HEALTH CARE

February 8, 2023

Health Care.(Project 5)

submitted by-somya kumari pandey

[1]:
```
#Importing required libraries

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler

from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import classification_report, accuracy_score

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV

%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

[3]:
```
dataset = pd.read_csv("1645792390_cep1_dataset.csv")
```

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

[4]:
```
dataset.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
```

[5]:
```
dataset.shape  #Shape of dataset
```

[5]: (303, 14)

[6]:
```
dataset.isnull().sum()   #Checking missing values.
```

[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
```

There are no missing values in the dataset

[7]:
```
dataset.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
```

[8]:
```
dataset[dataset.duplicated()]            # Checking duplicates in the dataset
```

[8]:
```
     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
```

there is one duplicate entry hence lets drop it

[9]:
```
dataset.drop_duplicates(inplace=True)   # Dropping duplicate entries
```

[10]:
```
dataset[dataset.duplicated()].shape  # rechecking for duplicates
```

[10]:
```
(0, 14)
```

[11]:
```
dataset.shape
```

[11]:
```
(302, 14)
```

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

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

[12]:
```
dataset.describe().T   #Statistical summary of dataset
```

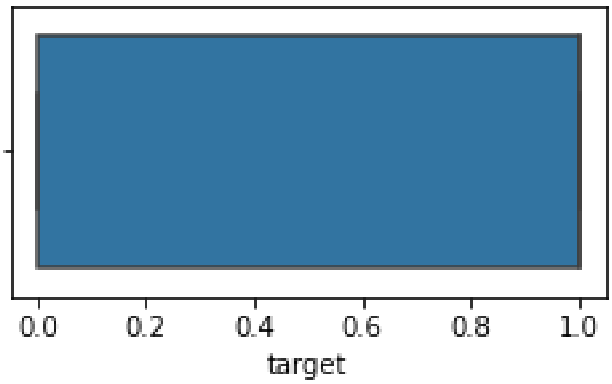
[12]:

	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

[13]:
```
plt.figure(figsize=(4,2))
sns.boxplot(dataset.target)          # No Outliers in Target
```

[13]: <AxesSubplot:xlabel='target'>

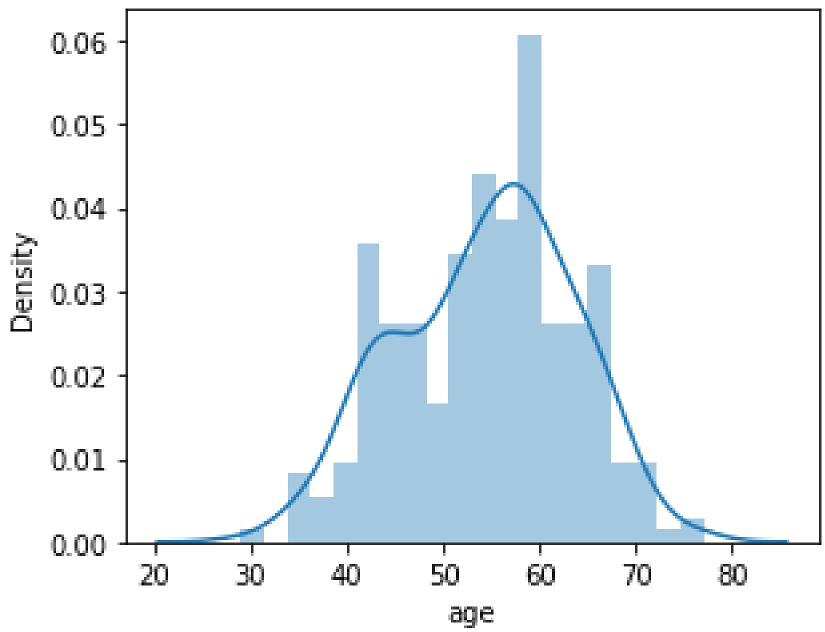


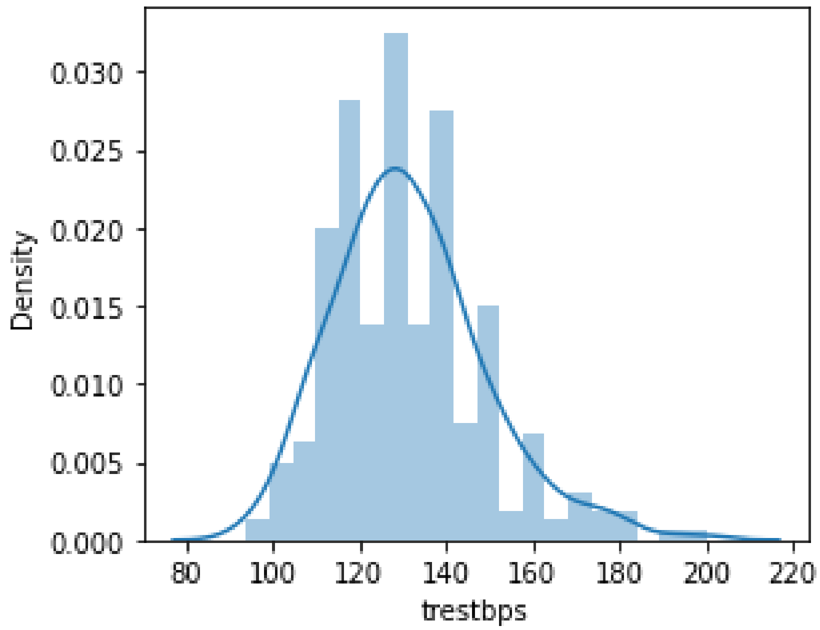
[14]:
```
dataset.nunique()

# here we identify that the variables with few unique values are categorical␣
↪and the variables with high unique values are numeric
```

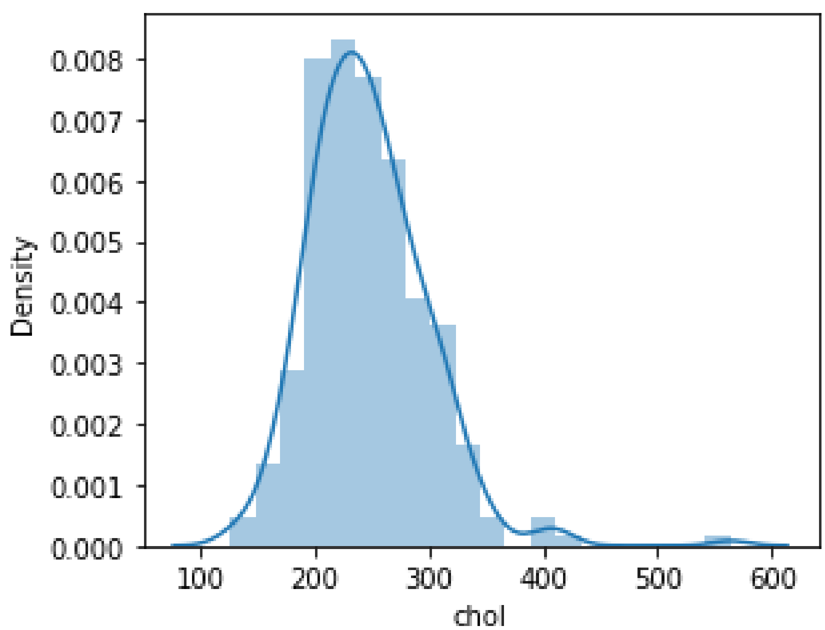
[14]:
```
age          41
sex           2
cp            4
trestbps     49
chol        152
fbs           2
restecg       3
thalach      91
exang         2
oldpeak      40
slope         3
ca            5
thal          4
target        2
dtype: int64
```

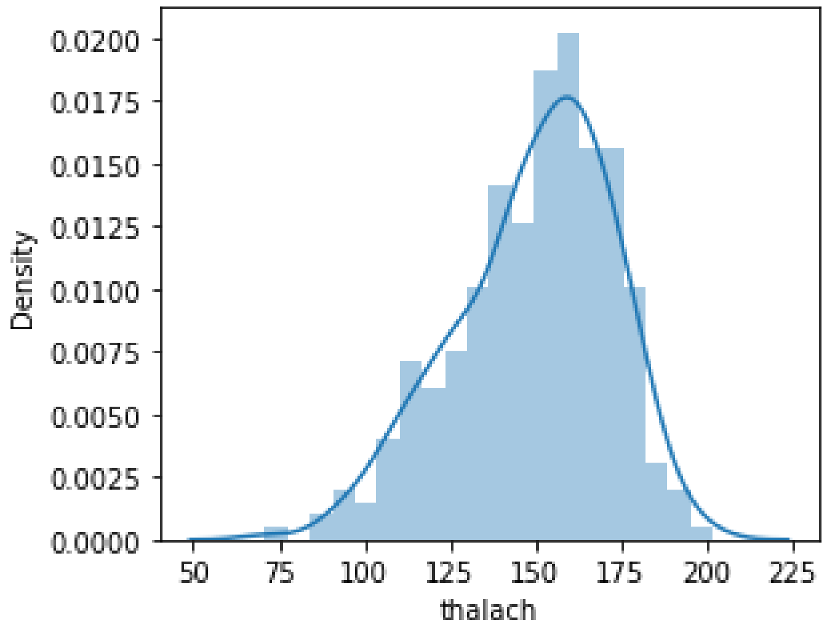
[15]:
```
numeric_cols=['age','trestbps','chol','thalach','oldpeak']

categorical_cols=['sex','cp','fbs','restecg','exang','slope','ca','thal','target']

#separating numeric and categorical columns
```

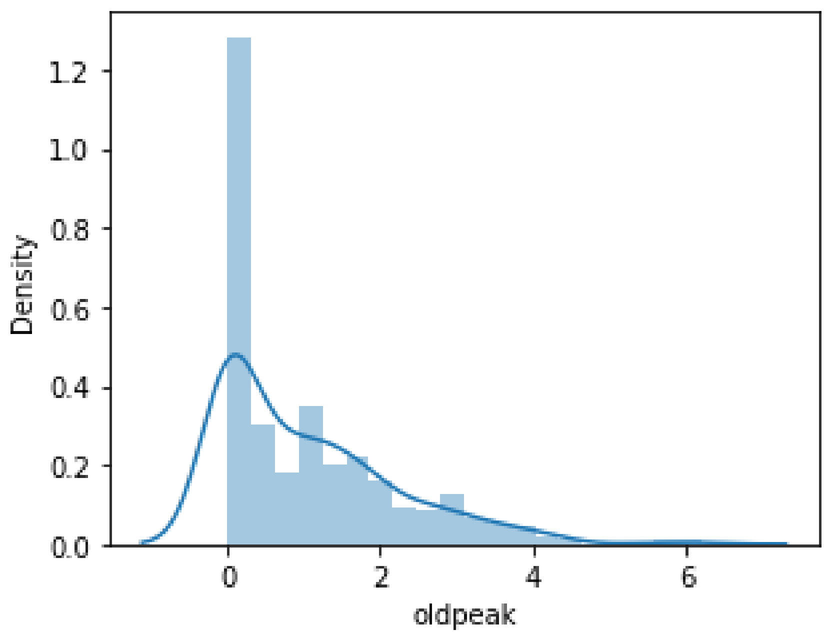
[16]:
```
#Exploring Numerical data

for i in numeric_cols:
    plt.figure(figsize=(4.5,3.5))
    sns.distplot(dataset[i],bins=20)

    plt.tight_layout()
    plt.show()
```




0.030
0.025
0.020
0.015
0.010
0.005
0.000
Density
80
100
120
140
160
180
200
220
trestbps


0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0.000
Density
100
200
300
400
500
600
chol





Analysis:

Age : The majority of patients are between 50 and 60 years age. Also there are less patients in the age range 45 to 50.

Trestbps : The resting blood pressure for most patients is between 110 and 140. Also patient traffic peaks at values around 115, 130 and 140.

Chol : Cholesterol values for most patients are between 200 to 300.

Thalach : The maximum heart rate achieved in most patients are between 150 to 160.

Oldpeak : Majority of patients are in the range 0 to 1.5.

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

[18]:
```
#Statistics for Categorical variables

dataset[categorical_cols].describe().T
```

[18]:

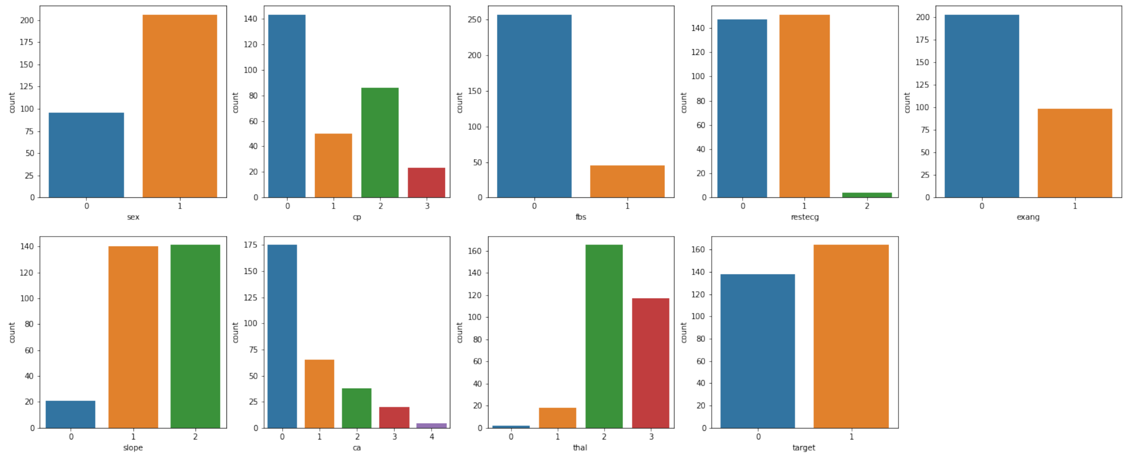
	count	mean	std	min	25%	50%	75%	max
sex	302.0	0.682119	0.466426	0.0	0.0	1.0	1.0	1.0
cp	302.0	0.963576	1.032044	0.0	0.0	1.0	2.0	3.0
fbs	302.0	0.149007	0.356686	0.0	0.0	0.0	0.0	1.0
restecg	302.0	0.526490	0.526027	0.0	0.0	1.0	1.0	2.0
exang	302.0	0.327815	0.470196	0.0	0.0	0.0	1.0	1.0
slope	302.0	1.397351	0.616274	0.0	1.0	1.0	2.0	2.0
ca	302.0	0.718543	1.006748	0.0	0.0	0.0	1.0	4.0
thal	302.0	2.314570	0.613026	0.0	2.0	2.0	3.0	3.0
target	302.0	0.543046	0.498970	0.0	0.0	1.0	1.0	1.0

[19]:
```
categorical=dataset[categorical_cols]
categorical.head()
```

[19]:

	sex	cp	fbs	restecg	exang	slope	ca	thal	target
0	1	3	1	0	0	0	0	1	1
1	1	2	0	1	0	0	0	2	1
2	0	1	0	0	0	2	0	2	1
3	1	1	0	1	0	2	0	2	1
4	0	0	0	1	1	2	0	2	1

[20]:
```
# count plot for categorical variables

plt.figure(figsize=(25,10))
for i in range(9):
    plt.subplot(2,5,i+1)
    sns.countplot(x= categorical_cols[i], data=categorical)
```



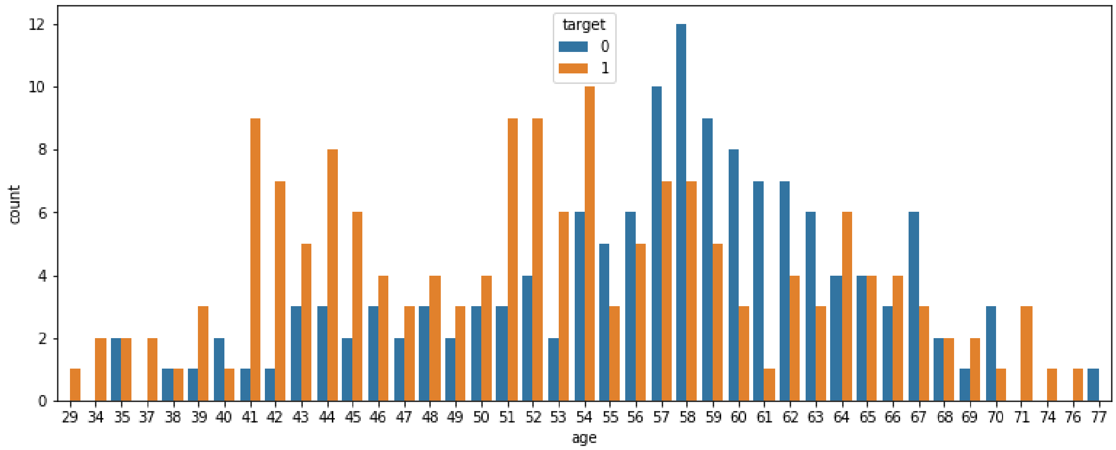
Analysis from the above Count plot

1. Sex (1 = male; 0 = female):The count of Male patient is almost double that of Females.
2. cp (Chest pain type): Chest pain of Type 0 is highest observation value in patients, followed by type 2.
3. fbs (Fasting blood sugar > 120 mg/dl (1 = true; 0 = false): Majority of patients have fasting Blood Sugar <120 mg/dl.
4. restecg (Resting electrocardiographic results): Most common observations are 0 and 1 while there are very less patients with values 2.
5. exang (Exercise induced angina (1 = yes, 0 = no)): Almost half of the patients have Exercise induced angina.
6. slope (Slope of the peak exercise ST segment): The minimum observation value is 0 and other two observations are almost equal
7. ca (Number of major vessels (0-3) colored by fluoroscopy): Mostly the number of large vessels colored by fluoroscopy is
absent.
8. thai (3 = normal; 6 = fixed defect; 7 = reversible defect): Majority of patients are in observations 2 followed by 3 which is normal.
9. target(1 or 0): More than half of the patients have a risk of heart attack.

2.c. Study the occurrence of CVD across the Age category

[21]:
```
#Occurrence of CVD across the Age category

plt.figure(figsize=(13,5))
sns.countplot(x='age', data=dataset, hue='target')
```

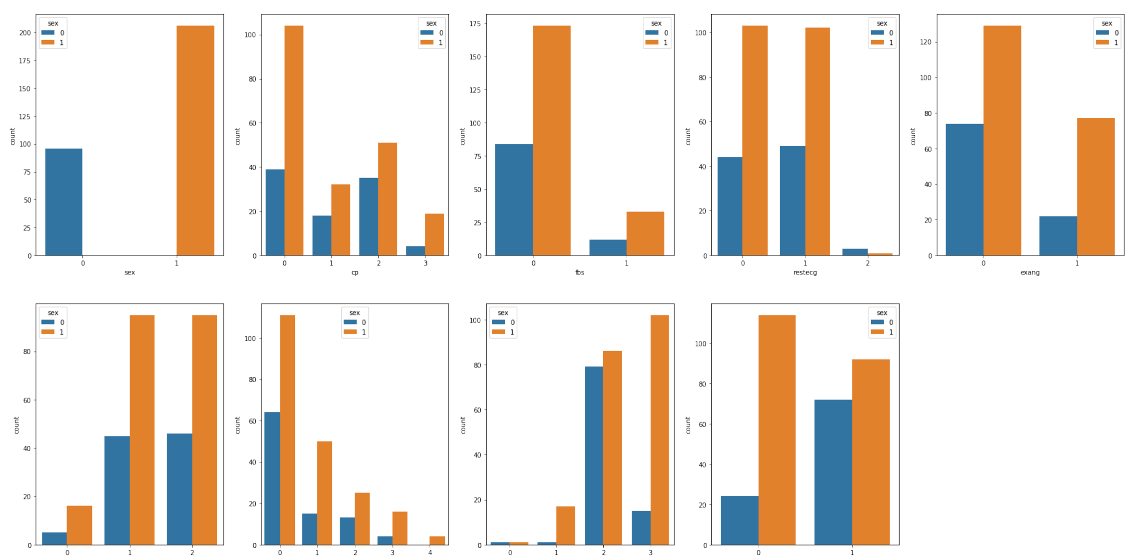
[21]: `<AxesSubplot:xlabel='age', ylabel='count'>`



It can be observed that people between age 41-45 and 51-54 are more exposed to CVD (target=1)

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

[22]:
```
#composition of patients with respect to Sex category

plt.figure(figsize=(30,15))
for i in range(9):
    plt.subplot(2,5,i+1)
    sns.countplot(x= categorical_cols[i], data=categorical, hue='sex')
```

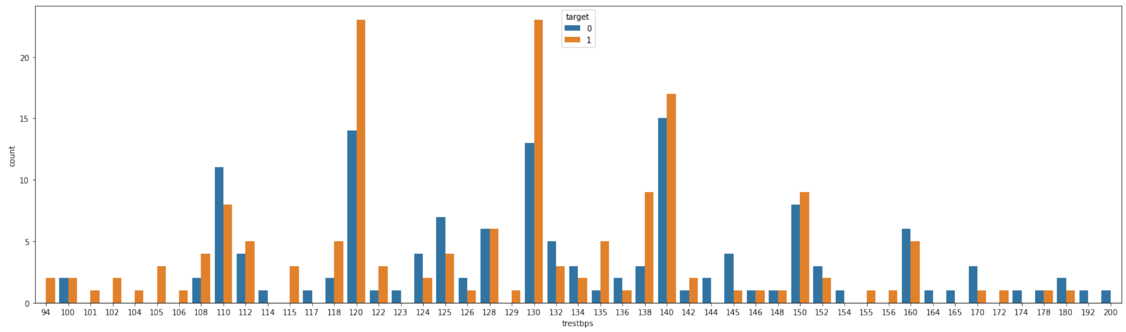


After observing the composition of all patients with respect to the Sex category, we can say that 'Males' are more exposed to CVD

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

[23]:
```
plt.figure(figsize=(25,7))
sns.countplot(x= 'trestbps', data= dataset, hue='target')
```

[23]:
```
<AxesSubplot:xlabel='trestbps', ylabel='count'>
```

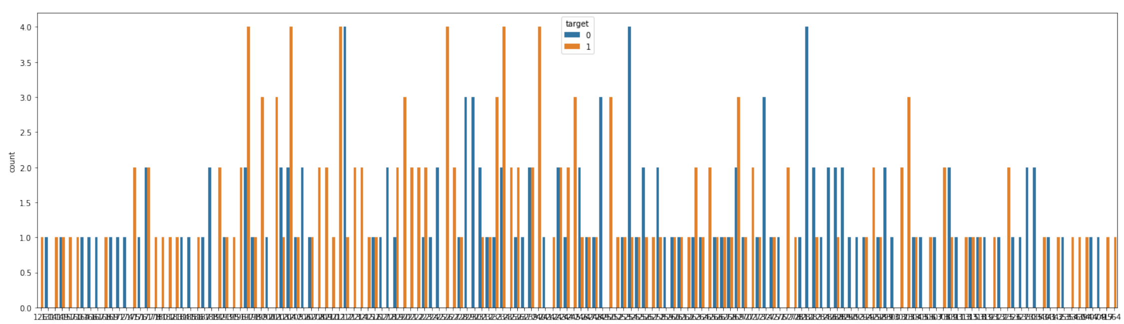


It is observed that patients are highly susceptible to heart attacks if the resting blood pressure (trestbps) values are 120, 130 and 140.

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

[24]:
```
plt.figure(figsize=(25,7))
sns.countplot(x= 'chol', data= dataset, hue='target')
```

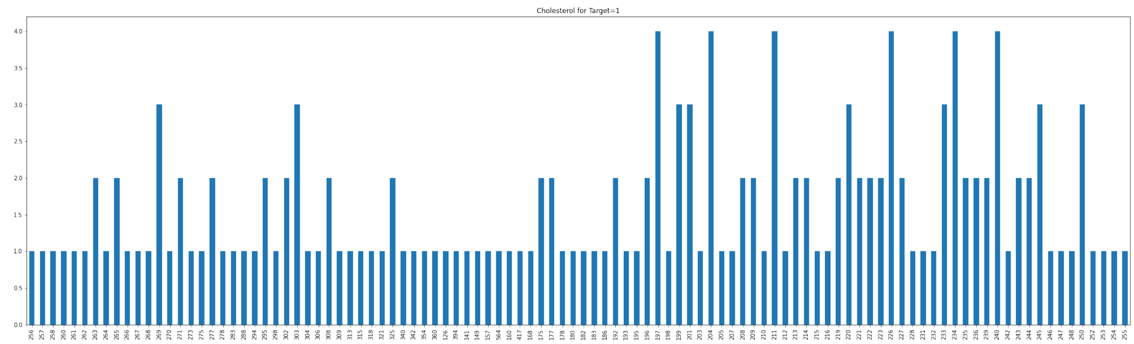
[24]:
```
<AxesSubplot:xlabel='chol', ylabel='count'>
```



[25]:
```
df=dataset.groupby('target')['chol']
```

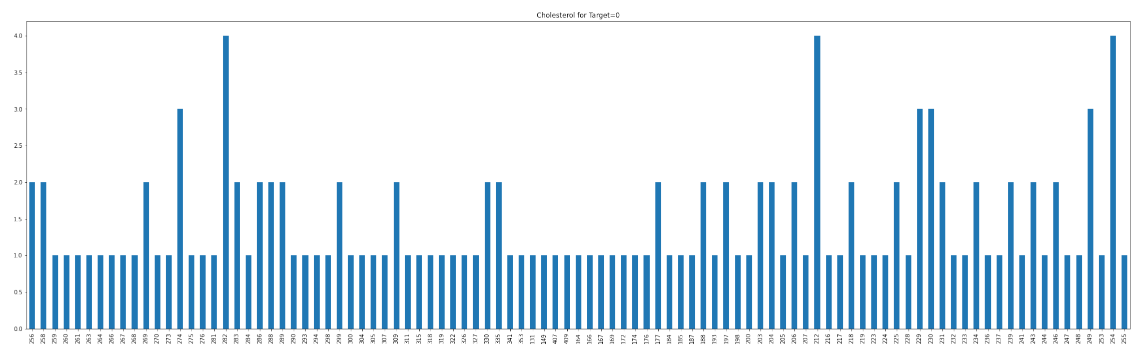
[26]:
```
#cholesterol graph for Target=1

df.get_group(1).value_counts(sort=False).plot(kind='bar',title="Cholesterol for␣
↪Target=1", figsize=(35,10))
```

[26]:
```
<AxesSubplot:title={'center':'Cholesterol for Target=1'}>
```



[27]:
```
#cholesterol graph for Target=0

df.get_group(0).value_counts(sort=False).plot(kind='bar',title="Cholesterol for␣
↪Target=0",figsize=(35,10))
```

[27]:
```
<AxesSubplot:title={'center':'Cholesterol for Target=0'}>
```



[28]:
```
dataset[['chol', 'target']].corr()  #Correlation between Cholesterol value and␣
↪Target
```

[28]:

	chol	target
chol	1.000000	-0.081437
target	-0.081437	1.000000

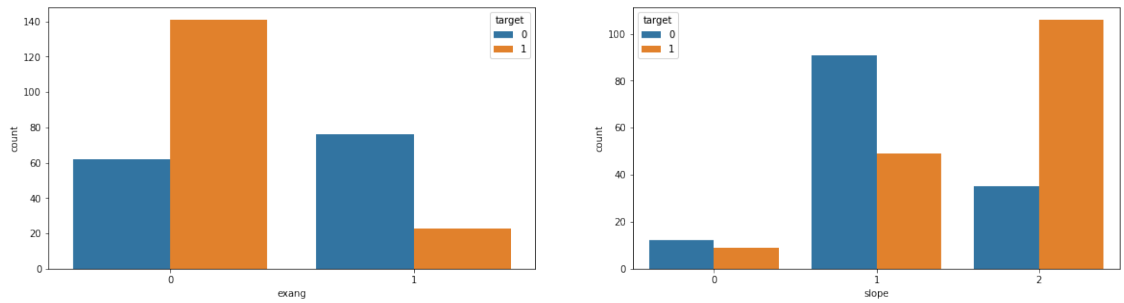
From the above graphs, we can say that it is difficult to predict patients having a heart attack using cholesterol values.

The correlation between the two variables is also negative.

We can also say that there are chances of having a heart attack for Cholestrol values between 190 to 250

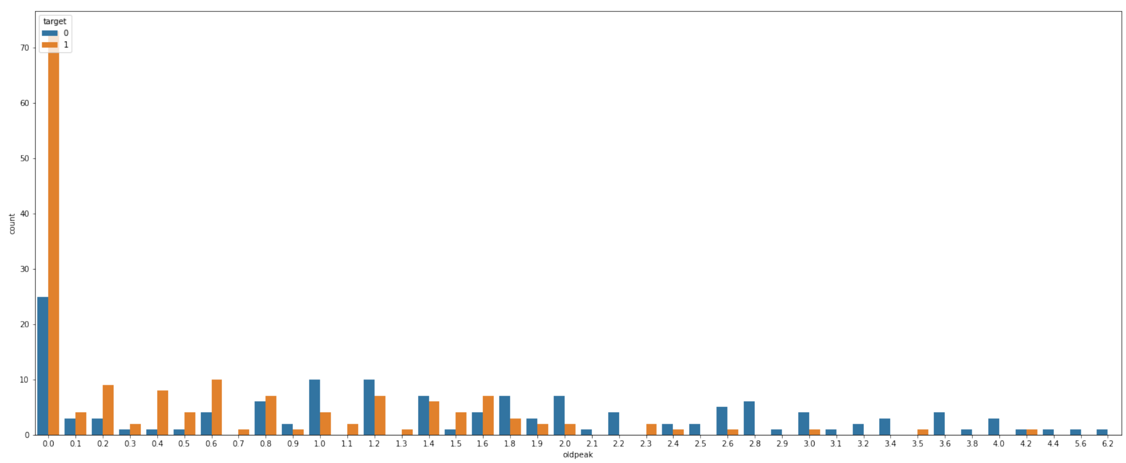
2.g. State what relationship exists between peak exercising and the occurrence of a heart attack

[29]:
```
cols=['exang','slope']
plt.figure(figsize=(20,5))
for i in range(len(cols)):
    plt.subplot(1,2,i+1)
    sns.countplot(x= cols[i],hue='target', data=dataset)
```



[30]:
```
plt.figure(figsize=(25,10))
sns.countplot(x= dataset['oldpeak'],hue='target', data=dataset)
```

[30]: <AxesSubplot:xlabel='oldpeak', ylabel='count'>



exang: Occurance of heat attacks in Exercise induced angina is less and it can be seen that patients with no exercise induced angina suffers from heart attacks.

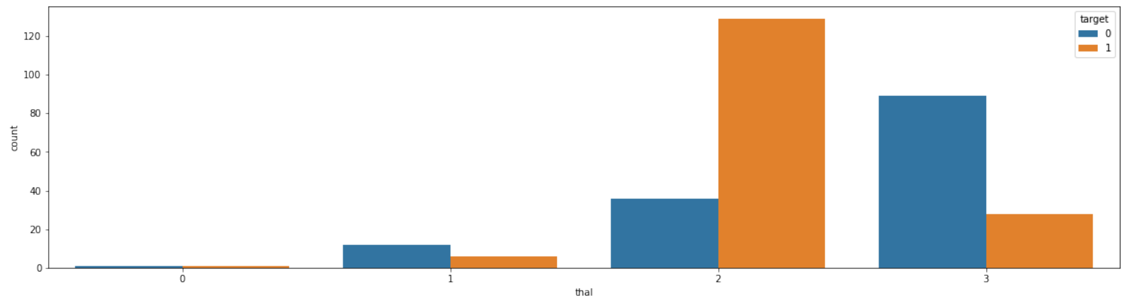
slope: occurance of heart attack is highest where Slope of the peak exercise ST segment value is 2.

oldpeak: Occurance of heart attack is highest where oldpeak value is 0

2.h. Check if thalassemia is a major cause of CVD

[31]:
```
plt.figure(figsize=(20,5))
sns.countplot(x= dataset['thal'],hue='target', data=dataset)
```

[31]: <AxesSubplot:xlabel='thal', ylabel='count'>



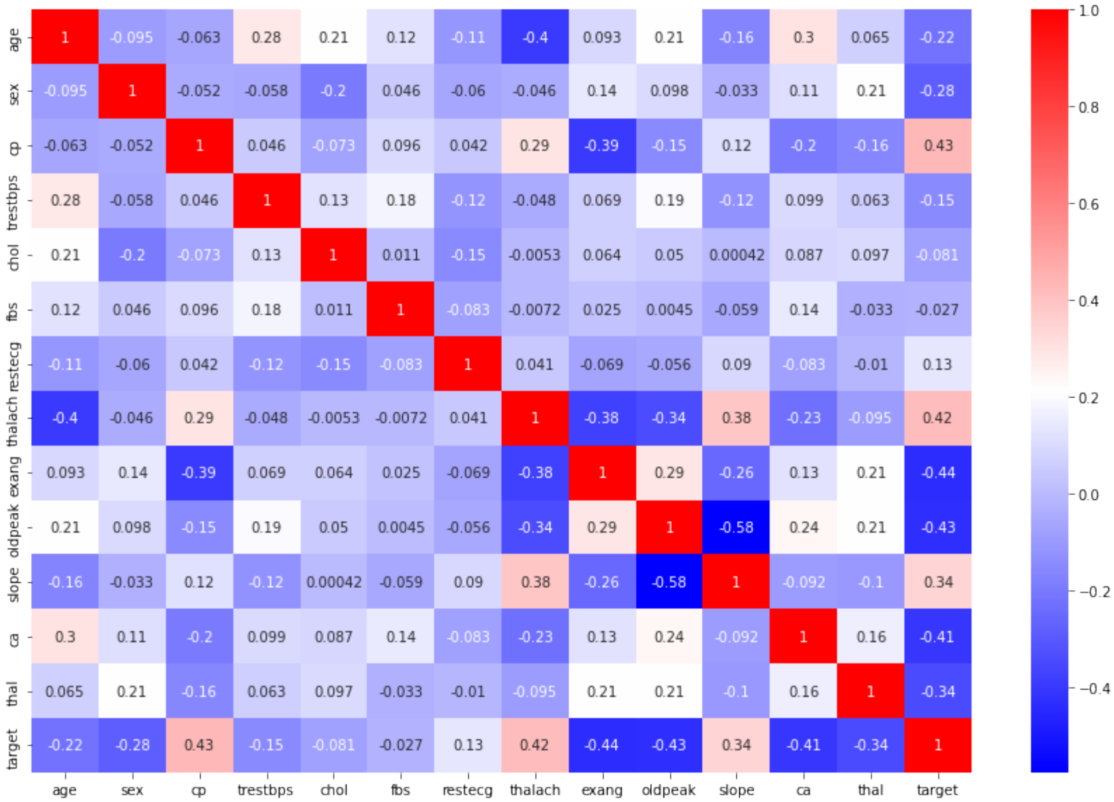
Patients having thal value as 2 have high risk of CVD

Also from the below heatmap, we can see that correlation between 'thal' and 'target' is -0.34, so 'thal' is not a major cause of CVD

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

[32]:
```
plt.figure(figsize=(15,10))
sns.heatmap(dataset.corr(),cmap='bwr',annot=True)
```

[32]: <AxesSubplot:>



From the above heat map we can conclude that 'Chest pain(cp)' and 'Maximum heart rate(thalach)' are the main triggers for occurance of CVD with correlation values 0.43 and 0.42 respectively.

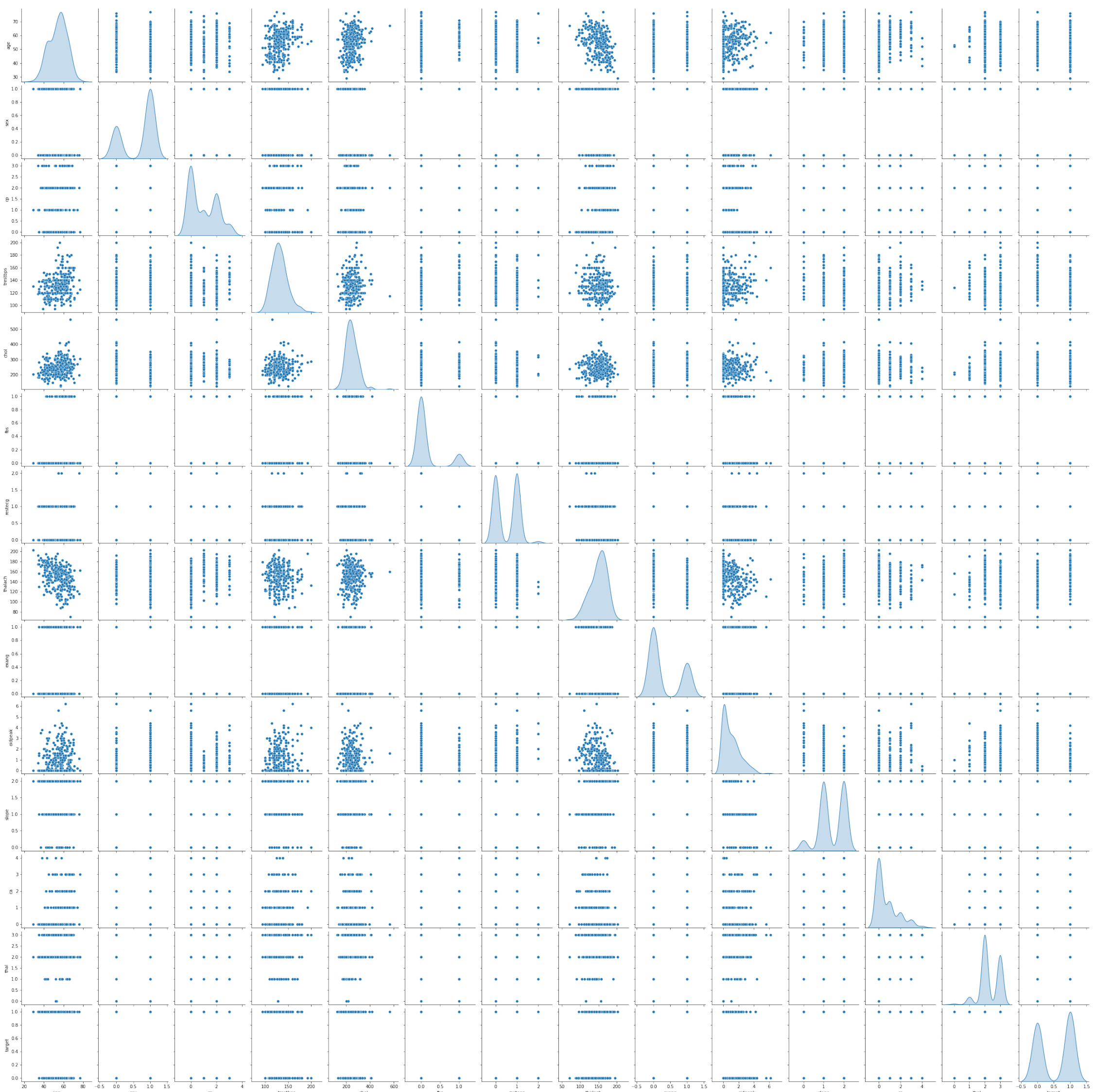
'Slope of the peak exercise ST segment(slope)' is also moderately correlated with 'target' variable(correlation value 0.34) and so is also a cause of CVD.

We can observe that 'thalach' variable is also highly correlated with 'cp' and 'slope' variables.

In general we can say that the "target" variable correlates with more than one variables. So there are multiple causes that can trigger CVD in patients.

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

[33]:
```
sns.pairplot(dataset,diag_kind='kde')
plt.show()
```



We can see that Pairplot is not of much help instead Heatmap provides better insights of relationship between all the variables.

We have already noted ”target” variable correlates maximum with ”cp”, ”thalach” and ”slope”

”age’ variable is highly correlated to ”trestbps” and ”ca”

”thalach” variable is highly correlated with ”cp” and ”slope” variables

”exang’ variable is highly correlated to ”oldpeak”

”chol” and ”fbs” have least correlation with ”target” variable

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

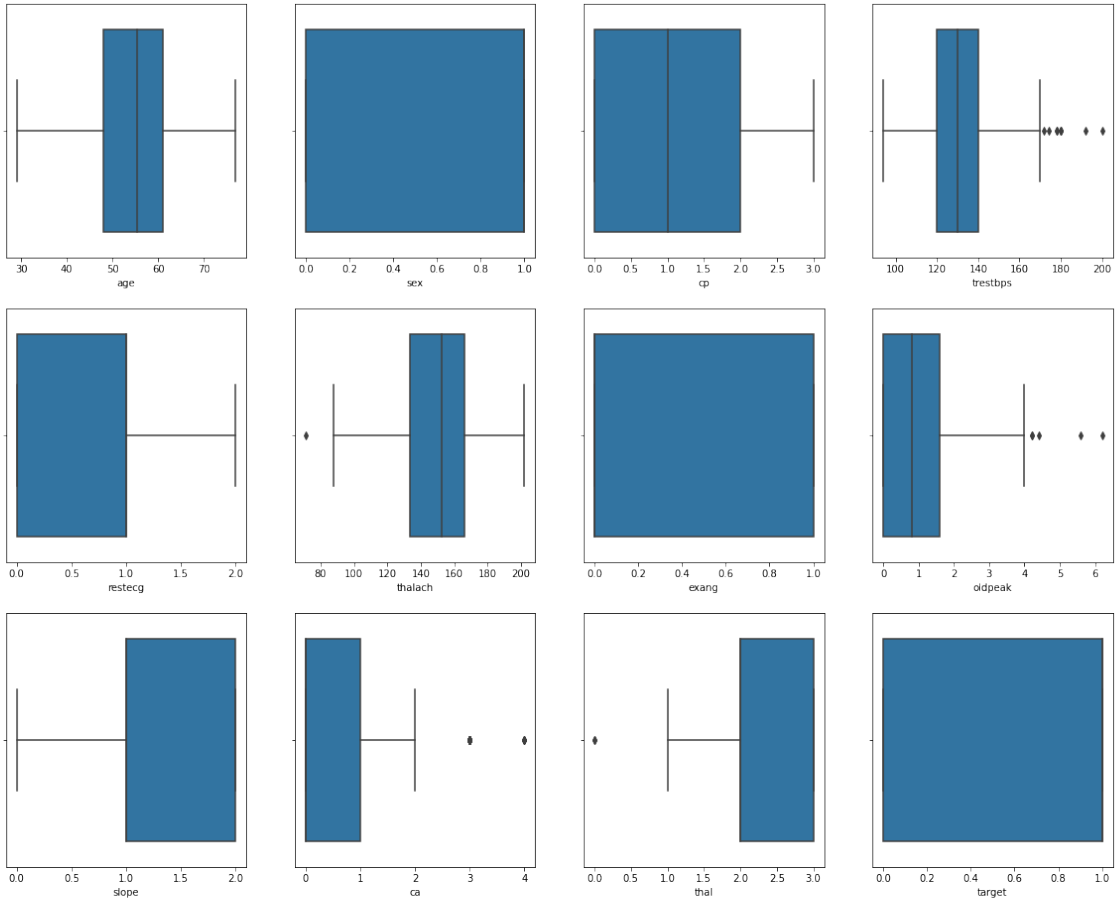
Preparing data for Modelling

[34]:
```
#dropping columns "chol" and "fbs" as they have very low correlation with target

dataset.drop(['chol','fbs'], axis=1, inplace = True)
```

[35]:
```
dataset.head()
```

[35]:
```
   age  sex  cp  trestbps  restecg  thalach  exang  oldpeak  slope  ca  thal  \
0   63    1   3       145        0      150      0      2.3      0   0     1
1   37    1   2       130        1      187      0      3.5      0   0     2
2   41    0   1       130        0      172      0      1.4      2   0     2
3   56    1   1       120        1      178      0      0.8      2   0     2
4   57    0   0       120        1      163      1      0.6      2   0     2

   target
0       1
1       1
2       1
3       1
4       1
```

[36]:
```
#checking outliers

plt.figure(figsize=(20,16))
for i in range(12):
    plt.subplot(3,4,i+1)
    sns.boxplot(dataset.iloc[:,i])
```



There are outliers in columns 'trestbps' ,'thalach' ,'oldpeak' ,'ca' and 'thal'. Lets treat these outliers. Note we will not treat outliers for 'ca'and 'thal' as they are categorical.

[37]:
```
#Treating Outliers for "trestbps"

Q3 = dataset.trestbps.quantile(0.75)
Q1 = dataset.trestbps.quantile(0.25)
IQR = Q3-Q1
upper = Q3 + 1.5 * (IQR)
```

[38]:
```
dataset[dataset.trestbps > upper] #number of outliers in "trestbps"
```

[38]:

	age	sex	cp	trestbps	restecg	thalach	exang	oldpeak	slope	ca	\
8	52	1	2	172	1	162	0	0.5	2	0	
101	59	1	3	178	0	145	0	4.2	0	0	
110	64	0	0	180	1	154	1	0.0	2	0	
203	68	1	2	180	0	150	1	1.6	1	0	
223	56	0	0	200	0	133	1	4.0	0	2	
241	59	0	0	174	1	143	1	0.0	1	0	
248	54	1	1	192	0	195	0	0.0	2	1	
260	66	0	0	178	1	165	1	1.0	1	2	

```
266   55   0   0      180       2     117      1      3.4      1   0

     thal  target
8       3       1
101     3       1
110     2       1
203     3       0
223     3       0
241     2       0
248     3       0
260     3       0
266     2       0
```

[39]:
```
dataset[dataset.trestbps > upper].shape
```

[39]:
```
(9, 12)
```

[40]:
```
dataset[dataset.trestbps > upper].shape[0]/dataset.shape[0]*100  #percentage of␣
↪outliers in "trestbps"
```

[40]:
```
2.980132450331126
```

[41]:
```
trestbps_index= dataset[dataset.trestbps > upper].index  #indexes of outliers␣
↪in "trestbps"
```

[42]:
```
# since our dataset is small we shall not remove the outliers and treat it␣
↪using capping method

dataset.loc[trestbps_index,'trestbps']=upper  #assigning upper value to outliers
```

[43]:
```
dataset.loc[trestbps_index,'trestbps']  #outliers capped to upper
```

[43]:
```
8      170.0
101    170.0
110    170.0
203    170.0
223    170.0
241    170.0
248    170.0
260    170.0
266    170.0
Name: trestbps, dtype: float64
```

[44]:
```
#Treating Outliers for "oldpeak" using capping method

Q3 = dataset.oldpeak.quantile(0.75)
Q1 = dataset.oldpeak.quantile(0.25)
```

```
IQR = Q3-Q1
upper_oldpeak = Q3 + 1.5 * (IQR)
```

[45]:
```
dataset[dataset.oldpeak > upper_oldpeak].shape  #number of outliers in "oldpeak"
```

[45]: (5, 12)

[46]:
```
oldpeak_index = dataset[dataset.oldpeak > upper_oldpeak].index   #indexes of␣
 ↪outliers in "oldpeak"

dataset.loc[oldpeak_index,'oldpeak'] = upper_oldpeak    #assigning upper value␣
 ↪to outliers
```

[47]:
```
dataset.loc[oldpeak_index,'oldpeak']   #capped outliers
```

[47]:
```
101    4.0
204    4.0
221    4.0
250    4.0
291    4.0
Name: oldpeak, dtype: float64
```

[48]:
```
#Treating Outliers for "thalach" using capping method

Q3 = dataset.thalach.quantile(0.85)
Q1 = dataset.thalach.quantile(0.15)
IQR = Q3-Q1
lower = Q3 - 1.5 * (IQR)

#we are changing the quantile value to 85% and 15% as there are lot of outliers␣
 ↪with 75% and 25% and we dont want to lose lot of information capping them
```

[49]:
```
dataset[dataset.thalach < lower].shape #number of outliers in "thalach"
```

[49]: (8, 12)

[50]:
```
thalach_index = dataset[dataset.thalach < lower].index  #indexes of outliers in␣
 ↪"thalach"

dataset.loc[thalach_index ,'thalach'] = lower    #assigning upper value to␣
 ↪outliers
```

[51]:
```
dataset.loc[thalach_index ,'thalach']  #capped outliers
```

[51]:
```
136    101.075
198    101.075
216    101.075
```

```
233    101.075
243    101.075
262    101.075
272    101.075
297    101.075
Name: thalach, dtype: float64
```

Encoding and Scaling of data

[52]:
```
dataset1= dataset.copy()  #creating a copy of dataset to apply Encoding and␣
↪Scaling
```

[53]:
```
dataset1.head()
```

[53]:
```
   age  sex  cp  trestbps  restecg  thalach  exang  oldpeak  slope  ca  thal  \
0   63    1   3     145.0        0    150.0      0      2.3      0   0     1
1   37    1   2     130.0        1    187.0      0      3.5      0   0     2
2   41    0   1     130.0        0    172.0      0      1.4      2   0     2
3   56    1   1     120.0        1    178.0      0      0.8      2   0     2
4   57    0   0     120.0        1    163.0      1      0.6      2   0     2

   target
0       1
1       1
2       1
3       1
4       1
```

[54]:
```
#separating numerical and Categorical columns

numeric=['age','trestbps','thalach','oldpeak']

categorical=['sex','cp','restecg','exang','slope','ca','thal']
```

[55]:
```
dataset1[numeric].head()
```

[55]:
```
   age  trestbps  thalach  oldpeak
0   63     145.0    150.0      2.3
1   37     130.0    187.0      3.5
2   41     130.0    172.0      1.4
3   56     120.0    178.0      0.8
4   57     120.0    163.0      0.6
```

[56]:
```
#scaling numeric columns

ss = StandardScaler()
```

```
dataset1[numeric] = ss.fit_transform(dataset1[numeric])
```

[57]:
```
dataset1.head()
```

[57]:
```
        age  sex  cp  trestbps  restecg   thalach  exang   oldpeak  slope  ca  \
0  0.949794    1   3  0.828927        0  0.007957      0  1.147606      0   0
1 -1.928548    1   2 -0.075902        1  1.672935      0  2.230096      0   0
2 -1.485726    0   1 -0.075902        0  0.997944      0  0.335739      2   0
3  0.174856    1   1 -0.679121        1  1.267940      0 -0.205506      2   0
4  0.285561    0   0 -0.679121        1  0.592949      1 -0.385921      2   0

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

[58]:
```
#Encoding Categorical Columns

dataset_dummies = pd.get_dummies(dataset1, columns=categorical, drop_first=True)
```

[60]:
```
dataset_dummies.head()
```

[60]:
```
        age  trestbps   thalach   oldpeak  target  sex_1  cp_1  cp_2  cp_3  \
0  0.949794  0.828927  0.007957  1.147606       1      1     0     0     1
1 -1.928548 -0.075902  1.672935  2.230096       1      1     0     1     0
2 -1.485726 -0.075902  0.997944  0.335739       1      0     1     0     0
3  0.174856 -0.679121  1.267940 -0.205506       1      1     1     0     0
4  0.285561 -0.679121  0.592949 -0.385921       1      0     0     0     0

   restecg_1  …  exang_1  slope_1  slope_2  ca_1  ca_2  ca_3  ca_4  thal_1  \
0          0  …        0        0        0     0     0     0     0       1
1          1  …        0        0        0     0     0     0     0       0
2          0  …        0        0        1     0     0     0     0       0
3          1  …        0        0        1     0     0     0     0       0
4          1  …        1        0        1     0     0     0     0       0

   thal_2  thal_3
0       0       0
1       1       0
2       1       0
3       1       0
4       1       0

[5 rows x 21 columns]
```

Our data is now ready for Modelling

[61]:
```
#Defining our X and y

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

Logistic Regression Model

[62]:
```
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size=0.3)
```

[63]:
```
log_reg = LogisticRegression()

log_reg.fit(train_X, train_y)
```

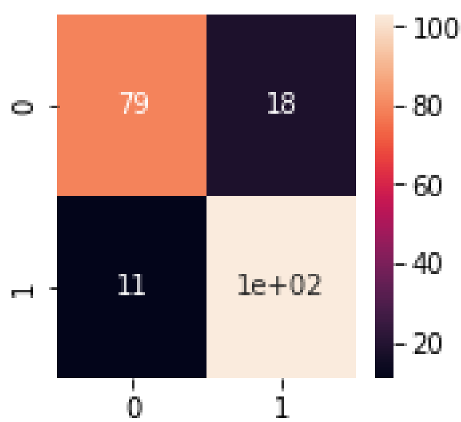
[63]:
```
LogisticRegression()
```

[64]:
```
print('Train Score: {}'.format(log_reg.score(train_X, train_y)))

print('Test Score: {}'.format(log_reg.score(test_X, test_y)))
```

```
Train Score: 0.8625592417061612
Test Score: 0.8791208791208791
```

Metrics for Train set

[65]:
```
plt.figure(figsize=(2.5,2.5))
sns.heatmap(metrics.confusion_matrix(train_y, log_reg.
 ↪predict(train_X)),annot=True);      #Confusion matrix for Train set
```

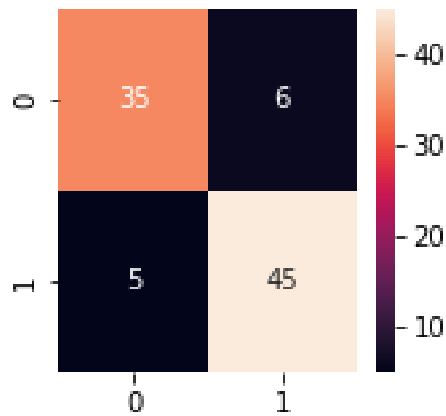


[66]:
```
print(metrics.classification_report(train_y, log_reg.predict(train_X)))   ␣
 ↪#Classification Report for Train set
```

```
              precision    recall  f1-score   support

           0       0.88      0.81      0.84        97
           1       0.85      0.90      0.88       114

    accuracy                           0.86       211
   macro avg       0.86      0.86      0.86       211
weighted avg       0.86      0.86      0.86       211
```

Metrics for Test set

```
[67]: plt.figure(figsize=(2.5,2.5))
sns.heatmap(metrics.confusion_matrix(test_y, log_reg.
 ↪predict(test_X)),annot=True);    #Confusion matrix Test set
```




```
[68]: print(metrics.classification_report(test_y, log_reg.predict(test_X)))
 ↪#Classification Report for Test Set
```

```
              precision    recall  f1-score   support

           0       0.88      0.85      0.86        41
           1       0.88      0.90      0.89        50

    accuracy                           0.88        91
   macro avg       0.88      0.88      0.88        91
weighted avg       0.88      0.88      0.88        91
```

Applying Dimentionality Reduction techniques to check if we can further improve the Scores

Using PCA and Logistic Regression

[69]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components=0.95)      #components explaining 95% of data
X_trf = pca.fit_transform(X)
```

[70]:
```
X_trf.shape    #we can see that dimention is reduced to 12 columns
```

[70]:
```
(302, 12)
```

[71]:
```
trainP_X, testP_X, trainP_y, testP_y = train_test_split(X_trf, y, test_size=0.3)

log_reg = LogisticRegression()

log_reg.fit(trainP_X, trainP_y)
```

[71]:
```
LogisticRegression()
```

[72]:
```
print('Train Score: {}'.format(log_reg.score(trainP_X, trainP_y)))

print('Test Score: {}'.format(log_reg.score(testP_X, testP_y)))
```

```
Train Score: 0.8483412322274881
Test Score: 0.7802197802197802
```

We can see there is no improvement in the scores. Lets now try LDA method Using LDA and Logistic Regression

[73]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

lda = LinearDiscriminantAnalysis()
```

[74]:
```
X_ld = lda.fit_transform(X, y)
X_ld.shape     #we can see that dimention is reduced to 1 column
```

[74]:
```
(302, 1)
```

[75]:
```
train_ld_X, test_ld_X, train_ld_y, test_ld_y = train_test_split(X_ld, y,␣
 ↪test_size=0.3)

log_reg = LogisticRegression()

log_reg.fit(train_ld_X, train_ld_y)
```

[75]:
```
LogisticRegression()
```

[76]:
```
print('Train Score: {}'.format(log_reg.score(train_ld_X, train_ld_y)))

print('Test Score: {}'.format(log_reg.score(test_ld_X, test_ld_y)))
```

```
Train Score: 0.8767772511848341
Test Score: 0.8571428571428571
```

We can see improvement in the scores after applying LDA.

[77]:
```
predict_ld_y=log_reg.predict(test_ld_X)
```

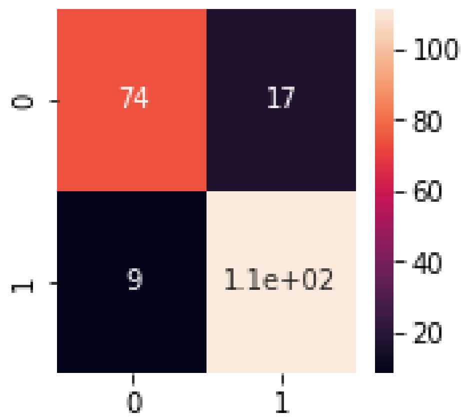
[78]:
```
print(metrics.classification_report(train_ld_y, log_reg.predict(train_ld_X))) ␣
↪#Report for Train set
```

```
              precision    recall  f1-score   support

           0       0.89      0.81      0.85        91
           1       0.87      0.93      0.90       120

    accuracy                           0.88       211
   macro avg       0.88      0.87      0.87       211
weighted avg       0.88      0.88      0.88       211
```

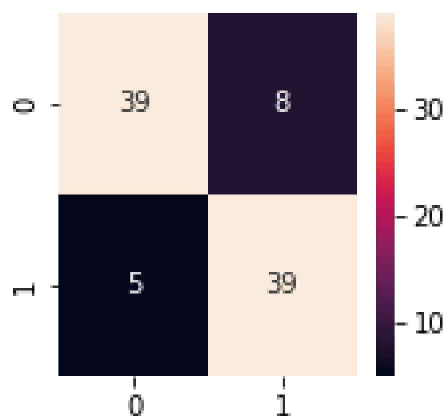
[79]:
```
print(metrics.classification_report(test_ld_y, predict_ld_y))  #Classification␣
↪Report for Test set
```

```
              precision    recall  f1-score   support

           0       0.89      0.83      0.86        47
           1       0.83      0.89      0.86        44

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

[80]:
```
plt.figure(figsize=(2.5,2.5))
sns.heatmap(metrics.confusion_matrix(train_ld_y, log_reg.
↪predict(train_ld_X)),annot=True);     #Confusion matrix for Train set
```



[81]:
```
plt.figure(figsize=(2.5,2.5))
sns.heatmap(metrics.confusion_matrix(test_ld_y, predict_ld_y ), annot=True);  ␣
↪#Confusion matrix for Test set
```



So we finalize our Logistic Regression Model using LDA

[82]:
```
#Accuracy Score

accuracy = accuracy_score(test_ld_y,predict_ld_y)

print("Test Accuracy of Logistic Regression with LDA : {}".format(accuracy*100))
```

```
Test Accuracy of Logistic Regression with LDA : 85.71428571428571
```

[83]:
```
#Cross Validation Score
```

```
scores = cross_val_score(log_reg, test_ld_X,test_ld_y, cv=5).mean()     #Model␣
 ↪Performance

print("Cross-Validation Accuracy Scores: ", scores*100)
```

```
Cross-Validation Accuracy Scores:  85.67251461988305
```

Random Forest Model

[84]:
```
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size=0.3)
```

[85]:
```
rfc=RandomForestClassifier()

rfc.fit(train_X,train_y)
```

[85]:
```
RandomForestClassifier()
```

[86]:
```
pred_y = rfc.predict(test_X)
```

[87]:
```
print('Test accuracy of Random Forest : ', accuracy_score(test_y, pred_y)*100)
```

```
Test accuracy of Random Forest :  73.62637362637363
```

[88]:
```
print('Test accuracy of Random Forest : ', accuracy_score(test_y, pred_y)*100)
```

```
Test accuracy of Random Forest :  73.62637362637363
```

[89]:
```
cross_val_score(rfc, train_X,train_y, cv=5).mean()  #training score
```

[89]:
```
0.8198228128460686
```

[90]:
```
#Cross Validation Score

cross_val_score(rfc, test_X, test_y, cv=5).mean()  #testing score
```

[90]:
```
0.7035087719298245
```

[92]:
```
#Applying grid search CV
param_grid = {
    'n_estimators': [20, 50, 100, 150,200],
    'max_depth': [3, 5, 7, None],
    'min_samples_leaf': [3, 5, 7, 9]
}

gscv = GridSearchCV(rfc, param_grid, cv=5, verbose=1)
gscv.fit(train_X,train_y)
```

```
Fitting 5 folds for each of 80 candidates, totalling 400 fits
```

[92]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [3, 5, 7, None],
                         'min_samples_leaf': [3, 5, 7, 9],
                         'n_estimators': [20, 50, 100, 150, 200]},
             verbose=1)
```

[94]:
```
cross_val_score(gscv.best_estimator_, train_X,train_y, cv=5).mean()  #training␣
↪score
```

[94]:
```
0.777076411960133
```

[96]:
```
#Cross Validation Score after Grid Search CV

cvs=cross_val_score(gscv.best_estimator_, test_X, test_y, cv=5).mean()

print("Cross-Validation Accuracy Scores: ", cvs*100)
```

```
Cross-Validation Accuracy Scores:  78.0701754385965
```

[97]:
```
y_pred = gscv.best_estimator_.predict(test_X)
```

[98]:
```
print('Test accuracy of Random Forest after Grid Search CV : ',␣
↪accuracy_score(test_y, y_pred)*100)
```

```
Test accuracy of Random Forest after Grid Search CV :  72.52747252747253
```

0.0.1 Conclusion

We prefer the Model created with ”Logistic Regression using LDA Algorithm” , which gives the best results as compared to Random Forest Algorithm.

[ ]:
```
```