**Name** - Nihalahmed Munir Barudwale

**Project name** - Prediction of Heart disease detection

#

**Import Required Libraries**

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import os
import warnings
warnings.filterwarnings('ignore')
```

**Import dataset**

```
dataset = pd.read_csv("/content/drive/MyDrive/TCR Internship
Project/heart.csv")
```

```
dataset
```

```
     age  sex  cp  trestbps  chol  fbs  ...  exang  oldpeak  slope  ca
thal  target
0     63    1   3       145   233    1  ...      0      2.3      0   0
1       1
1     37    1   2       130   250    0  ...      0      3.5      0   0
2       1
2     41    0   1       130   204    0  ...      0      1.4      2   0
2       1
3     56    1   1       120   236    0  ...      0      0.8      2   0
2       1
4     57    0   0       120   354    0  ...      1      0.6      2   0
2       1
..   ...  ...  ..       ...   ...  ...  ...    ...      ...    ...  ..
...     ...
298   57    0   0       140   241    0  ...      1      0.2      1   0
3       0
299   45    1   3       110   264    0  ...      0      1.2      1   0
3       0
300   68    1   0       144   193    1  ...      0      3.4      1   2
3       0
301   57    1   0       130   131    0  ...      1      1.2      1   1
3       0
302   57    0   1       130   236    0  ...      0      0.0      1   1
2       0

[303 rows x 14 columns]
```

**Shape of dataset**

```
dataset.shape
```

```
(303, 14)
```

**Some Operations on dataset**

```
dataset.head()
```

```
   age  sex  cp  trestbps  chol  fbs  ...  exang  oldpeak  slope  ca  
thal  target
0   63    1   3       145   233    1  ...      0      2.3      0   0
1       1
1   37    1   2       130   250    0  ...      0      3.5      0   0
2       1
2   41    0   1       130   204    0  ...      0      1.4      2   0
2       1
3   56    1   1       120   236    0  ...      0      0.8      2   0
2       1
4   57    0   0       120   354    0  ...      1      0.6      2   0
2       1

[5 rows x 14 columns]
```

```
dataset.tail()
```

```
     age  sex  cp  trestbps  chol  fbs  ...  exang  oldpeak  slope  ca  
thal  target
298   57    0   0       140   241    0  ...      1      0.2      1   0
3       0
299   45    1   3       110   264    0  ...      0      1.2      1   0
3       0
300   68    1   0       144   193    1  ...      0      3.4      1   2
3       0
301   57    1   0       130   131    0  ...      1      1.2      1   1
3       0
302   57    0   1       130   236    0  ...      0      0.0      1   1
2       0

[5 rows x 14 columns]
```

```
type(dataset)
```

```
pandas.core.frame.DataFrame
```

```
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
```

```
dataset.describe()
```

```
              age         sex          cp  ...          ca        thal
target
count  303.000000  303.000000  303.000000  ...  303.000000  303.000000
303.000000
mean    54.366337    0.683168    0.966997  ...    0.729373    2.313531
0.544554
std      9.082101    0.466011    1.032052  ...    1.022606    0.612277
0.498835
min     29.000000    0.000000    0.000000  ...    0.000000    0.000000
0.000000
25%     47.500000    0.000000    0.000000  ...    0.000000    2.000000
0.000000
50%     55.000000    1.000000    1.000000  ...    0.000000    2.000000
1.000000
75%     61.000000    1.000000    2.000000  ...    1.000000    3.000000
1.000000
max     77.000000    1.000000    3.000000  ...    4.000000    3.000000
1.000000

[8 rows x 14 columns]
```

```
dataset.columns
```

```
Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg',
'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
      dtype='object')
```

**Checking total number of NA values**

```
dataset.isna().sum()
```

```
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 total number of NULL values

```
dataset.isnull().sum()
```

```
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
```

#

#### Exploratory Data Analysis (EDA)

#### Analysing the 'target' variable

```
dataset.target.describe()
```

```
count    303.000000
mean       0.544554
std        0.498835
min        0.000000
25%        0.000000
50%        1.000000
75%        1.000000
```

```
max          1.000000
Name: target, dtype: float64
```

```
dataset.target.unique()
```

```
array([1, 0])
```

```
#Checking correlation between columns
dataset.corr()["target"].abs().sort_values(ascending=False)
```

```
target      1.000000
exang       0.436757
cp          0.433798
oldpeak     0.430696
thalach     0.421741
ca          0.391724
slope       0.345877
thal        0.344029
sex         0.280937
age         0.225439
trestbps    0.144931
restecg     0.137230
chol        0.085239
fbs         0.028046
Name: target, dtype: float64
```

```
#This shows that most columns are moderately correlated with target,
but 'fbs' is very weakly correlated.
```

```
dataset.target.value_counts()
```

```
1    165
0    138
Name: target, dtype: int64
```

Patient without heart problems - labeled as 0

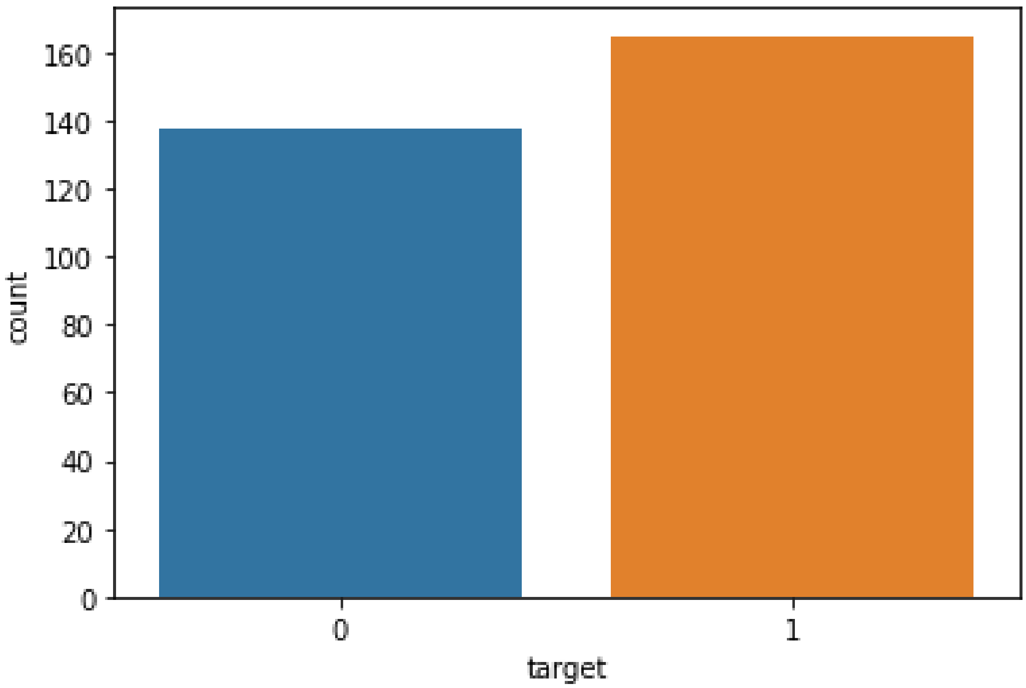
Patient with heart problems - labeled as 1

```
print("Percentage of patients without heart problems: 
"+str(round(138*100/303,2)))
print("Percentage of patients with heart problems: 
"+str(round(165*100/303,2)))
```

```
Percentage of patient without heart problems: 45.54
Percentage of patient with heart problems: 54.46
```

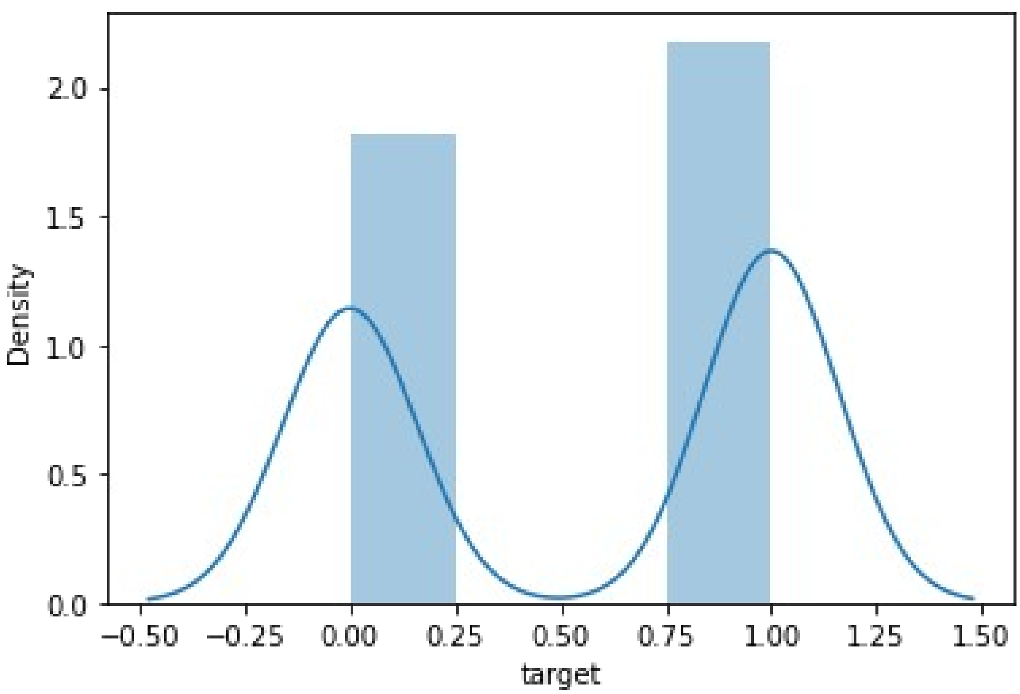
```
y = dataset["target"]
sns.countplot(y)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a51e5d90>
```




```
sns.distplot(dataset['target'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8991c58910>
```



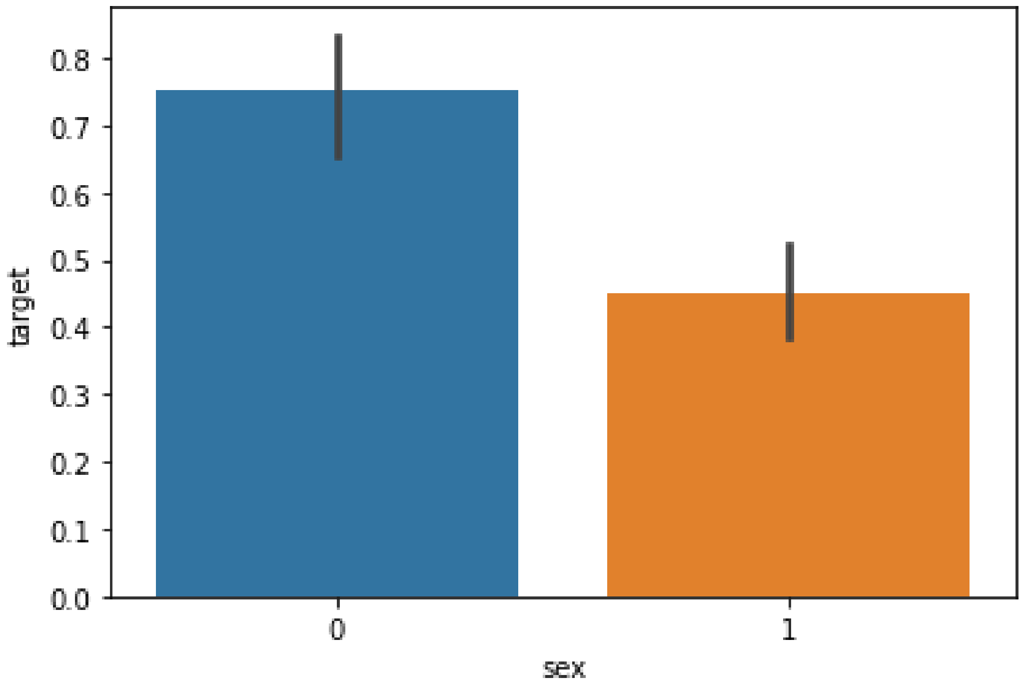

**Analysing the 'sex' variable**

```
dataset.sex.value_counts()
```

```
1    207
0     96
Name: sex, dtype: int64
```

```
sns.barplot(dataset["sex"],y)
```

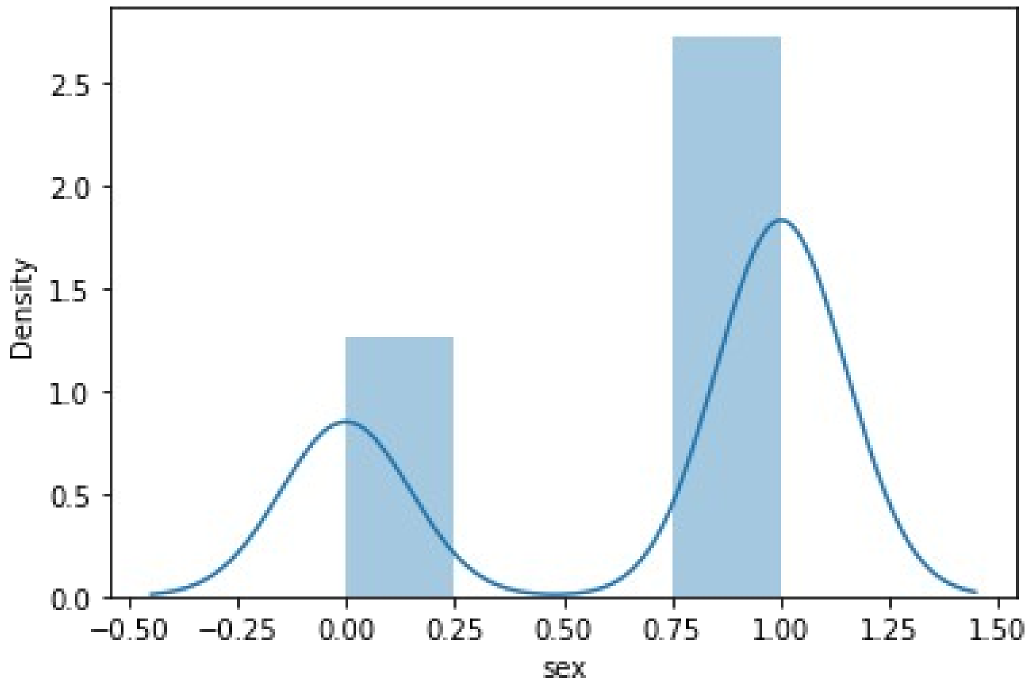
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a5127550>
```




We notice that the 'sex' feature has 2 unique features.

```
sns.distplot(dataset['sex'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8991cd29d0>
```



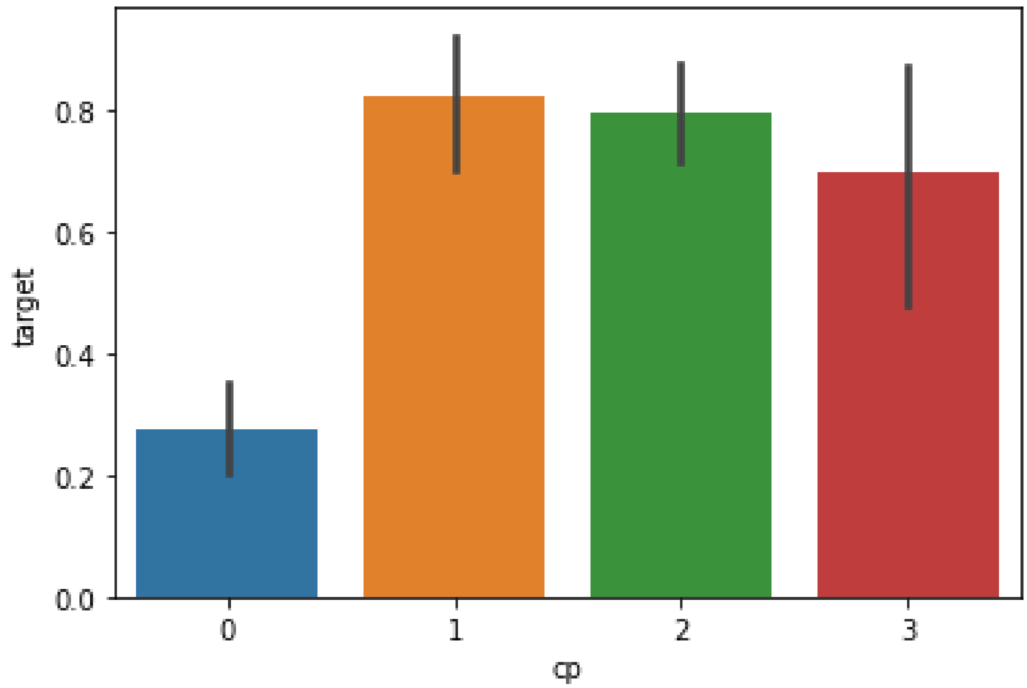

**Analysing the 'cp' variable**

```
dataset.cp.value_counts()
```

```
0    143
2     87
1     50
3     23
Name: cp, dtype: int64
```

```
sns.barplot(dataset["cp"],y)
```

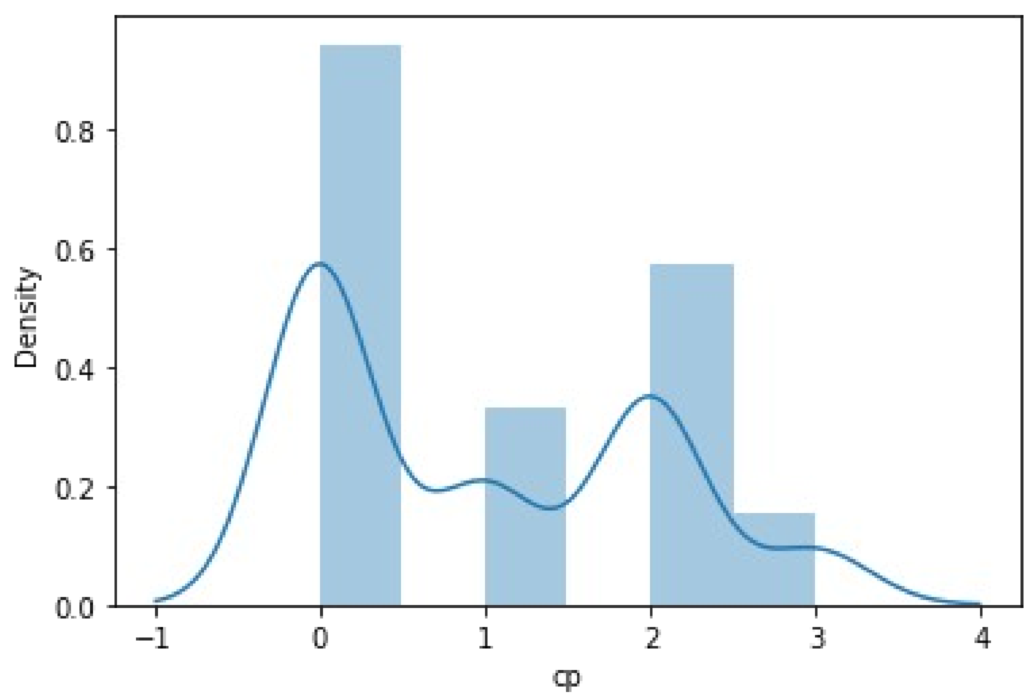
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a4c5a810>
```




The CP feature has values from 0 to 3.We notice, that chest pain of '0', are much less likely to have heart problems

```
sns.distplot(dataset['cp'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8991d89c90>
```



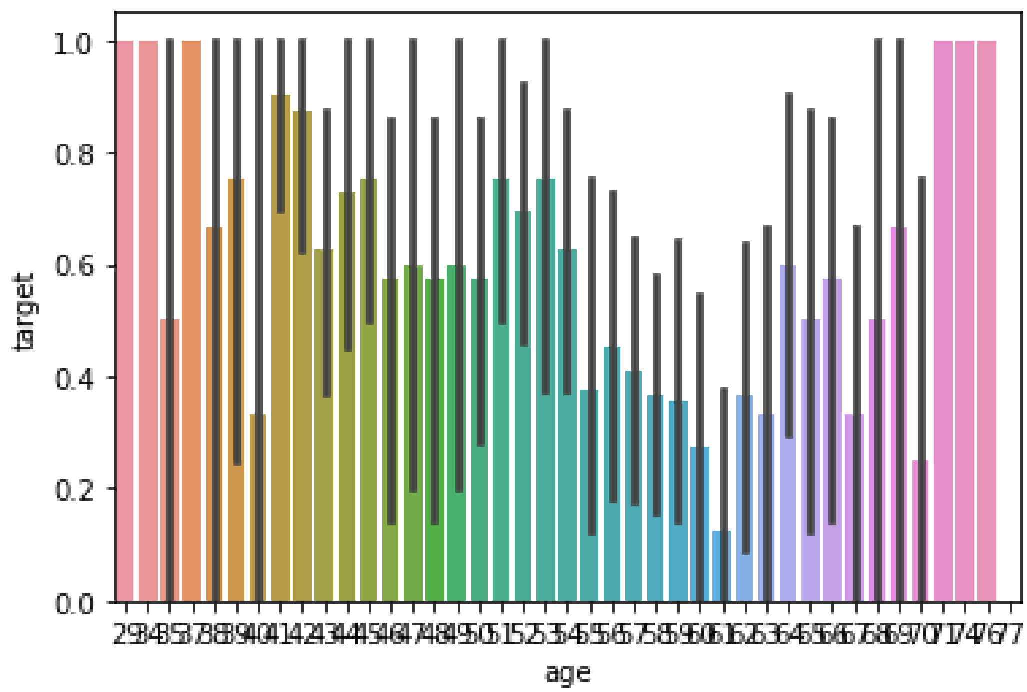

**Analysing the 'age' variable**

```
dataset.age.value_counts()
```

```
58    19
57    17
54    16
59    14
52    13
51    12
62    11
44    11
60    11
56    11
64    10
41    10
63     9
67     9
55     8
45     8
42     8
53     8
61     8
65     8
43     8
66     7
50     7
48     7
46     7
49     5
47     5
39     4
35     4
68     4
70     4
40     3
71     3
69     3
38     3
34     2
37     2
77     1
76     1
74     1
29     1
Name: age, dtype: int64
```

```
sns.barplot(dataset["age"],y)
```

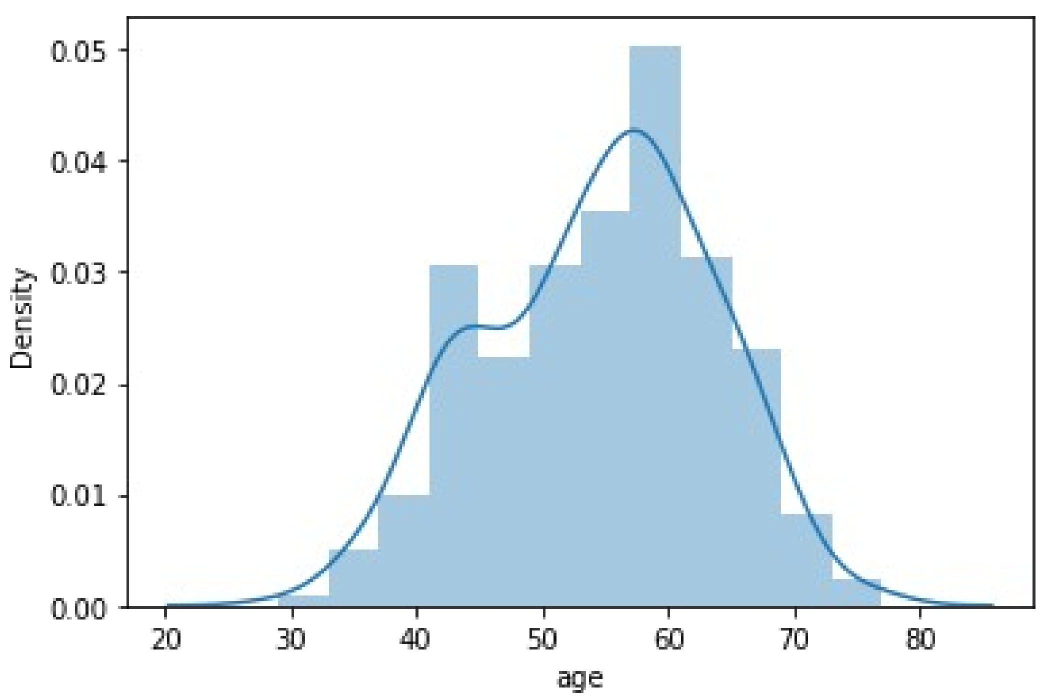
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a4bd5a90>
```




Nothing special here.

```
sns.distplot(dataset['age'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8991d66b90>
```




**Analysing the 'trestbps' variable**

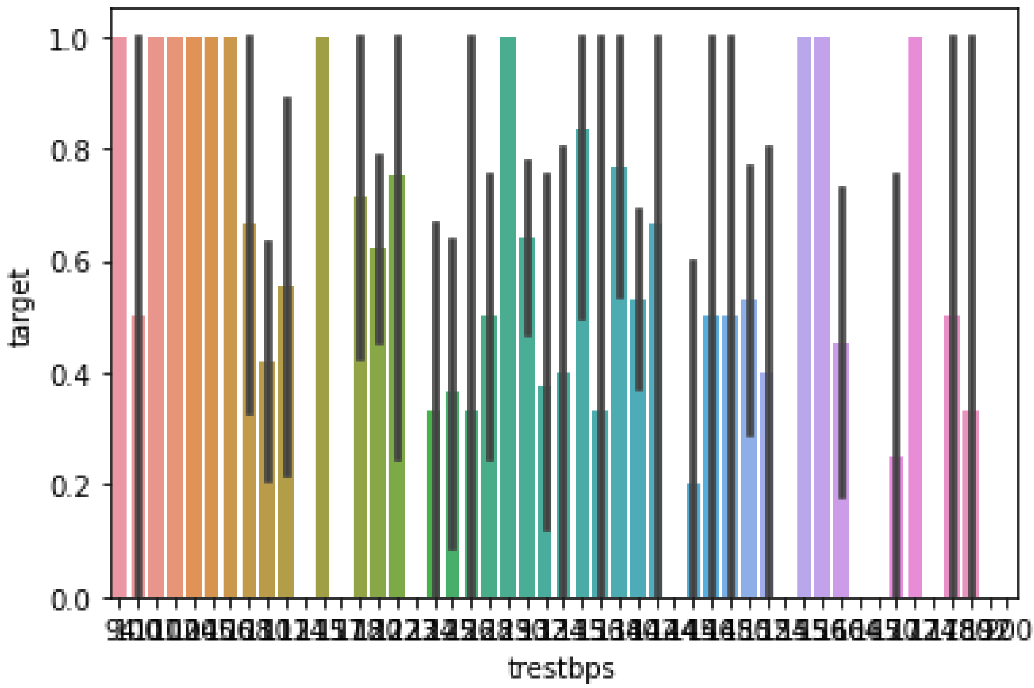
```
dataset.trestbps.value_counts()
```

```
120    37
130    36
140    32
110    19
150    17
138    13
128    12
125    11
160    11
112     9
132     8
118     7
135     6
108     6
124     6
145     5
134     5
152     5
122     4
170     4
100     4
142     3
115     3
136     3
105     3
180     3
126     3
102     2
94      2
144     2
178     2
146     2
148     2
129     1
165     1
101     1
174     1
104     1
172     1
106     1
156     1
164     1
192     1
114     1
155     1
117     1
154     1
123     1
```

```
200      1
Name: trestbps, dtype: int64
```

```
sns.barplot(dataset["trestbps"],y)
```

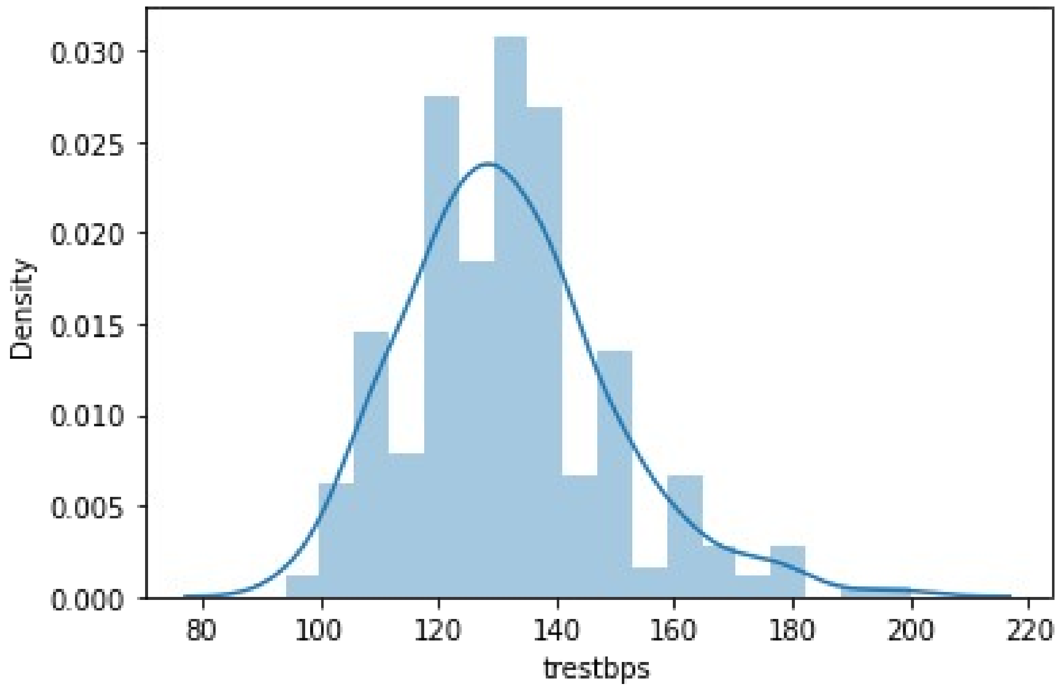
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a4bbb850>
```




Nothing special here.

```
sns.distplot(dataset['trestbps'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8991bd31d0>
```



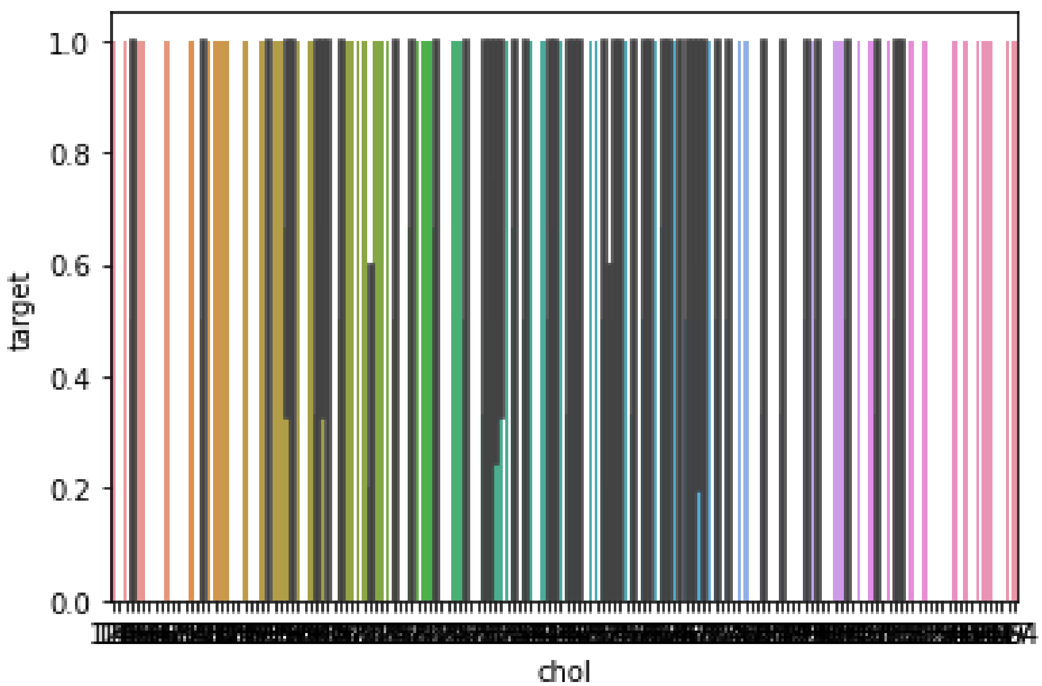

**Analysing the 'chol' variable**

```
dataset.chol.value_counts()
```

```
234    6
204    6
197    6
269    5
212    5
      ..
278    1
281    1
284    1
290    1
564    1
Name: chol, Length: 152, dtype: int64
```

```
sns.barplot(dataset["chol"],y)
```

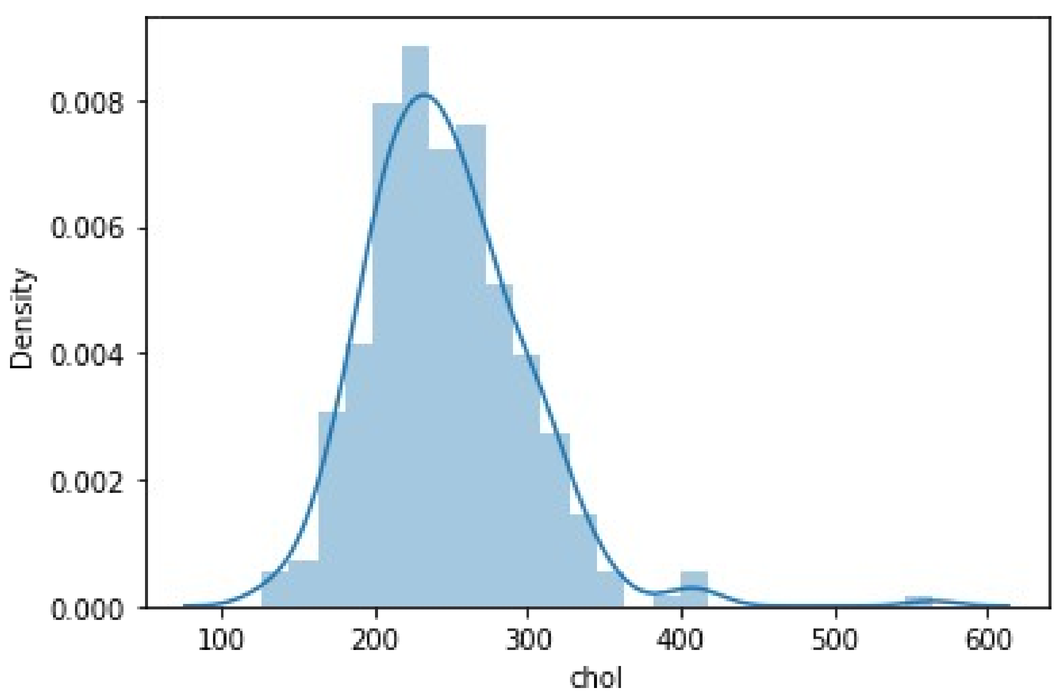
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a4736d10>
```




Nothing special here

```
sns.distplot(dataset['chol'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8991b3ba10>
```



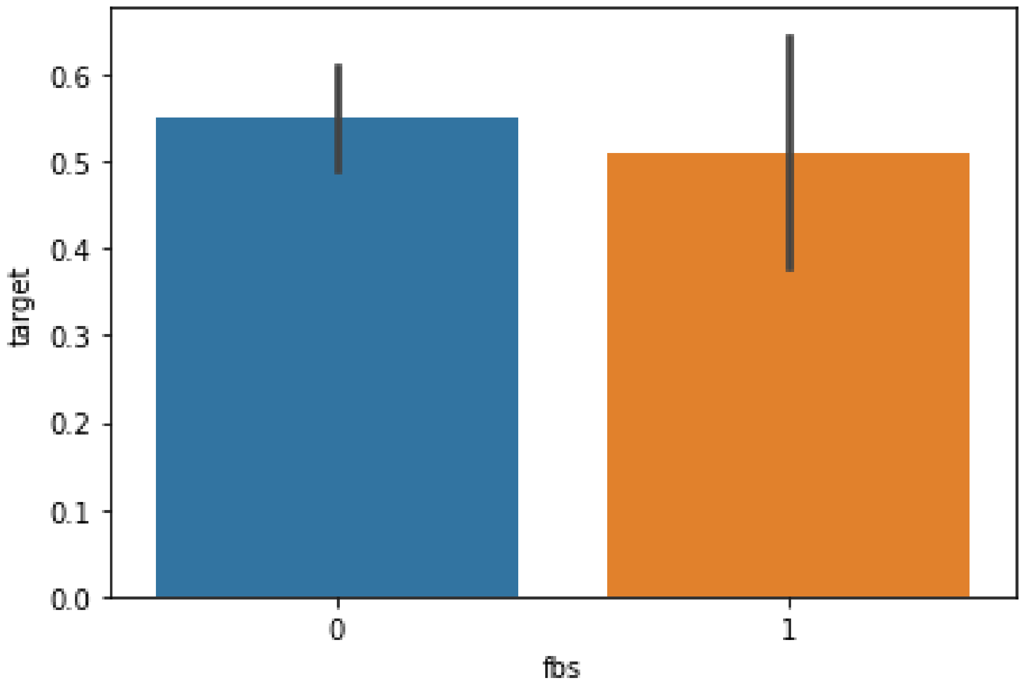

**Analysing the 'fbs' variable**

```
dataset.fbs.value_counts()
```

```
0    258
1     45
Name: fbs, dtype: int64
```

```
sns.barplot(dataset["fbs"],y)
```

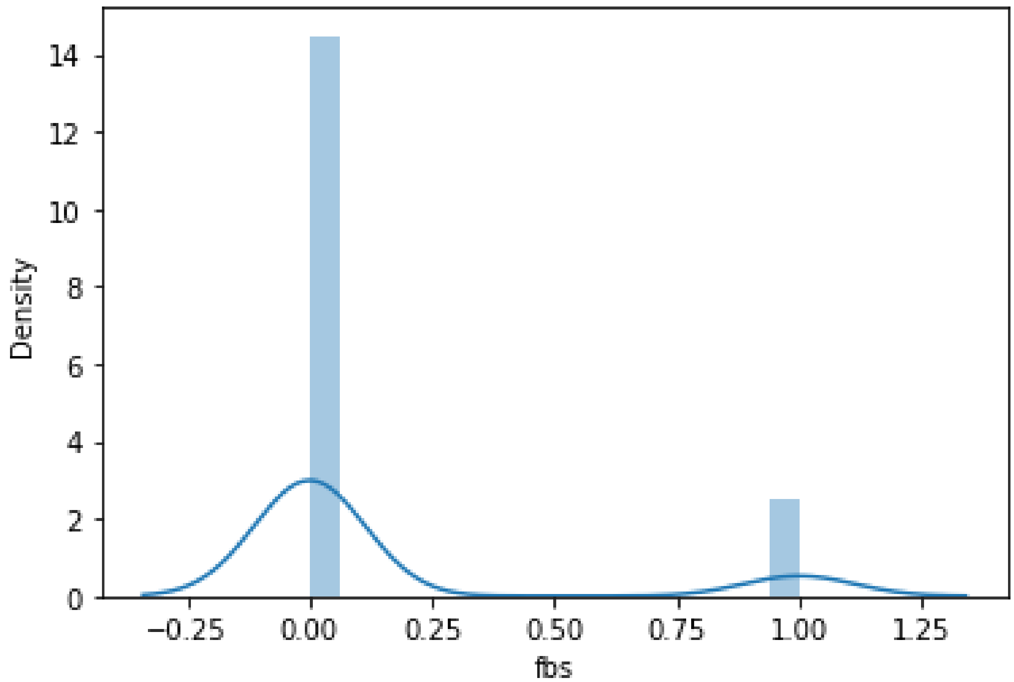
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a4738490>
```




Not much difference here.

```
sns.distplot(dataset['fbs'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8991aa1050>
```



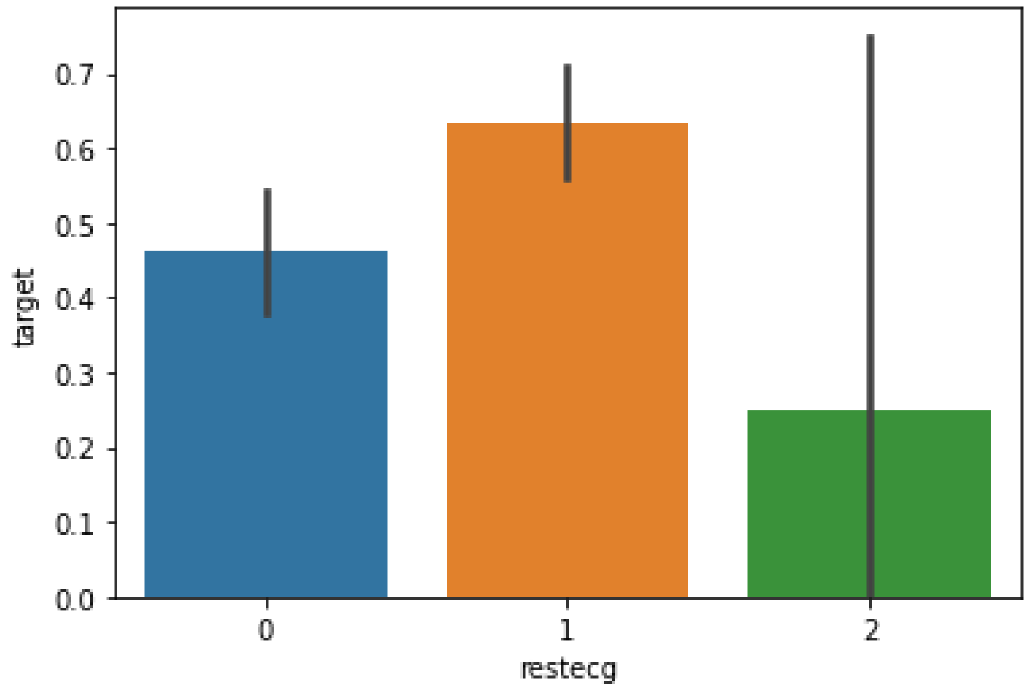

**Analysing the 'restecg' variable**

```
dataset.restecg.value_counts()
```

```
1    152
0    147
2      4
Name: restecg, dtype: int64
```

```
sns.barplot(dataset["restecg"],y)
```

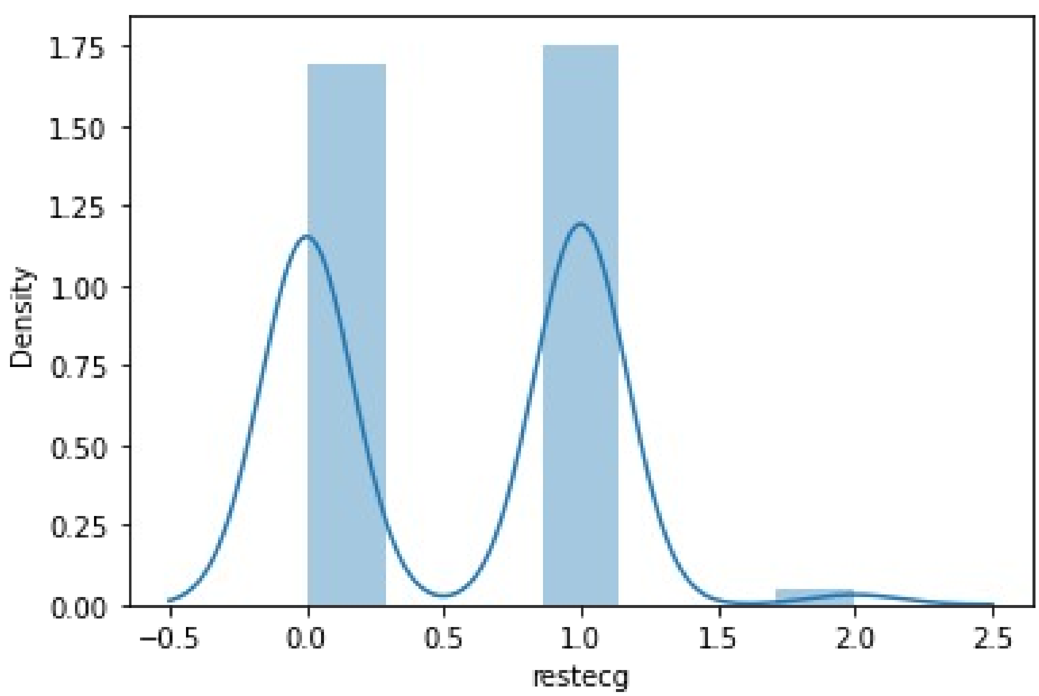
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a41a4f10>
```




We realize that people with restecg '1' and '0' are much more likely to have a heart disease than with restecg '2'

```
sns.distplot(dataset['restecg'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89919bc990>
```



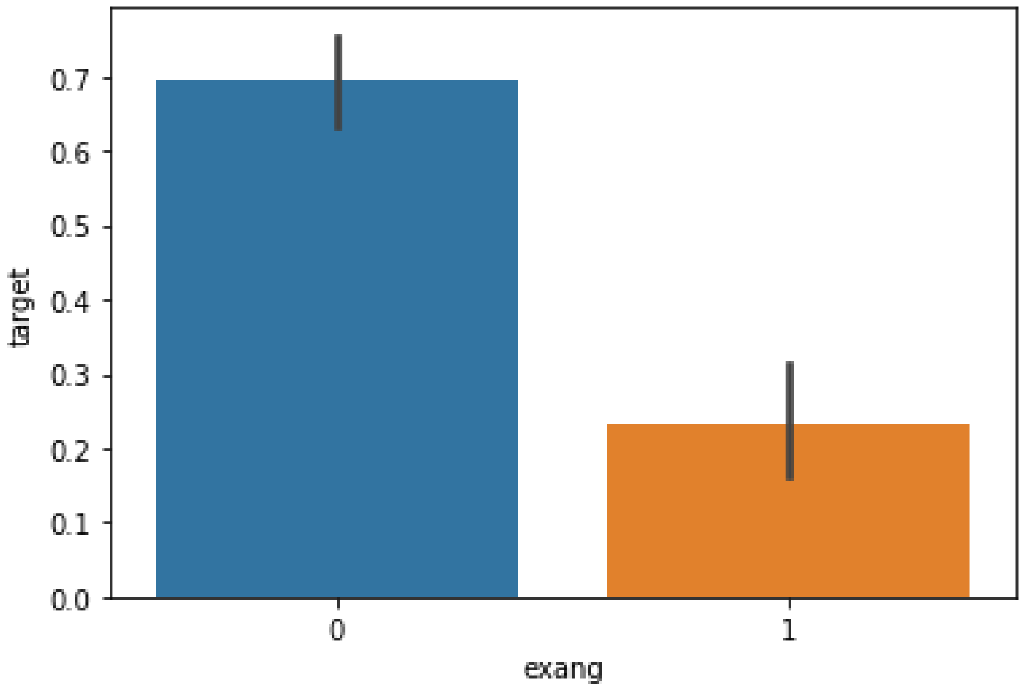

**Analysing the 'exang' variable**

```
dataset.exang.value_counts()
```

```
0    204
1     99
Name: exang, dtype: int64
```

```
sns.barplot(dataset["exang"],y)
```

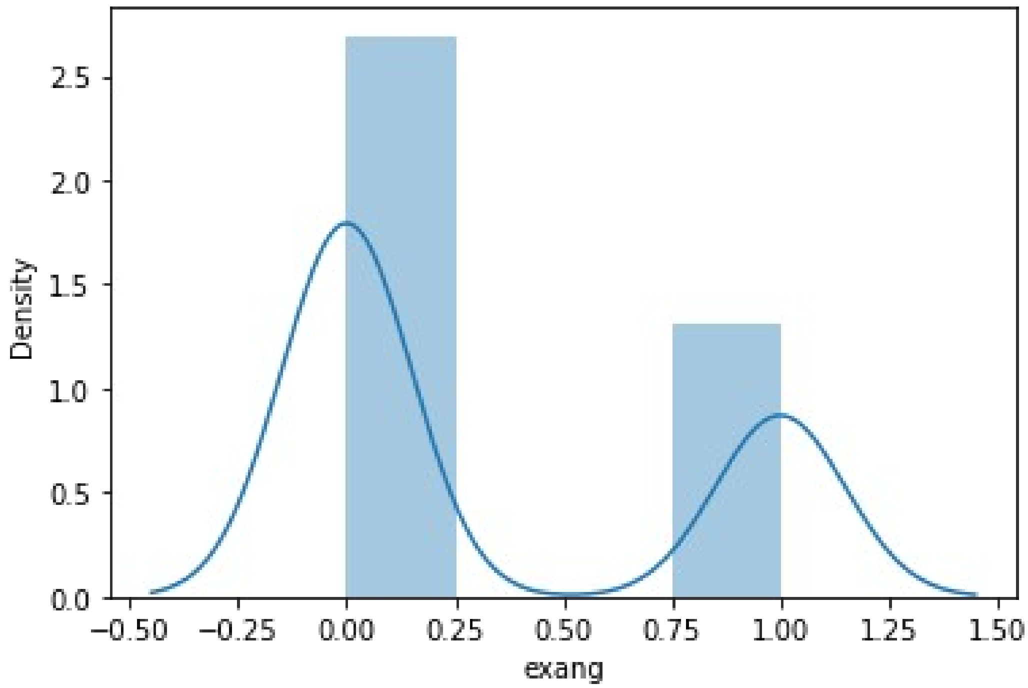
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a4120e90>
```




We notice here that people with exang=1, are much less likely to have heart problems.

```
sns.distplot(dataset['exang'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8991934290>
```



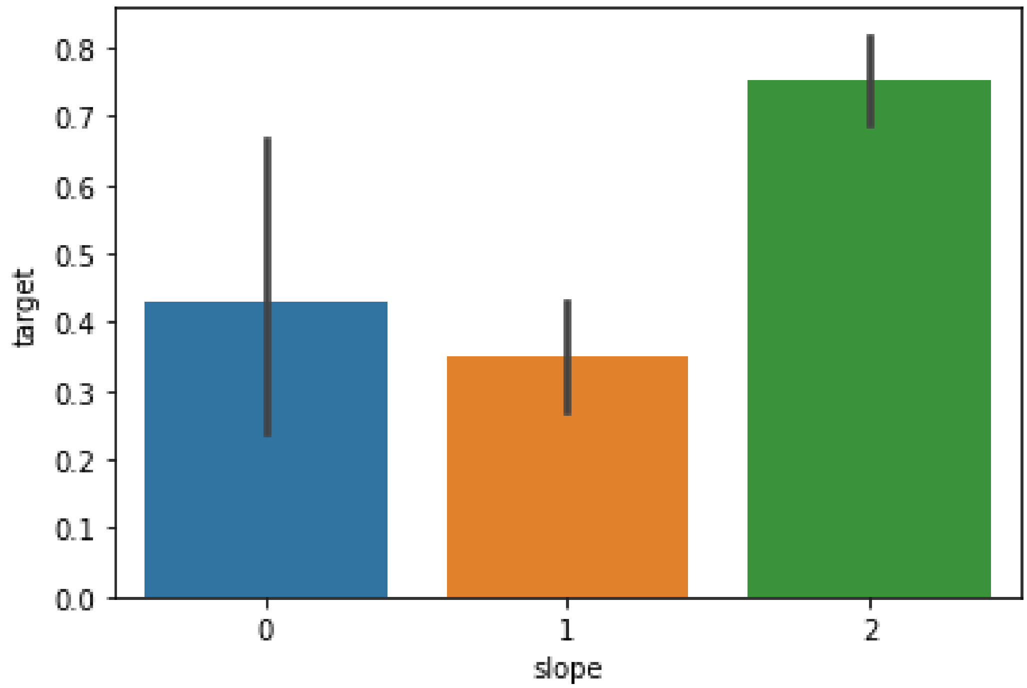

**Analysing the 'slope' variable**

```
dataset.slope.value_counts()
```

```
2    142
1    140
0     21
Name: slope, dtype: int64
```

```
sns.barplot(dataset["slope"],y)
```

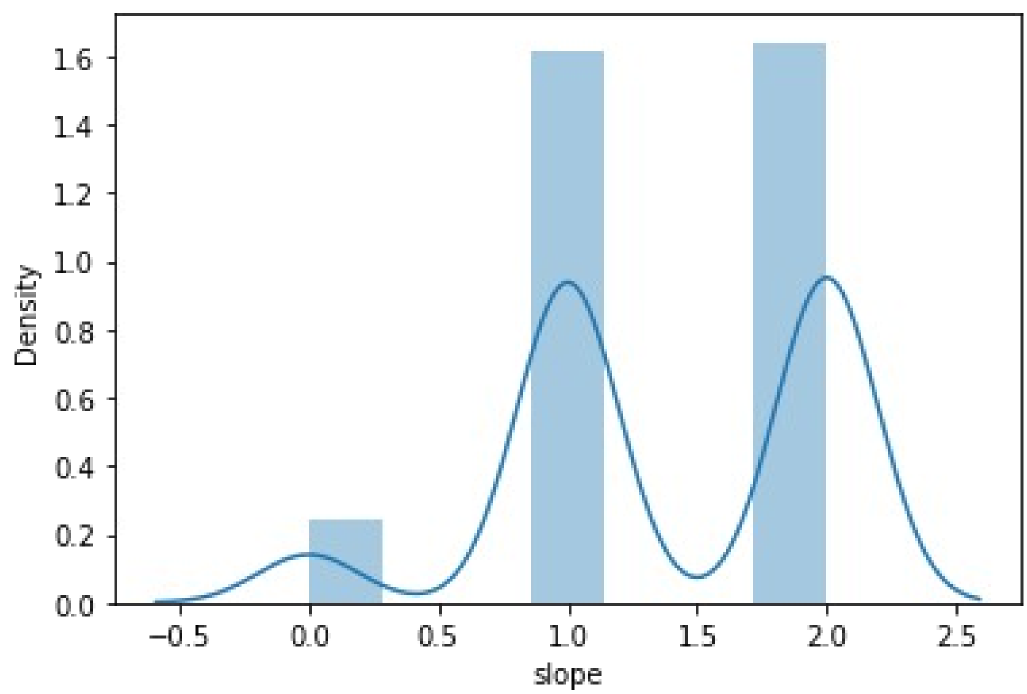
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a40e8b50>
```




We observe, that Slope '2' causes heart pain much more than Slope '0' and '1'

```
sns.distplot(dataset['slope'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8991915b90>
```



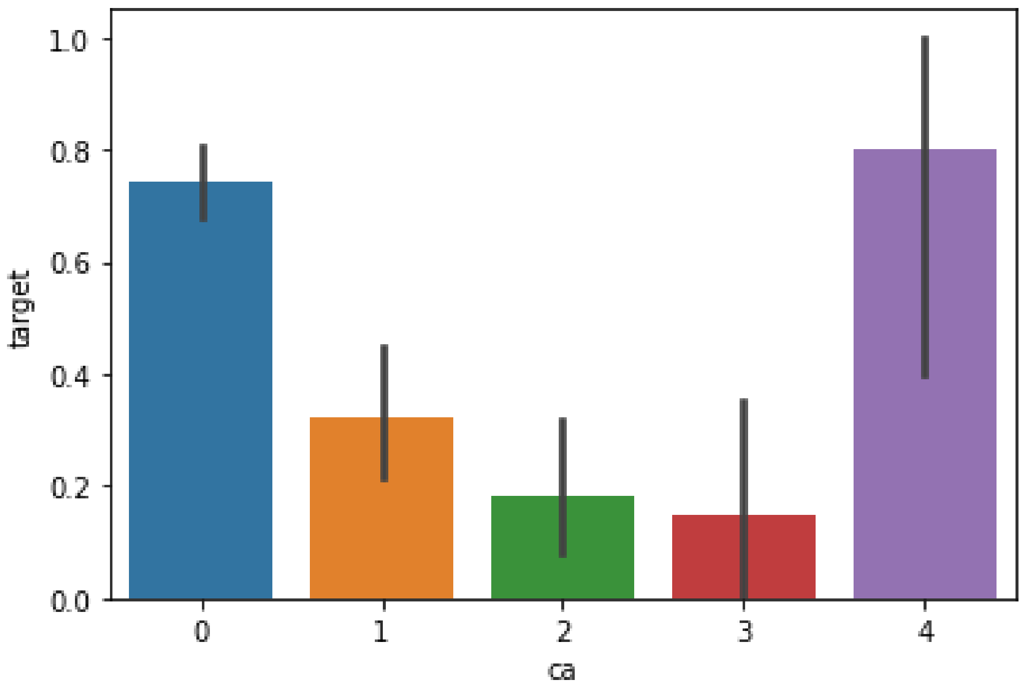

**Analysing the 'ca' variable**

```
dataset.ca.value_counts()
```

```
0    175
1     65
2     38
3     20
4      5
Name: ca, dtype: int64
```

```
sns.barplot(dataset["ca"],y)
```

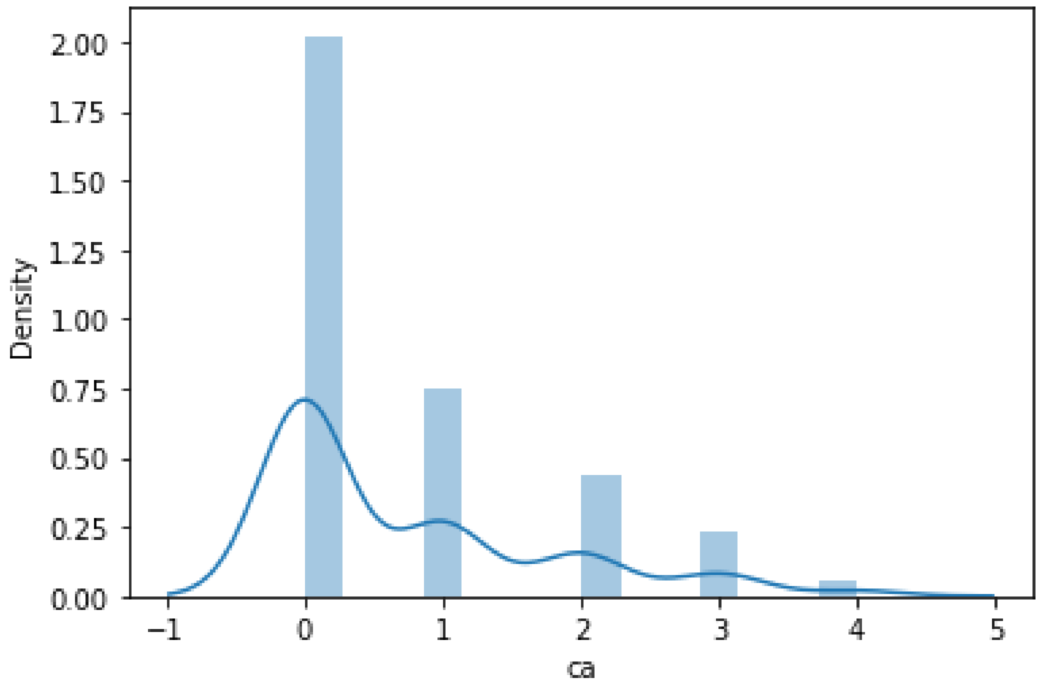
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a406fa90>
```




We notice that ca=4 has large number of heart patients.

```
sns.distplot(dataset['ca'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89918781d0>
```



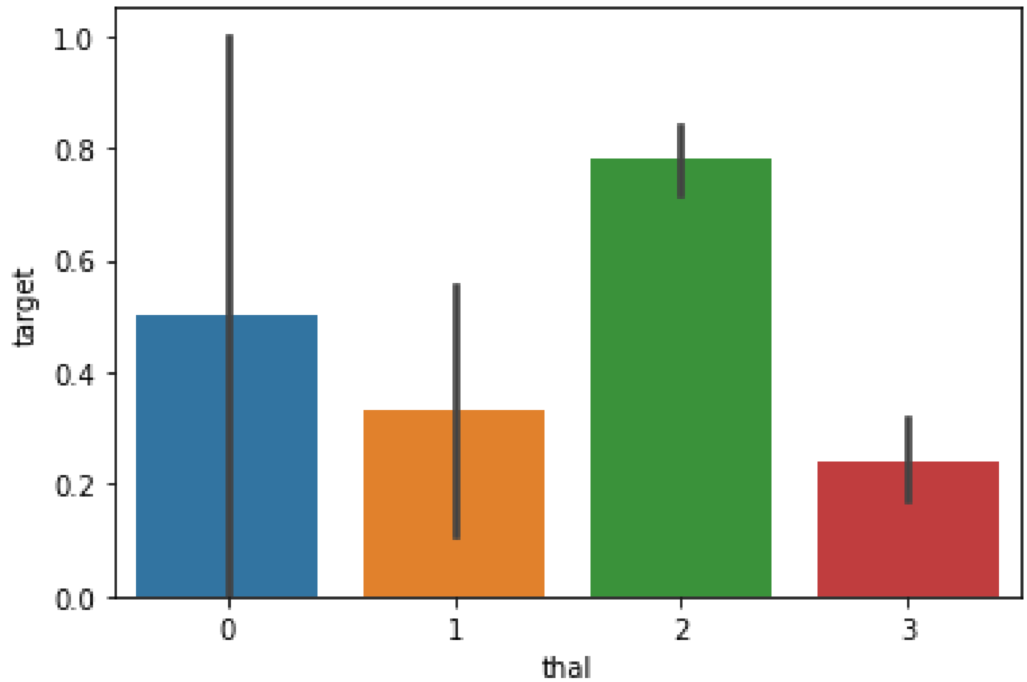

**Analysing the 'thal' variable**

```
dataset.thal.value_counts()
```

```
2    166
3    117
1     18
0      2
Name: thal, dtype: int64
```

```
sns.barplot(dataset["thal"],y)
```

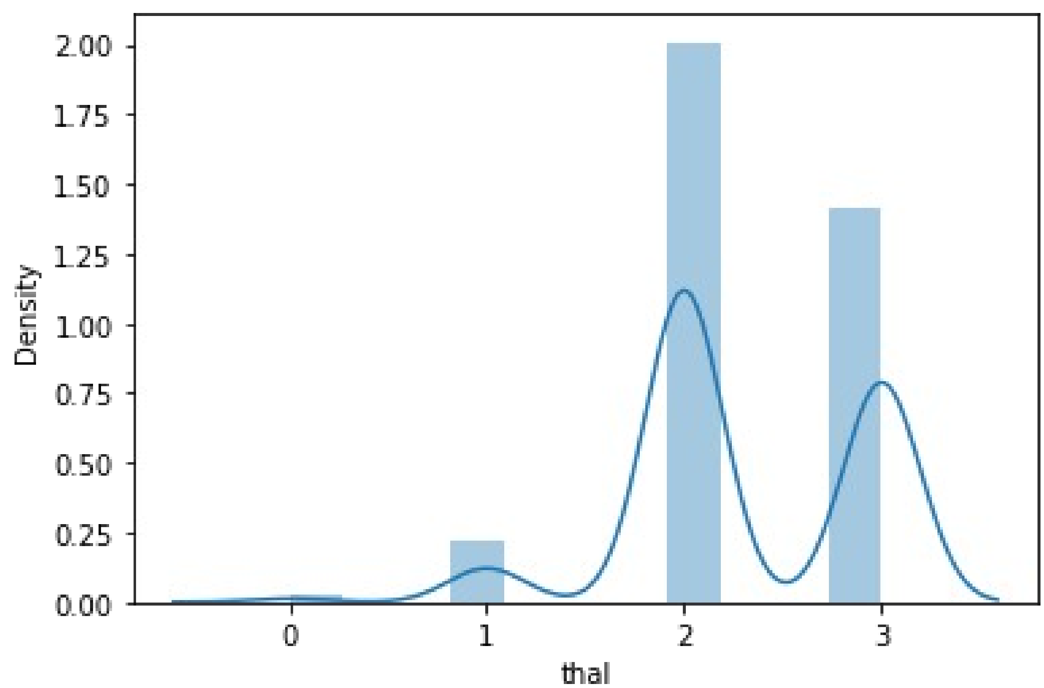
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89a3fd8450>
```




thal=2 has large number of heart patients.

```
sns.distplot(dataset['thal'])
```

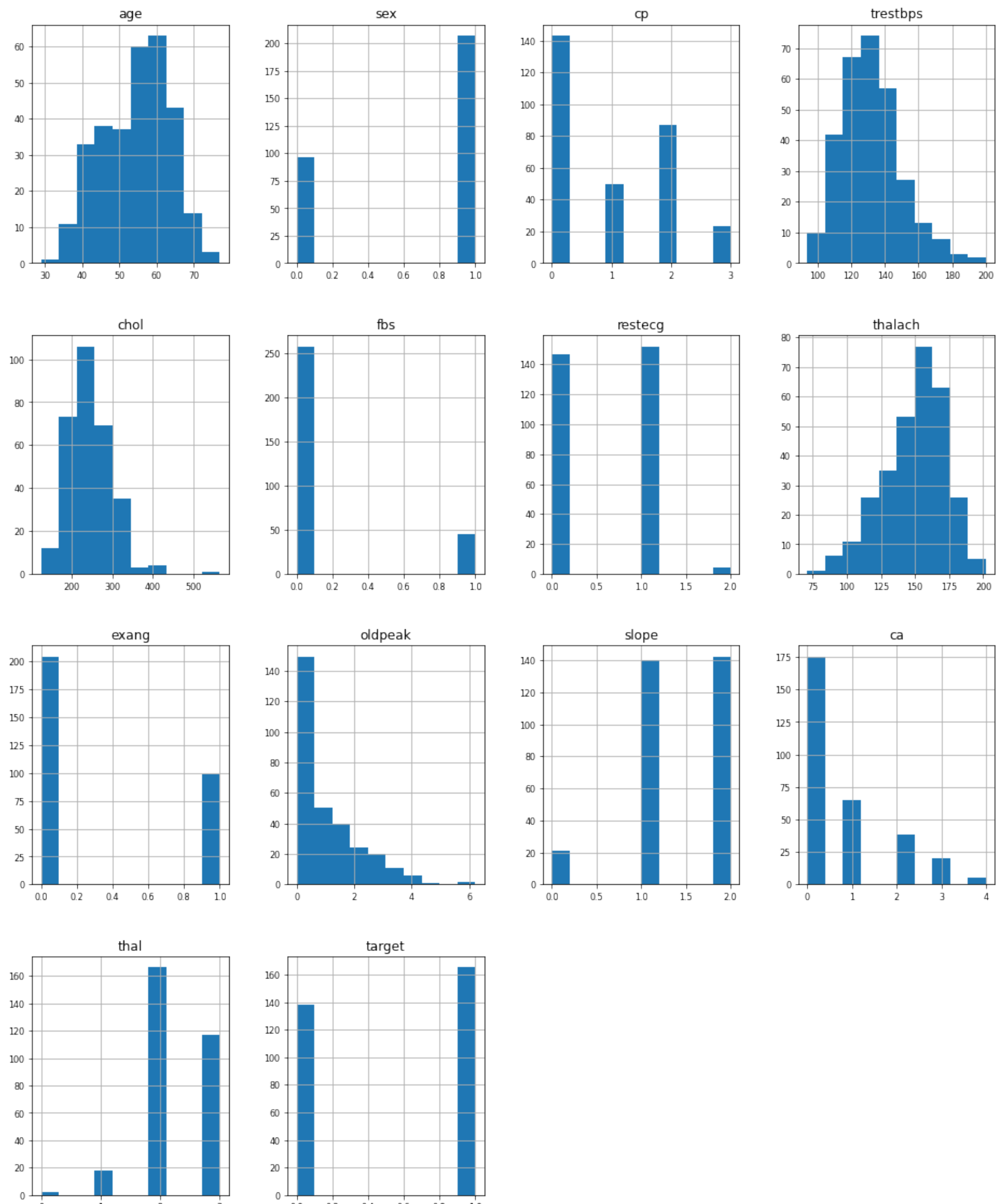
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8991835f50>
```




**Get an overview distribution of each column**

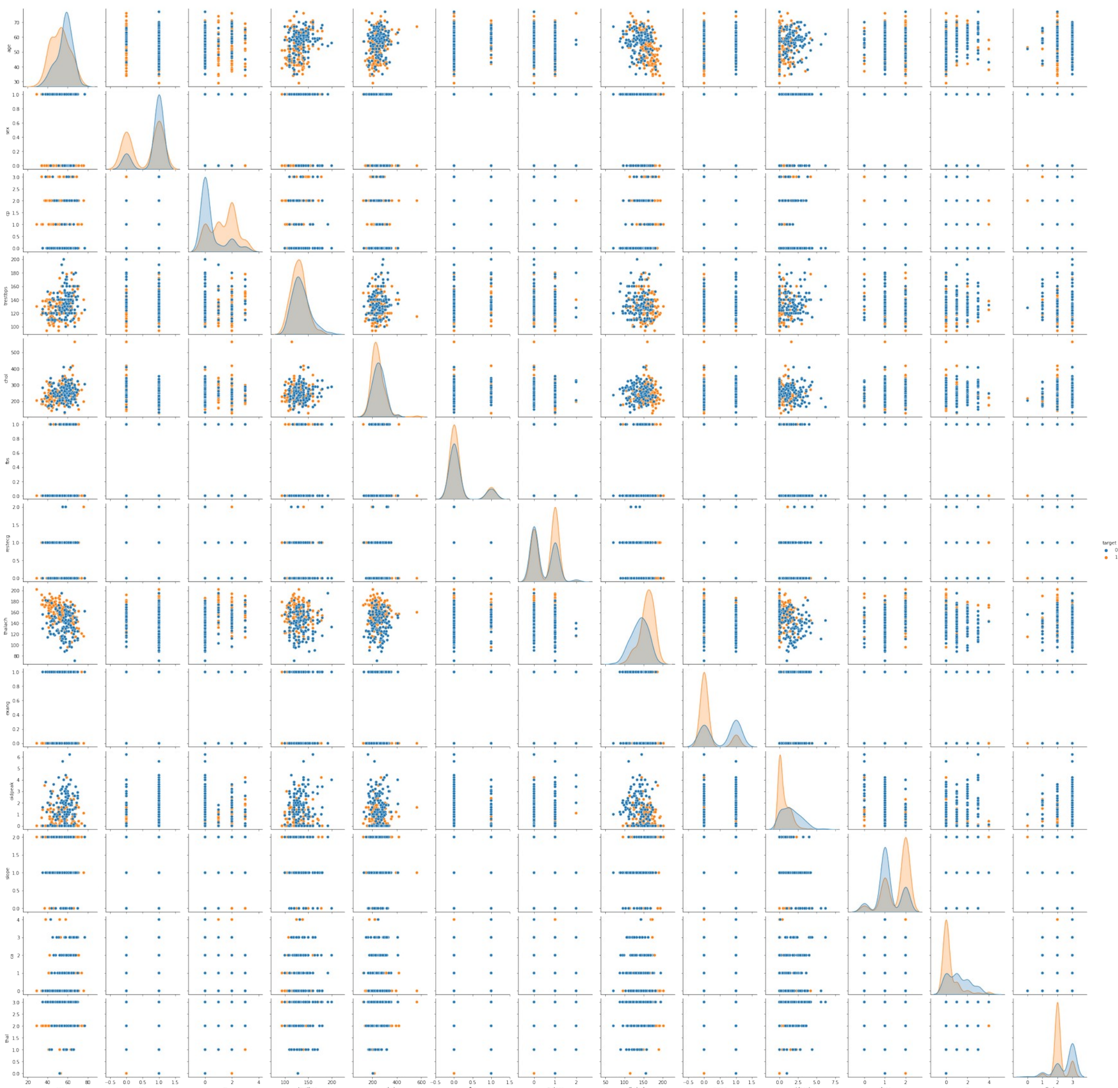
```
dataset.hist(figsize=(16, 20), xlabelsize=8, ylabelsize=8)
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3f11d10>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3ecd390>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3e83990>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3e39f90>],
       [<matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3dfe2d0>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3db57d0>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3de9d50>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3dab1d0>],
       [<matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3dab210>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3d63810>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3cdb150>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3c92650>],
       [<matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3c46b10>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3bf2b90>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3bc0590>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x7f89a3b75a90>]],
      dtype=object)
```




```
sns.pairplot(dataset, hue='target')
```

<seaborn.axisgrid.PairGrid at 0x7f89a512fbd0>



## Correlation heatmap

```
dataset.corr()
```

```
               age       sex        cp  ...        ca      thal
target
age       1.000000 -0.098447 -0.068653  ...  0.276326  0.068001 -
0.225439
sex      -0.098447  1.000000 -0.049353  ...  0.118261  0.210041 -
0.280937
cp       -0.068653 -0.049353  1.000000  ... -0.181053 -0.161736
0.433798
trestbps  0.279351 -0.056769  0.047608  ...  0.101389  0.062210 -
0.144931
chol      0.213678 -0.197912 -0.076904  ...  0.070511  0.098803 -
0.085239
fbs       0.121308  0.045032  0.094444  ...  0.137979 -0.032019 -
0.028046
```

```
restecg  -0.116211 -0.058196  0.044421  ... -0.072042 -0.011981
0.137230
thalach  -0.398522 -0.044020  0.295762  ... -0.213177 -0.096439
0.421741
exang     0.096801  0.141664 -0.394280  ...  0.115739  0.206754 -
0.436757
oldpeak   0.210013  0.096093 -0.149230  ...  0.222682  0.210244 -
0.430696
slope    -0.168814 -0.030711  0.119717  ... -0.080155 -0.104764
0.345877
ca        0.276326  0.118261 -0.181053  ...  1.000000  0.151832 -
0.391724
thal      0.068001  0.210041 -0.161736  ...  0.151832  1.000000 -
0.344029
target   -0.225439 -0.280937  0.433798  ... -0.391724 -0.344029
1.000000

[14 rows x 14 columns]
```

```
f, ax = plt.subplots(figsize=(15, 10))
sns.heatmap(dataset.corr(),annot=True,cmap='PiYG',linewidths=.5)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89921d6f10>
```


**Splitting the data - Train Test split**

```
from sklearn.model_selection import train_test_split
x = dataset.drop("target",axis=1)
y= dataset["target"]

X_train,X_test,Y_train,Y_test =
train_test_split(x,y,test_size=0.20,random_state=0)
```

```
X_train.shape
```

```
(242, 13)
```

```
X_test.shape
```

```
(61, 13)
```

```
Y_train.shape
```

```
(242,)
```

```
Y_test.shape
```

```
(61,)
```

```
from sklearn.metrics import accuracy_score
```

**Logistic Regression**

```
from sklearn.linear_model import LogisticRegression
model_logistic_reg = LogisticRegression()
model_logistic_reg.fit(X_train,Y_train)
Y_pred_logistic_reg = model_logistic_reg.predict(X_test)
```

```
Y_pred_logistic_reg.shape
```

```
(61,)
```

```
print("Predicted Values : ",Y_pred_logistic_reg)
```

```
Predicted Values :  [0 1 1 0 0 0 0 0 0 0 1 1 0 1 1 1 0 1 0 1 1 0 0 0 1
0 0 0 1 1 1 0 1 1 1 1 0
 1 0 0 1 1 0 0 0 1 1 1 0 1 1 1 1 1 1 0 1 1 1 1 1]
```

```
Y_test[0:10] #You can check accuracy by observing predicted results
and test data.
```

```
225    0
152    1
228    0
201    0
52     1
245    0
175    0
168    0
223    0
```

```
217    0
Name: target, dtype: int64
```

```
accuracy_score_logistic_reg =
round(accuracy_score(Y_pred_logistic_reg,Y_test)*100,2)
print("The accuracy score achieved using Logistic Regression is:
"+str(accuracy_score_logistic_reg)+" %")
```

```
The accuracy score achieved using Logistic Regression is: 85.25 %
```

**SVM**

```
from sklearn import svm
model_svm = svm.SVC(kernel='linear')
model_svm.fit(X_train, Y_train)
Y_pred_svm = model_svm.predict(X_test)
```

```
Y_pred_svm.shape
```

```
(61,)
```

```
print("Predicted Values : ",Y_pred_svm)
```

```
Predicted Values :  [0 1 1 0 0 1 0 0 0 0 1 1 0 1 1 1 0 1 0 1 1 0 0 0 1
1 0 0 1 1 1 0 1 1 1 1 0
 1 0 0 1 1 0 0 0 1 1 1 0 1 1 1 1 1 1 0 1 1 1 1 1]
```

```
Y_test[0:10] #You can check accuracy by observing predicted results
and test data.
```

```
225    0
152    1
228    0
201    0
52     1
245    0
175    0
168    0
223    0
217    0
Name: target, dtype: int64
```

```
accuracy_score_svm = round(accuracy_score(Y_pred_svm,Y_test)*100,2)
print("The accuracy score achieved using Linear SVM is:
"+str(accuracy_score_svm)+" %")
```

```
The accuracy score achieved using Linear SVM is: 81.97 %
```

**K Nearest Neighbors**

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=7)
```

```
knn.fit(X_train,Y_train)
Y_pred_knn=knn.predict(X_test)
```

```
Y_pred_knn.shape
```

```
(61,)
```

```
print("Predicted Values : ",Y_pred_knn)
```

```
Predicted Values :  [0 0 1 0 1 1 0 0 0 0 1 1 0 1 1 1 0 1 0 1 1 1 0 0 0
0 1 0 1 1 0 0 1 0 1 1 0
 1 0 1 0 1 1 0 0 1 1 1 1 1 1 0 1 0 1 0 0 1 0 1 0]
```

```
Y_test[0:10] #You can check accuracy by observing predicted results
and test data.
```

```
225    0
152    1
228    0
201    0
52     1
245    0
175    0
168    0
223    0
217    0
Name: target, dtype: int64
```

```
accuracy_score_knn = round(accuracy_score(Y_pred_knn,Y_test)*100,2)
print("The accuracy score achieved using KNN is:
"+str(accuracy_score_knn)+" %")
```

```
The accuracy score achieved using KNN is: 67.21 %
```

### Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
max_accuracy = 0
for x in range(200):
    dt = DecisionTreeClassifier(random_state=x)
    dt.fit(X_train,Y_train)
    Y_pred_dt = dt.predict(X_test)
    current_accuracy = round(accuracy_score(Y_pred_dt,Y_test)*100,2)
    if(current_accuracy>max_accuracy):
        max_accuracy = current_accuracy
        best_x = x

dt = DecisionTreeClassifier(random_state=best_x)
dt.fit(X_train,Y_train)
Y_pred_dt = dt.predict(X_test)
```

```
print(Y_pred_dt.shape)
```

```
(61,)
```

```
print("Predicted Values : ",Y_pred_dt)
```

```
Predicted Values :  [0 1 0 0 0 0 0 0 0 0 0 1 0 1 1 1 0 1 0 1 1 0 0 0 1
1 0 0 1 1 1 0 1 1 1 1 0
 1 0 0 1 0 1 0 1 0 1 1 0 1 1 1 1 0 1 0 1 1 1 1 1]
```

```
Y_test[0:10] #You can check accuracy by observing predicted results
and test data.
```

```
225    0
152    1
228    0
201    0
52     1
245    0
175    0
168    0
223    0
217    0
Name: target, dtype: int64
```

```
accuracy_score_dt = round(accuracy_score(Y_pred_dt,Y_test)*100,2)
print("The accuracy score achieved using Decision Tree is:
"+str(accuracy_score_dt)+" %")
```

```
The accuracy score achieved using Decision Tree is: 81.97 %
```

**Random Forest**

```
from sklearn.ensemble import RandomForestClassifier
max_accuracy = 0
for x in range(2000):
    rf = RandomForestClassifier(random_state=x)
    rf.fit(X_train,Y_train)
    Y_pred_rf = rf.predict(X_test)
    current_accuracy = round(accuracy_score(Y_pred_rf,Y_test)*100,2)
    if(current_accuracy>max_accuracy):
        max_accuracy = current_accuracy
        best_x = x

rf = RandomForestClassifier(random_state=best_x)
rf.fit(X_train,Y_train)
Y_pred_rf = rf.predict(X_test)
```

```
Y_pred_rf.shape
```

```
(61,)
```

```
print("Predicted Values : ",Y_pred_rf)
```

```
Predicted Values :  [0 1 1 0 0 1 0 0 0 0 1 1 0 1 1 1 0 1 0 1 1 0 0 0 1
0 0 0 1 1 1 0 1 1 1 0 0
 1 0 0 1 1 1 0 1 1 1 0 0 1 1 1 1 1 1 0 1 1 1 1 1]
```

```
Y_test[0:10] #You can check accuracy by observing predicted results
and test data.
```

```
225    0
152    1
228    0
201    0
52     1
245    0
175    0
168    0
223    0
217    0
Name: target, dtype: int64
```

```
accuracy_score_rf = round(accuracy_score(Y_pred_rf,Y_test)*100,2)
print("The accuracy score achieved using Random Forest is:
"+str(accuracy_score_rf)+" %")
```

```
The accuracy score achieved using Random Forest is: 90.16 %
```

**Summary of accuracy scores**

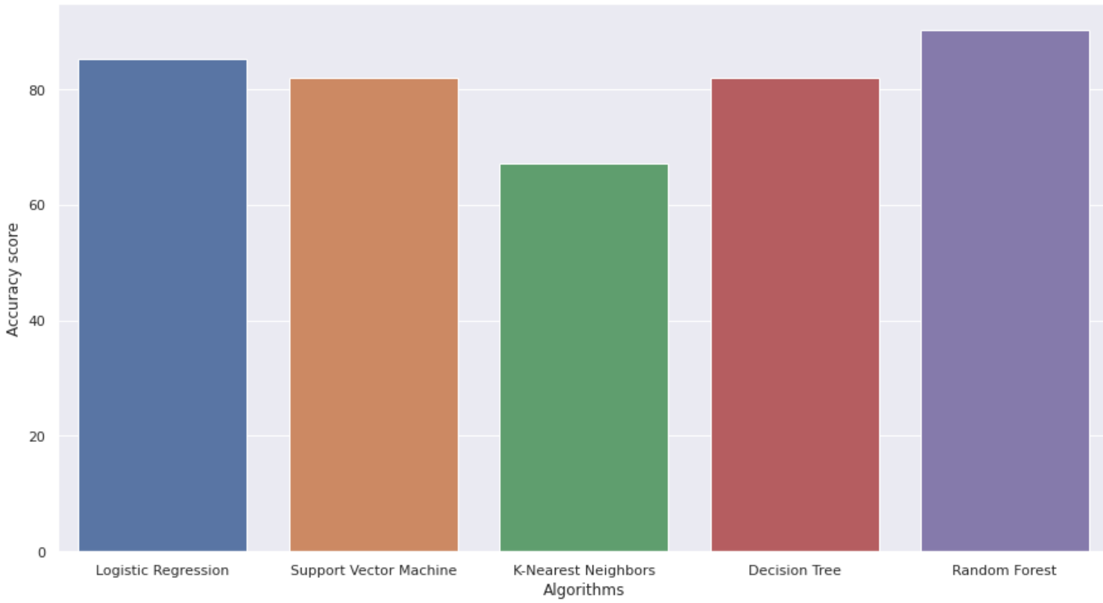
```
all_accuracy_scores =
[accuracy_score_logistic_reg,accuracy_score_svm,accuracy_score_knn,acc
uracy_score_dt,accuracy_score_rf]
algorithms_used = ["Logistic Regression","Support Vector Machine","K-
Nearest Neighbors","Decision Tree","Random Forest"]

for i in range(len(algorithms_used)):
    print("\nThe accuracy score achieved using "+algorithms_used[i]+"
is: "+str(all_accuracy_scores[i])+" %")
```

```

The accuracy score achieved using Logistic Regression is: 85.25 %

The accuracy score achieved using Support Vector Machine is: 81.97 %

The accuracy score achieved using K-Nearest Neighbors is: 67.21 %

The accuracy score achieved using Decision Tree is: 81.97 %

The accuracy score achieved using Random Forest is: 90.16 %
```

```
sns.set(rc={'figure.figsize':(15,8)})
plt.xlabel("Algorithms")
plt.ylabel("Accuracy score")
```

```
sns.barplot(algorithms_used,all_accuracy_scores)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f898ac16590>
```




**Here we can see that Random Forest is better than other algorithms.**