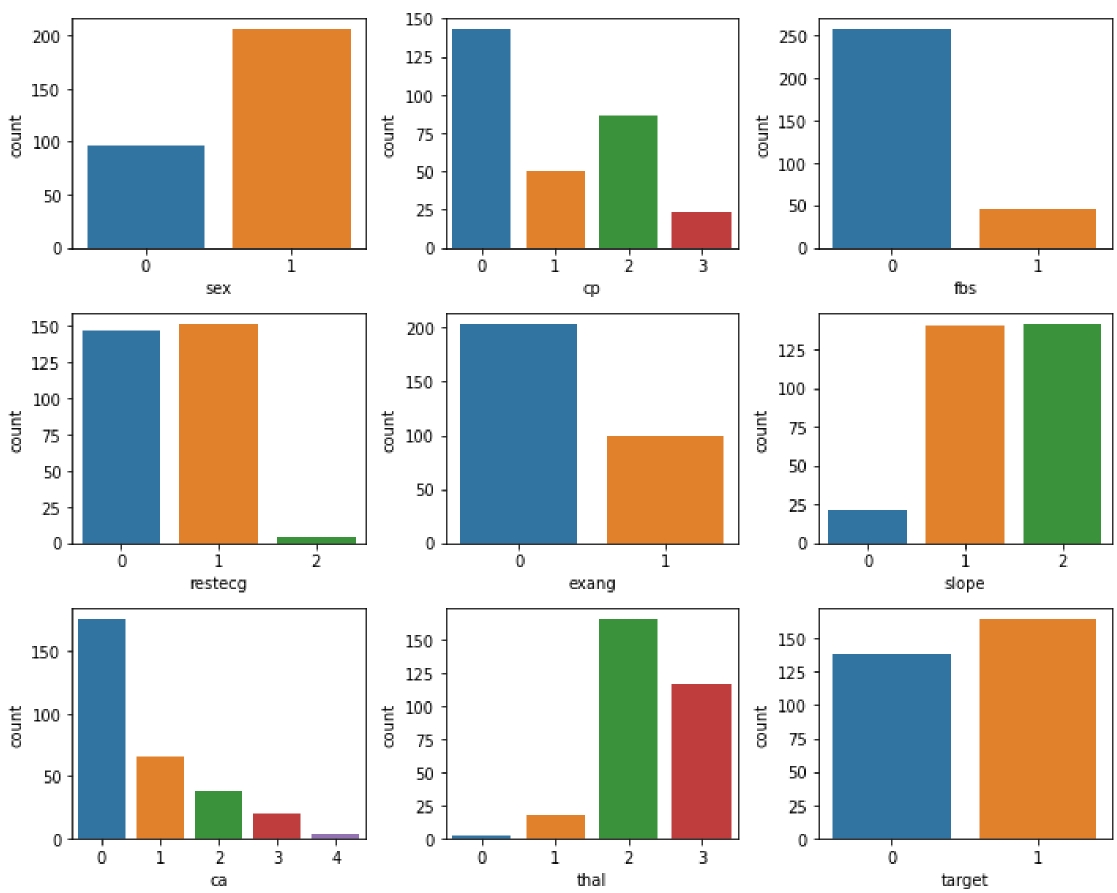
	sex	cp	fbs	restecg	exang	slope	\
count	302.000000	302.000000	302.000000	302.000000	302.000000	302.000000	
mean	0.682119	0.963576	0.149007	0.526490	0.327815	1.397351	
std	0.466426	1.032044	0.356686	0.526027	0.470196	0.616274	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	

```
50%        1.000000    1.000000    0.000000    1.000000    0.000000    1.000000
75%        1.000000    2.000000    0.000000    1.000000    1.000000    2.000000
max        1.000000    3.000000    1.000000    2.000000    1.000000    2.000000

                ca        thal      target
count  302.000000  302.000000  302.000000
mean     0.718543    2.314570    0.543046
std      1.006748    0.613026    0.498970
min      0.000000    0.000000    0.000000
25%      0.000000    2.000000    0.000000
50%      0.000000    2.000000    1.000000
75%      1.000000    3.000000    1.000000
max      4.000000    3.000000    1.000000
```

[12]:

```python
# Exploring the variables using count plot
plt.figure(figsize=(10,8))
for i in range(0,9):
    plt.subplot(3,3,i+1)
    sns.countplot(healthcare_category.iloc[:,i])
    i=i+1
    plt.tight_layout();
```



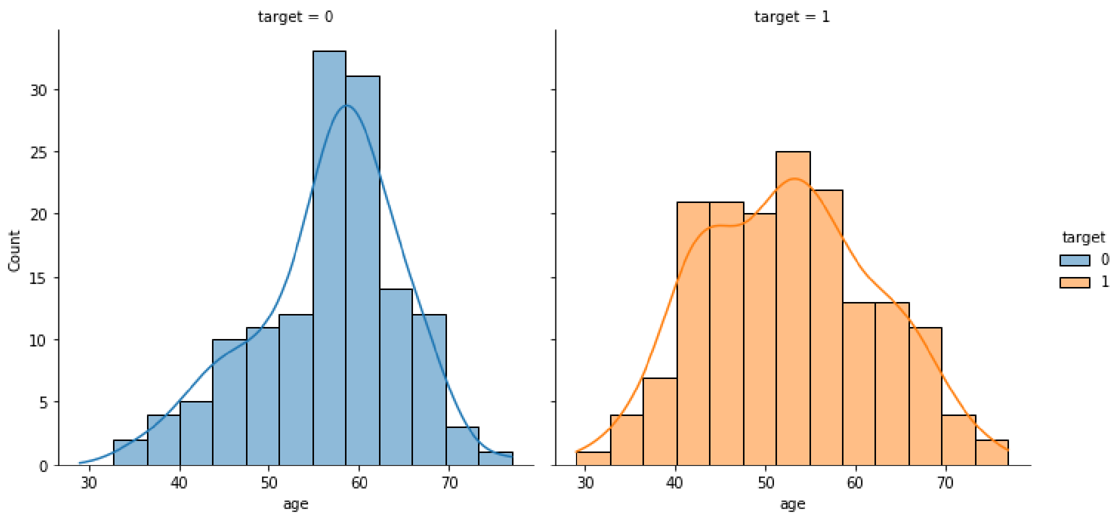
c. Study the occurrence of CVD across the Age category

[13]:
```
# Agewise distribution of patients : target column 1 indicates diseased and␣
↪column 0 indicates non diseased
healthcare.
↪pivot_table(index=['age'],values=['sex'],columns='target',aggfunc='count')
```

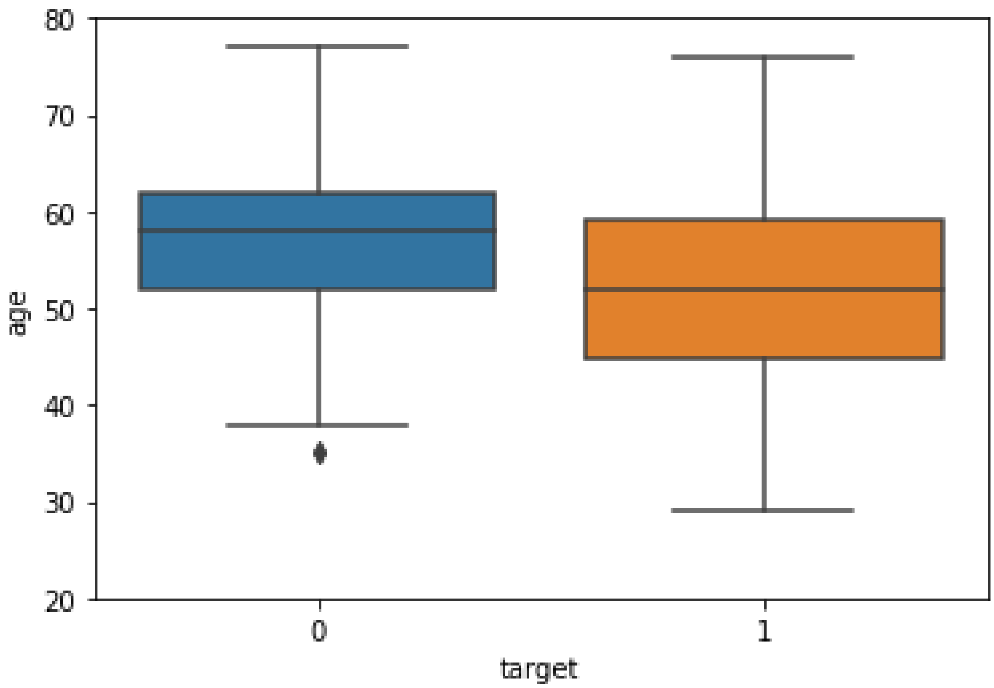
[13]:
```
         sex
target     0     1
age
29       NaN   1.0
34       NaN   2.0
35       2.0   2.0
37       NaN   2.0
38       1.0   1.0
39       1.0   3.0
40       2.0   1.0
41       1.0   9.0
42       1.0   7.0
43       3.0   5.0
44       3.0   8.0
45       2.0   6.0
46       3.0   4.0
47       2.0   3.0
48       3.0   4.0
49       2.0   3.0
50       3.0   4.0
51       3.0   9.0
52       4.0   9.0
53       2.0   6.0
54       6.0  10.0
55       5.0   3.0
56       6.0   5.0
57      10.0   7.0
58      12.0   7.0
59       9.0   5.0
60       8.0   3.0
61       7.0   1.0
62       7.0   4.0
63       6.0   3.0
64       4.0   6.0
65       4.0   4.0
66       3.0   4.0
67       6.0   3.0
68       2.0   2.0
```

```
69          1.0    2.0
70          3.0    1.0
71          NaN    3.0
74          NaN    1.0
76          NaN    1.0
77          1.0    NaN
```

[14]:
```
# Age wise data distribution plot, target=1 for diseased and target=0 for non␣
↪diseased
sns.displot(healthcare,x='age',col='target',hue='target',kde=True);
```



[15]:
```
# Age wise data distribution showed using boxplot, target=1 for diseased and␣
↪target=0 for non diseased
sns.boxplot(x=healthcare['target'],y=healthcare['age'])
plt.ylim(20,80);
```



d. Study the composition of all patients with respect to the Sex category

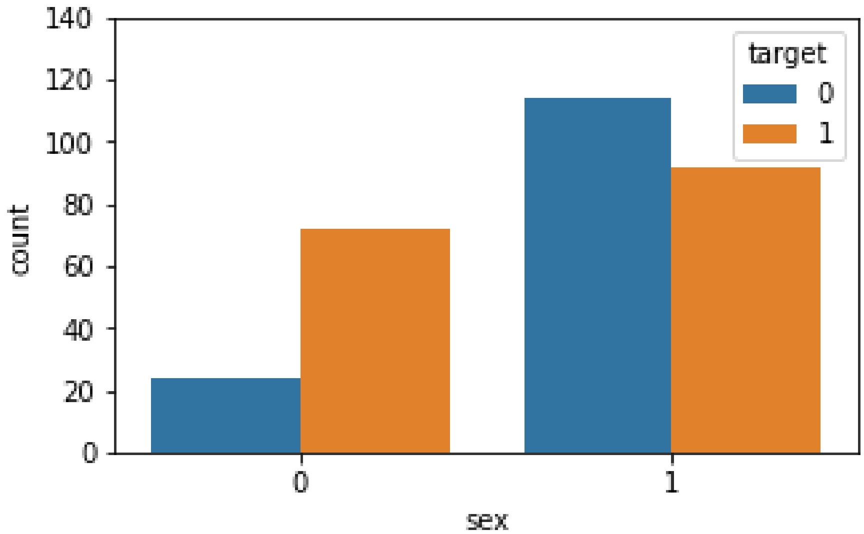
[16]:
```
# Composition of all patients with respect to sex (1=male,0=female) and␣
↪diseased (target=1)
# and non diseased (target=0)
CVD_by_sex=pd.DataFrame({"Count":healthcare.groupby('target')['sex'].
↪value_counts()})
CVD_by_sex
```

[16]:

target	sex	Count
0	1	114
	0	24
1	1	92
	0	72

[17]:
```
# plot shows male and female distribution with respect to diseased and␣
↪nondiseased

plt.figure(figsize=(5,3))
sns.countplot(data=healthcare,x='sex',hue='target')
plt.ylim(0,140);
```



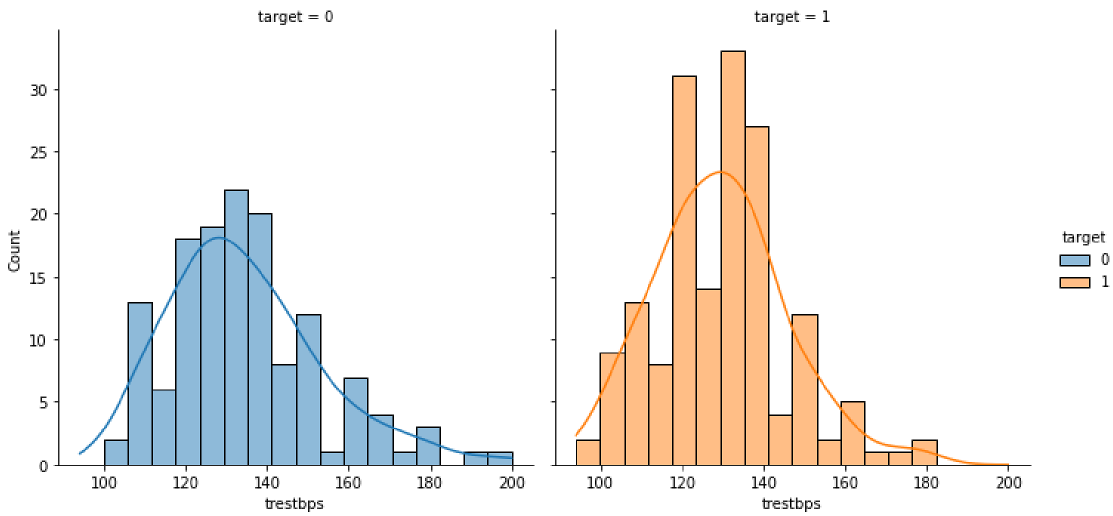
e. Study if one can detect heart attacks based on anomalies in the resting blood pressure (trestbps) of a patient

[18]:
```
# Statistical summary of the patients blood pressure
healthcare.groupby('target')['trestbps'].describe()
```

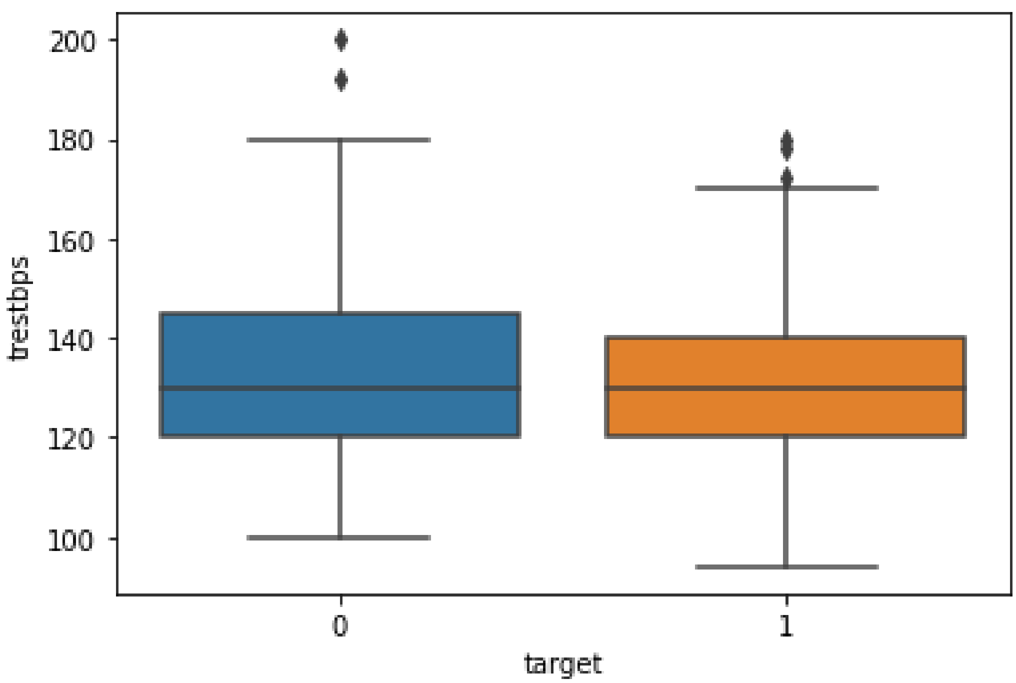
[18]:

target	count	mean	std	min	25%	50%	75%	max
0	138.0	134.398551	18.729944	100.0	120.0	130.0	144.75	200.0
1	164.0	129.250000	16.204739	94.0	120.0	130.0	140.00	180.0

[19]:
```
# Resting Blood pressure of the patients distribution plot for diseased␣
↪(target=1) and
# nondiseased patients (target=0)
sns.displot(healthcare,x='trestbps',col='target',hue='target',kde=True);
```



[20]:
```
# Representation of the blood pressure distribution using boxplot  for diseased␣
↪(target=1) and
# nondiseased patients (target=0)
sns.boxplot(x=healthcare['target'],y=healthcare['trestbps']);
```



f. Describe the relationship between cholesterol levels and a target variable

[21]:
```python
# Statistical summary of cholestrol level for diseased (target=1) and non␣
↪diseased patients (target=0)
healthcare.groupby('target')['chol'].describe()
```

[21]:

target	count	mean	std	min	25%	50%	75%	max
0	138.0	251.086957	49.454614	131.0	217.25	249.0	283.00	409.0
1	164.0	242.640244	53.456580	126.0	208.75	234.5	267.25	564.0

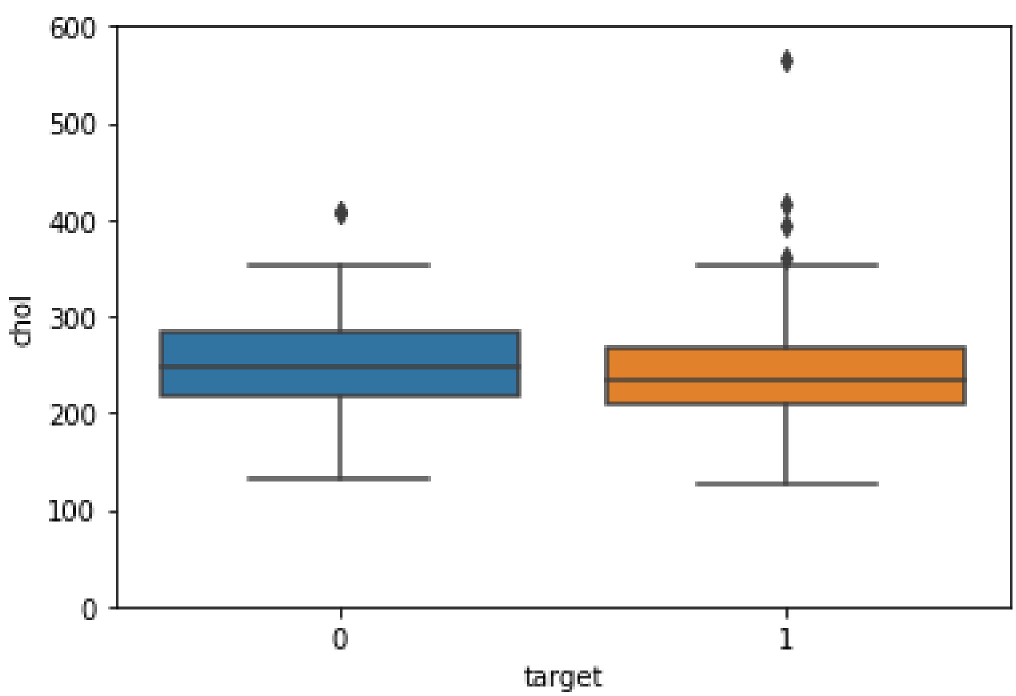
[22]:
```python
# Correlation between cholesterol levels and a target variable
healthcare[['target','chol']].corr()
```

[22]:

	target	chol
target	1.000000	-0.081437
chol	-0.081437	1.000000

Cholesterol variable is negatively correlated with the target variable

[23]:
```python
# Distribution of cholestrol level for diseased (target=1) and non diseased␣
↪patients (target=0)
sns.boxplot(x=healthcare['target'],y=healthcare['chol'])
plt.ylim(0,600);
```



g. State what relationship exists between peak exercising and the occurrence of a heart attack

[24]:
```
# Statistical summary of exercise parameters( exang-Exercise induced anigna,
# Old peak -ST depression induced by exercise relative to rest,Slope-slope of␣
 ↪Peak exercise ST Segment)
#with respect to target variable
healthcare.groupby('target')[['exang','oldpeak','slope']].describe().T
```

[24]:
```
target                 0           1
exang   count  138.000000  164.000000
        mean     0.550725    0.140244
        std      0.499232    0.348303
        min      0.000000    0.000000
        25%      0.000000    0.000000
        50%      1.000000    0.000000
        75%      1.000000    0.000000
        max      1.000000    1.000000
oldpeak count  138.000000  164.000000
        mean     1.585507    0.586585
        std      1.300340    0.781734
        min      0.000000    0.000000
        25%      0.600000    0.000000
        50%      1.400000    0.200000
        75%      2.500000    1.025000
        max      6.200000    4.200000
slope   count  138.000000  164.000000
        mean     1.166667    1.591463
        std      0.561324    0.594598
        min      0.000000    0.000000
        25%      1.000000    1.000000
        50%      1.000000    2.000000
        75%      1.750000    2.000000
        max      2.000000    2.000000
```

[25]:
```
# Correlation of exercise parameters with respect to target variable
exe_corr=healthcare[['exang','oldpeak','slope','target']].corr()
sns.heatmap(exe_corr,annot=True)
```

[25]: <AxesSubplot:>

Slope (slope of Peak exercise ST Segment) is positively correlated to target variable

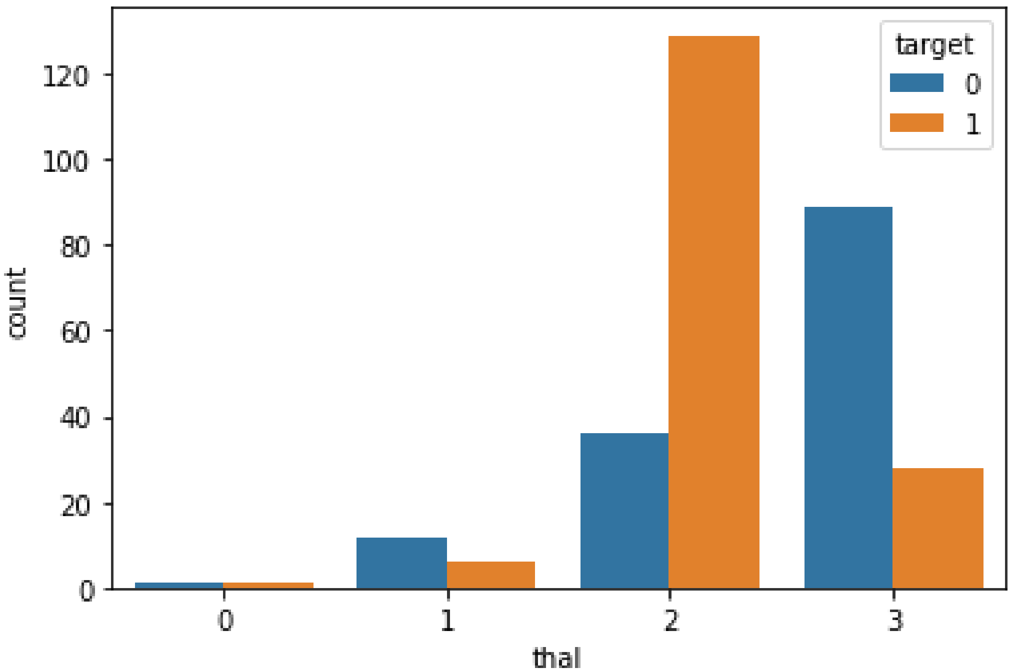
Old peak (ST depression induced by exercise relative to rest) and exang (Exercise induced anigna) variables are negatively correlated to target variable

h. Check if thalassemia is a major cause of CVD

[26]:
```python
# Distribution of diseased(target =1)and non diseased (target=0) patients␣
↪across thalassemia categories
healthcare.
↪pivot_table(index='thal',values='age',columns='target',aggfunc='count')
```

[26]:
```
target   0    1
thal
0        1    1
1       12    6
2       36  129
3       89   28
```

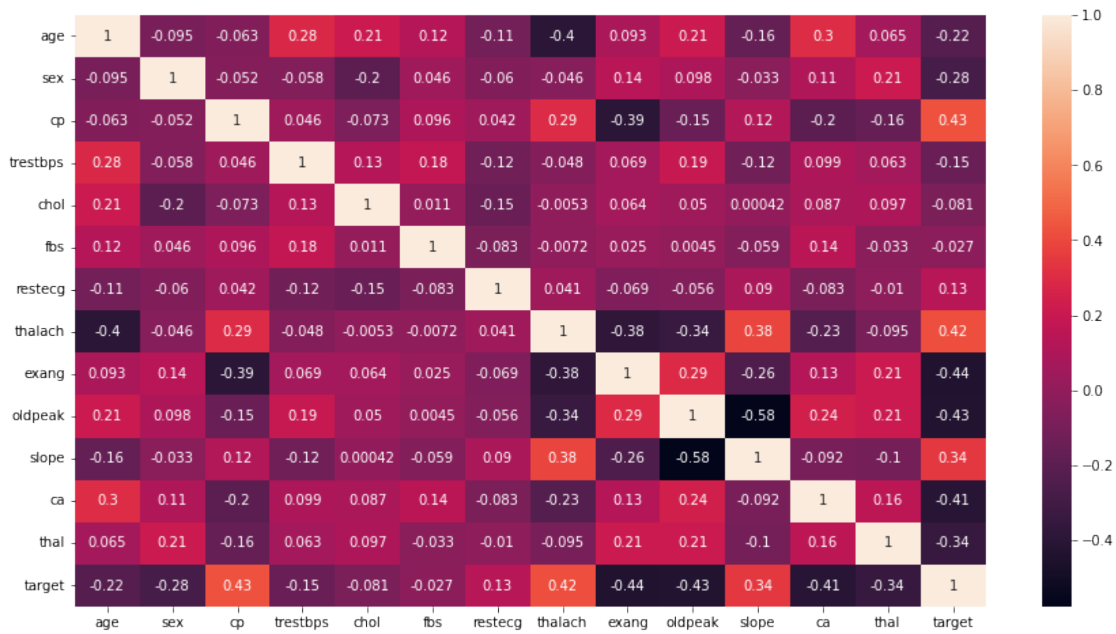
[27]:
```python
# Distribution of diseased(target =1)and non diseased (target=0) patients␣
↪across thalassemia categories
sns.countplot(healthcare['thal'],hue=healthcare['target']);
```



Diseased patients are more in thalassemia category 2 (fixed_defect)

i. List how the other factors determine the occurrence of CVD

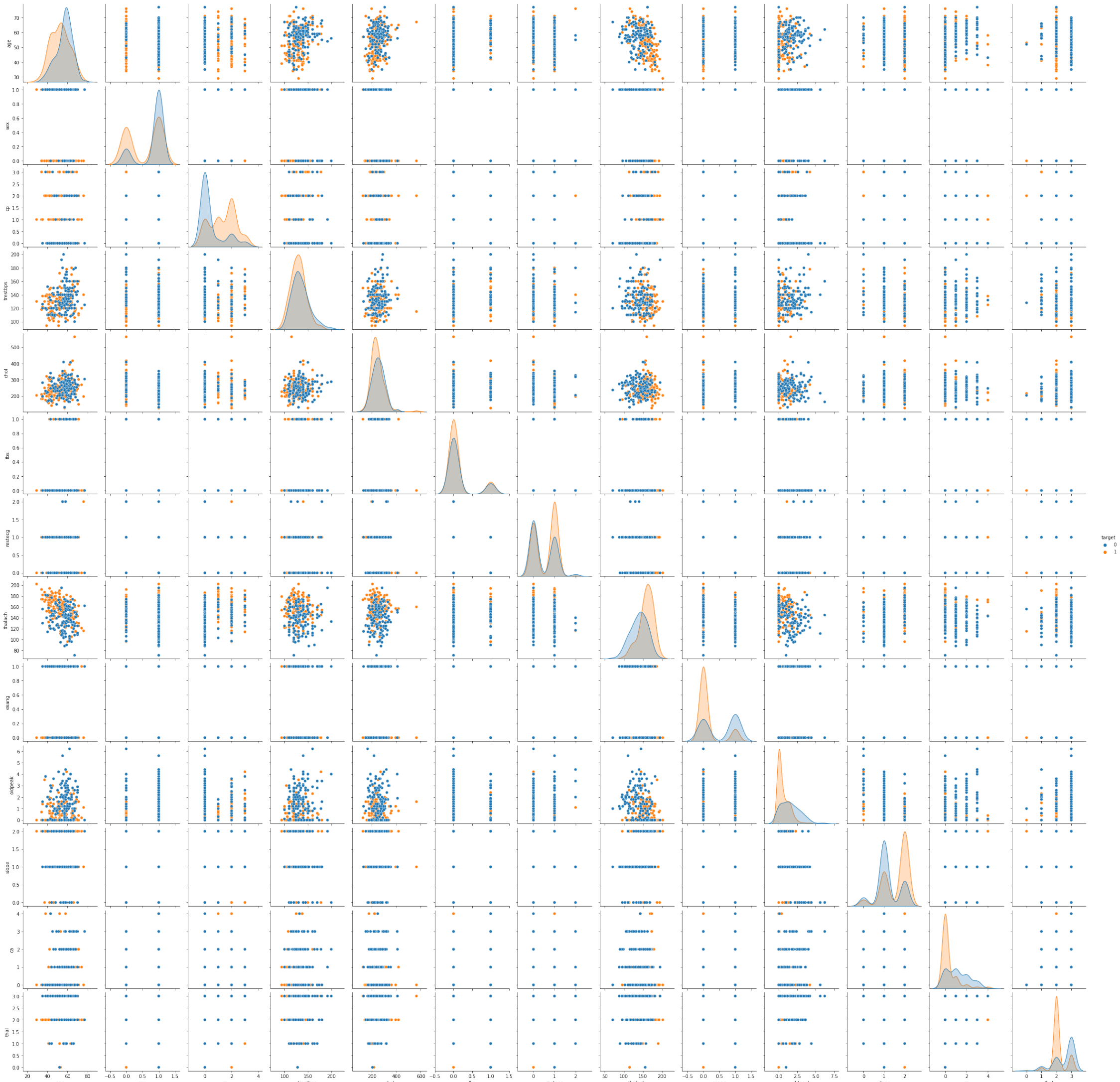
[28]:
```python
# Correlation of all the variables are represented using heatmap
plt.figure(figsize=(15,8))
sns.heatmap(healthcare.corr(),annot=True);
```



Variable Name	Correlation with Target Variable
Age	Negatively corrleated
Sex	Negatively correlated
cp(chest pain type)	Positively correlated
trestbps(Resting blood pressure)	Negatively corrleated
chol (Serum cholestrol)	Negatively corrleated
fbs (Fasting blood sugar)	Negatively corrleated
restecg (Resting electrocardio-graphic results)	Positively correlated
thalach (Maximum heart rate achieved)	Positively correlated
exang (Exercise induced angina)	Negatively corrleated
oldpeak (ST depression induced by exercise relative to rest)	Negatively corrleated
slope (Slope of the peak exercise ST segment)	Positively correlated
ca (Number of major vessels)	Negatively corrleated
thal (thalassemia)	Negatively corrleated

Use a pair plot to understand the relationship between all the given variables

[29]:
```
sns.pairplot(healthcare,hue="target");
```



0.1.5 3. Build a baseline model to predict the risk of a heart attack using a logistic regression and random forest and explore the results while using correlation analysis and logistic regression (leveraging standard error and p-values from statsmodels) for feature selection

[30]:
```
# Defining X and y variables for the model
X=healthcare.drop('target',axis=1)
y=healthcare['target']
```

[31]:
```
X.shape,y.shape
```

[31]: ((302, 13), (302,))

[32]:
```
# Scaling the X variables data
scaler=StandardScaler()
X_scaled=pd.DataFrame(scaler.fit_transform(X),columns=X.columns)
```

[33]:
```
X_scaled.describe().T
```

[33]:
```
          count          mean      std       min       25%       50%  \
age       302.0 -2.724090e-16  1.00166 -2.814192 -0.710788  0.119503
sex       302.0 -2.492487e-16  1.00166 -1.464866 -1.464866  0.682656
cp        302.0 -1.666943e-16  1.00166 -0.935208 -0.935208  0.035352
trestbps  302.0 -8.053712e-16  1.00166 -2.144521 -0.661712 -0.091401
chol      302.0 -2.086263e-17  1.00166 -2.332210 -0.687083 -0.116127
fbs       302.0 -3.529186e-17  1.00166 -0.418446 -0.418446 -0.418446
restecg   302.0  8.455341e-17  1.00166 -1.002541 -1.002541  0.901657
thalach   302.0 -4.087974e-16  1.00166 -3.436149 -0.713716  0.128160
exang     302.0 -5.440828e-17  1.00166 -0.698344 -0.698344 -0.698344
oldpeak   302.0 -1.948405e-16  1.00166 -0.899544 -0.899544 -0.209608
slope     302.0  5.168787e-16  1.00166 -2.271182 -0.645834 -0.645834
ca        302.0 -1.224186e-15  1.00166 -0.714911 -0.714911 -0.714911
thal      302.0  7.183364e-16  1.00166 -3.781916 -0.513994 -0.513994

               75%       max
age       0.728383  2.499671
sex       0.682656  0.682656
cp        1.005911  1.976470
trestbps  0.478910  3.900776
chol      0.546763  6.145034
fbs      -0.418446  2.389793
restecg   0.901657  2.805854
thalach   0.718568  2.292987
exang     1.431958  1.431958
oldpeak   0.480328  4.447460
slope     0.979514  0.979514
ca        0.280034  3.264871
thal      1.119967  1.119967
```

[34]:
```
train_X,test_X,train_Y,test_Y=train_test_split(X_scaled,y,test_size=0.
↪3,random_state=200)
```

[35]:
```
train_X.shape,test_X.shape,train_Y.shape,test_Y.shape
```

[35]: ((211, 13), (91, 13), (211,), (91,))

Logistic Regression Model

[36]:
```
log_reg=LogisticRegression()
log_reg.fit(train_X,train_Y)
```

[36]: LogisticRegression()

[37]:
```
# Accuracy score for Train and test data
print('Train Score:{}'.format(log_reg.score(train_X,train_Y)))
print('Test Score:{}'.format(log_reg.score(test_X,test_Y)))
```

```
Train Score:0.8530805687203792
Test Score:0.8901098901098901
```

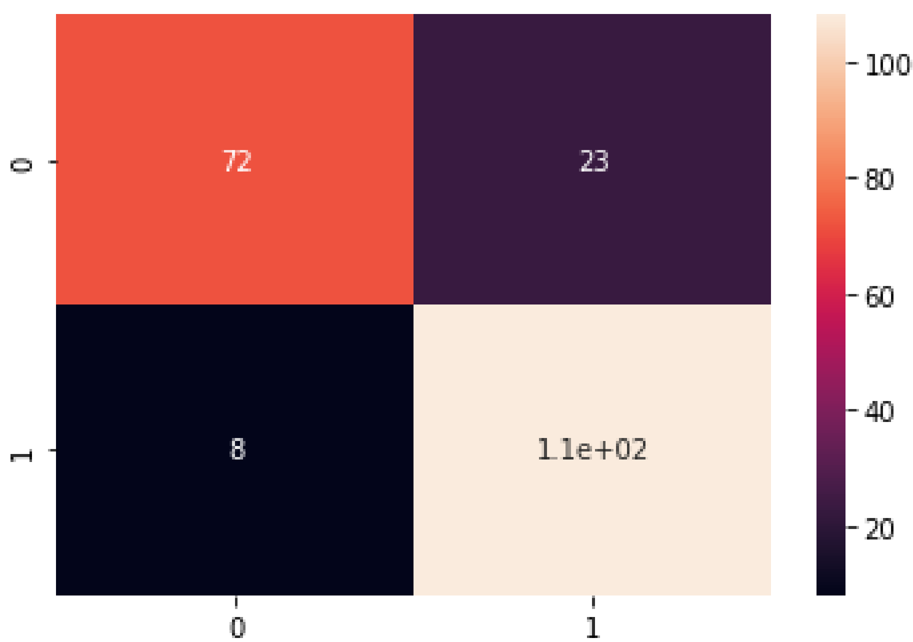
[38]:
```
# Accuracy score for test data
##print('Train score:{}'.format(metrics.accuracy_score(train_Y,log_reg.
 ↪predict(train_X))))
Logistic_reg_test_score = metrics.accuracy_score(test_Y,log_reg.predict(test_X))
Logistic_reg_test_score
```

[38]: 0.8901098901098901

[39]:
```
# Confusion matrix for train data
metrics.confusion_matrix(train_Y,log_reg.predict(train_X))
```

[39]:
```
array([[ 72,  23],
       [  8, 108]])
```

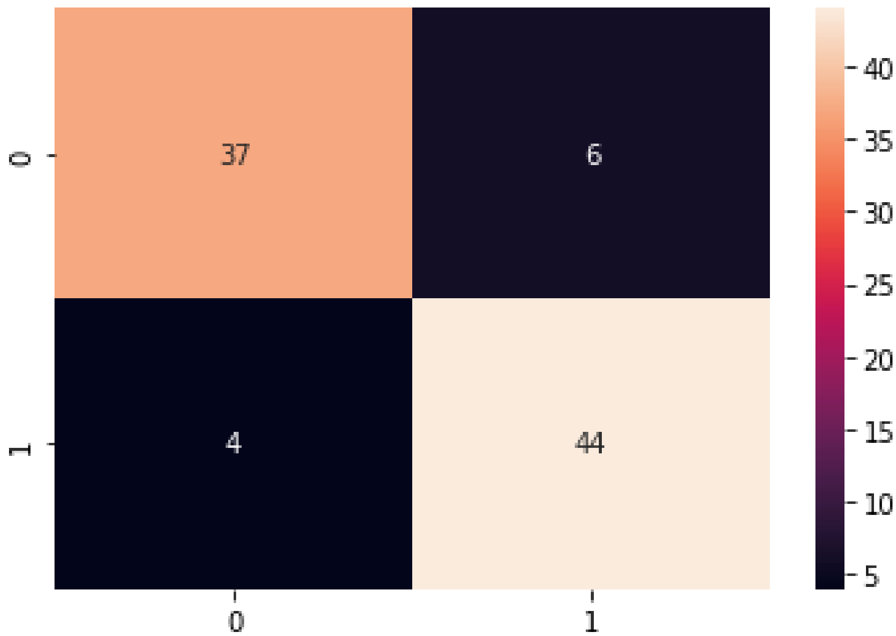
[40]:
```
sns.heatmap(metrics.confusion_matrix(train_Y,log_reg.
 ↪predict(train_X)),annot=True);
```



[41]:
```
# Confusion matrix for test data
metrics.confusion_matrix(test_Y,log_reg.predict(test_X))
```

[41]:
```
array([[37,  6],
       [ 4, 44]])
```

[42]:
```
sns.heatmap(metrics.confusion_matrix(test_Y,log_reg.
 ↪predict(test_X)),annot=True);
```



[43]:
```
# Classification Report for Train Data
print(metrics.classification_report(train_Y,log_reg.predict(train_X)))
```

```
              precision    recall  f1-score   support

           0       0.90      0.76      0.82        95
           1       0.82      0.93      0.87       116

    accuracy                           0.85       211
   macro avg       0.86      0.84      0.85       211
weighted avg       0.86      0.85      0.85       211
```

[44]:
```
# Classification Report for Test Data
print(metrics.classification_report(test_Y,log_reg.predict(test_X)))
```

```
              precision    recall  f1-score   support
```

```
              0       0.90      0.86      0.88        43
              1       0.88      0.92      0.90        48

       accuracy                           0.89        91
      macro avg       0.89      0.89      0.89        91
   weighted avg       0.89      0.89      0.89        91
```

0.1.6 Random Forest Classifier

[45]:
```
random_forest=RandomForestClassifier(max_depth=7,min_samples_leaf=7)
#random_forest=RandomForestClassifier(max_depth=5,min_samples_leaf=5)
#random_forest=RandomForestClassifier()
random_forest.fit(train_X,train_Y)
```

[45]:
```
RandomForestClassifier(max_depth=7, min_samples_leaf=7)
```

[46]:
```
# Accuracy score for Train and Test Data
print('Train Score:{}'.format(random_forest.score(train_X,train_Y)))
print('Test Score:{}'.format(random_forest.score(test_X,test_Y)))
```

```
Train Score:0.8862559241706162
Test Score:0.8571428571428571
```

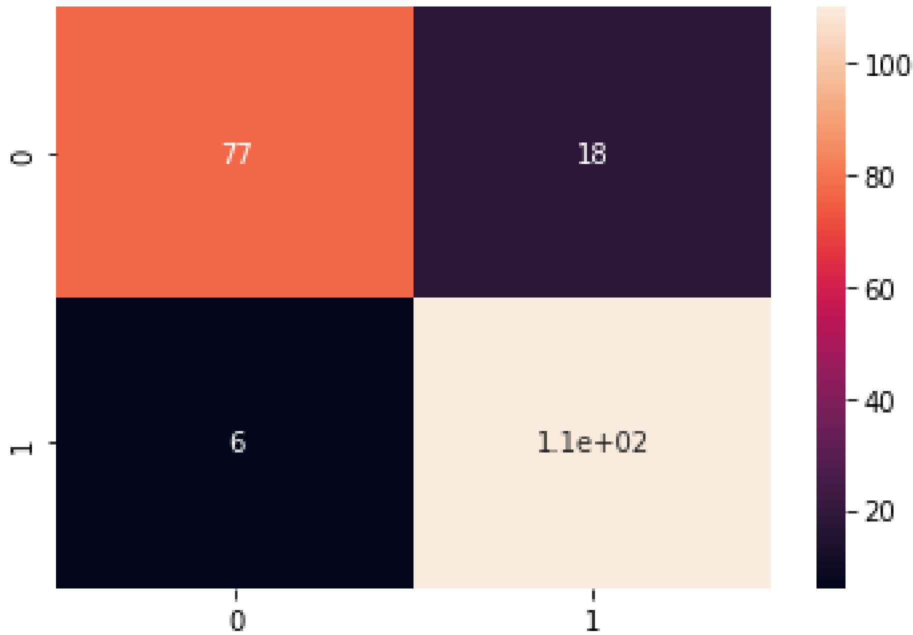
[47]:
```
# Accuracy score for Test Data
#print('Train score:{}'.format(metrics.accuracy_score(train_Y,random_forest.
 ↪predict(train_X))))
Random_forest_test_score=metrics.accuracy_score(test_Y,random_forest.
 ↪predict(test_X))
Random_forest_test_score
```

[47]:
```
0.8571428571428571
```

[48]:
```
# Confusion matrix for Train data
metrics.confusion_matrix(train_Y,random_forest.predict(train_X))
```

[48]:
```
array([[ 77,  18],
       [  6, 110]])
```

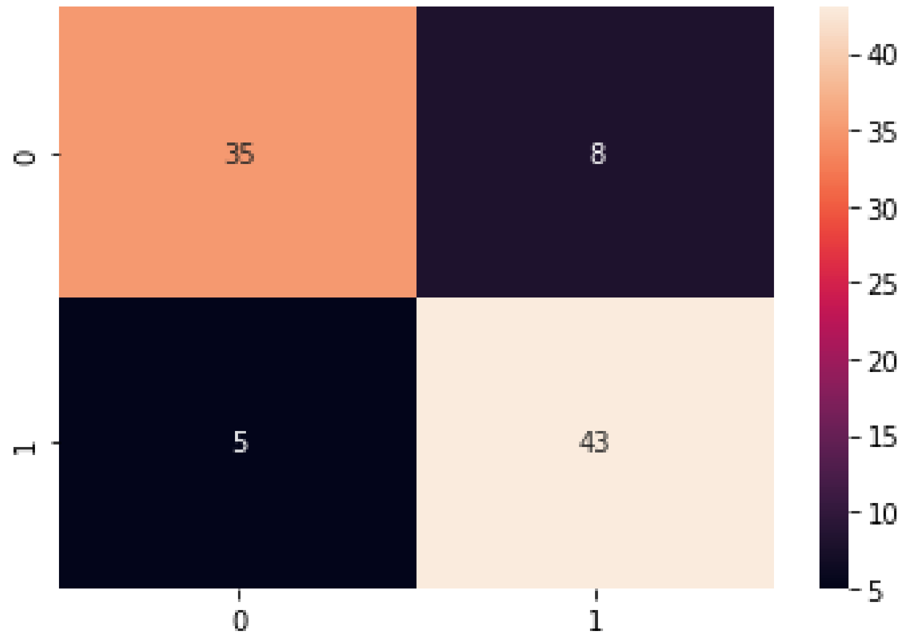
[49]:
```
sns.heatmap(metrics.confusion_matrix(train_Y,random_forest.
 ↪predict(train_X)),annot=True);
```



[50]:
```
# Confusion matrix for Test data
metrics.confusion_matrix(test_Y,random_forest.predict(test_X))
```

[50]:
```
array([[35,  8],
       [ 5, 43]])
```

[51]:
```
sns.heatmap(metrics.confusion_matrix(test_Y,random_forest.
 ↪predict(test_X)),annot=True);
```



[52]:
```
# Classification Report for Train Data
print(metrics.classification_report(train_Y,random_forest.predict(train_X)))
```

```
              precision    recall  f1-score   support

           0       0.93      0.81      0.87        95
           1       0.86      0.95      0.90       116

    accuracy                           0.89       211
   macro avg       0.89      0.88      0.88       211
weighted avg       0.89      0.89      0.89       211
```

[53]:
```
# Classification Report for Test Data
print(metrics.classification_report(test_Y,random_forest.predict(test_X)))
```

```
              precision    recall  f1-score   support

           0       0.88      0.81      0.84        43
           1       0.84      0.90      0.87        48

    accuracy                           0.86        91
   macro avg       0.86      0.85      0.86        91
weighted avg       0.86      0.86      0.86        91
```

0.1.7 Logistic regression using Stats model

[54]:
```
import statsmodels.api as sm
```

[55]:
```
train_Y_1=np.array(train_Y)
```

[56]:
```
Log_reg_sm= sm.Logit(train_Y.values,train_X).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.359148
         Iterations 7
```

[57]:
```
Log_reg_sm.summary()
```

[57]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  211
Model:                          Logit   Df Residuals:                      198
Method:                           MLE   Df Model:                           12
Date:                Tue, 06 Dec 2022   Pseudo R-squ.:                  0.4781
Time:                        17:59:26   Log-Likelihood:                -75.780
converged:                       True   LL-Null:                       -145.21
Covariance Type:            nonrobust   LLR p-value:                 1.020e-23
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
age            0.1166      0.248      0.470      0.638      -0.369       0.602
sex           -0.6397      0.242     -2.638      0.008      -1.115      -0.164
cp             0.8529      0.242      3.529      0.000       0.379       1.327
trestbps      -0.5406      0.216     -2.501      0.012      -0.964      -0.117
chol          -0.2159      0.227     -0.953      0.341      -0.660       0.228
fbs            0.1245      0.224      0.555      0.579      -0.315       0.564
restecg        0.3307      0.220      1.501      0.133      -0.101       0.763
thalach        0.4072      0.280      1.454      0.146      -0.142       0.956
exang         -0.2798      0.233     -1.201      0.230      -0.736       0.177
oldpeak       -0.7826      0.304     -2.578      0.010      -1.378      -0.188
slope          0.3360      0.255      1.317      0.188      -0.164       0.836
ca            -0.9001      0.248     -3.628      0.000      -1.386      -0.414
thal          -0.6481      0.224     -2.896      0.004      -1.087      -0.209
==============================================================================
"""
```

[58]:
```
Y_pred=Log_reg_sm.predict(test_X)
YPrediction=list(map(round,Y_pred))
```

[59]:
```
metrics.confusion_matrix(test_Y,YPrediction)
```

[59]:
```
array([[37,  6],
       [ 6, 42]])
```

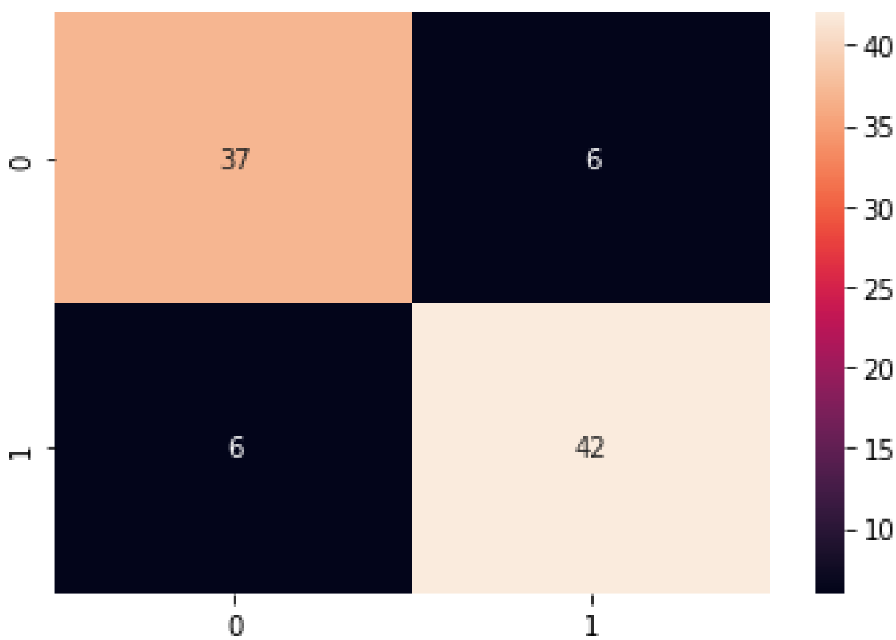
[60]:
```
# Accuracy Score for the Test data
#print('Test score:{}'.format(metrics.accuracy_score(test_Y,YPrediction)))
logistic_reg_stats_test_score=metrics.accuracy_score(test_Y,YPrediction)
logistic_reg_stats_test_score
```

[60]:
```
0.8681318681318682
```

[61]:
```
# Confusion matrix for Test data
metrics.confusion_matrix(test_Y,YPrediction)
```

[61]:
```
array([[37,  6],
       [ 6, 42]])
```

[62]:
```
sns.heatmap(metrics.confusion_matrix(test_Y,YPrediction),annot=True);
```



[63]:
```
# Classification Report for Test Data
print(metrics.classification_report(test_Y,YPrediction))
```

```
              precision    recall  f1-score   support

           0       0.86      0.86      0.86        43
```

```
           1       0.88      0.88      0.88        48

    accuracy                           0.87        91
   macro avg       0.87      0.87      0.87        91
weighted avg       0.87      0.87      0.87        91
```

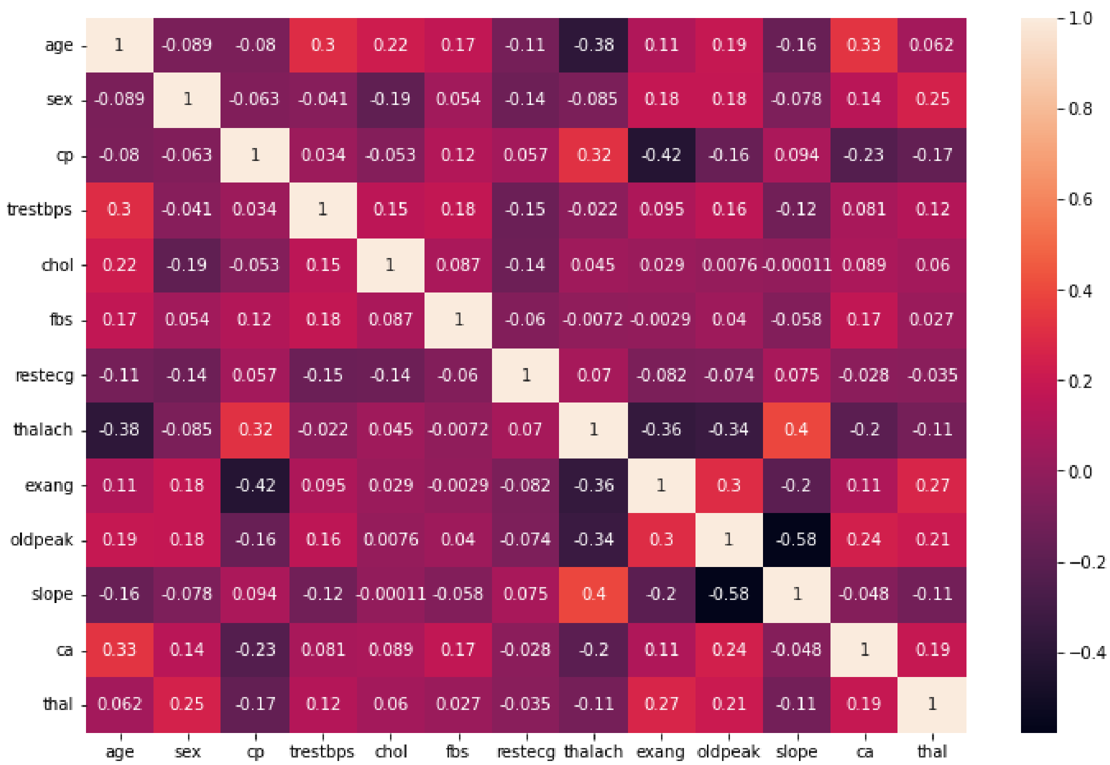
Feature Selection based on Correlation

[64]:
```python
# Correlation of independent variables
corr_ind_var=train_X.corr()
corr_ind_var
```

[64]:
```
               age       sex        cp  trestbps      chol       fbs  \
age       1.000000 -0.088888 -0.079607  0.299860  0.217779  0.169457
sex      -0.088888  1.000000 -0.062774 -0.040646 -0.189423  0.053978
cp       -0.079607 -0.062774  1.000000  0.034001 -0.052710  0.116436
trestbps  0.299860 -0.040646  0.034001  1.000000  0.150089  0.175946
chol      0.217779 -0.189423 -0.052710  0.150089  1.000000  0.086540
fbs       0.169457  0.053978  0.116436  0.175946  0.086540  1.000000
restecg  -0.108391 -0.136695  0.057402 -0.145760 -0.139000 -0.059884
thalach  -0.382699 -0.084951  0.316480 -0.021759  0.045140 -0.007209
exang     0.108494  0.182232 -0.422369  0.094766  0.028881 -0.002879
oldpeak   0.190188  0.182580 -0.156448  0.157824  0.007579  0.040375
slope    -0.158363 -0.077929  0.093695 -0.117523 -0.000111 -0.058079
ca        0.331479  0.138717 -0.229376  0.080567  0.089466  0.169910
thal      0.061831  0.252357 -0.171442  0.123491  0.060424  0.026549

           restecg   thalach     exang   oldpeak     slope        ca      thal
age      -0.108391 -0.382699  0.108494  0.190188 -0.158363  0.331479  0.061831
sex      -0.136695 -0.084951  0.182232  0.182580 -0.077929  0.138717  0.252357
cp        0.057402  0.316480 -0.422369 -0.156448  0.093695 -0.229376 -0.171442
trestbps -0.145760 -0.021759  0.094766  0.157824 -0.117523  0.080567  0.123491
chol     -0.139000  0.045140  0.028881  0.007579 -0.000111  0.089466  0.060424
fbs      -0.059884 -0.007209 -0.002879  0.040375 -0.058079  0.169910  0.026549
restecg   1.000000  0.070325 -0.082340 -0.074029  0.075366 -0.028335 -0.035332
thalach   0.070325  1.000000 -0.356470 -0.336265  0.395393 -0.203949 -0.108303
exang    -0.082340 -0.356470  1.000000  0.297818 -0.203783  0.105776  0.266513
oldpeak  -0.074029 -0.336265  0.297818  1.000000 -0.578136  0.238262  0.206469
slope     0.075366  0.395393 -0.203783 -0.578136  1.000000 -0.048210 -0.112830
ca       -0.028335 -0.203949  0.105776  0.238262 -0.048210  1.000000  0.191124
thal     -0.035332 -0.108303  0.266513  0.206469 -0.112830  0.191124  1.000000
```

[65]:
```python
plt.figure(figsize=(12,8))
sns.heatmap(corr_ind_var,annot=True);
```




```
[66]: # with the following function we can select highly correlated feature
      # it will remove the first feature that is correlated with anything other␣
       ↪feature
      def correlation(data,threshold):
          col_corr=list()
          corr_matrix=data.corr()
          for i in range(len(corr_matrix.columns)):
              for j in range(i):
                  if abs(corr_matrix.iloc[i,j]) >threshold:
                      col_name = corr_matrix.columns[i]
                      col_corr.append(col_name)

          return col_corr
```

```
[67]: corr_features= correlation(train_X,0.9)
```

```
[68]: corr_features
```

```
[68]: []
```

Using Correlation method, none of the features having a correlation greater than 0.9

Hence cannot drop any features based on correlation

Feature selection based on p value

[69]:
```
# P values are assigned to a variable
P_values=round(Log_reg_sm.pvalues,3)
```

[70]:
```
P_values
```

[70]:
```
age         0.638
sex         0.008
cp          0.000
trestbps    0.012
chol        0.341
fbs         0.579
restecg     0.133
thalach     0.146
exang       0.230
oldpeak     0.010
slope       0.188
ca          0.000
thal        0.004
dtype: float64
```

[71]:
```
# features are selected where P value >=0.01
Features=P_values[P_values>=0.01]
features_col=list(Features.index)
```

[72]:
```
Features
```

[72]:
```
age         0.638
trestbps    0.012
chol        0.341
fbs         0.579
restecg     0.133
thalach     0.146
exang       0.230
oldpeak     0.010
slope       0.188
dtype: float64
```

[73]:
```
# selected the columns P values >=0.01 in train and test data
train_X_featured=train_X[features_col]
test_X_featured=test_X[features_col]
```

[74]:
```
# checked the shape of train and test data
train_X_featured.shape,test_X_featured.shape,train_Y.shape,test_Y.shape
```

[74]:
```
((211, 9), (91, 9), (211,), (91,))
```

[75]:
```python
# fitting the logistic regression model
Log_reg_sm= sm.Logit(train_Y.values,train_X_featured).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.504609
         Iterations 6
```

[76]:
```python
Y_pred_featured=Log_reg_sm.predict(test_X_featured)
YPrediction_featured=list(map(round,Y_pred_featured))
```

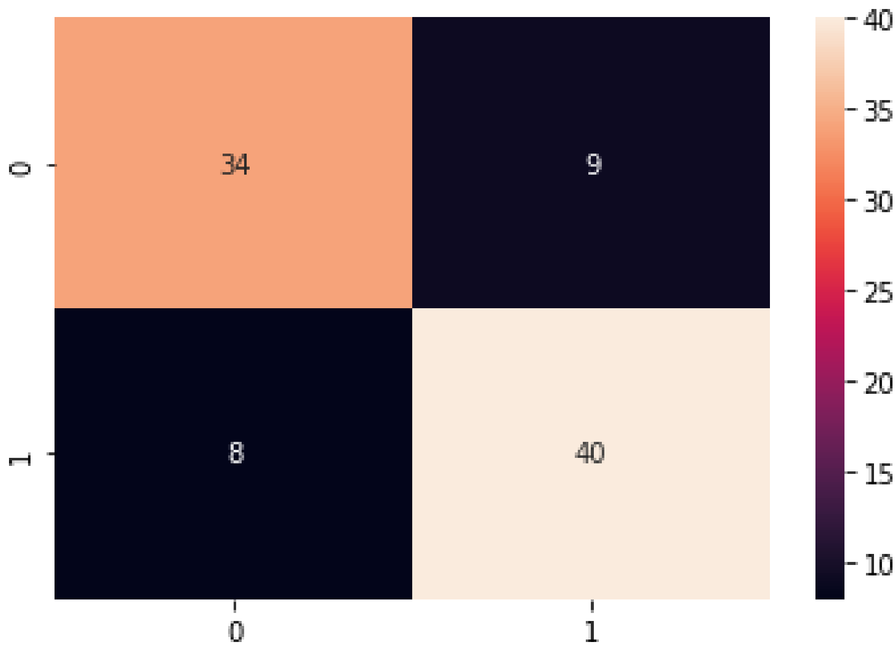
[77]:
```python
# Test Accuracy score after feature selection
#print('Test score:{}'.format(metrics.
 ↪accuracy_score(test_Y,YPrediction_featured)))
Logistic_reg_feature_score=metrics.accuracy_score(test_Y,YPrediction_featured)
Logistic_reg_feature_score
```

[77]:
```
0.8131868131868132
```

[78]:
```python
# Confusion matirx for the test data after feature engineering
metrics.confusion_matrix(test_Y,YPrediction_featured)
```

[78]:
```
array([[34,  9],
       [ 8, 40]])
```

[79]:
```python
sns.heatmap(metrics.confusion_matrix(test_Y,YPrediction_featured),annot=True);
```



[80]:
```
# Classification Report for Test Data
print(metrics.classification_report(test_Y,YPrediction_featured))
```

```
              precision    recall  f1-score   support

           0       0.81      0.79      0.80        43
           1       0.82      0.83      0.82        48

    accuracy                           0.81        91
   macro avg       0.81      0.81      0.81        91
weighted avg       0.81      0.81      0.81        91
```

0.1.8 Scores of all the models

[82]:
```
# Test Accuracy Score for the models built
print("Test Accuracy score for Logistic regression model built using sklearn :
↪{}".format(Logistic_reg_test_score))
print("Test Accuracy score for Random forest classification model built using␣
↪sklearn :{}".format(Random_forest_test_score))
print("Test Accuracy score for Logistic regression model built using stats␣
↪model :{}".format(logistic_reg_stats_test_score))
print("Test Accuracy score after feature selection using p-value>=0.01,Logistic␣
↪regression model built using stats model :{}".
↪format(Logistic_reg_feature_score))
```

```
Test Accuracy score for Logistic regression model built using sklearn
:0.8901098901098901
Test Accuracy score for Random forest classification model built using sklearn
:0.8571428571428571
Test Accuracy score for Logistic regression model built using stats model
:0.8681318681318682
Test Accuracy score after feature selection using p-value>=0.01,Logistic
regression model built using stats model :0.8131868131868132
```

Comparing the Test accuracy score for all the built models, logistic regression model using Sklearn provides better accuracy