Project on Health Care

Prediction of Cardio Vascular Disease using Machine Learning

In [1]:
```python
#import the required libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns

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

In [2]:
```python
data=pd.read_excel('1645792390_cep1_dataset.xlsx')    #read the data
```

In [3]:
```python
data.head()    # display the first five rows of the dataframe
```

Out[3]:

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

Preliminary Analysis:

In [4]:
```python
data.shape    # check the number of rows and columns
```

Out[4]:
```
(303, 14)
```

In [5]:
```python
data.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
```

In [6]:
```python
d2=data.duplicated(keep='first')    #Chech for duplicate values. False means unique values.
d2
```

Out[6]:
```
0      False
1      False
2      False
3      False
4      False
       ...
298    False
299    False
300    False
301    False
302    False
Length: 303, dtype: bool
```

After checking for duplicates, we have got back all the 303 rows without discarding any of the rows. This means that there are no duplicate values

In [7]:
```python
d1=data.isnull().sum()   #check for missing values
d3=data.nunique()        #check for unique values
d4= data.dtypes          #check for the datatypes
```

In [8]:
```python
#convert all the data into dataframes
d1=d1.to_frame().reset_index()
d3=d3.to_frame().reset_index()
d4=d4.to_frame().reset_index()
```

In [9]:
```python
#rename the columns relevantly
d1=d1.rename(columns= {0: 'Missing Data'})
d3=d3.rename(columns={0: 'Unique Data'})
d4=d4.rename(columns={0: 'Data Type'})
```

In [10]:
```python
# merge all the dataframes into one
df=pd.merge(d1, d3, on='index')
df=pd.merge(df, d4, on='index')
print(df)
```

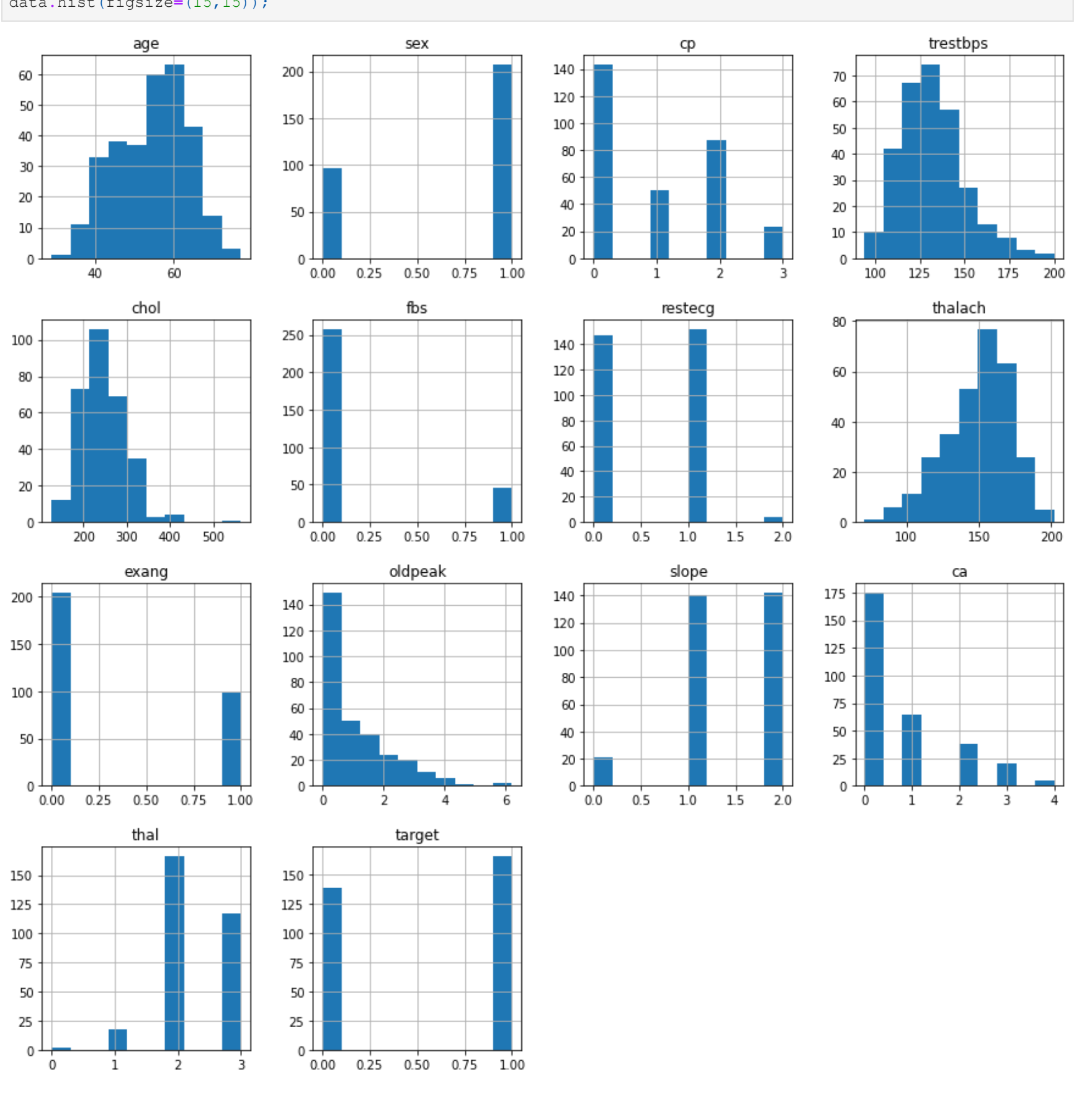
```
       index  Missing Data  Unique Data Data Type
0        age             0           41     int64
1        sex             0            2     int64
2         cp             0            4     int64
3   trestbps             0           49     int64
4       chol             0          152     int64
5        fbs             0            2     int64
6    restecg             0            3     int64
7    thalach             0           91     int64
8      exang             0            2     int64
9    oldpeak             0           40   float64
10     slope             0            3     int64
11        ca             0            5     int64
12      thal             0            4     int64
13    target             0            2     int64
```

In [11]:
```python
data.describe()
```

Out[11]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.646865	0.326733	1.039604	1.399340
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469794	1.161075	0.616226
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	1.000000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.800000	1.000000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.600000	2.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000

In [12]:
```python
#Let us Visualise the data
data.hist(figsize=(15,15));
```



From the above graphs, we can see that 'sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal' and 'target' columns are categorical columns

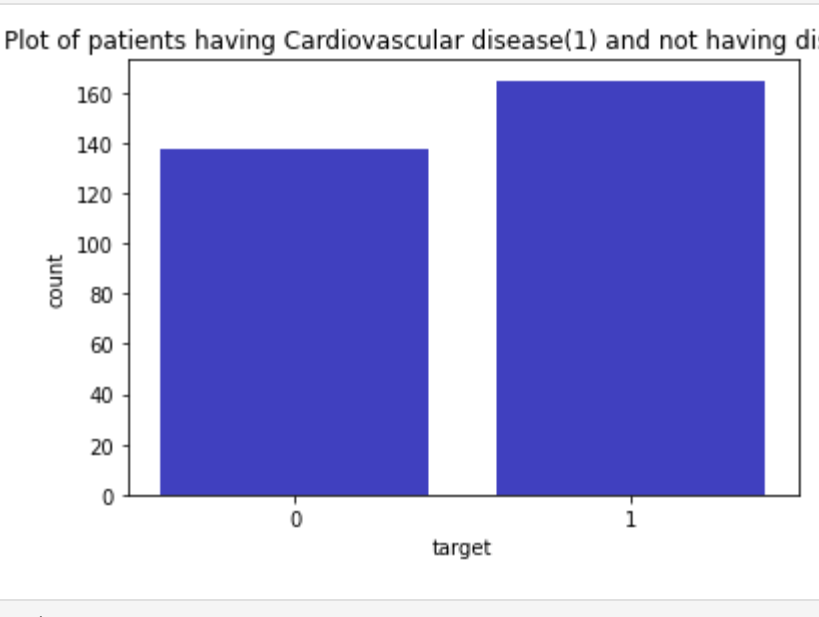
Visualizing the Categorical columns

In [13]:
```python
target_values= data.target.value_counts()   #1 = having cardiovascular disease. 0 = not having cardiovascular
target_values
```

Out[13]:
```
1    165
0    138
Name: target, dtype: int64
```

In [14]:
```python
# visualize the patients having Heart disease and not having Heart disease
sns.countplot(x='target', data=data, color='blue', saturation=0.5)
plt.title('Plot of patients having Cardiovascular disease(1) and not having disease(0)')
plt.show()
```

Plot of patients having Cardiovascular disease(1) and not having disease(0)



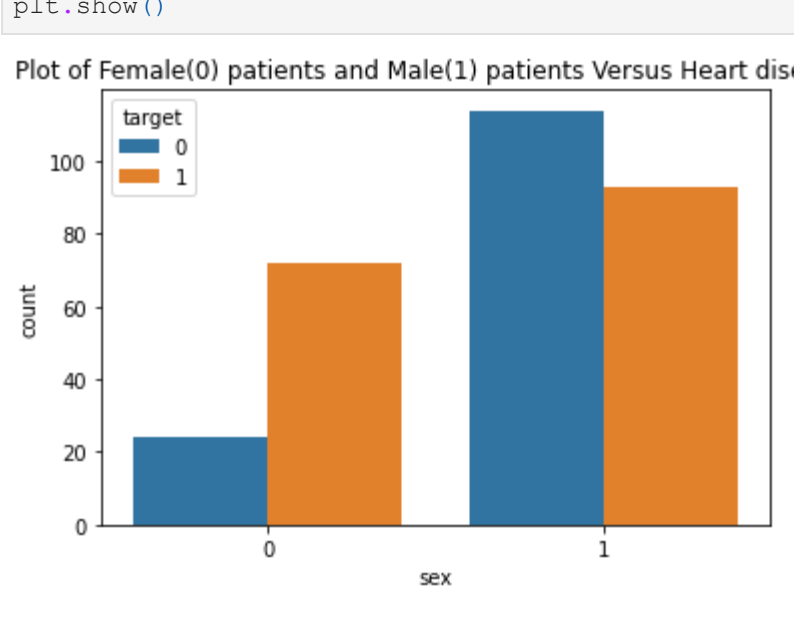
In [15]:
```python
print(data.sex.value_counts())
```

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

1 indicates Male. 0 indicates Female

In [16]:
```python
sns.countplot(x='sex', data=data, hue='target')

plt.title('Plot of Female(0) patients and Male(1) patients Versus Heart disease ')
plt.show()
```

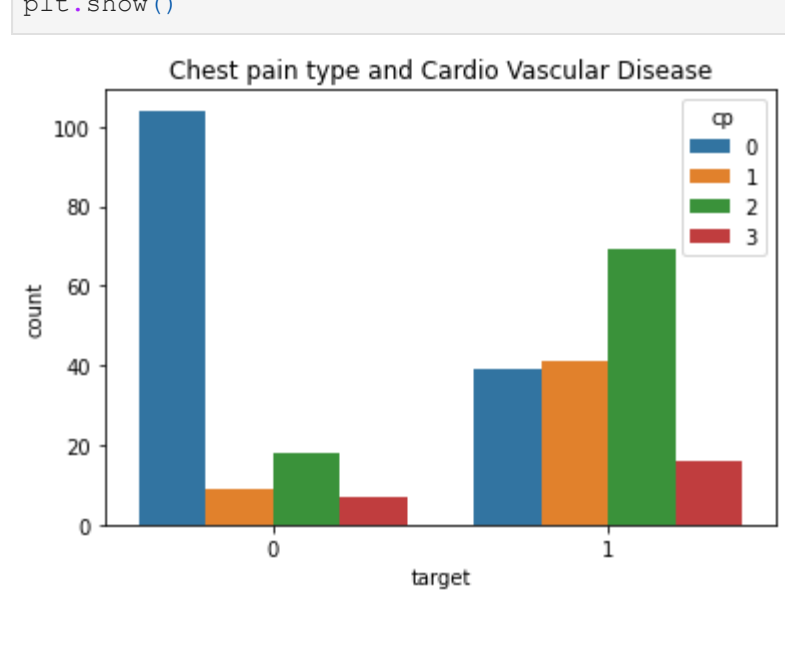
Plot of Female(0) patients and Male(1) patients Versus Heart disease



Plot shows that more number of Female patients have Heart Disease than Male patients

In [17]:
```python
sns.countplot(x='target', data=data, hue='cp')
plt.title('Chest pain type and Cardio Vascular Disease')
plt.show()
```

Chest pain type and Cardio Vascular Disease



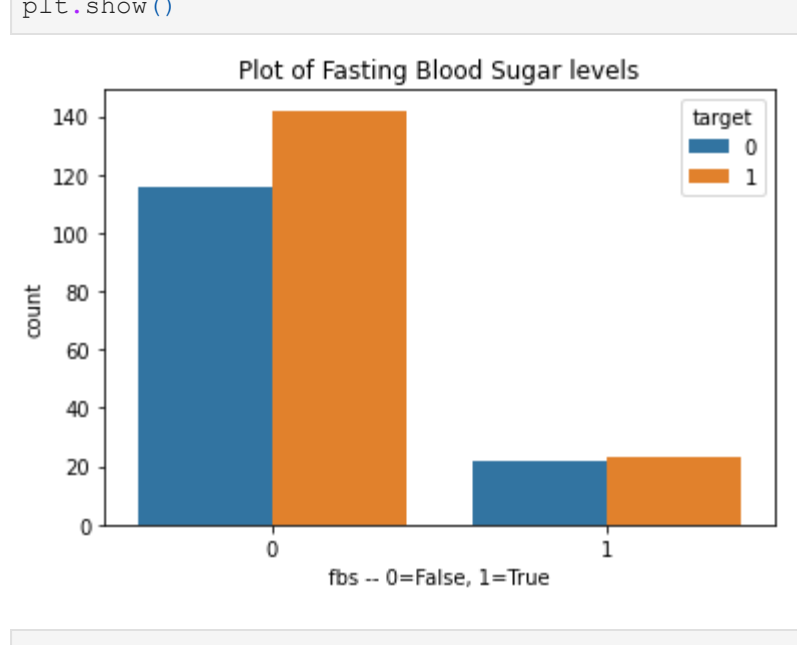
Plot shows that Chest pain type 2 have maximum heart attacks and Chest pain type 0 do not have Heart Attacks

In [18]:
```python
data.fbs.value_counts()   #fasting blood pressure >120. 1=True and 0=False
```

Out[18]:
```
0    258
1     45
Name: fbs, dtype: int64
```

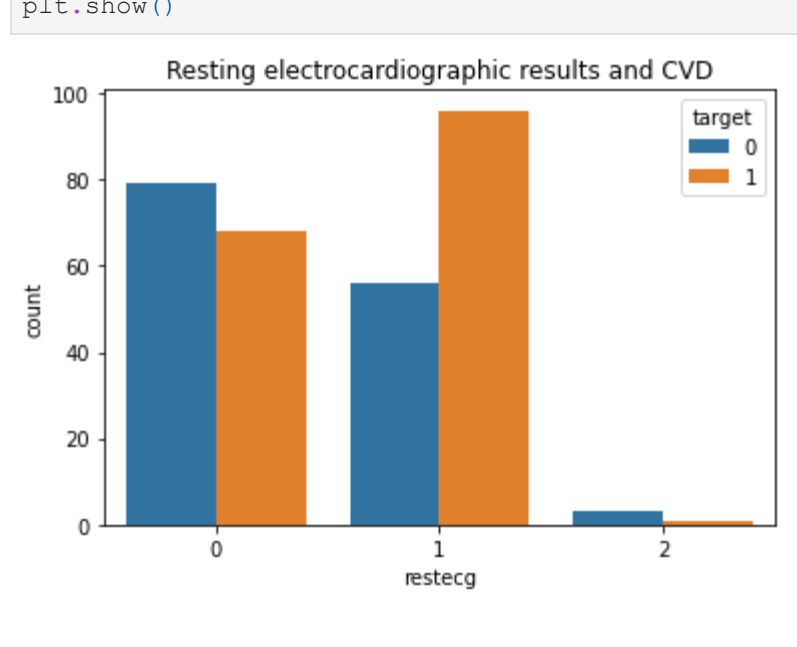
In [19]:
```python
sns.countplot(x='fbs', data=data, hue='target')
plt.title('Plot of Fasting Blood Sugar levels')
plt.xlabel('fbs -- 0=False, 1=True')
plt.show()
```

Plot of Fasting Blood Sugar levels



In [20]:
```python
sns.countplot(x='restecg', data=data, hue='target')
plt.title('Resting electrocardiographic results and CVD')
plt.show()
```

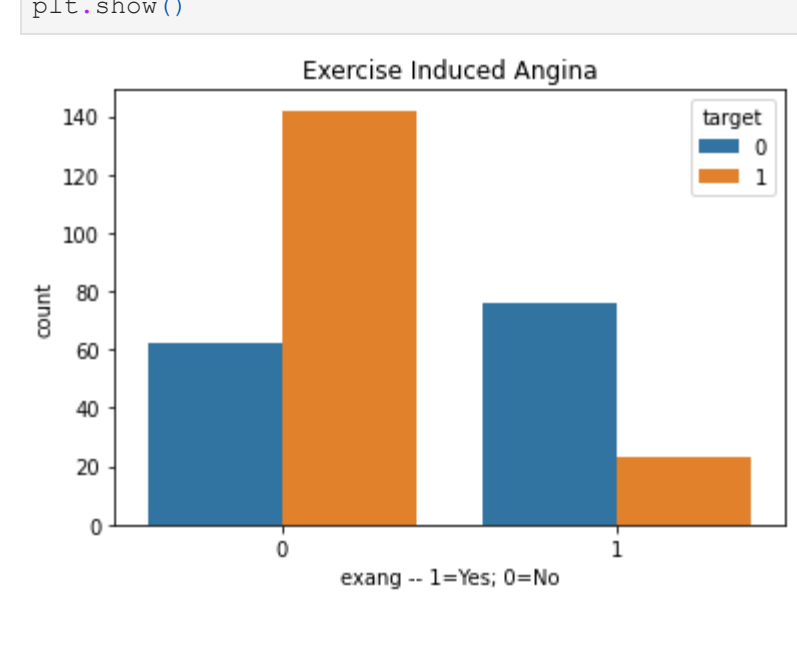
Resting electrocardiographic results and CVD



Graph shows that Resting ECG of type 1 have maximum number of Heart Attacks

In [21]:
```python
sns.countplot(x='exang', data=data, hue='target')
plt.title('Exercise Induced Angina')
plt.xlabel('exang -- 1=Yes; 0=No')
plt.show()
```

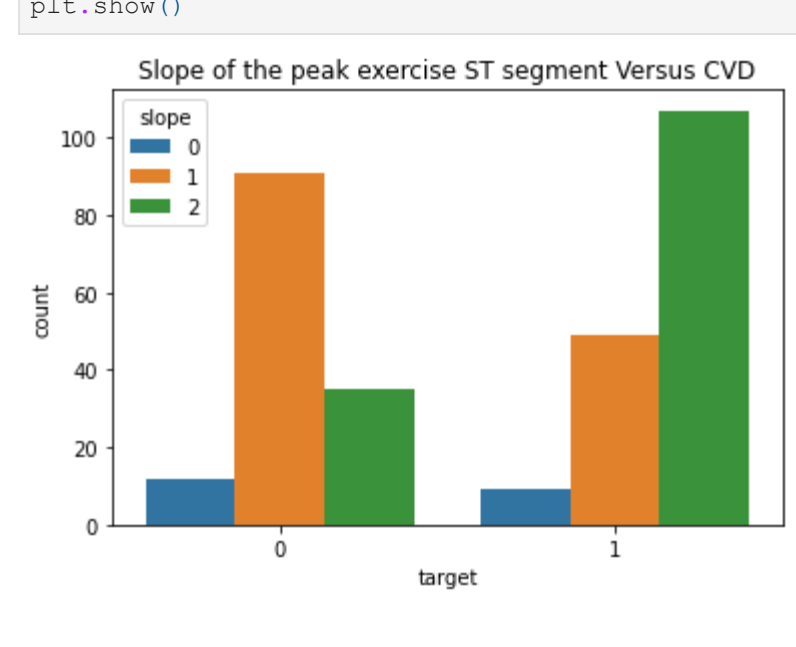
Exercise Induced Angina



Feature 'Exercise Induced Angina = No' has higher number of Heart Attacks

In [22]:
```python
sns.countplot(x='target', data=data, hue='slope')
plt.title('Slope of the peak exercise ST segment Versus CVD')
plt.show()
```

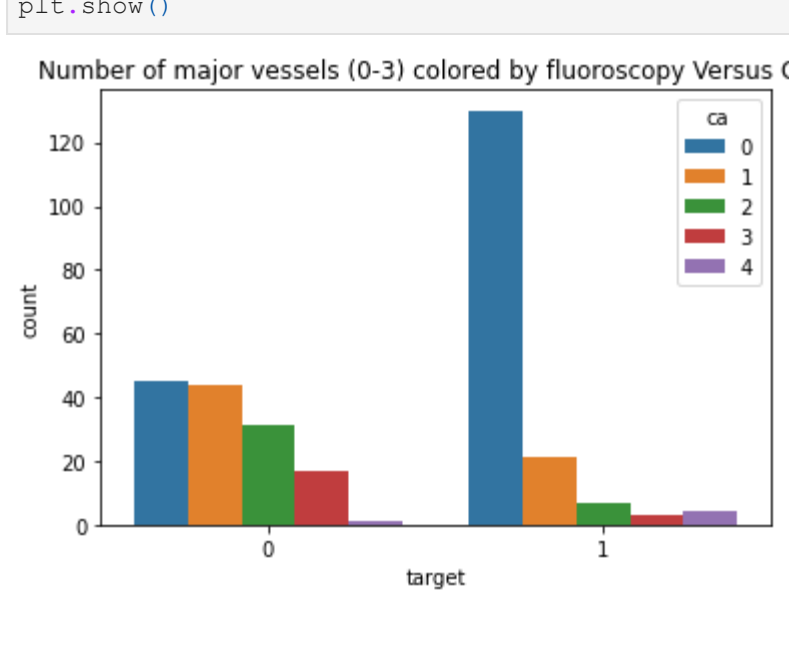
Slope of the peak exercise ST segment Versus CVD



Slope of the peak exercise ST segment of type 2 have maximum Heart Disease

In [23]:
```python
sns.countplot(x='target', data=data, hue='ca')
plt.title('Number of major vessels (0-3) colored by fluoroscopy Versus CVD')
plt.show()
```

Number of major vessels (0-3) colored by fluoroscopy Versus CVD



Number of major vessels (0-3) colored by fluoroscopy of Type 0 has maximum number of Heart Attacks

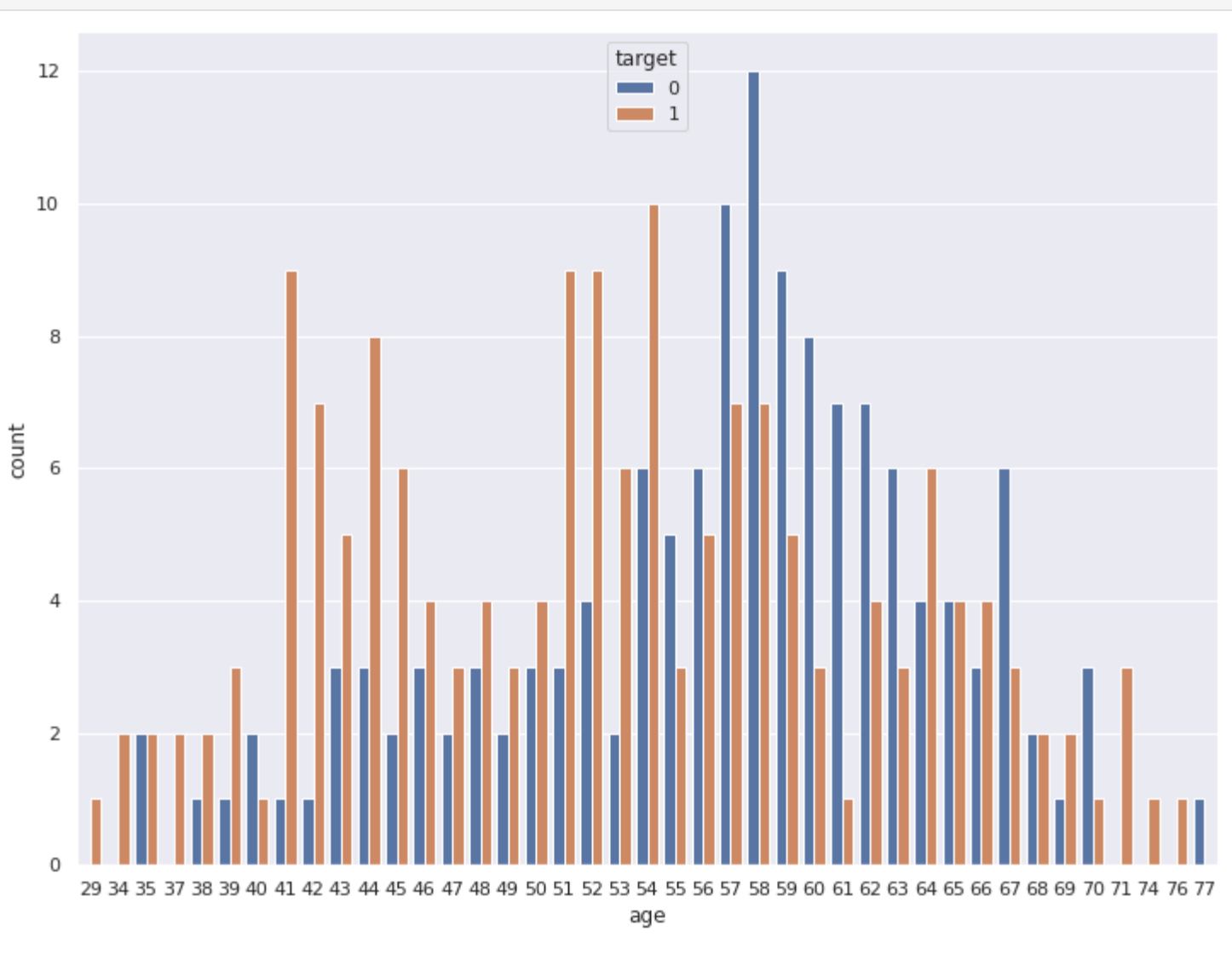
Composition of all the patients with respect to 'Gender'. 0--> Female, 1-->Male

In [24]:
```python
print(data.groupby('sex').agg(['mean', 'count']))
```

```
          age              cp           trestbps              chol        \
         mean count      mean count       mean count        mean count
sex
0   55.677083    96  1.041667    96  133.083333    96  261.302083    96
1   53.758454   207  0.932367   207  130.946860   207  239.289855   207

         fbs        ...   oldpeak           slope              ca        \
        mean count  ...      mean count      mean count      mean count
sex                 ...
0    0.12500    96  ...  0.876042    96  1.427083    96  0.552083    96
1    0.15942   207  ...  1.115459   207  1.386473   207  0.811594   207

         thal           target
         mean count      mean count
sex
0    2.125000    96  0.750000    96
1    2.400966   207  0.449275   207

[2 rows x 26 columns]
```

Let us compare the CVD with respect to 'Age' feature

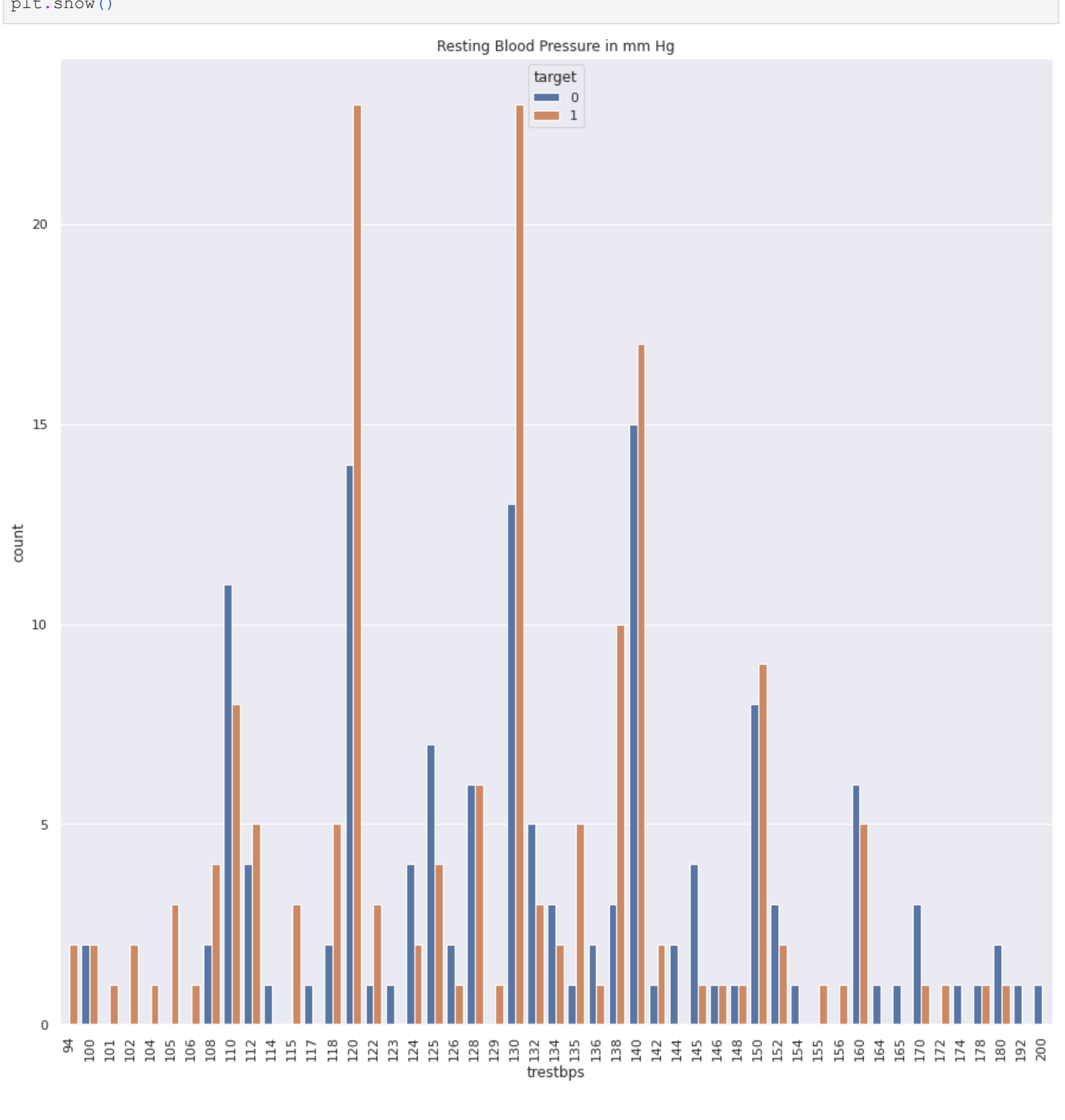
In [25]:
```python
sns.set(rc={'figure.figsize':(12,9)})
sns.set_style=('darkgrid')
sns.countplot(x='age',hue='target', data=data)
plt.show()
```



The plot shows that the CardioVascular disease is highest at 54 years of age, followed by 41, 51 and 52 years

Visualize the 'Resting Blood Pressure' with respect to the target

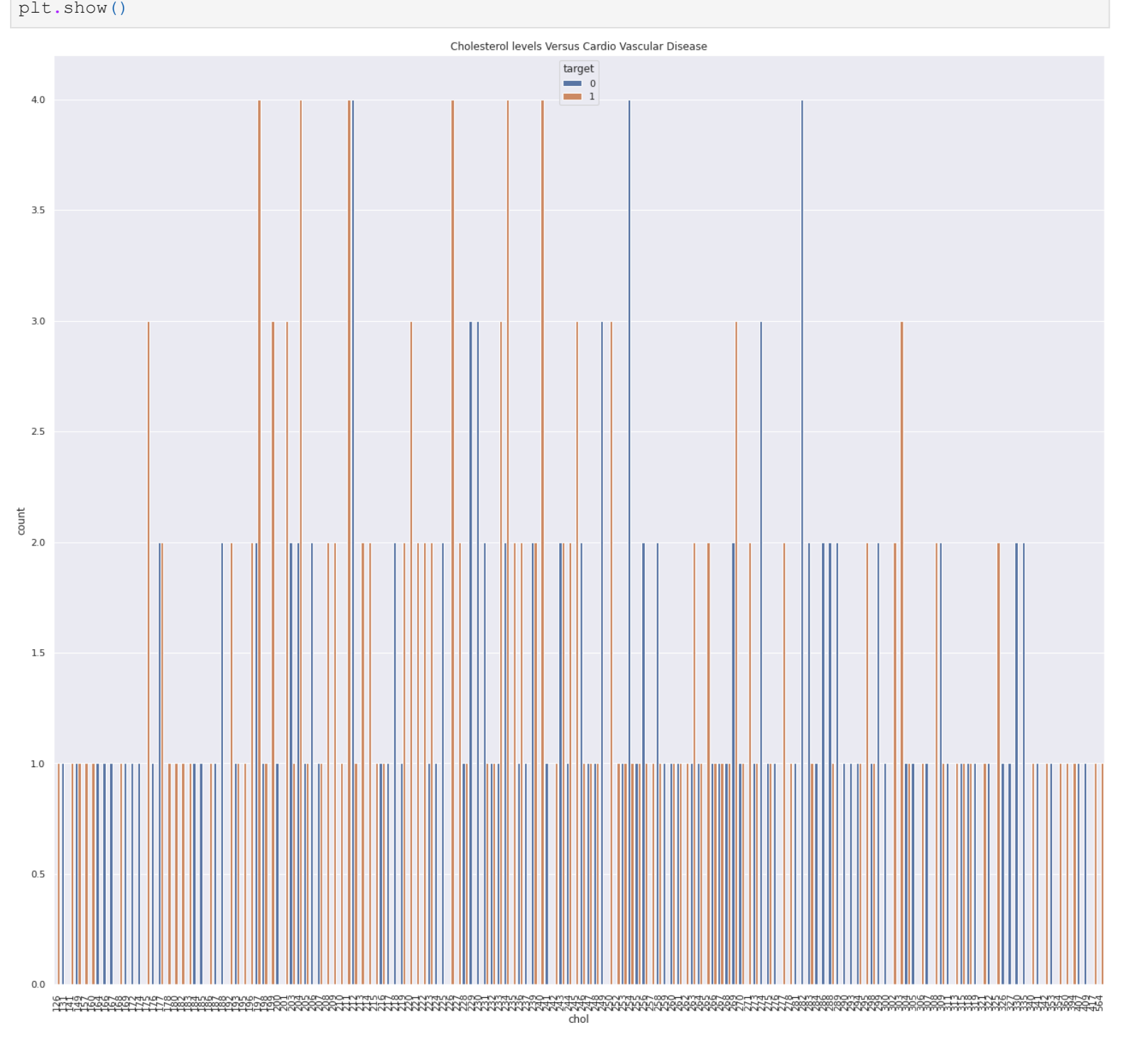
In [26]:
```python
sns.set(rc={'figure.figsize':(15,15)})
sns.countplot(x='trestbps', data=data, hue='target')
plt.xticks(rotation=90)
plt.title('Resting Blood Pressure in mm Hg')
plt.show()
```



Plot shows that 'trestbps' is right skewed. Maximum heart attacks have occured at Resting Blood Pressure = 120 and 130

Plot of Cholesterol versus Cardio Vascular Disease

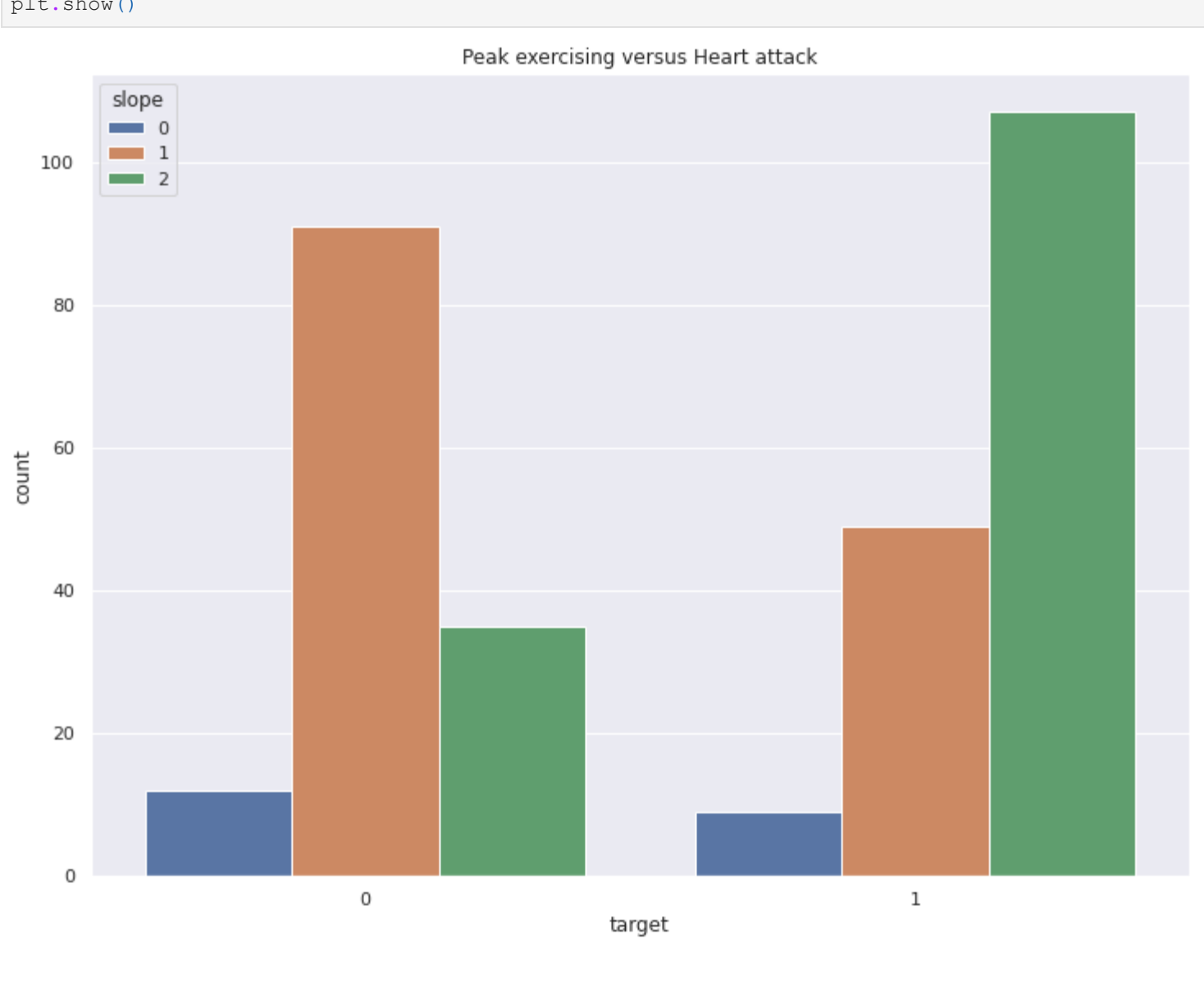
In [27]:
```python
sns.set(rc={'figure.figsize':(22,20)})
plt.xticks(rotation=90)
plt.title('Cholesterol levels Versus Cardio Vascular Disease')
sns.countplot(x='chol', data=data, hue='target')
plt.show()
```



At cholesterol levels between 195 and 240, there is a good chance of having a heart attack.

Visualization of Peak Exercising with respect to the Occurance of a Heart Attack

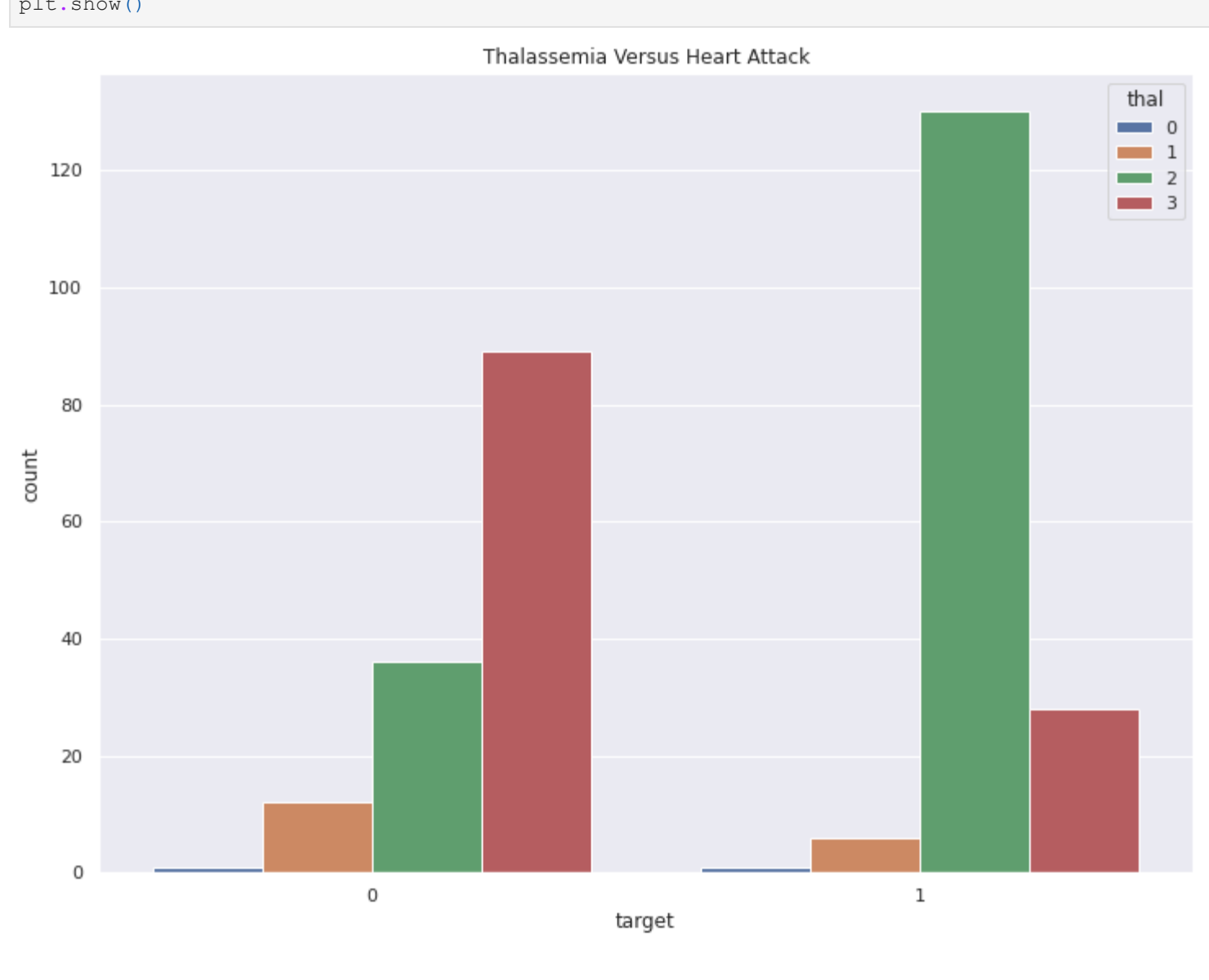
In [28]:
```python
sns.set(rc={'figure.figsize':(12,9)})
sns.countplot(x='target', data=data, hue='slope')
plt.title('Peak exercising versus Heart attack')
plt.show()
```



Peak exercising '2' has a significant impact on Heart Attack.

Graph of Thalassemia versus Heart attack

In [29]:
```python
sns.set(rc={'figure.figsize':(12,9)})
sns.countplot(x='target', data=data, hue='thal')
plt.title('Thalassemia Versus Heart Attack')
plt.show()
```

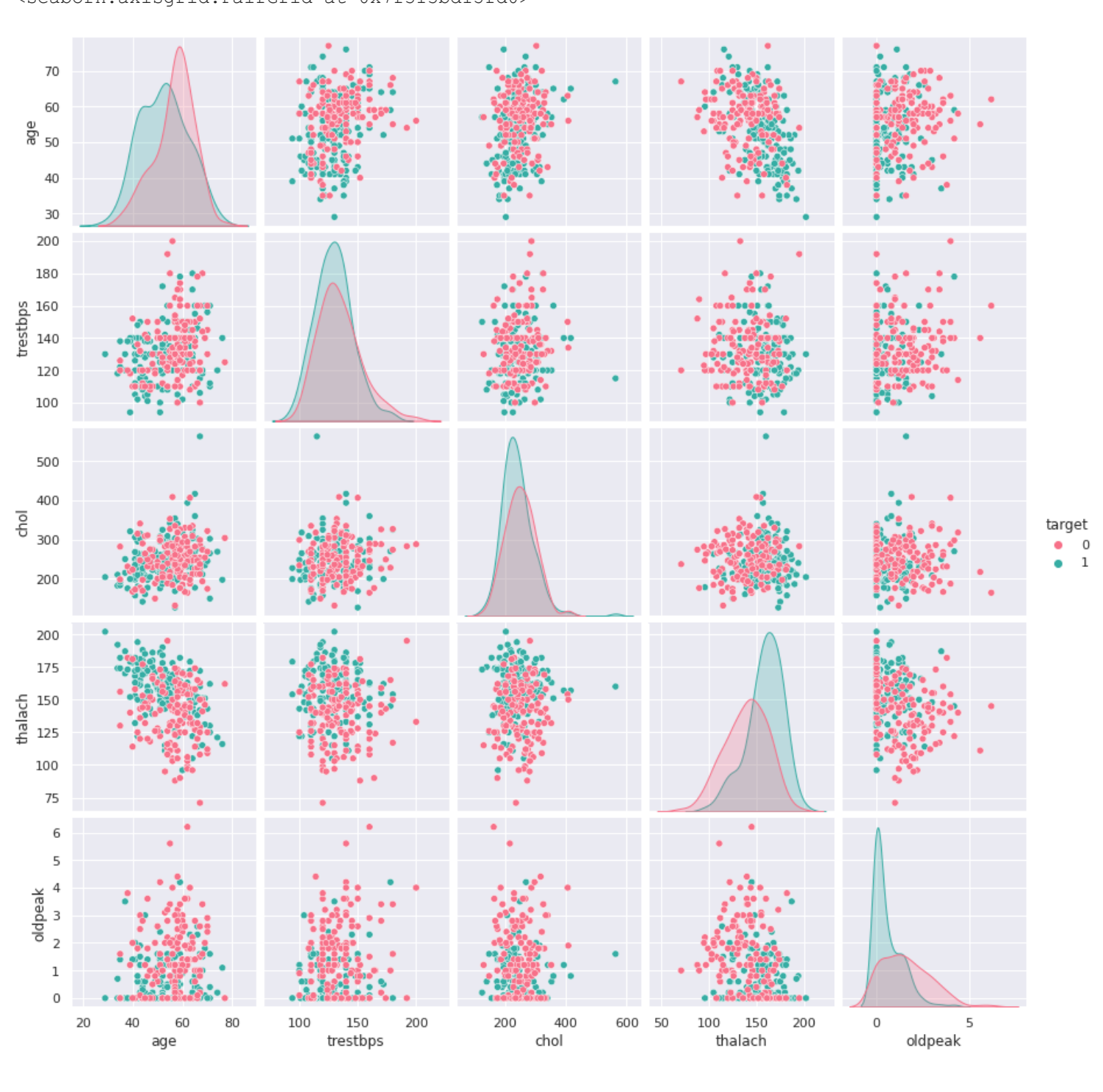


Thalassemia of type '2' has a significant impact on the occurance of a Heart Attack

In [30]:
```python
#store Numerical columns and Categorical columns separately
num_cols=data[['age','trestbps','chol','thalach', 'oldpeak', 'target']]
#num_cols
cat_cols=data[['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal', 'target']]
#cat_cols
```

In [31]:
```python
#pair plot of Numerical columns
sns.pairplot(num_cols, hue='target', palette='husl')
```

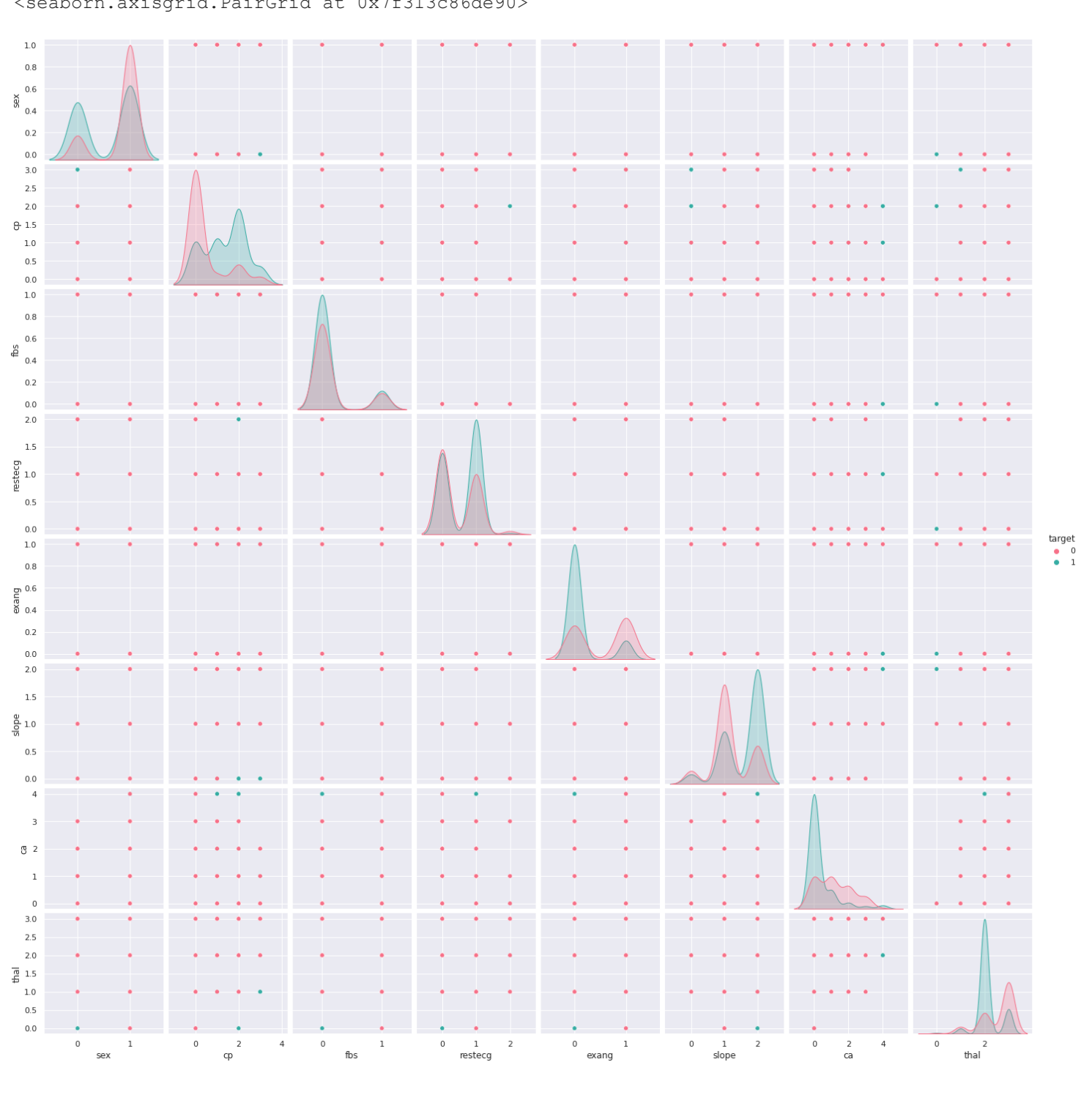
Out[31]:
```
<seaborn.axisgrid.PairGrid at 0x7f313bd15fd0>
```



Pair plot shows relationship of Numerical columns with respect to target column. Except for the feature 'Age', all the other features show correlation with the target.

In [32]:
```python
#pair plot of categorical columns
sns.pairplot(cat_cols, hue='target', palette='husl')
```

Out[32]:
```
<seaborn.axisgrid.PairGrid at 0x7f313c86de90>
```



Pair plot shows the relationship of Categorical Columns with the target column. We can see that the number of Male patients 'not having' a Heart disease is higher. Heart disease among Female patients is high.

Patients with the feature 'Chest Pain type (cp)' 0 have no Heart disease.

Patients with the feature 'Slope of the peak exercise ST segment (Slope)' of type 2 have Heart Attacks as compared to 'Slope 0' and 'Slope 1'.

Feature 'Restecg' of type 1 have Heart Attacks.

Features 'Number of major vessels (0-3) colored by fluoroscopy (ca)' of type 0 show Heart attacks and 'Thalassemia (thal)' of type 2 have maximum number of Heart Attacks.

In [33]:
```python
#store the target column in target_col
target_col=data[['target']]
```

In [34]:
```python
#drop the target column from the num_cols since we have to use it to train the model
num_cols=num_cols.drop(['target'], axis=1)
```

In [35]:
```python
num_cols.head()
```

Out[35]:

	age	trestbps	chol	thalach	oldpeak
0	63	145	233	150	2.3
1	37	130	250	187	3.5
2	41	130	204	172	1.4
3	56	120	236	178	0.8
4	57	120	354	163	0.6

In [36]:
```python
#delete the target column from the cat_cols dataframe
cat_cols=cat_cols.drop(['target'], axis=1)
cat_cols.head()
```

Out[36]:

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

Feature engineering the multiclass categorical columns using one hot encoding

In [37]:
```
cat_cols_1=pd.get_dummies(cat_cols.cp, prefix='cp').iloc[:, 1:]
cat_cols_2=pd.get_dummies(cat_cols.restecg, prefix='restecg').iloc[:, 1:]
cat_cols_3=pd.get_dummies(cat_cols.slope, prefix='slope').iloc[:, 1:]
cat_cols_4=pd.get_dummies(cat_cols.ca, prefix='ca').iloc[:, 1:]
cat_cols_5=pd.get_dummies(cat_cols.thal, prefix="thal").iloc[:, 1:]
```

In [38]:
```
#drop the original multiclass categorical columns
cat_cols=cat_cols.drop(['cp', 'restecg', 'slope', 'ca', 'thal'], axis=1)
#cat_cols
```

In [39]:
```
#concat the numerical columns, binary columns and feature engineered columns
df_new= pd.concat([num_cols, cat_cols, cat_cols_1, cat_cols_2, cat_cols_3, cat_cols_4, cat_c
```

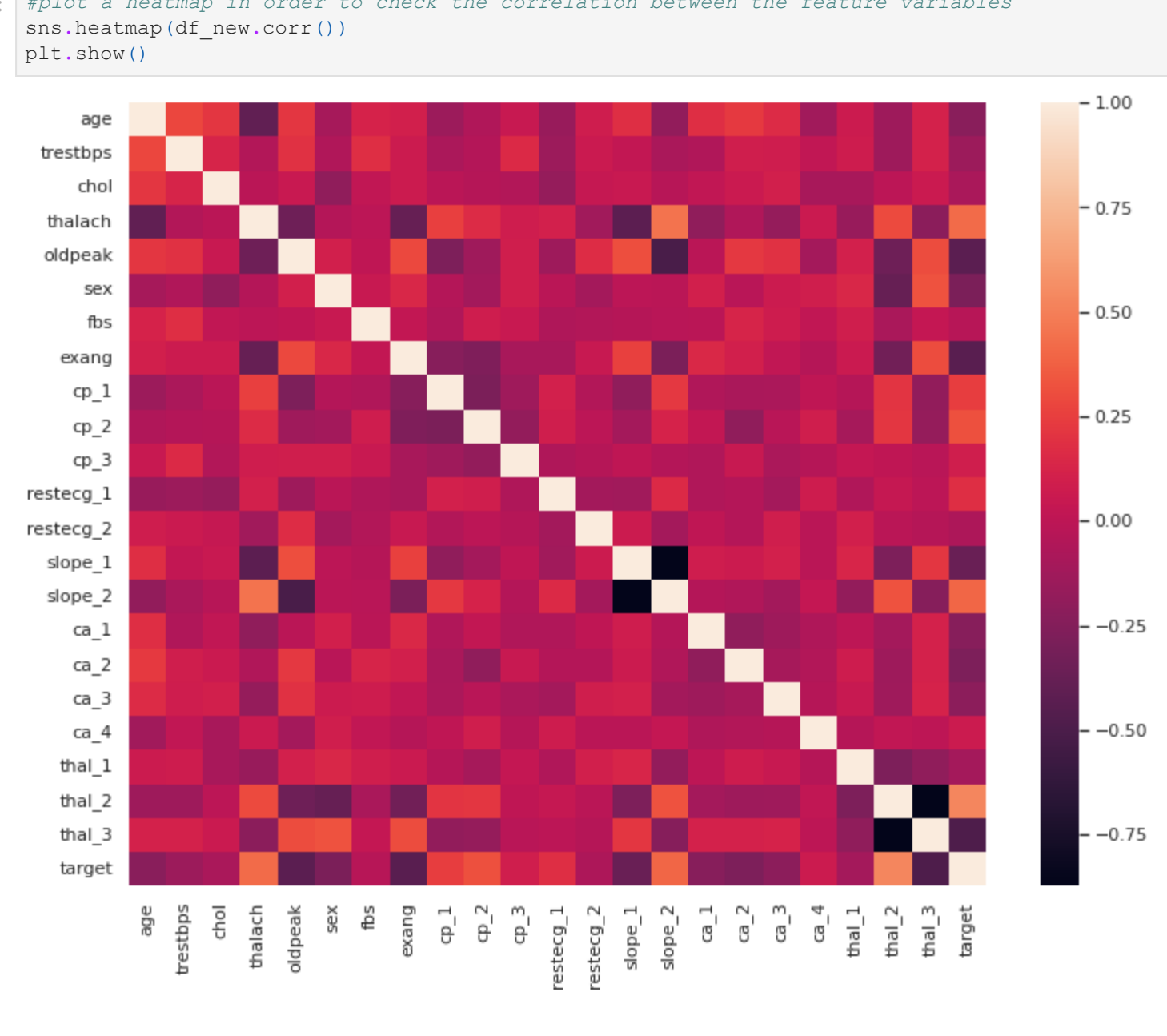
In [40]:
```
#display the first 5 rows of the new dataframe
df_new.head()
```

Out[40]:

	age	trestbps	chol	thalach	oldpeak	sex	fbs	exang	cp_1	cp_2	...	slope_1	slope_2	ca_1	ca_2	ca_3	ca_4
0	63	145	233	150	2.3	1	1	0	0	0	...	0	0	0	0	0	0
1	37	130	250	187	3.5	1	0	0	0	1	...	0	0	0	0	0	0
2	41	130	204	172	1.4	0	0	0	1	0	...	0	1	0	0	0	0
3	56	120	236	178	0.8	1	0	0	1	0	...	0	1	0	0	0	0
4	57	120	354	163	0.6	0	0	1	0	0	...	0	1	0	0	0	0

5 rows × 23 columns

In [41]:
```
#plot a heatmap in order to check the correlation between the feature variables
sns.heatmap(df_new.corr())
plt.show()
```



Correlation Analysis:

The heatmap shows dark areas as negatively correlated and light areas as positively correlated features. From the heatmap we can see that 'thalach', 'cp_2', 'slope_2 and 'thal_2' are positively correlated with the target. 'slope_2' is positively correlated with 'thalach' and negatively correlated with 'oldpeak'. 'thalach' is negatively correlated with 'age'

Model Building

In [42]:
```
#let's split the data into training and testing using train_test_split model
from sklearn.model_selection import train_test_split
X=df_new.drop(['target'], axis=1)
y=df_new["target"]
```

In [43]:
```
print(X.shape)
print(y.shape)
```

```
(303, 22)
(303,)
```

In [44]:
```
#set the testing size to 20% and training size to 80%
X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.2, random_state=1)
```

In [45]:
```
#fit the data using Logistic Regression
from sklearn.linear_model import LogisticRegression
Logreg=LogisticRegression()
Logreg.fit(X_train, y_train)
```

Out[45]:
```
LogisticRegression()
```

In [46]:
```
#check the accuracy score and f1 score
accuracy=Logreg.score(X_test, y_test)
print('Accuracy of Logistic Regression :  ', accuracy*100)

from sklearn.metrics import f1_score
y_pred=Logreg.predict(X_test)
f1=f1_score(y_pred, y_test)
print('f1_score : ', f1)
```

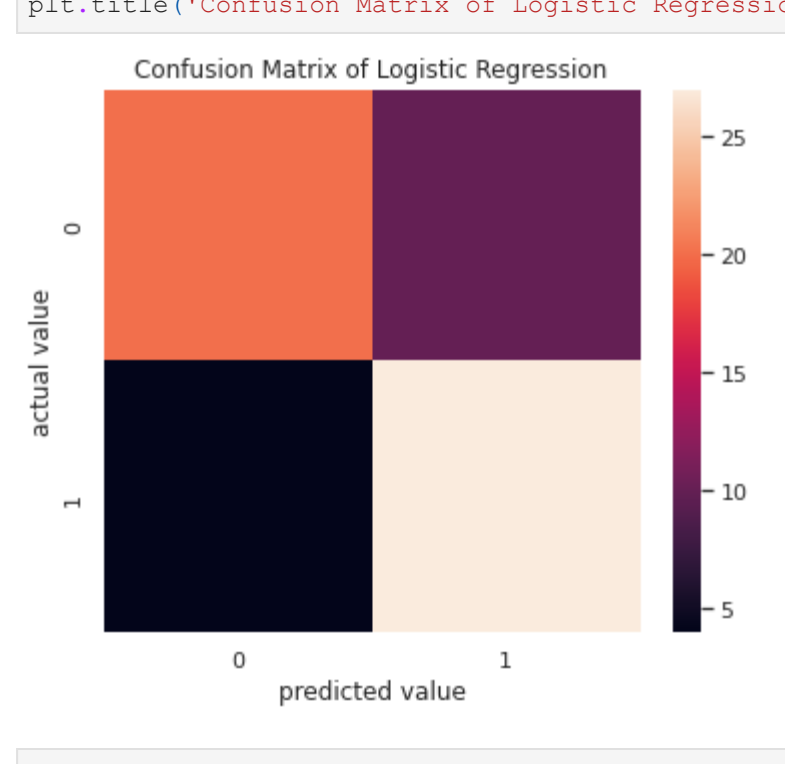
```
Accuracy of Logistic Regression :   77.04918032786885
f1_score :  0.7941176470588235
```

In [47]:
```
#print the confusion matrix
from sklearn.metrics import confusion_matrix
con_mat=confusion_matrix(y_test, y_pred)
print(con_mat)
```

```
[[20 10]
 [ 4 27]]
```

From the confusion matrix, we can see that the model predicted 20 true positives (occurance of a Heart Attack) and 27 true negatives (Non occurance of a Heart Attack)

In [48]:
```
f, ax = plt.subplots(figsize = (6,5))
sns.heatmap(con_mat)
plt.xlabel('predicted value')
plt.ylabel('actual value')
plt.title('Confusion Matrix of Logistic Regression');
```



In [49]:
```
# get the Precision, Recall and f1 score
from sklearn.metrics import classification_report
print(classification_report(y_pred, y_test))
```

```
              precision    recall  f1-score   support

           0       0.67      0.83      0.74        24
           1       0.87      0.73      0.79        37

    accuracy                           0.77        61
   macro avg       0.77      0.78      0.77        61
weighted avg       0.79      0.77      0.77        61
```

Precision is the ratio of True Positive and Sum of True Positive and False Positive. Precision gives us the percentage of Positive Cases from Total Predicted cases. Precision = 0.87 Recall is the ratio of True Positive and Sum of True Positive and False Negative. Recall gives us the percentage of how many total Positive cases were Predicted correctly with our model. Recall = 0.73 f1-score gives the combined result of Precision and Recall. f1-score=0.79

In [50]:
```
#import the required library
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

In [51]:
```
# let us check for different n_estimators between 10 and 100 in steps of 10 to check the
for i in range(10, 100, 10):
    rfc=RandomForestClassifier(n_estimators=i, random_state=0)

    rfc.fit(X_train, y_train)
    y_predict=rfc.predict(X_test)
    print('n_estimators =  ', i)
    accu=(accuracy_score(y_test, y_predict)*100)
    print('accuracy of Random Forest Classifier =  ',accu)
    print('___________________________________________')
```

```
n_estimators =   10
accuracy of Random Forest Classifier =   72.1311475409836
___________________________________________
n_estimators =   20
accuracy of Random Forest Classifier =   72.1311475409836
___________________________________________
n_estimators =   30
accuracy of Random Forest Classifier =   73.77049180327869
___________________________________________
n_estimators =   40
accuracy of Random Forest Classifier =   75.40983606557377
___________________________________________
n_estimators =   50
accuracy of Random Forest Classifier =   75.40983606557377
___________________________________________
n_estimators =   60
accuracy of Random Forest Classifier =   78.68852459016394
___________________________________________
n_estimators =   70
accuracy of Random Forest Classifier =   77.04918032786885
___________________________________________
n_estimators =   80
accuracy of Random Forest Classifier =   77.04918032786885
___________________________________________
n_estimators =   90
accuracy of Random Forest Classifier =   77.04918032786885
___________________________________________
```

The best fit is when n_estimators = 60, where the accuracy is maximum at 78.6885%.

In [52]:
```
#fit the data to a Random Forest Classifier to train the model
rfc=RandomForestClassifier(n_estimators=60, random_state=0)

rfc.fit(X_train, y_train)
y_predict=rfc.predict(X_test)
```

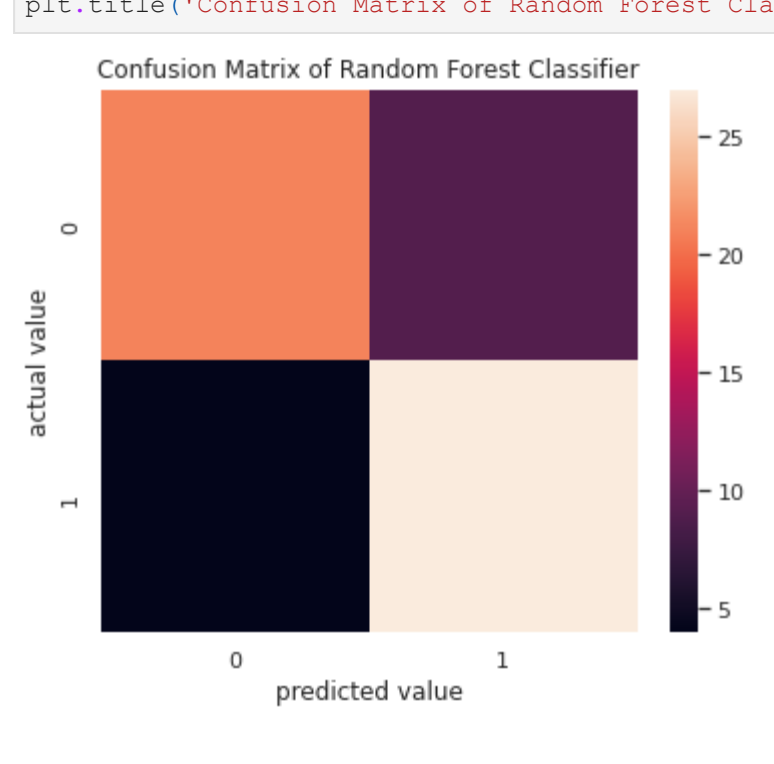
In [53]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
print('Accuracy with Random Forest: ',accuracy_score(y_test, y_predict)*100)
print(confusion_matrix(y_test, y_predict))
print(classification_report(y_test, y_predict))
```

```
Accuracy with Random Forest:  78.68852459016394
[[21  9]
 [ 4 27]]
              precision    recall  f1-score   support

           0       0.84      0.70      0.76        30
           1       0.75      0.87      0.81        31

    accuracy                           0.79        61
   macro avg       0.79      0.79      0.78        61
weighted avg       0.79      0.79      0.79        61
```

Accuracy Check:

Accuracy of the Random Forest Classifier is slightly better at 78.6885% as compared to that of Logistic Regression at 77.0492%

In [54]:
```
f, ax = plt.subplots(figsize = (6,5))
sns.heatmap(confusion_matrix(y_test, y_predict))
plt.xlabel('predicted value')
plt.ylabel('actual value')
plt.title('Confusion Matrix of Random Forest Classifier');
```



Statistical Analysis:

In [55]:
```
#let us check the p-values of all the features using statsmodel for feature selection
import statsmodels.api as sm
log_reg=sm.Logit(y_train,X_train).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.272951
         Iterations 8
```

In [56]:
```
#print the result of the statsmodel Logit Regression
print(log_reg.summary())
```

```
                           Logit Regression Results
==============================================================================
Dep. Variable:                 target   No. Observations:                  242
Model:                          Logit   Df Residuals:                      220
Method:                           MLE   Df Model:                           21
Date:                Tue, 02 Aug 2022   Pseudo R-squ.:                  0.6029
Time:                        06:52:04   Log-Likelihood:                -66.054
converged:                       True   LL-Null:                       -166.34
Covariance Type:            nonrobust   LLR p-value:                 2.791e-31
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
age            0.0143      0.028      0.515      0.607      -0.040       0.069
trestbps      -0.0349      0.014     -2.512      0.012      -0.062      -0.008
chol          -0.0054      0.005     -1.045      0.296      -0.016       0.005
thalach        0.0364      0.014      2.615      0.009       0.009       0.064
oldpeak       -0.4925      0.293     -1.679      0.093      -1.067       0.082
sex           -2.7372      0.759     -3.606      0.000      -4.225      -1.249
fbs            0.6417      0.688      0.933      0.351      -0.706       1.989
exang         -0.9690      0.535     -1.810      0.070      -2.018       0.080
cp_1           1.4078      0.711      1.980      0.048       0.014       2.802
cp_2           2.1700      0.602      3.606      0.000       0.991       3.349
cp_3           3.5798      0.975      3.673      0.000       1.670       5.490
restecg_1      0.7301      0.480      1.520      0.129      -0.212       1.672
restecg_2      0.1158      3.445      0.034      0.973      -6.637       6.868
slope_1       -0.6033      1.048     -0.576      0.565      -2.657       1.450
slope_2        0.3139      1.139      0.276      0.783      -1.919       2.546
ca_1          -2.0823      0.603     -3.450      0.001      -3.265      -0.899
ca_2          -3.3713      0.953     -3.538      0.000      -5.239      -1.504
ca_3          -1.5915      1.038     -1.533      0.125      -3.626       0.444
ca_4           0.8562      1.906      0.449      0.653      -2.880       4.592
thal_1         2.2434      2.317      0.968      0.333      -2.299       6.786
thal_2         2.5401      2.166      1.173      0.241      -1.705       6.786
thal_3         1.5610      2.202      0.709      0.478      -2.755       5.877
==============================================================================
```

For some of the features, the p-value is less than 0.05. There is a strong relationship between these variables and target (occurance or non-occurance of a heart attack). we can choose those features whose p-value is less than 0.05 and also standard error less than 1.

In [57]:
```
# compare the predicted values by the statts model against the actual values
yhat = log_reg.predict(X_test)
prediction = list(map(round, yhat))

print('Actual values', list(y_test.values))
print('Predictions :', prediction)
```

```
Actual values [0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1,
1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1,
0, 0, 1, 1, 1, 1, 0, 0, 0, 1]
Predictions : [0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1,
1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1,
0, 1, 1, 1, 1, 1, 0, 1, 0, 1]
```

In [58]:
```
print(confusion_matrix(y_test, prediction))
print('Accuracy = ', accuracy_score(y_test, prediction)*100)
```

```
[[21  9]
 [ 4 27]]
Accuracy =  78.68852459016394
```

In [59]:
```
#Let's select those features whose p-value<0.05 and also standard error<1 and train

X_reduced=df_new[[ 'thalach','trestbps','sex', 'cp_2', 'cp_3', 'ca_1', 'ca_2']]
y=df_new[['target']]
```

In [60]:
```
from sklearn.model_selection import train_test_split
X_reduced_train, X_reduced_test, y_train, y_test = train_test_split(X_reduced, y, te
```

In [61]:
```
from sklearn.linear_model import LogisticRegression    #fit training data into Logis
Logreg=LogisticRegression()
Logreg.fit(X_reduced_train, y_train)

y_predt=Logreg.predict(X_reduced_test)
```

In [62]:
```
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report

print('Accuracy of Logistic Regression = ', accuracy_score(y_test,y_predt)*100)
print(confusion_matrix(y_test, y_predt))
print(classification_report(y_test, y_predt))
```

```
Accuracy of Logistic Regression =  81.9672131147541
[[22  5]
 [ 6 28]]
              precision    recall  f1-score   support

           0       0.79      0.81      0.80        27
           1       0.85      0.82      0.84        34

    accuracy                           0.82        61
   macro avg       0.82      0.82      0.82        61
weighted avg       0.82      0.82      0.82        61
```

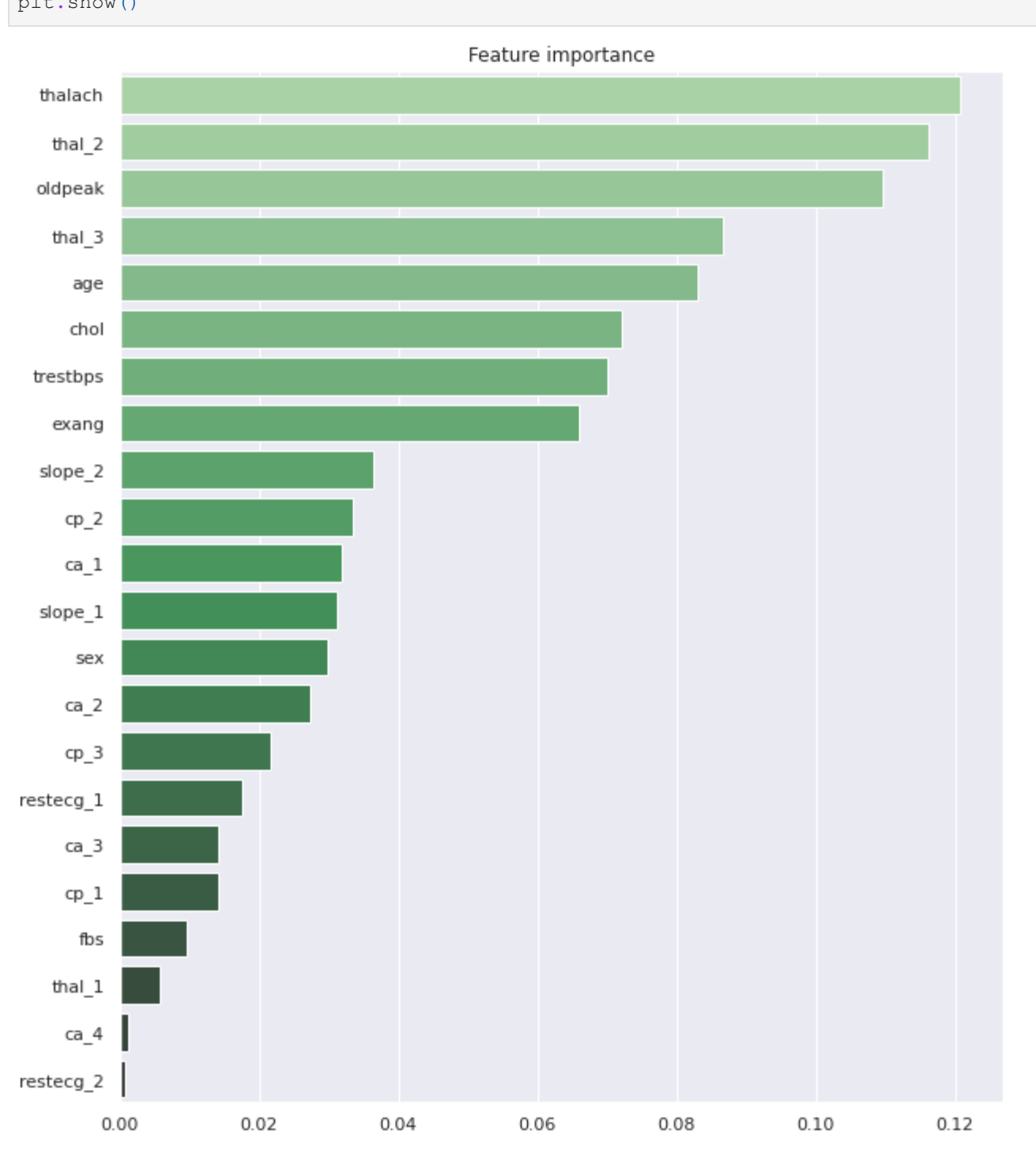
In [63]:
```
rfc=RandomForestClassifier(n_estimators=550, random_state=0)  # fit the training dat
                                                              # the target values
rfc.fit(X_reduced_train, y_train)
y_predicted=rfc.predict(X_reduced_test)
```

In [64]:
```
print('Accuracy of Random Forest Classifier = ',accuracy_score(y_test, y_predicted)*
print(confusion_matrix(y_test, y_predicted))
print(classification_report(y_test, y_predicted))
```

```
Accuracy of Random Forest Classifier =  75.40983606557377
[[19  8]
 [ 7 27]]
              precision    recall  f1-score   support

           0       0.73      0.70      0.72        27
           1       0.77      0.79      0.78        34

    accuracy                           0.75        61
   macro avg       0.75      0.75      0.75        61
weighted avg       0.75      0.75      0.75        61
```

After feature selection using statsmodel (p-value<0.05) the accuracy of the Logistic Regression Model has improved from 77.0492% to 81.9672%. Whereas, the accuracy of Random Forest Classifier Model has reduced from 78.6885% to 75.4098%

In [65]:
```
#let's check for the important features using a Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier
params={'random_state':0, 'n_jobs':-1, 'n_estimators':500, 'max_depth':8}

classifier=RandomForestClassifier(**params)
classifier=classifier.fit(X,y)

important_features = pd.Series(data=classifier.feature_importances_, index=X.column
plt.figure(figsize=(10,12))
plt.title("Feature importance")
ax = sns.barplot(y=important_features.index, x=important_features.values, palette="
plt.show()
```



From the above graph, we see that 'thalach' or Maximum Heart Rate Achieved is the most important feature in predicting a Heart Attack, followed by thal_2 (Thalassemia_2, oldpeak(ST depression induced by exercise relative to rest), Thalassemia_3, age etc.

In [66]:
```
#Let's train the model using the first five important features from the Random For
X_reduce=df_new[['thalach', 'thal_2', 'oldpeak', 'thal_3', 'age']]
y=df_new[['target']]
```

In [67]:
```
from sklearn.model_selection import train_test_split
X_reduce_train, X_reduce_test, y_train, y_test = train_test_split(X_reduce, y, tes
```

In [68]:
```
Logreg=LogisticRegression()
Logreg.fit(X_reduce_train, y_train)
y_pred1=Logreg.predict(X_reduce_test)

print('Accuracy of Logistic Regression =  ', accuracy_score(y_test,y_pred1)*100)
print(confusion_matrix(y_test, y_pred1))
print(classification_report(y_test, y_pred1))
```

```
Accuracy of Logistic Regression =   83.60655737704919
[[21  6]
 [ 4 30]]
              precision    recall  f1-score   support

           0       0.84      0.78      0.81        27
           1       0.83      0.88      0.86        34

    accuracy                           0.84        61
   macro avg       0.84      0.83      0.83        61
weighted avg       0.84      0.84      0.84        61
```

In [69]:
```
rfc=RandomForestClassifier(n_estimators=100, random_state=0)

rfc.fit(X_reduce_train, y_train)
y_pred2=rfc.predict(X_reduce_test)

print('Accuracy of Random Forest Classifier =  ',accuracy_score(y_test, y_pred2)*1
print(confusion_matrix(y_test, y_pred2))
print(classification_report(y_test, y_pred2))
```

```
Accuracy of Random Forest Classifier =   81.9672131147541
[[23  4]
 [ 7 27]]
              precision    recall  f1-score   support

           0       0.77      0.85      0.81        27
           1       0.87      0.79      0.83        34

    accuracy                           0.82        61
   macro avg       0.82      0.82      0.82        61
weighted avg       0.82      0.82      0.82        61
```

After using features from Random Forest Classifier Feature Selection, the accuracy of Logistic Regression has slightly improved to 83.6066% and the accuracy of Random Forest Classifier to 81.9672%

Inference:

After selecting all the features:

Accuracy of Logistic Regression with all the features : 77.0492%

```
f1_score :  0.79
```

Accuracy of Random Forest Classifier with all the features : 78.6885%

```
f1_score : 0.81
```

After selecting features based on p-value from statts model:

Accuracy of Logistic Regression with 7 features : 81.9672%

```
f1_score : 0.84
```

Accuracy of Random Forest Classifier with 7 features : 75.4098%

```
f1_score: 0.78
```

Using Feature Selection by Random Forest Classifier:

Accuracy of Logistic Regression using 5 important features: 83.6066%

```
f1_score: 0.86
```

Accuracy of Random Forest Classifier using 5 important features: 81.9672%

```
f1_score:0.83
```

In [ ]: