Problem Statement:

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

Dataset Description:

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

Import Libraries/modules

In [105…

```
import os
import pandas as pd
import numpy as np
import pandas_profiling as pp
import statistics
```

```
pd.set_option('display.max_rows',20)
pd.set_option('display.max_columns',None)

# For Warnings
import warnings
warnings.simplefilter("ignore")

#For Visualizations
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import style
%matplotlib inline

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

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score , classification_report, confusion_matrix, ro

#HyperParameter tuning Learning
import statsmodels.api as sm
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
```

In [106…

```
# This prints the notebook location
os.getcwd()
```

Out[106]:

```
'C:\\Users\\shaz5\\Desktop\\Learn\\AI\\Course\\Class 4 Machine Learning\\Projects\\Healt
hcare Cardiovascular diseases'
```

In [107…

```
# Print all the filen names in the folder
os.listdir(os.getcwd())
```

Out[107]:

```
['.ipynb_checkpoints',
 '1645792364_cep1_machinelearning.docx',
 'cep1_dataset.xlsx',
 'Healthcare_Cardiovascular_diseases_Project.ipynb',
 'Untitled.ipynb',
 '~$45792364_cep1_machinelearning.docx']
```

load the dataset in panda dataframe

In [108…

```
#import the cep1_dataset dataset xlsx into the panda dataframe#

df = pd.read_excel('cep1_dataset.xlsx')
df.head()
```

Out[108]:

	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

Task 1.Preliminary analysis:

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

In [109…
```
df.describe().transpose()
```

Out[109]:

	count	mean	std	min	25%	50%	75%	max
age	303.0	54.366337	9.082101	29.0	47.5	55.0	61.0	77.0
sex	303.0	0.683168	0.466011	0.0	0.0	1.0	1.0	1.0
cp	303.0	0.966997	1.032052	0.0	0.0	1.0	2.0	3.0
trestbps	303.0	131.623762	17.538143	94.0	120.0	130.0	140.0	200.0
chol	303.0	246.264026	51.830751	126.0	211.0	240.0	274.5	564.0
fbs	303.0	0.148515	0.356198	0.0	0.0	0.0	0.0	1.0
restecg	303.0	0.528053	0.525860	0.0	0.0	1.0	1.0	2.0
thalach	303.0	149.646865	22.905161	71.0	133.5	153.0	166.0	202.0
exang	303.0	0.326733	0.469794	0.0	0.0	0.0	1.0	1.0
oldpeak	303.0	1.039604	1.161075	0.0	0.0	0.8	1.6	6.2
slope	303.0	1.399340	0.616226	0.0	1.0	1.0	2.0	2.0
ca	303.0	0.729373	1.022606	0.0	0.0	0.0	1.0	4.0
thal	303.0	2.313531	0.612277	0.0	2.0	2.0	3.0	3.0
target	303.0	0.544554	0.498835	0.0	0.0	1.0	1.0	1.0

Structure of the Dataset

In [110…
```
df.shape
```

Out[110]:
```
(303, 14)
```

Datatype of Columns

In [111…
```
df.dtypes
```

Out[111]:
```
age           int64
sex           int64
cp            int64
trestbps      int64
chol          int64
fbs           int64
restecg       int64
thalach       int64
exang         int64
oldpeak     float64
slope         int64
ca            int64
thal          int64
target        int64
dtype: object
```

check column names

In [112…
```
df.columns
```

Out[112]:
```
Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
      dtype='object')
```

check indexes

In [113…
```
df.index
```

Out[113]:
```
RangeIndex(start=0, stop=303, step=1)
```

Understand data set information

In [114…
```
df.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
```

Identify missing records

In [115…
```
df.isnull().sum()
```

Out[115]:
```
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
```

Identify duplicate records

In [116…
```
df[df.duplicated(keep=False)]
```

Out[116]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
163	38	1	2	138	175	0	1	173	0	0.0	2	4	2	1

164	38	1	2	138	175	0	1	173	0	0.0	2	4	2	1

Look into Sample data

In [117…

```
df.head()
```

Out[117]:

	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

Look into Unique records

In [118…

```
for i in df.columns:
    print("'{}' column has below unique records\n".format(i))
    print(df[i].sort_values(inplace=False).unique())
    print("\n")
```

```
'age' column has below unique records

[29 34 35 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57
 58 59 60 61 62 63 64 65 66 67 68 69 70 71 74 76 77]


'sex' column has below unique records

[0 1]


'cp' column has below unique records

[0 1 2 3]


'trestbps' column has below unique records

[ 94 100 101 102 104 105 106 108 110 112 114 115 117 118 120 122 123 124
 125 126 128 129 130 132 134 135 136 138 140 142 144 145 146 148 150 152
 154 155 156 160 164 165 170 172 174 178 180 192 200]


'chol' column has below unique records

[126 131 141 149 157 160 164 166 167 168 169 172 174 175 176 177 178 180
 182 183 184 185 186 187 188 192 193 195 196 197 198 199 200 201 203 204
 205 206 207 208 209 210 211 212 213 214 215 216 217 218 219 220 221 222
 223 224 225 226 227 228 229 230 231 232 233 234 235 236 237 239 240 241
 242 243 244 245 246 247 248 249 250 252 253 254 255 256 257 258 259 260
 261 262 263 264 265 266 267 268 269 270 271 273 274 275 276 277 278 281
 282 283 284 286 288 289 290 293 294 295 298 299 300 302 303 304 305 306
 307 308 309 311 313 315 318 319 321 322 325 326 327 330 335 340 341 342
 353 354 360 394 407 409 417 564]


'fbs' column has below unique records

[0 1]
```

```
'restecg' column has below unique records

[0 1 2]


'thalach' column has below unique records

[ 71  88  90  95  96  97  99 103 105 106 108 109 111 112 113 114 115 116
 117 118 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 136
 137 138 139 140 141 142 143 144 145 146 147 148 149 150 151 152 153 154
 155 156 157 158 159 160 161 162 163 164 165 166 167 168 169 170 171 172
 173 174 175 177 178 179 180 181 182 184 185 186 187 188 190 192 194 195
 202]


'exang' column has below unique records

[0 1]


'oldpeak' column has below unique records

[0.  0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.  1.1 1.2 1.3 1.4 1.5 1.6 1.8
 1.9 2.  2.1 2.2 2.3 2.4 2.5 2.6 2.8 2.9 3.  3.1 3.2 3.4 3.5 3.6 3.8 4.
 4.2 4.4 5.6 6.2]


'slope' column has below unique records

[0 1 2]


'ca' column has below unique records

[0 1 2 3 4]


'thal' column has below unique records

[0 1 2 3]


'target' column has below unique records

[0 1]
```

In [119…

```python
df.nunique(axis=0)
```

Out[119]:

```
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
```

In [120…

```
pp.ProfileReport(df)
```

```
Summarize dataset:   0%|          | 0/28 [00:00<?, ?it/s]
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
```

Pandas Profiling Report

Overview

Overview Warnings 3 Reproduction

Dataset statistics

Number of variables	14
Number of observations	303
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	1
Duplicate rows (%)	0.3%
Total size in memory	33.3 KiB
Average record size in memory	112.4 B

Variable types

NUM	6
BOOL	4
CAT	4

Out[120]:

Check Data balance

In [121…

```
df['target'].value_counts()
```

Out[121]:
```
1    165
0    138
Name: target, dtype: int64
```

Analysis

- There are total of 14 columns in the dataset
- There are total 303 records in the dataset
- Datatype of all the columns are either int or Float none of the columns are of object type
- There are no null/missing records in dataset hence no missing value treatment is needed
- There is one duplicate record present in the dataset which needs to be removed
- There is no data imbalance in 'target' field between the two binary outputs. We have 165 person with heart disease and 138 person without heart disease, so our problem is balanced.

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

In [122…
```
df.drop_duplicates(subset = None, keep = 'first', inplace = True, ignore_index = False)
```

In [123…
```
df.shape
```

Out[123]:
```
(302, 14)
```

Analysis

- There are total 302 records in the dataset after removal of 1 duplicate record
- There are no null/missing records in dataset, hence missing value treatment is not required.

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

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

In [124…
```
df.describe().transpose()
```

Out[124]:

	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

Explore the measures of central tendencies

In [125…

```
for i in df.columns:
    print(i)
    print("Mean : ",df[i].mean())
    print("median : ",df[i].median())
    print("mode : ",df[i].mode())
    print("harmonic_mean : ",statistics.harmonic_mean(df[i]))
    print("median_low : ",statistics.median_low(df[i]))
    print("median_high  :  ",statistics.median_high(df[i]))
    print("median_grouped  :  ",statistics.median_grouped(df[i]))  # This is the 50th pe
    print("\n")
```

```
age
Mean :  54.420529801324506
median :  55.5
mode :  0    58
Name: age, dtype: int64
harmonic_mean :  52.79865724382573
median_low :  55
median_high  :   56
median_grouped  :   55.5


sex
Mean :  0.6821192052980133
median :  1.0
mode :  0    1
Name: sex, dtype: int64
harmonic_mean :  0
median_low :  1
median_high  :   1
median_grouped  :   0.7669902912621359


cp
Mean :  0.9635761589403974
median :  1.0
mode :  0    0
Name: cp, dtype: int64
harmonic_mean :  0
median_low :  1
median_high  :   1
median_grouped  :   0.66


trestbps
Mean :  131.60264900662253
median :  130.0
mode :  0    120
Name: trestbps, dtype: int64
harmonic_mean :  129.39158227824313
median_low :  130
median_high  :   130
```

```
median_grouped  :   129.94444444444446


chol
Mean :  246.5
median :  240.5
mode :  0    197
1    204
2    234
Name: chol, dtype: int64
harmonic_mean :  236.5205394621995
median_low :  240
median_high  :   241
median_grouped  :   240.5


fbs
Mean :  0.1490066225165563
median :  0.0
mode :  0    0
Name: fbs, dtype: int64
harmonic_mean :  0
median_low :  0
median_high  :   0
median_grouped  :   0.08754863813229574


restecg
Mean :  0.5264900662251656
median :  1.0
mode :  0    1
Name: restecg, dtype: int64
harmonic_mean :  0
median_low :  1
median_high  :   1
median_grouped  :   0.5264900662251656


thalach
Mean :  149.56953642384107
median :  152.5
mode :  0    162
Name: thalach, dtype: int64
harmonic_mean :  145.56643218312428
median_low :  152
median_high  :   153
median_grouped  :   152.5


exang
Mean :  0.32781456953642385
median :  0.0
mode :  0    0
Name: exang, dtype: int64
harmonic_mean :  0
median_low :  0
median_high  :   0
median_grouped  :   0.24384236453201968


oldpeak
Mean :  1.0430463576158941
median :  0.8
mode :  0    0.0
Name: oldpeak, dtype: float64
harmonic_mean :  0
```

```
median_low :  0.8
median_high  :   0.8
median_grouped  :   0.4538461538461539


slope
Mean :  1.3973509933774835
median :  1.0
mode :  0    2
Name: slope, dtype: int64
harmonic_mean :  0
median_low :  1
median_high  :   1
median_grouped  :   1.4285714285714286


ca
Mean :  0.7185430463576159
median :  0.0
mode :  0    0
Name: ca, dtype: int64
harmonic_mean :  0
median_low :  0
median_high  :   0
median_grouped  :   0.3628571428571429


thal
Mean :  2.314569536423841
median :  2.0
mode :  0    2
Name: thal, dtype: int64
harmonic_mean :  0
median_low :  2
median_high  :   2
median_grouped  :   2.293939393939394


target
Mean :  0.543046357615894
median :  1.0
mode :  0    1
Name: target, dtype: int64
harmonic_mean :  0
median_low :  1
median_high  :   1
median_grouped  :   0.5792682926829268
```

Explore spread of the data

The spread of the data is a measure that tells us how much variation is there in the data. Dispersion/spread gives us an idea of how the data strays from the typical value.

Standard metrics to quantify the spread are the variance,pvariance,Stdev and pstdev.

In [126…

```
for i in df.columns:
    print(i)
    print("variance : ",statistics.variance(df[i]))
    print("pvariance : ",statistics.pvariance(df[i]))
    print("stdev : ",statistics.stdev(df[i]))
    print("pstdev : ",statistics.pstdev(df[i]))
    print("\n")
```

```
age
variance :  81.86575652900926
pvariance :  81.59467786500592
stdev :  9.047969746247457
pstdev :  9.032977242582088


sex
variance :  0.21755296913159225
pvariance :  0.2168325950616201
stdev :  0.4664257380672643
pstdev :  0.46565286970190584


cp
variance :  1.065114078898154
pvariance :  1.0615872110872329
stdev :  1.0320436419542314
pstdev :  1.030333543609657


trestbps
variance :  308.4728168797166
pvariance :  307.45138371124074
stdev :  17.56339423003756
pstdev :  17.534291651254144


chol
variance :  2678.423588039867
pvariance :  2669.5546357615895
stdev :  51.75348865574056
pstdev :  51.66773302324759


fbs
variance :  0.12722492354403644
pvariance :  0.1268036489627648
stdev :  0.3566860293648133
pstdev :  0.35609499991261434


restecg
variance :  0.2767045829574707
pvariance :  0.2757883426165519
stdev :  0.5260271694099752
pstdev :  0.5251555413556558


thalach
variance :  524.5715605817254
pvariance :  522.8345686592693
stdev :  22.903527251969845
pstdev :  22.86557606226594


exang
variance :  0.22108424457107653
pvariance :  0.22035217753607297
stdev :  0.4701959640097696
pstdev :  0.469416848372609


oldpeak
variance :  1.348971419770742
pvariance :  1.3445046269900442
```

```
stdev :  1.1614522890634562
pstdev :  1.1595277603360965


slope
variance :  0.3797936239026644
pvariance :  0.3785360291215298
stdev :  0.6162739844441467
pstdev :  0.6152528172398155


ca
variance :  1.0135420562803898
pvariance :  1.0101859567562825
stdev :  1.0067482586428396
pstdev :  1.0050800747981639


thal
variance :  0.3758003124243691
pvariance :  0.37455594052892416
stdev :  0.6130255397814752
pstdev :  0.6120097552563392


target
variance :  0.2489714197707421
pvariance :  0.24814701109600457
stdev :  0.4989703596114123
pstdev :  0.4981435647441454
```

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

In [127…

```python
Categorical_Columns = []
Continious_Columns = []
for column in df.columns:
    if len(df[column].unique()) <= 8:
        Categorical_Columns.append(column)
    else:
        Continious_Columns.append(column)



print("\n Categorical Variables are : " , Categorical_Columns)
print(" \n Continiuous Variables are : " , Continious_Columns)
```

```
 Categorical Variables are :  ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 't
hal', 'target']

 Continiuous Variables are :  ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
```

In [128…

```python
df1 = df.copy()
```

In [129…

```python
def Change_sex(sex):
    if sex == 0:
        return 'female'
    else:
        return 'male'

def Change_fbs(fbs):
    if fbs == 0:
```

```
            return 'false'
        else:
            return 'true'

def Change_exang(exang):
    if exang == 0:
        return 'no'
    else:
        return 'yes'

def change_target(target):
    if target == 0:
        return 'No Heart Disease'
    else:
        return 'Heart Disease'


df1['sex'] = df1['sex'].apply(Change_sex)
df1['fbs'] = df1['fbs'].apply(Change_fbs)
df1['exang'] = df1['exang'].apply(Change_exang)
df1['target'] = df1['target'].apply(change_target)

df1.head()
```

Out[129]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	male	3	145	233	true	0	150	no	2.3	0	0	1	Heart Disease
1	37	male	2	130	250	false	1	187	no	3.5	0	0	2	Heart Disease
2	41	female	1	130	204	false	0	172	no	1.4	2	0	2	Heart Disease
3	56	male	1	120	236	false	1	178	no	0.8	2	0	2	Heart Disease
4	57	female	0	120	354	false	1	163	yes	0.6	2	0	2	Heart Disease

Assumption :

- We are considering that if target = 0 means there is no heart disease and if target = 1 then there is a heart Disease

Analysis: Variable Types:

- Categorical Variables are : ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal', 'target']
- Continuous Variables are : ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']

Count Plots

Count plot for Categorical Variables

- Lets look into each Categorical_Columns one by one.

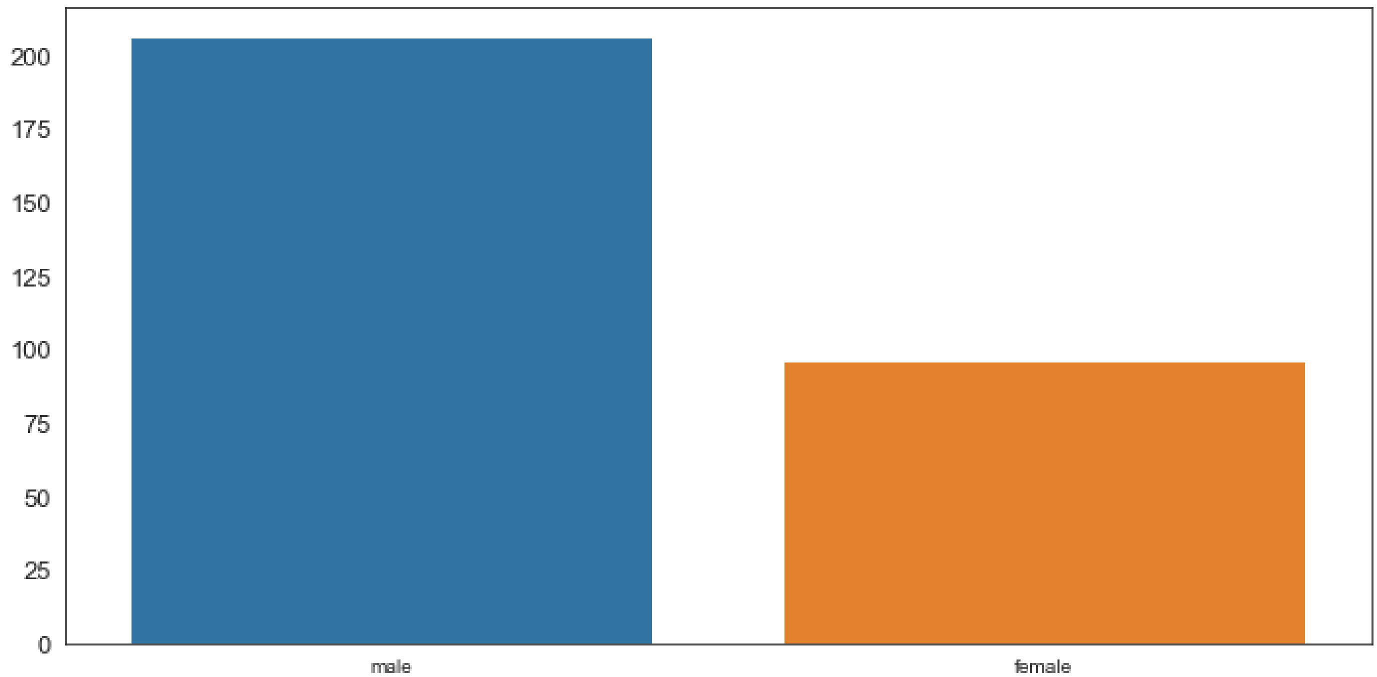
In [130…

```
sns.despine(left=True, right=True, bottom=True, top=True)
sns.set_style('white')

for i in Categorical_Columns:
  print(i, "\n\n",df1[i].value_counts(),'\n' )
  print("\n\n",df1[i].value_counts(normalize=True)*100,'\n' )
  fig, ax = plt.subplots(1,1, figsize=(12, 6))
  sns.countplot(data= df1, x=i)
  fig.text(0.1, 0.95, f'Count plot for variable {i}', fontsize=16, fontweight='bold', fo
```

```
    plt.xlabel(' ', fontsize=20)
    plt.ylabel('')
    plt.yticks(fontsize=13)
    plt.show()
```

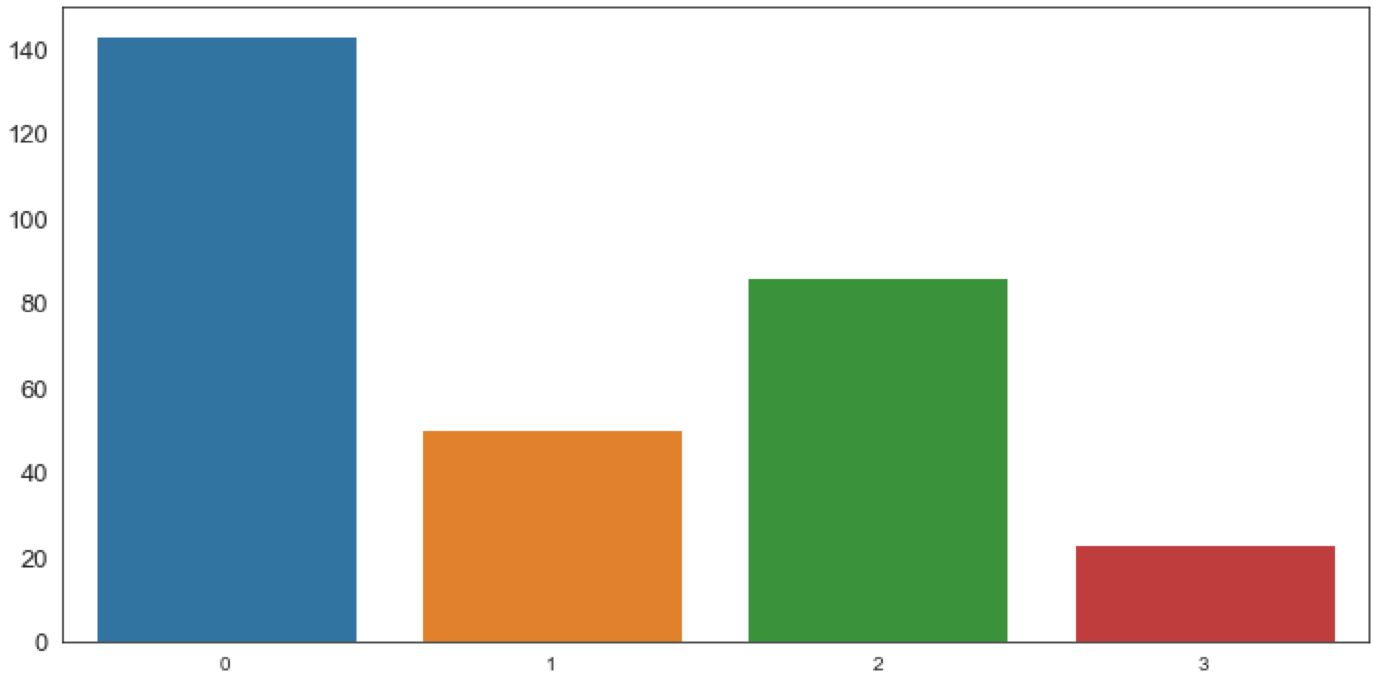
```
sex

 male      206
female     96
Name: sex, dtype: int64



 male      68.211921
female    31.788079
Name: sex, dtype: float64

<Figure size 432x288 with 0 Axes>
```

Count plot for variable sex



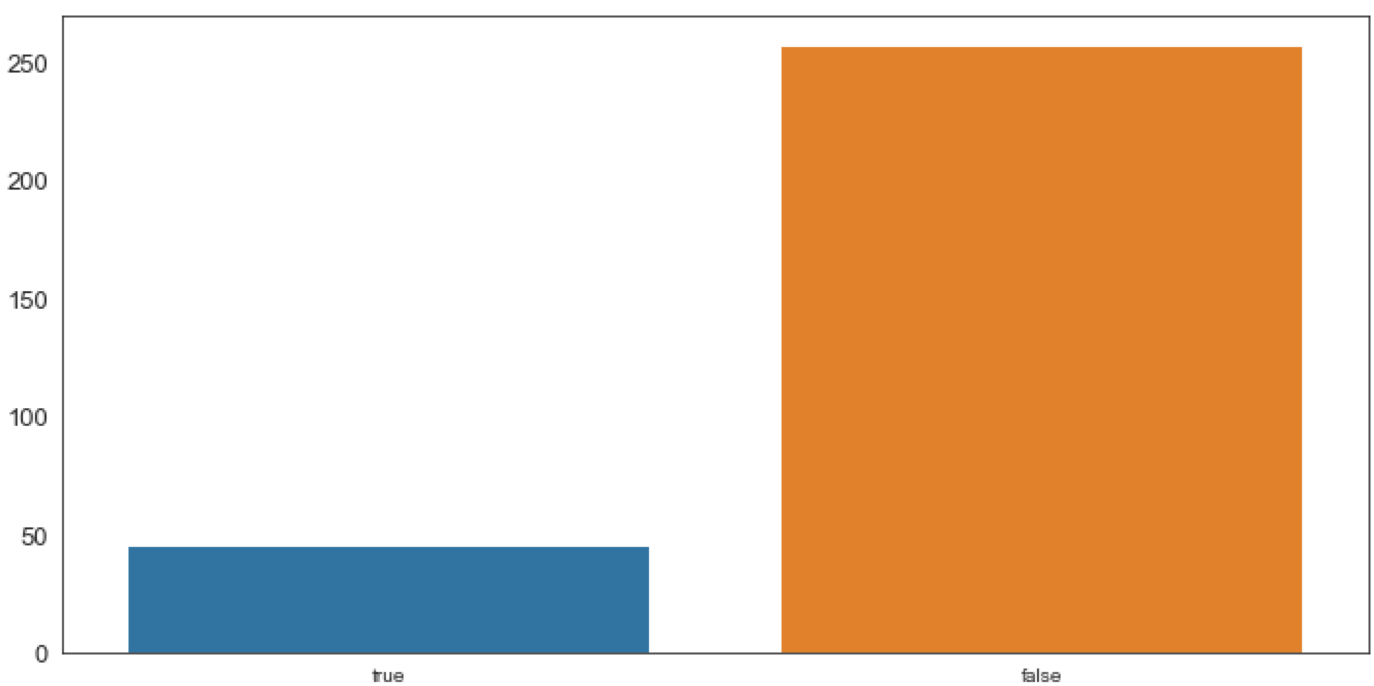

```
cp

 0    143
2     86
1     50
3     23
Name: cp, dtype: int64



 0    47.350993
2    28.476821
1    16.556291
3     7.615894
Name: cp, dtype: float64
```

Count plot for variable cp




```
fbs

 false    257
true      45
Name: fbs, dtype: int64



 false    85.099338
true     14.900662
Name: fbs, dtype: float64
```

Count plot for variable fbs

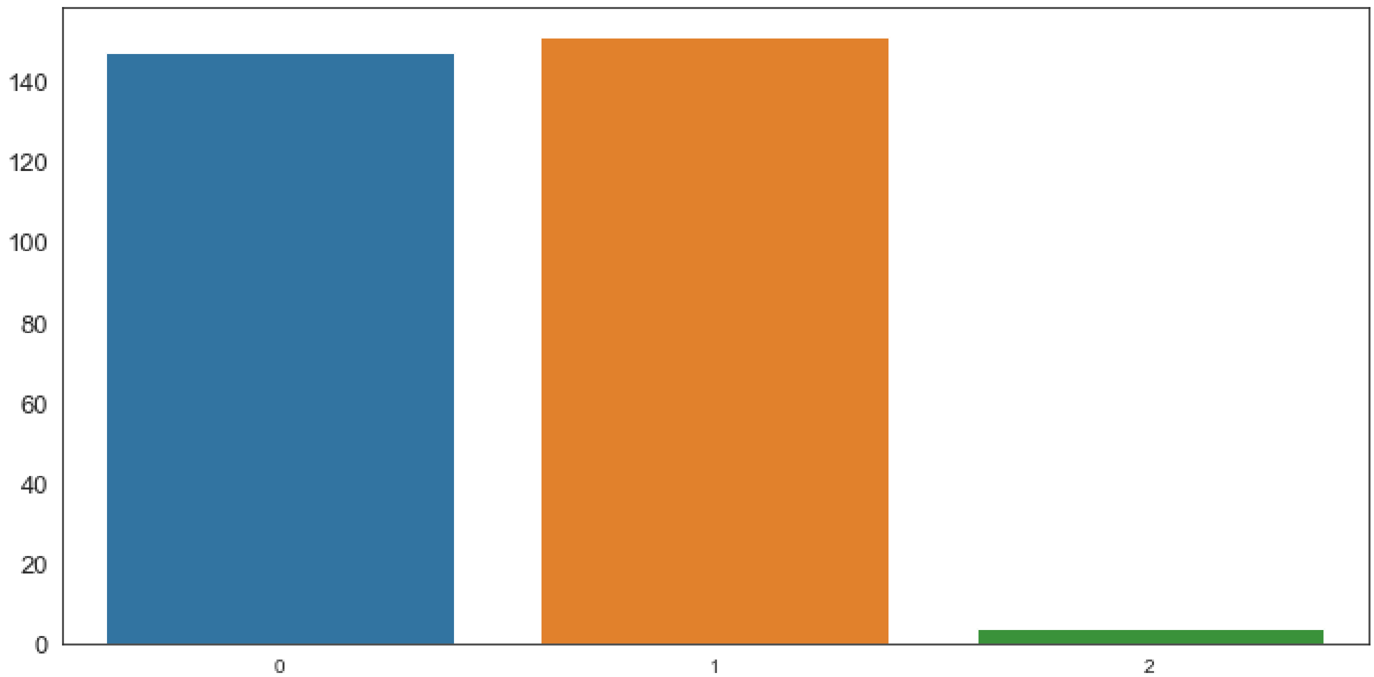



```
restecg
```

```
 1    151
0    147
2      4
Name: restecg, dtype: int64
```

```
 1    50.000000
0    48.675497
2     1.324503
Name: restecg, dtype: float64
```

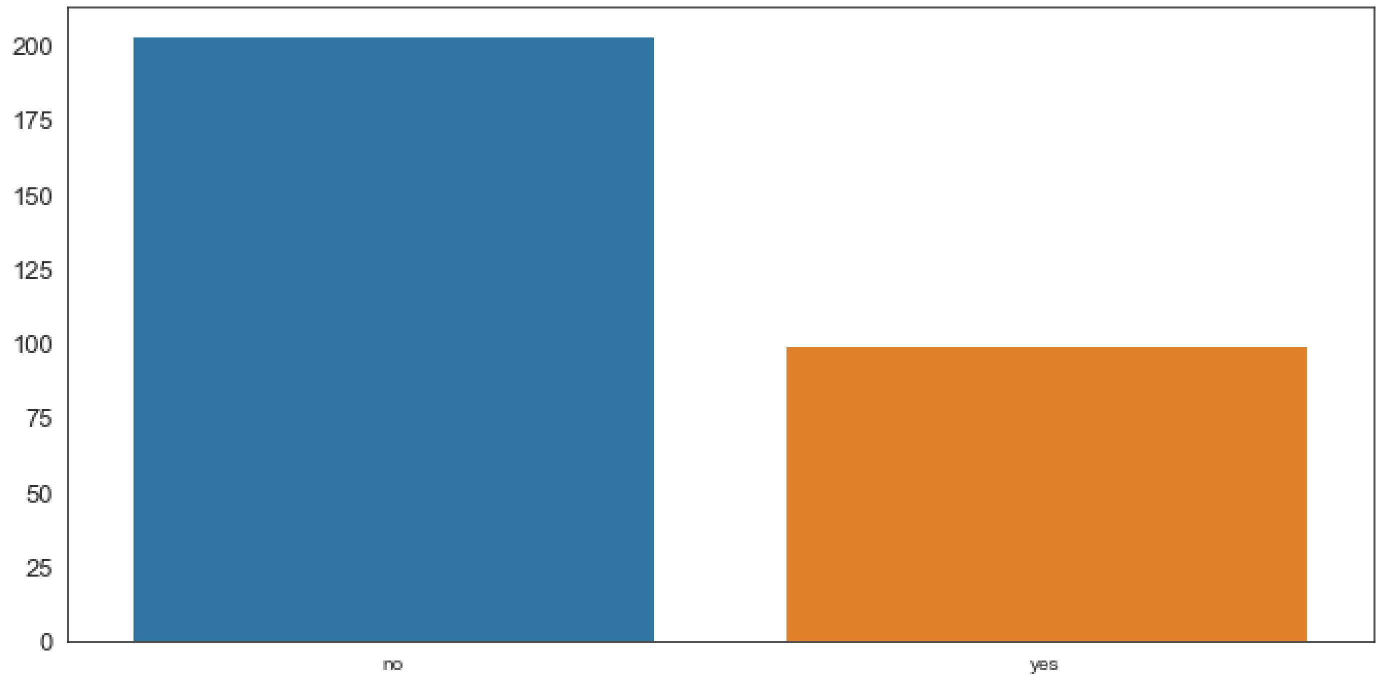
Count plot for variable restecg



```
exang

 no     203
yes     99
Name: exang, dtype: int64
```

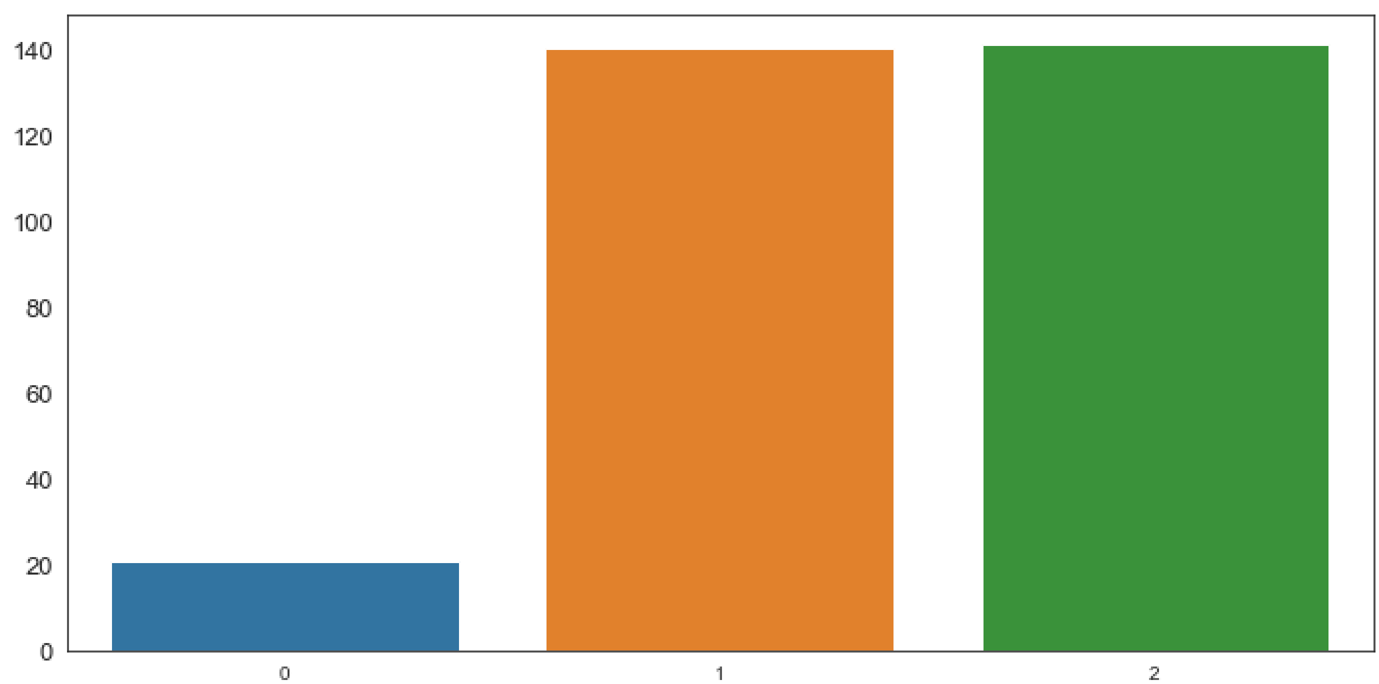
```
 no     67.218543
yes    32.781457
Name: exang, dtype: float64
```

Count plot for variable exang



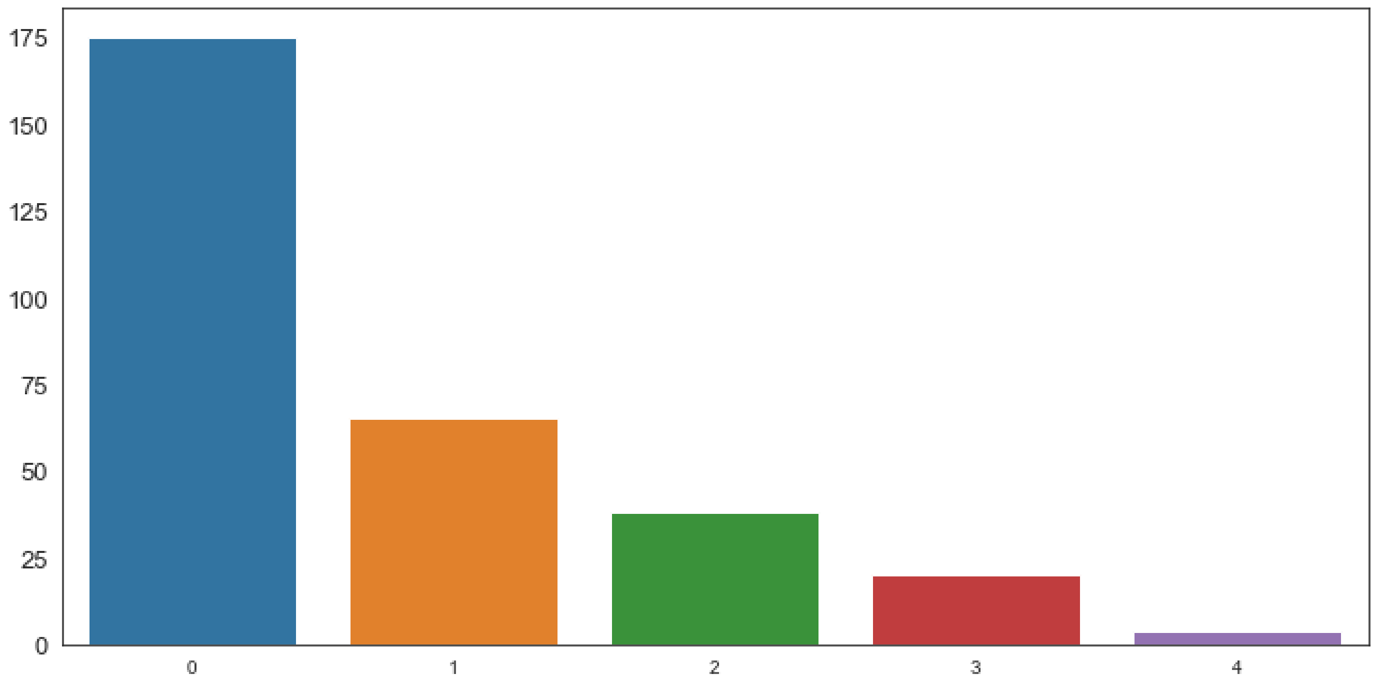

```
slope

 2    141
1    140
0     21
Name: slope, dtype: int64



 2    46.688742
1    46.357616
0     6.953642
Name: slope, dtype: float64
```

Count plot for variable slope



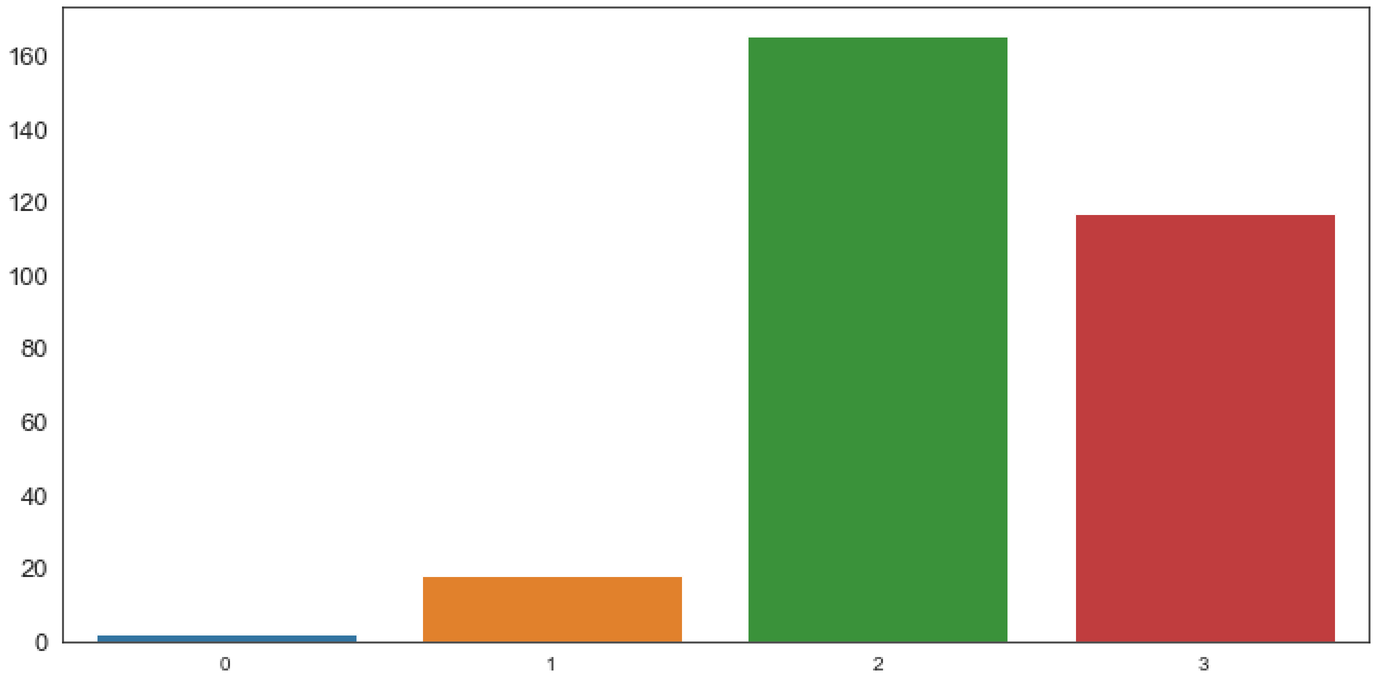
```
ca

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



 0    57.947020
1    21.523179
2    12.582781
3     6.622517
4     1.324503
Name: ca, dtype: float64
```

Count plot for variable ca



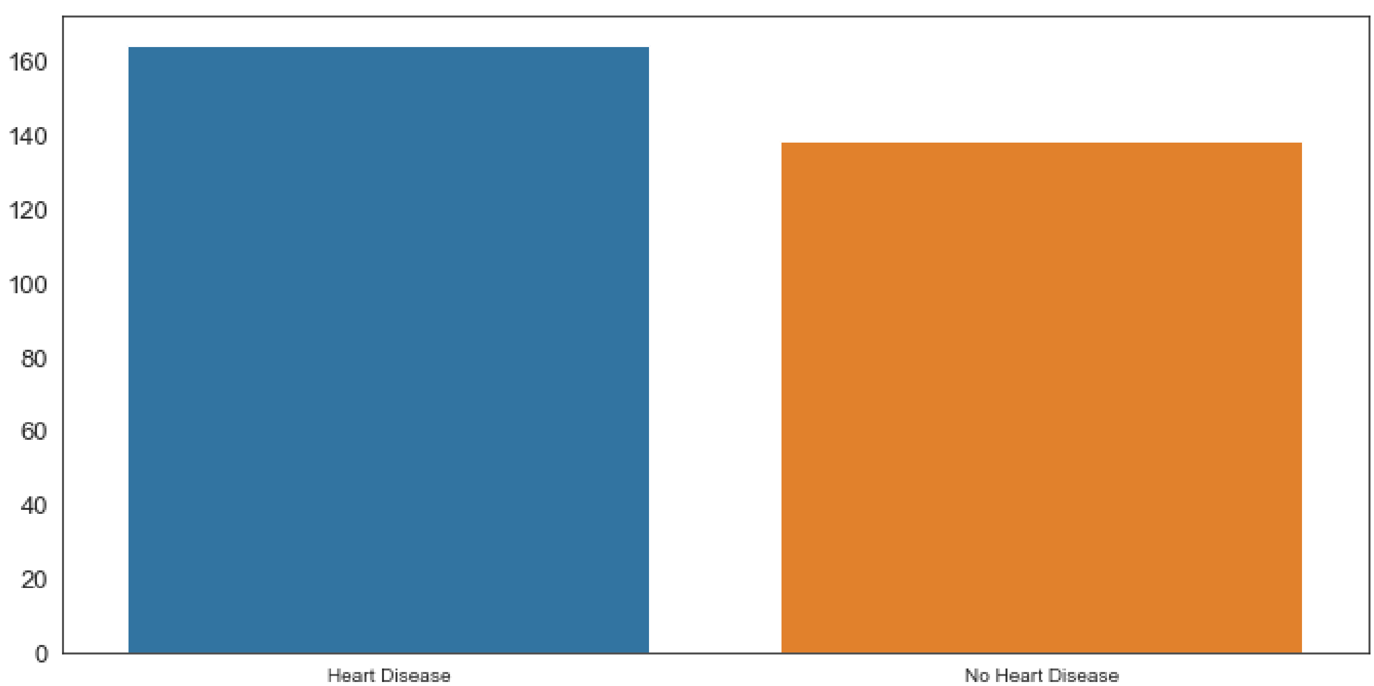

```
thal

 2    165
3    117
1     18
0      2
Name: thal, dtype: int64



 2    54.635762
3    38.741722
1     5.960265
0     0.662252
Name: thal, dtype: float64
```

Count plot for variable thal




```
target

 Heart Disease       164
No Heart Disease    138
Name: target, dtype: int64



 Heart Disease       54.304636
No Heart Disease    45.695364
Name: target, dtype: float64
```

Count plot for variable target

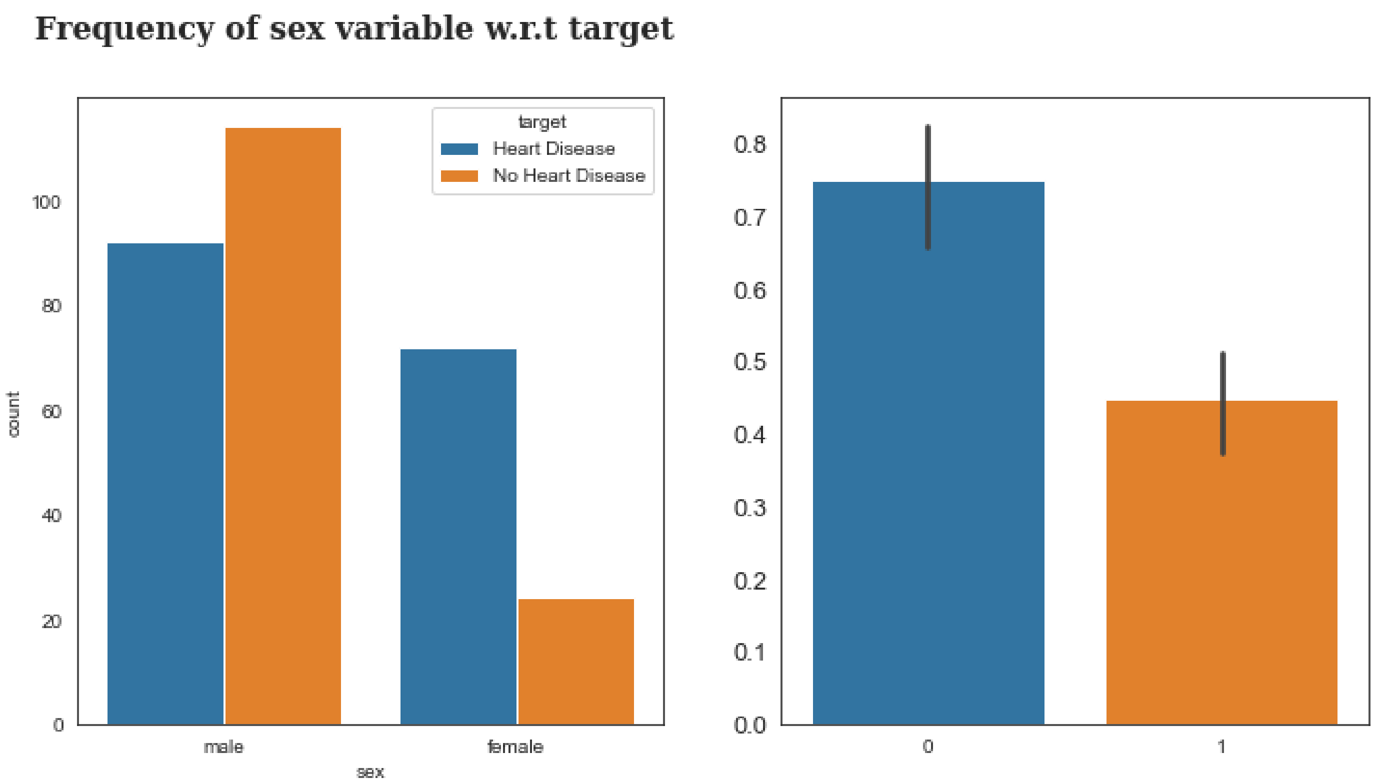


Lets look into the Count plot for Categorical Variables with respect to Target

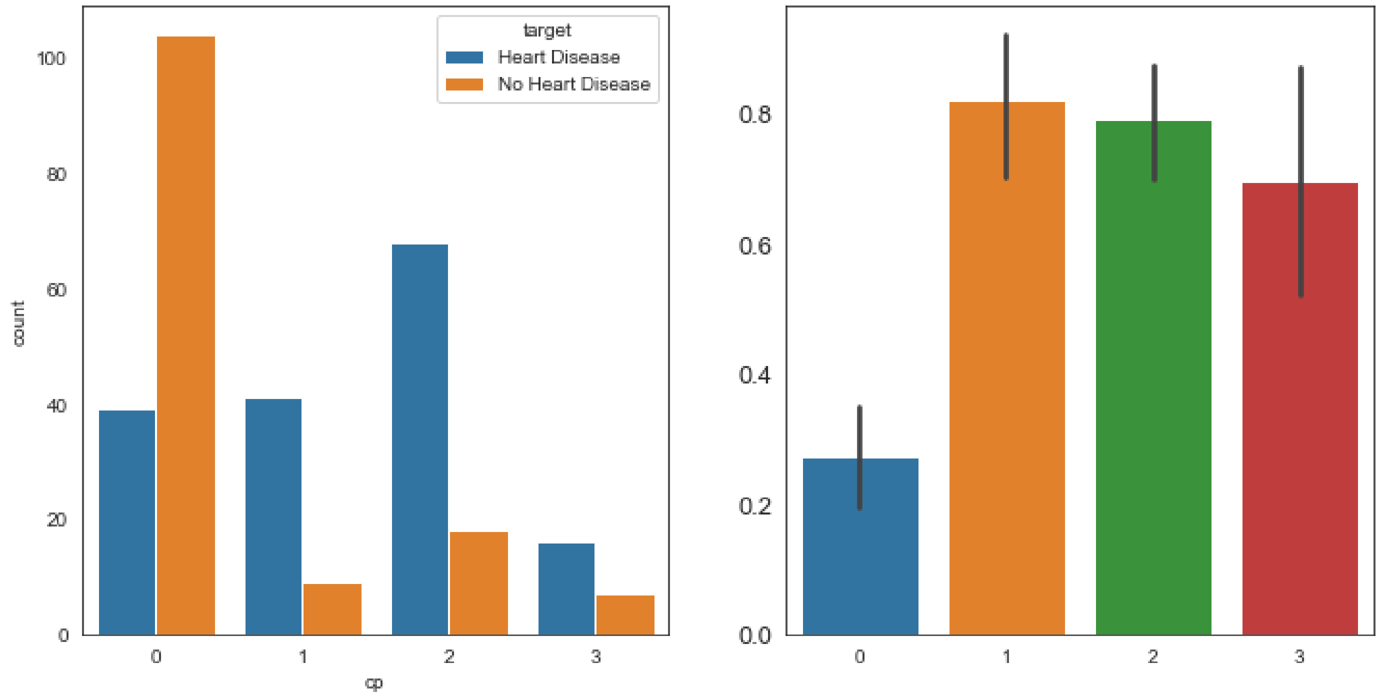
In [131…

```
sns.despine(left=True, right=True, bottom=True, top=True)
sns.set_style('white')

for i in Categorical_Columns:
  fig, ax = plt.subplots(1,2, figsize=(12, 6))
  sns.countplot(data= df1, x=i, hue='target', ax=ax[0])
  sns.barplot(data= df, x=i, y='target',  ax=ax[1])
  fig.text(0.1, 0.95, f'Frequency of {i} variable w.r.t target', fontsize=16, fontweight
  plt.xlabel(' ', fontsize=20)
  plt.ylabel('')
  plt.yticks(fontsize=13)
  plt.show()
```

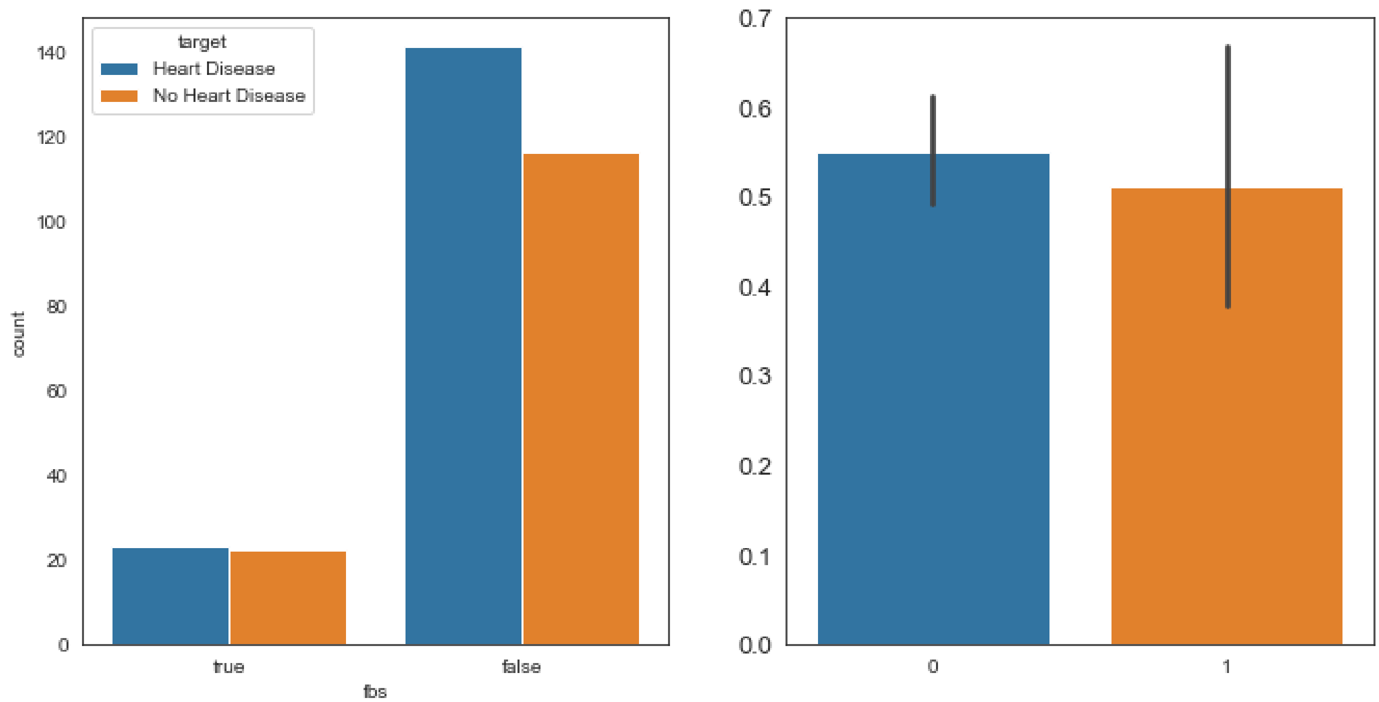
```
<Figure size 432x288 with 0 Axes>
```



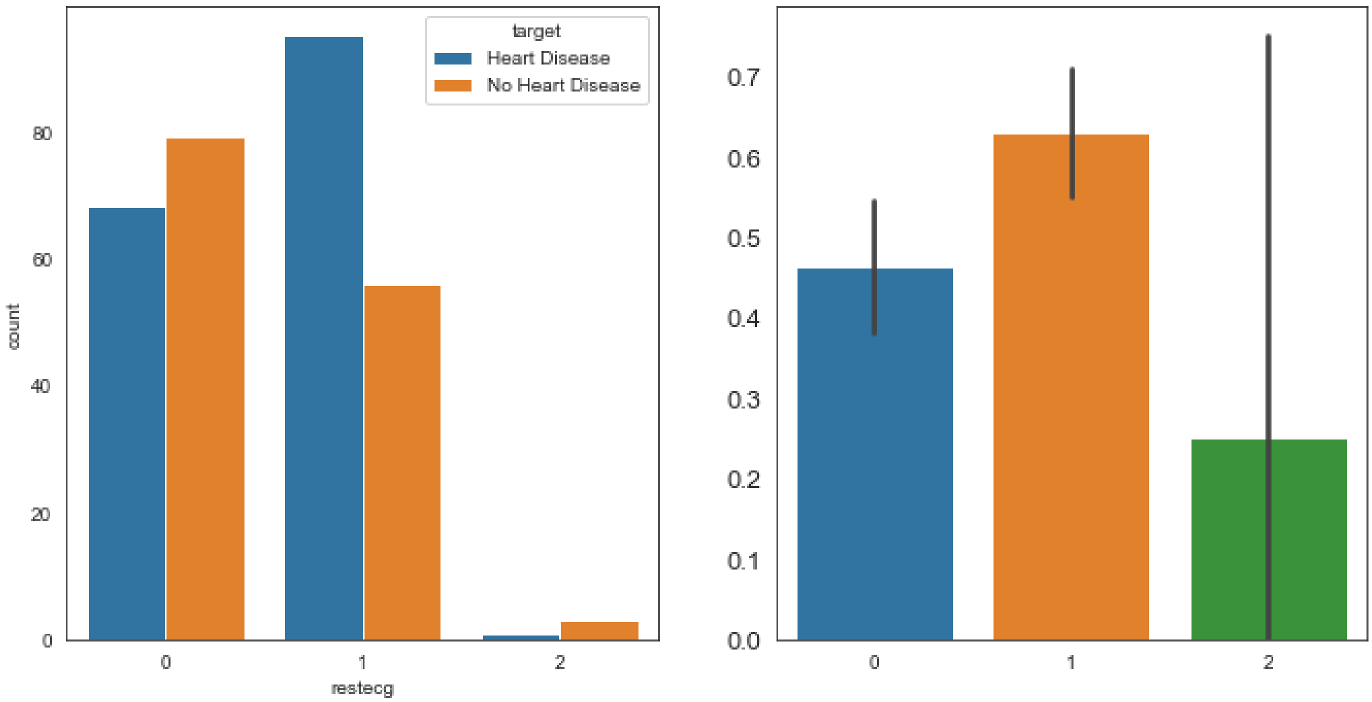
Frequency of cp variable w.r.t target



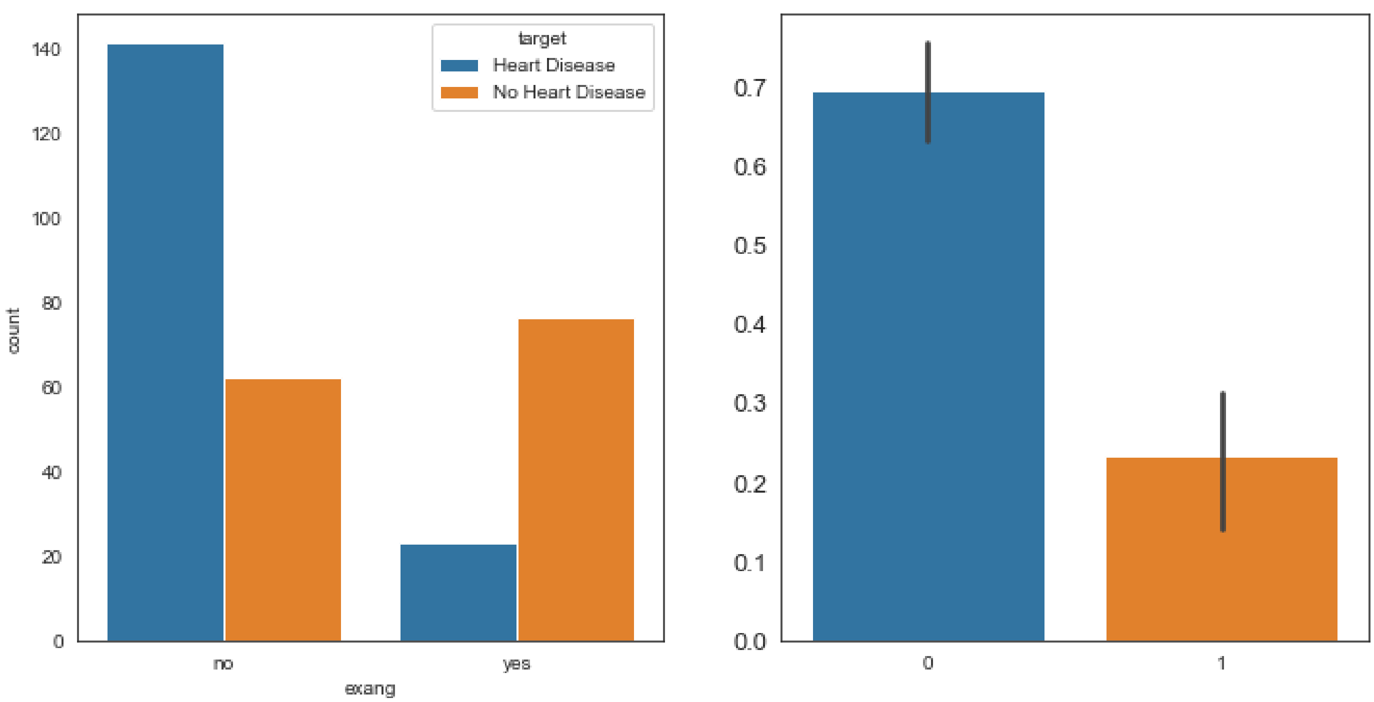
Frequency of fbs variable w.r.t target



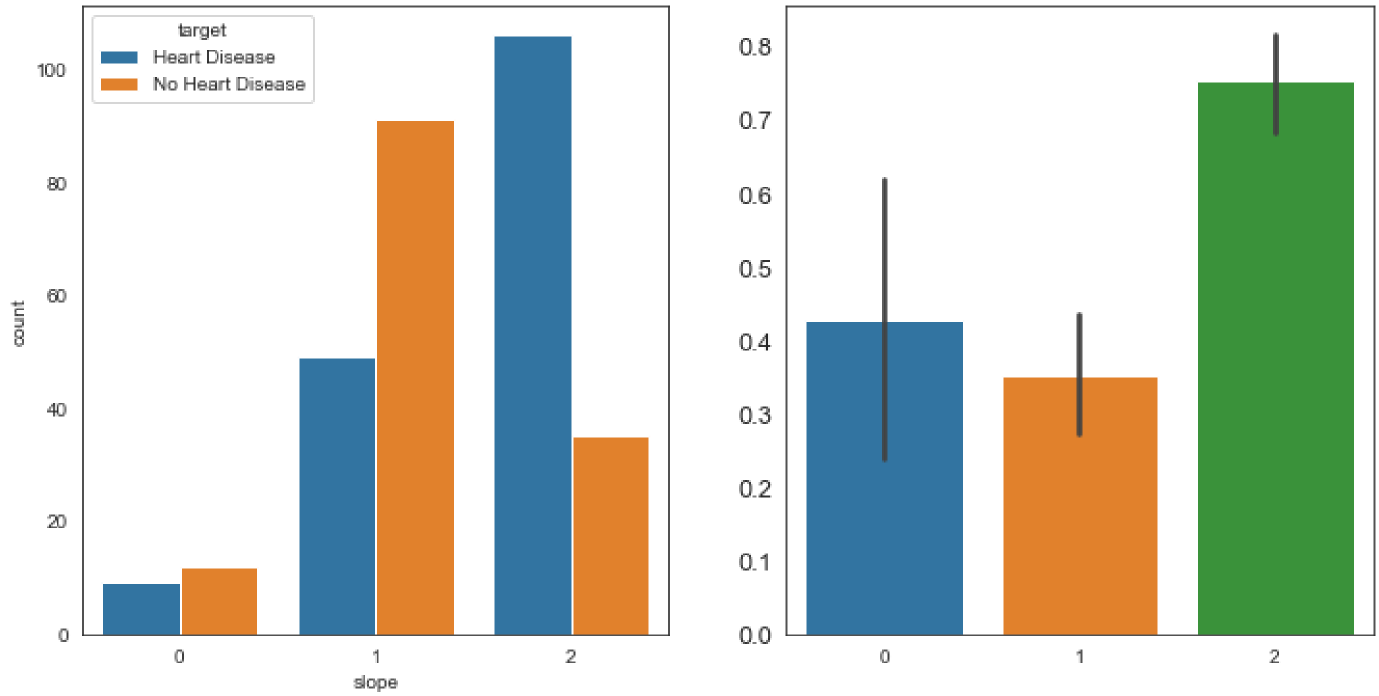
Frequency of restecg variable w.r.t target



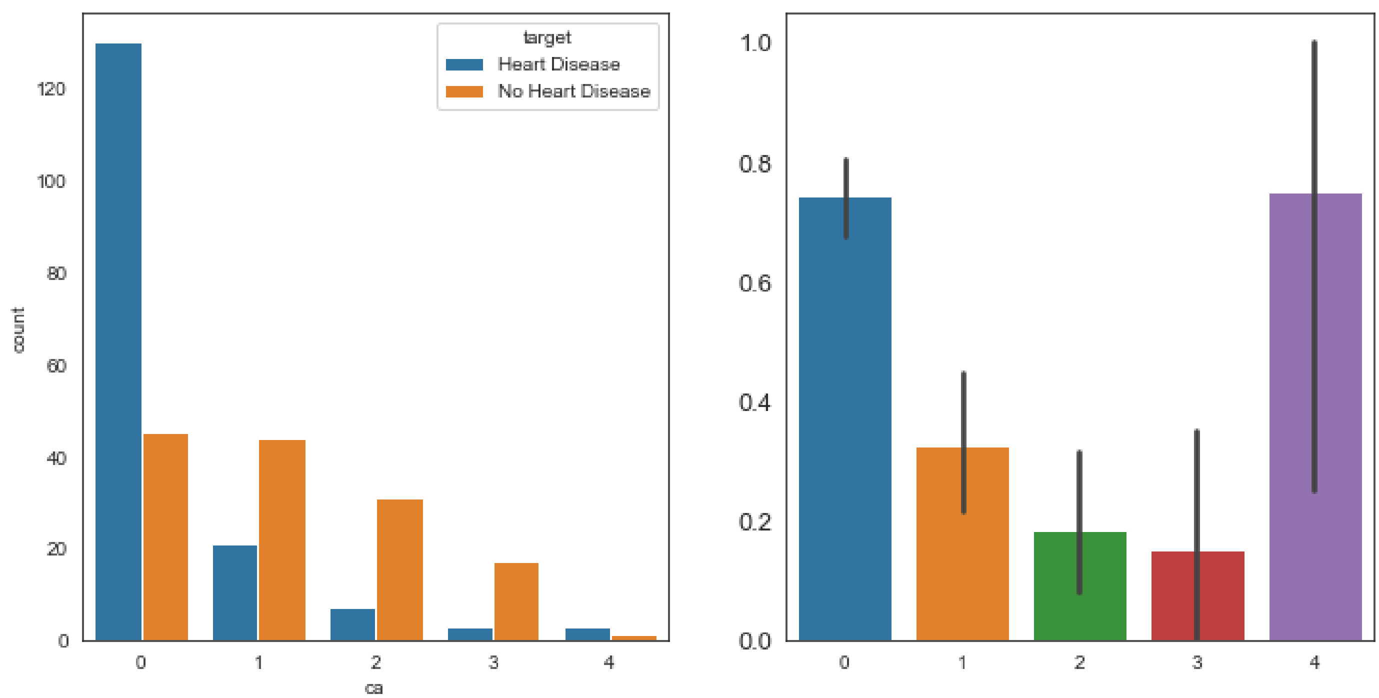
Frequency of exang variable w.r.t target



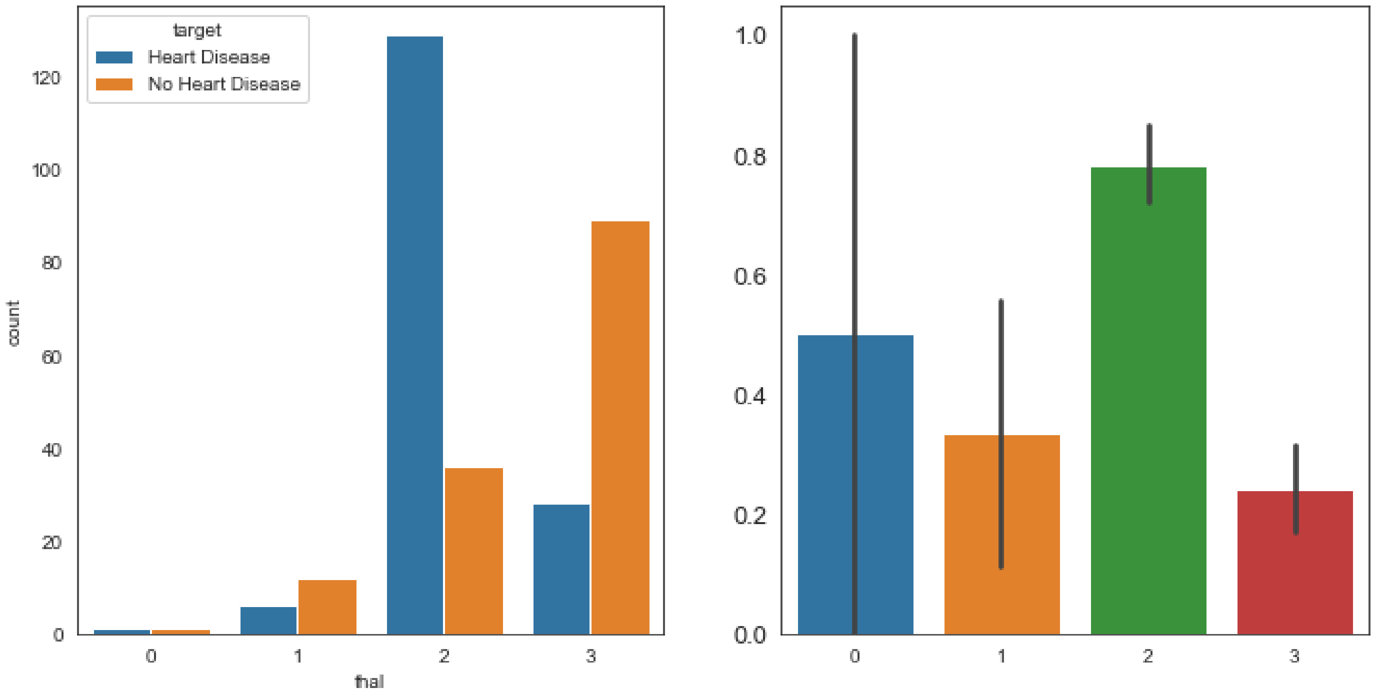
Frequency of slope variable w.r.t target



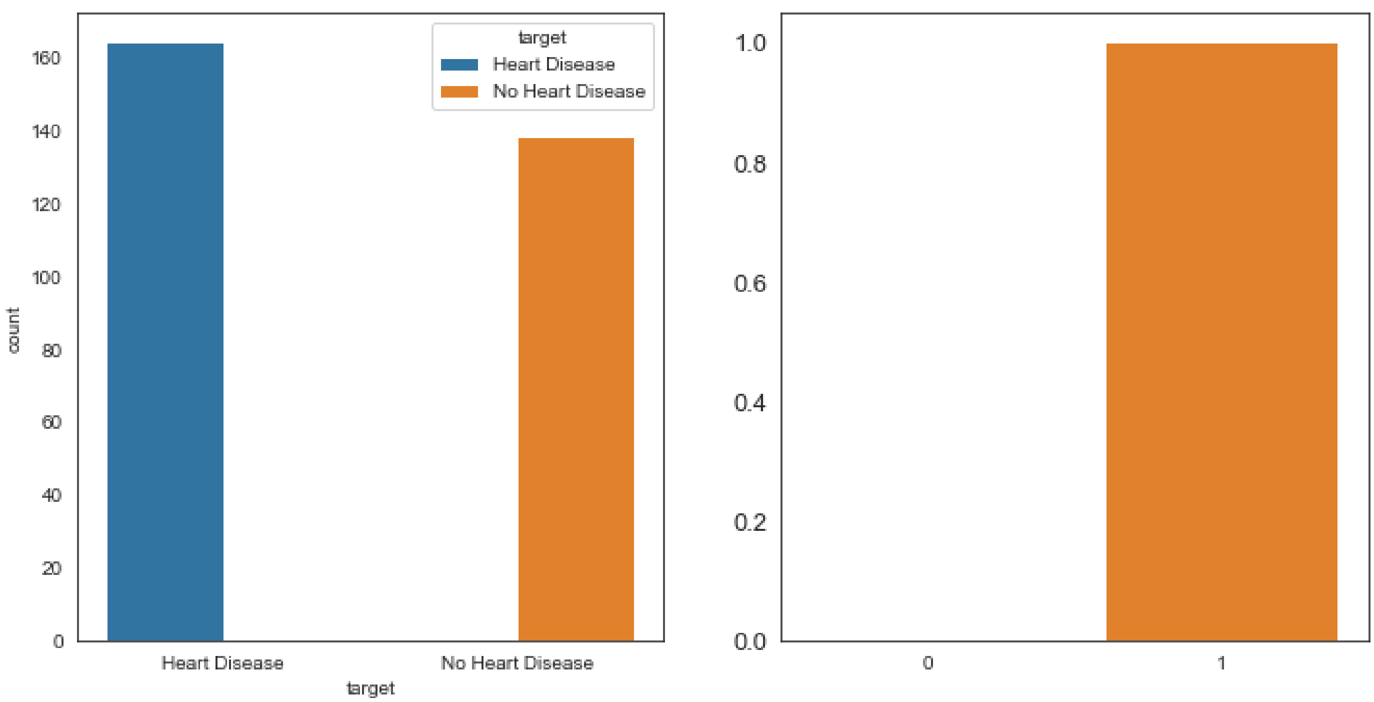
Frequency of ca variable w.r.t target



Frequency of thal variable w.r.t target



Frequency of target variable w.r.t target



Univariate Analysis: The above analysis from count plot shows that:

- Sex:
  - There are approx 68.2% Male patients and approx 31.8% Female patients.
  - Male have more chances of getting heart problems
- Chest Pain(Cp) :
  - Chest pain type 0 is 47%, type 1 is 16%, type 2 is 28%, type 3 is 7% approximately
  - Most of the patients have type Value 1
  - chest pain of '0', i.e. the ones with typical angina are much less likely to have heart problems

- Fasting Blood sugar(Fbs):
    - Fasting blood sugar > 120 mg/dl (1 = true; 0 = false) is Approx. 85% and and <120mg/dl is 15%
    - Most of the patients' blood pressure is more than 120.
    - There is not much difference w.r.t target
- Resting electrocardiographic results(restecg):
    - Type 0 is 49%, Type 1 is 50% and Type 2 is 1% approximately
    - people with restecg '1' and '0' are much more likely to have a heart disease than with restecg '2'
- Exercise induced angina (1 = yes; 0 = no) (exgang):
    - Exercise induced angina is present in 33% population and not present in 67% population
    - People with exang=1 i.e. Exercise induced angina are much less likely to have heart problems
- Slope of the peak exercise ST segment (slope):
    - Type 0 , Type 1, Type 2 is present in approx. 7%, 46% and 47% population respectively
    - Slope '2' causes heart pain much more than Slope '0' and '1'
- Ca:
    - Type 0 , Type 1, Type 2, Type 3 , Type 4 is present in approx. 57%, 22%, 13%,7%and 1% population respectively
    - ca=4 has astonishingly large number of heart patients
- Thal:
    - Type 0 , Type 1, Type 2, Type 3 is present in approx. 1%, 6%, 55% and 39% population respectively
    - thal=2 has astonishingly large number of heart patients

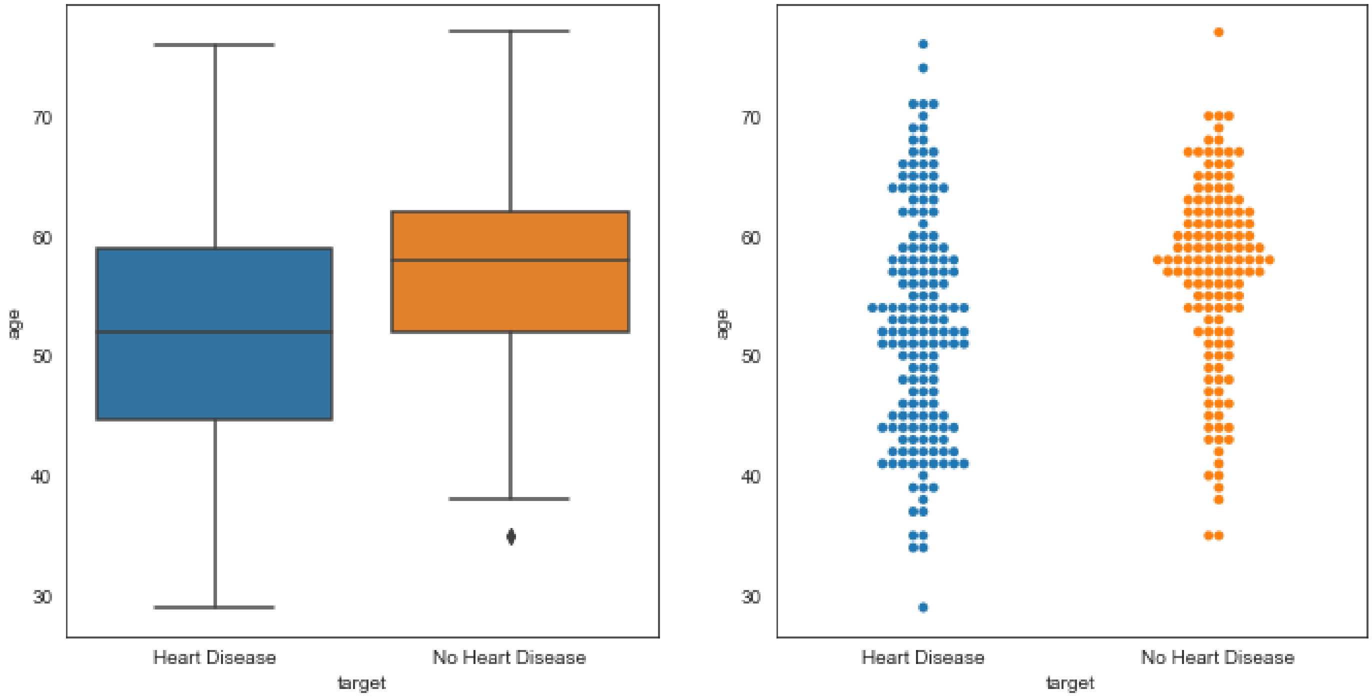
c. Study the occurrence of CVD across the Age category

In [132…

```
#Boxplot and swarmplot
fig, axes = plt.subplots(1,2, figsize=(12, 6))
sns.boxplot(data=df1, x='target', y='age', ax=axes[0])
sns.swarmplot(data=df1, x='target', y='age', ax=axes[1])
```

Out[132]:

```
<AxesSubplot:xlabel='target', ylabel='age'>
```

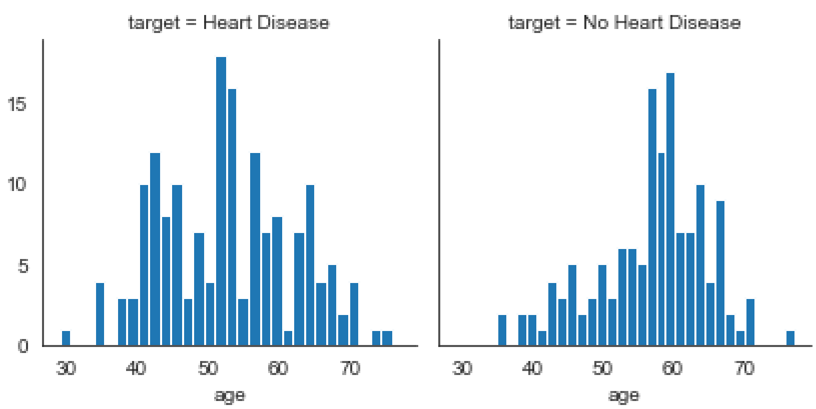


In [133…

```
g = sns.FacetGrid(df1, col='target')
g.map(plt.hist, 'age', bins=30)
```

Out[133]:

```
<seaborn.axisgrid.FacetGrid at 0x1c5343557f0>
```

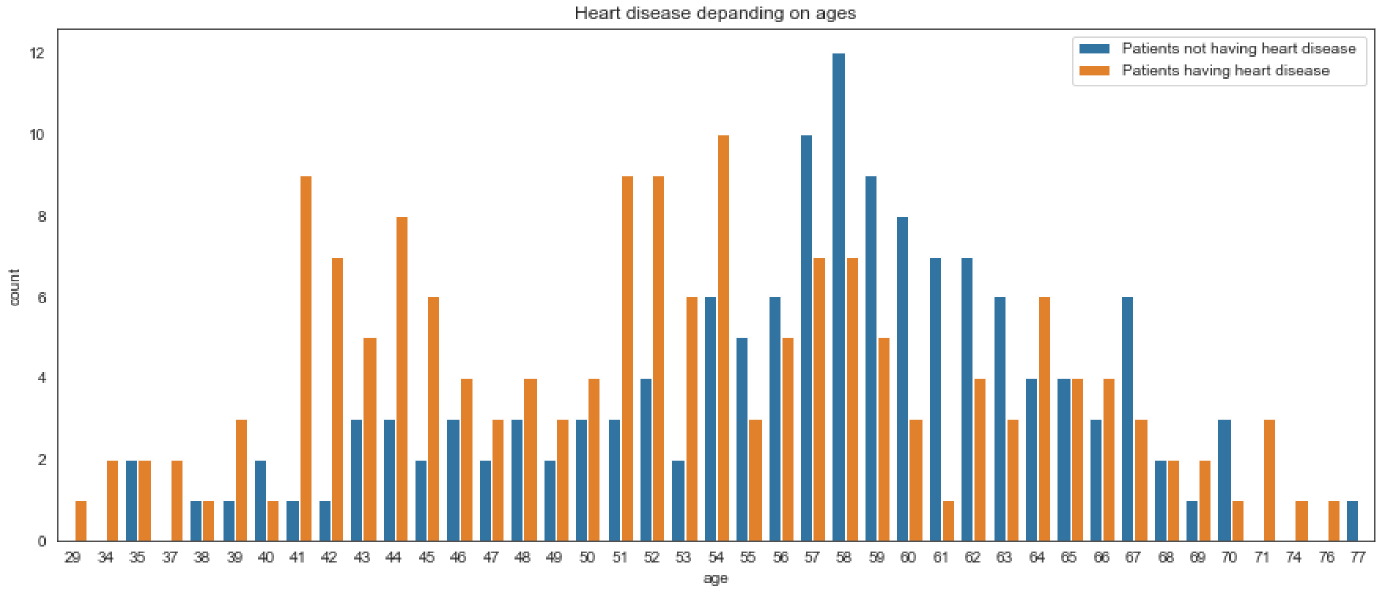


In [134…

```
# To study the occurrence of CVD across different ages.

plt.figure(figsize=(15,6))
sns.countplot(x = 'age', hue = 'target', data = df)
plt.title("Heart disease depanding on ages")
plt.legend(["Patients not having heart disease ","Patients having heart disease "], loc=
```

Out[134]:

```
<matplotlib.legend.Legend at 0x1c5346f9df0>
```

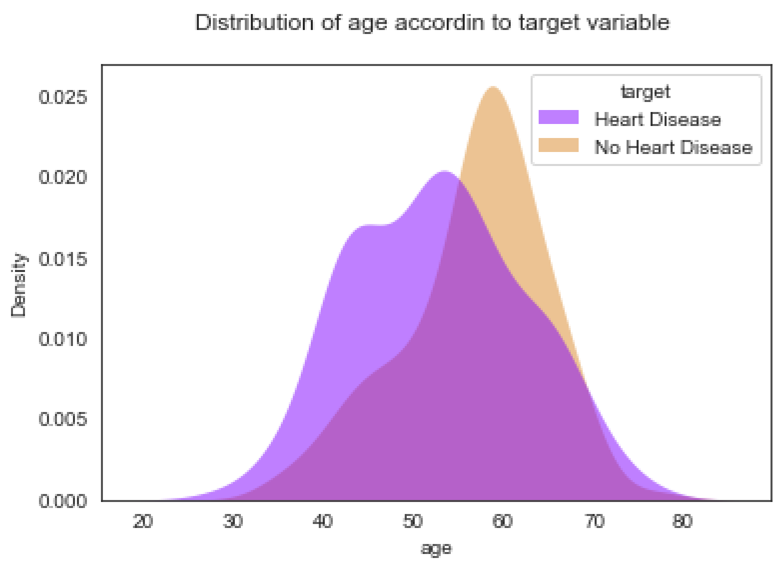


In [135…

```
sns.kdeplot(data=df1, x=df1.age,hue="target", fill=True,palette=["#8000ff","#da8829"], a
plt.title('Distribution of age accordin to target variable \n')
```

Out[135]:

```
Text(0.5, 1.0, 'Distribution of age accordin to target variable \n')
```

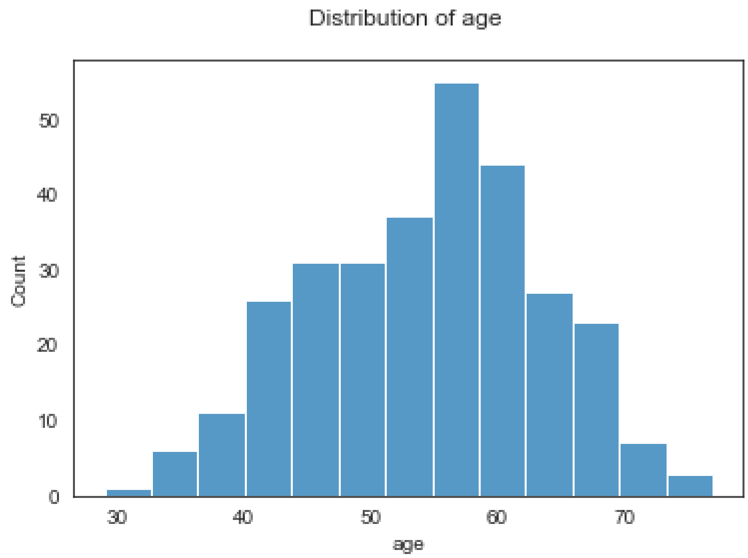


In [136…

```
sns.histplot(data=df1, x=df1.age)
plt.title('Distribution of age \n')
```

Out[136]:

```
Text(0.5, 1.0, 'Distribution of age \n')
```



In [137…

```
df.groupby([pd.cut(df['age'],4)])['target'].agg(['count','mean'])
```

Out[137]:

age	count	mean
(28.952, 41.0]	28	0.750000
(41.0, 53.0]	99	0.686869
(53.0, 65.0]	142	0.408451
(65.0, 77.0]	33	0.515152

Analysis

- Most of the patients have age (53–65)
- Most of the distribution of the CVD are between 40 to 65 age gap
- CVD is peak between age 55 and 60
- less heart disease occurring below age 30 and above age 70
- Occurence of CVD is highest in particular age groups, the data shows that a higher number of patients within the same age do not suffer any coronary artery disease.

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

In [138…

```
df1.groupby(['sex','target'])['target'].agg('count')
```

Out[138]:

```
sex     target
female  Heart Disease        72
        No Heart Disease     24
male    Heart Disease        92
        No Heart Disease    114
Name: target, dtype: int64
```

In [139…

```
df.groupby([pd.cut(df['sex'],2)])['target'].mean()
```

Out[139]:

```
sex
(-0.001, 0.5]    0.750000
(0.5, 1.0]       0.446602
Name: target, dtype: float64
```

In [140…

```
display(
    df1['sex'].value_counts(),
```

```
    df1['sex'].value_counts(normalize=True)*100
)
```

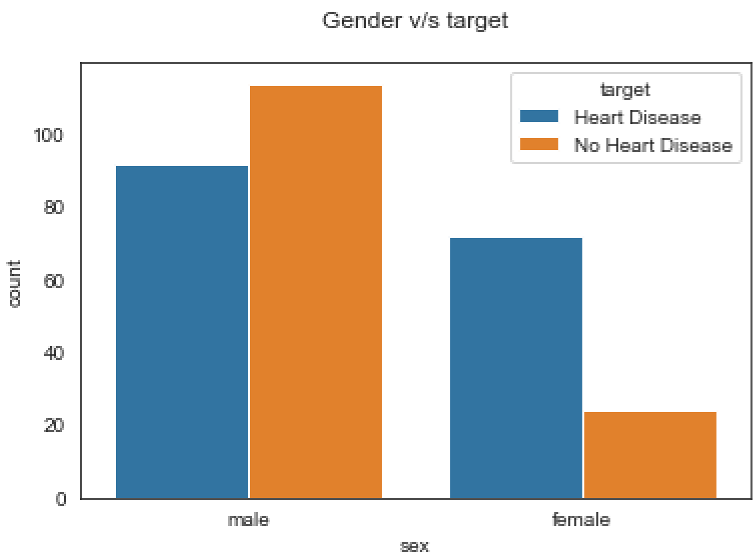
```
male      206
female     96
Name: sex, dtype: int64
male      68.211921
female    31.788079
Name: sex, dtype: float64
```

In [141…

```
sns.countplot(data= df1, x='sex',hue='target')
plt.title('Gender v/s target\n')
```

Out[141]:

```
Text(0.5, 1.0, 'Gender v/s target\n')
```



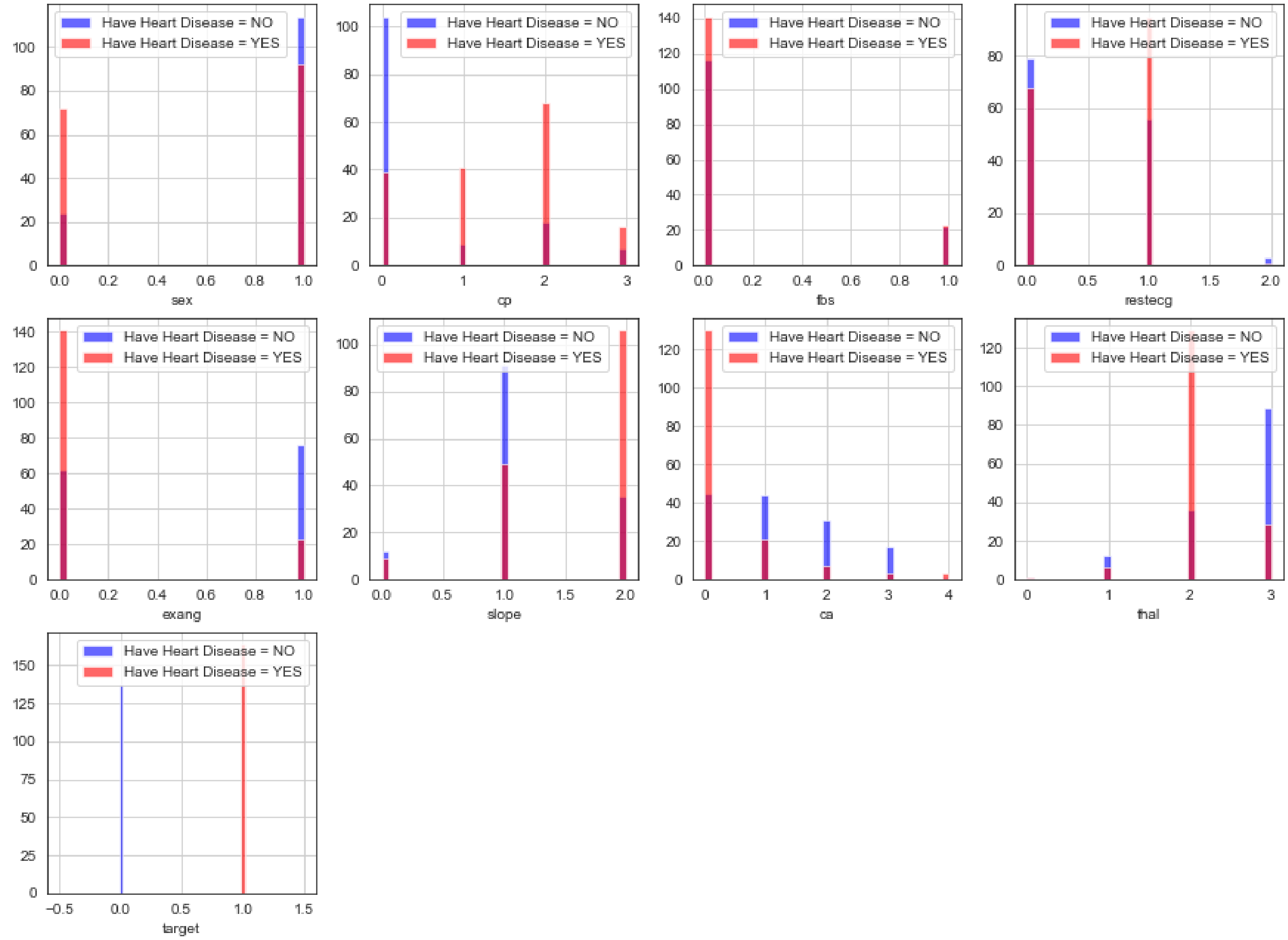
Analysis

- There are more no of male patients than female patients
- Heart attack rate is more in men than women.

End to End Analysis of Continious features

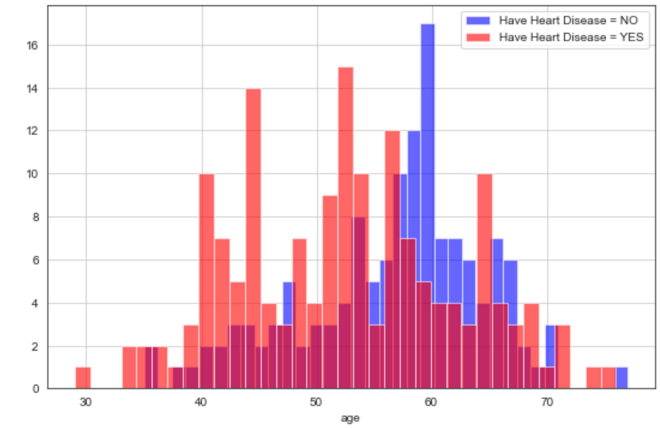
In [142…

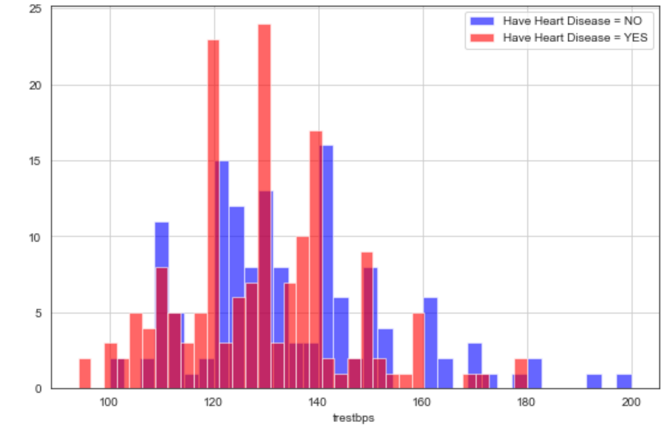
```
plt.figure(figsize=(15, 15))

for i, column in enumerate(Categorical_Columns, 1):
    plt.subplot(4, 4, i)
    df[df["target"] == 0][column].hist(bins=35, color='blue', label='Have Heart Disease
    df[df["target"] == 1][column].hist(bins=35, color='red', label='Have Heart Disease =
    plt.legend()
    plt.xlabel(column)
```

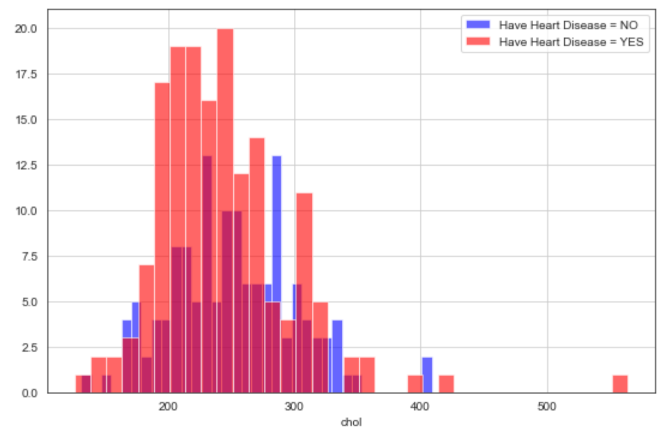


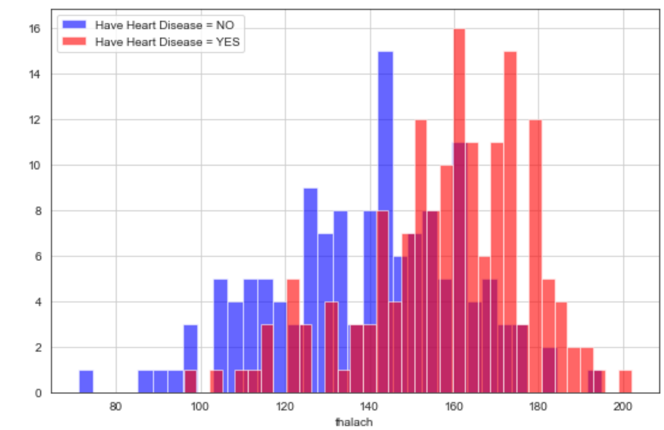
In [143…

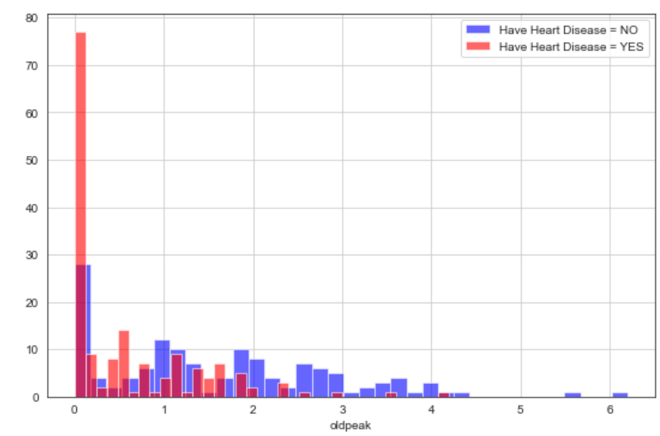
```
plt.figure(figsize=(20, 20))

for i, column in enumerate(Continious_Columns, 1):
    plt.subplot(3, 2, i)
    df[df["target"] == 0][column].hist(bins=35, color='blue', label='Have Heart Disease
    df[df["target"] == 1][column].hist(bins=35, color='red', label='Have Heart Disease =
    plt.legend()
    plt.xlabel(column)
```











In [144…

```
Continious_Columns
```

Out[144]:

```
['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
```

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

In [145…

```
df["trestbps"].describe()
```

Out[145]:

```
count    302.000000
mean     131.602649
std       17.563394
min       94.000000
25%      120.000000
50%      130.000000
75%      140.000000
max      200.000000
Name: trestbps, dtype: float64
```

In [146…

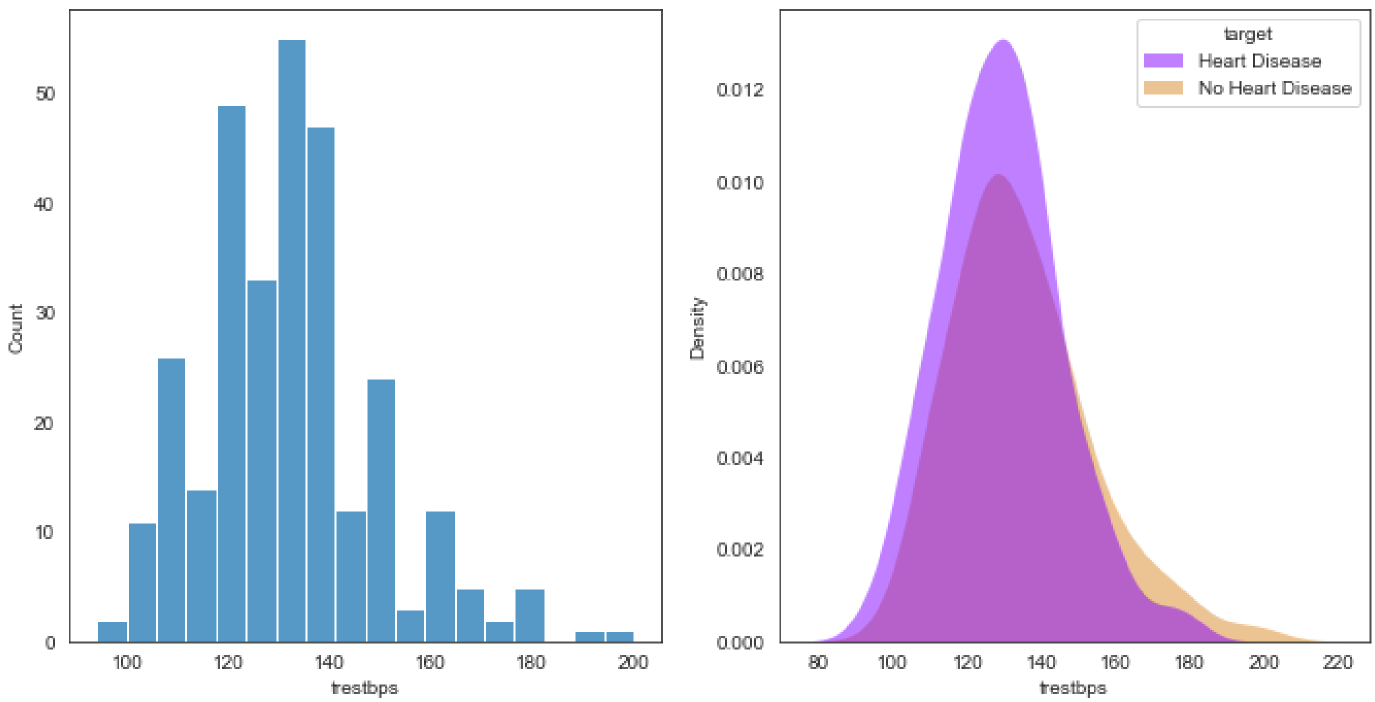
```
df.groupby([pd.cut(df['trestbps'],5)])['target'].mean()
```

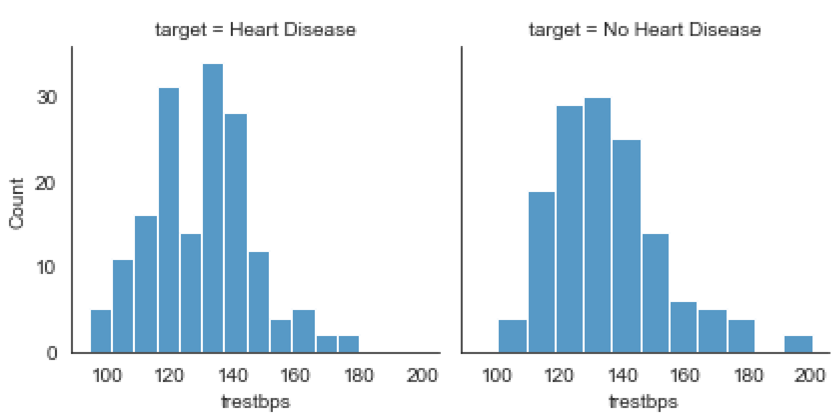
```
Out[146]: trestbps
(93.894, 115.2]     0.615385
(115.2, 136.4]      0.560284
(136.4, 157.6]      0.530120
(157.6, 178.8]      0.380952
(178.8, 200.0]      0.200000
Name: target, dtype: float64
```

In [147…

```
fig, axes = plt.subplots(1,2, figsize=(12, 6))

sns.histplot(df["trestbps"], ax=axes[0])
sns.kdeplot(ax=axes[1], data=df1, x =df.trestbps,hue="target", fill=True,palette=["#8000


g = sns.FacetGrid(data=df1, col='target', col_wrap=2)
#add histograms to each plot
g.map(sns.histplot, 'trestbps')
```

Out[147]: <seaborn.axisgrid.FacetGrid at 0x1c52da32a90>

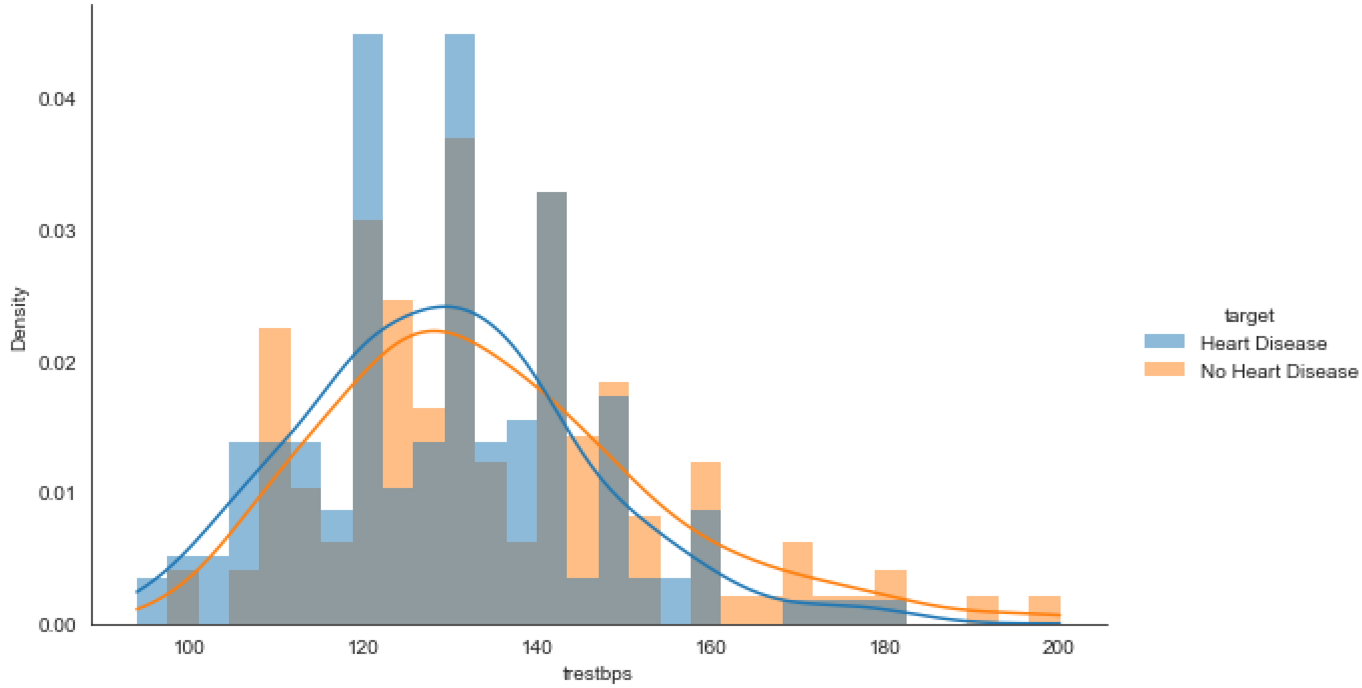




In [148…

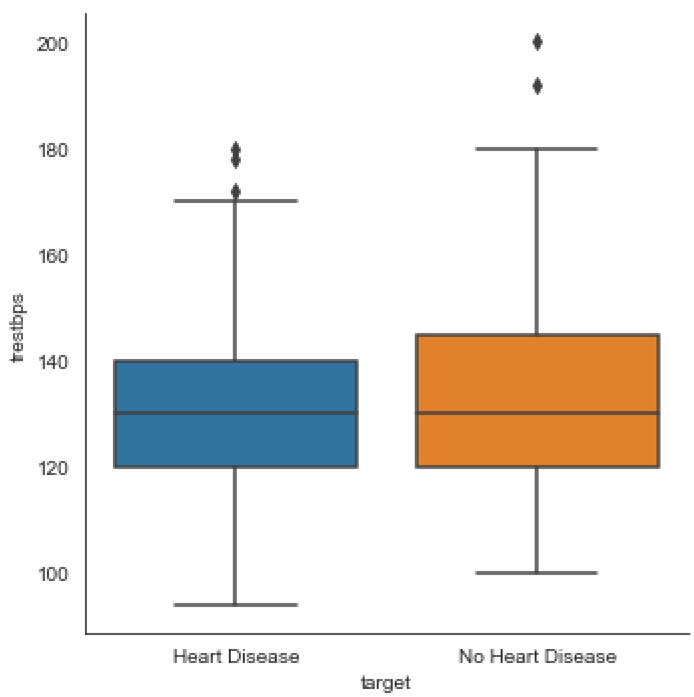
```
sns.displot(
    df1, x='trestbps', hue='target',
    bins=30, linewidth=0, kde=True,
    stat="density", common_norm=False,
    height=5, aspect=1.6
)
```

Out[148]: <seaborn.axisgrid.FacetGrid at 0x1c513d7b400>



In [149…

```
sns.catplot(x='target',y='trestbps',kind='box',data=df1)
plt.show()
```



Analysis

- There are some anomalies in the data after 170 to 190 trestbps and 190 to 205.
- it can be assumed, if the resting blood pressure value is more than 190 , there is less chance of cardiovascular disease.
- Still there are people with 170-180 trestbps range with CVD disease.
- Higher resting blood pressure is shown to have a high correlation with incidence of coronary artery disease.
- resting blood pressure anything above 120-140 is typically cause for concern.

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

In [150…
```
df["chol"].describe()
```

Out[150]:
```
count    302.000000
mean     246.500000
std       51.753489
min      126.000000
25%      211.000000
50%      240.500000
75%      274.750000
max      564.000000
Name: chol, dtype: float64
```

In [151…
```
df[['chol','target']].corr()
```

Out[151]:

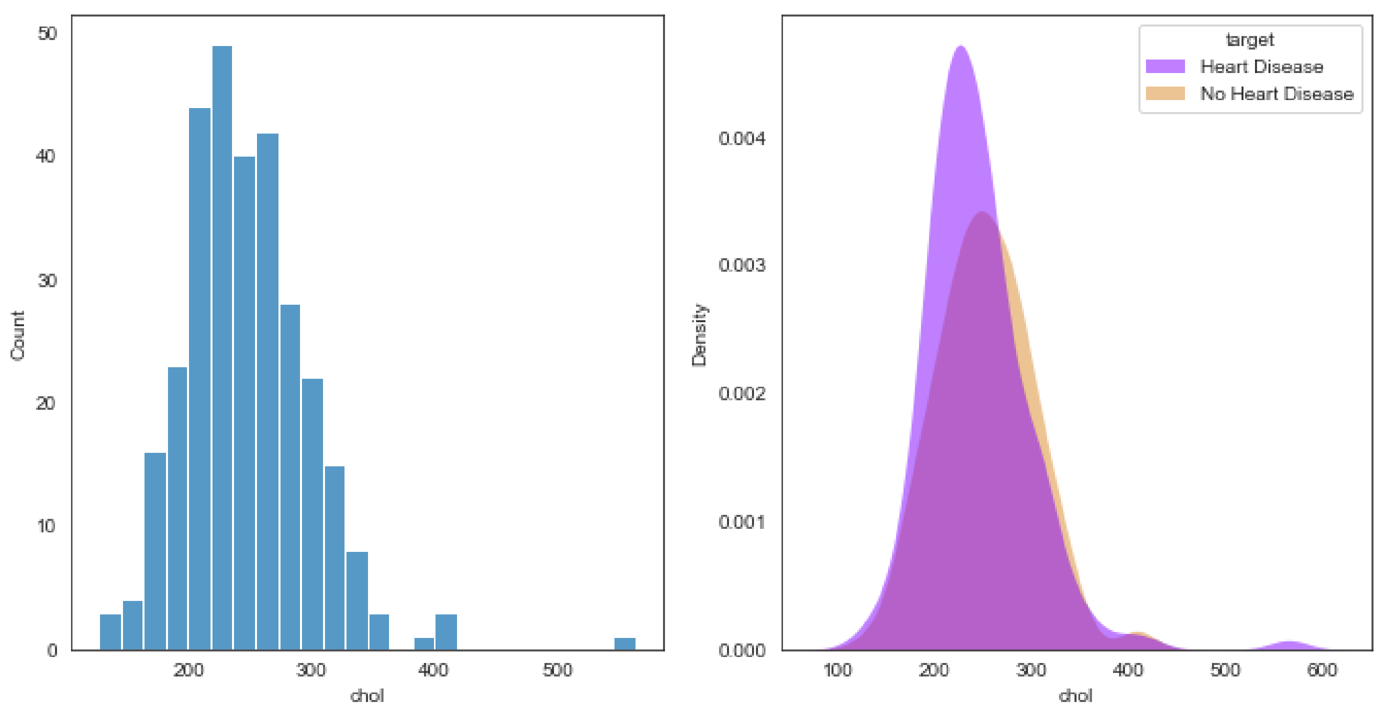
	chol	target
chol	1.000000	-0.081437
target	-0.081437	1.000000

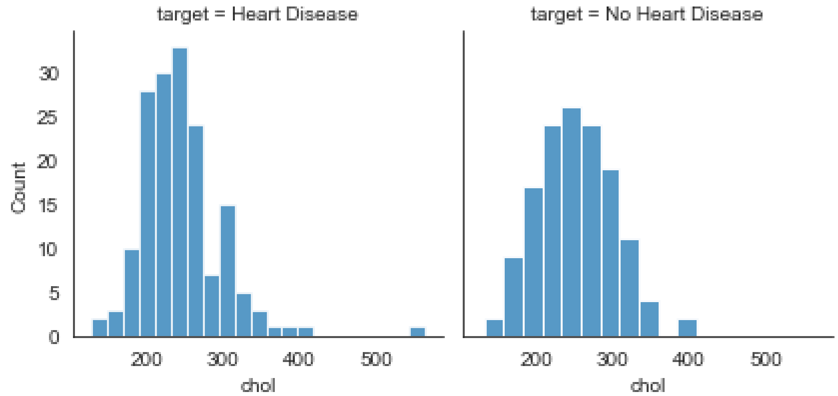
In [152…
```
df.groupby([pd.cut(df["chol"],5)])['target'].mean()
```

Out[152]:
```
chol
(125.562, 213.6]    0.607143
(213.6, 301.2]      0.514286
(301.2, 388.8]      0.526316
(388.8, 476.4]      0.500000
(476.4, 564.0]      1.000000
Name: target, dtype: float64
```

In [153…
```
fig, axes = plt.subplots(1,2, figsize=(12, 6))

sns.histplot(df["chol"], ax=axes[0])
sns.kdeplot(ax=axes[1], data=df1, x =df.chol,hue="target", fill=True,palette=["#8000ff",


g = sns.FacetGrid(data=df1, col='target', col_wrap=2)
#add histograms to each plot
g.map(sns.histplot, 'chol')
```

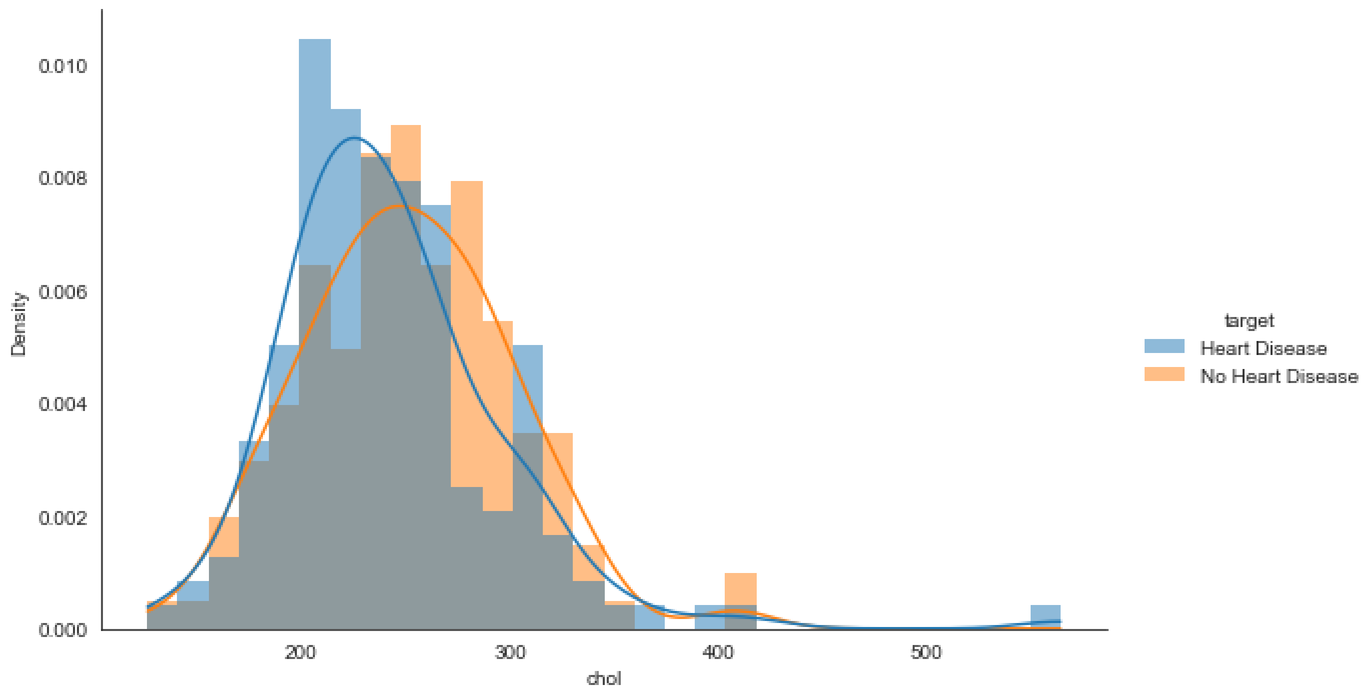
Out[153]:
```
<seaborn.axisgrid.FacetGrid at 0x1c5300d5730>
```





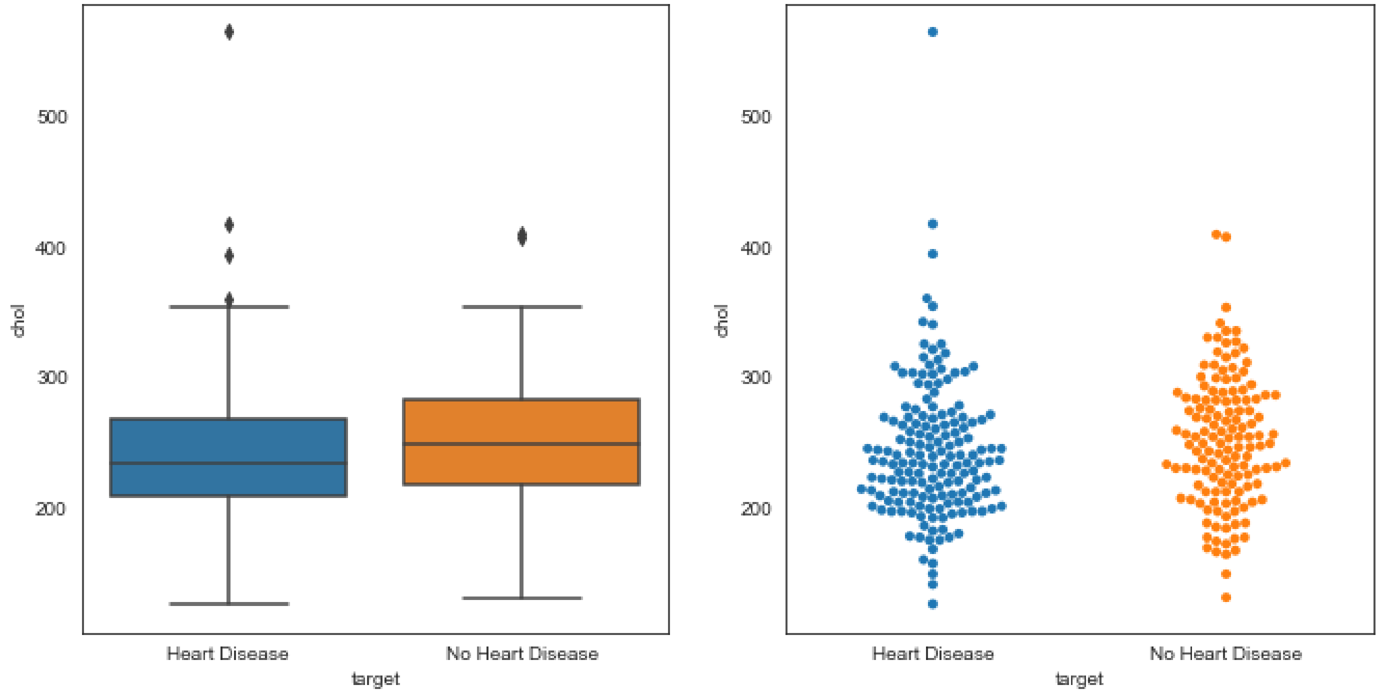
In [154…
```
sns.displot(
    df1, x='chol', hue='target',
    bins=30, linewidth=0, kde=True,
    stat="density", common_norm=False,
    height=5, aspect=1.6
)
```

Out[154]: <seaborn.axisgrid.FacetGrid at 0x1c531aec610>



In [155…
```
fig, axes = plt.subplots(1,2, figsize=(12, 6))

sns.boxplot(x='target',y='chol',ax=axes[0],data=df1)
sns.swarmplot(x='target',y='chol',ax=axes[1],data=df1)
```

Out[155]: <AxesSubplot:xlabel='target', ylabel='chol'>



Analysis

- Higher resting blood pressure is shown to have a high correlation with incidence of coronary artery disease.
- High serum cholesterol (200–300) is very strongly associated with incidence of coronary artery disease. Most of the patients' serum cholesterol level lies between the range (200–250).

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

In [156…

```
df[['oldpeak','target']].corr()
```

Out[156]:

	oldpeak	target
oldpeak	1.000000	-0.429146
target	-0.429146	1.000000

In [157…

```
df.groupby([pd.cut(df['oldpeak'],5)])['target'].mean()
```

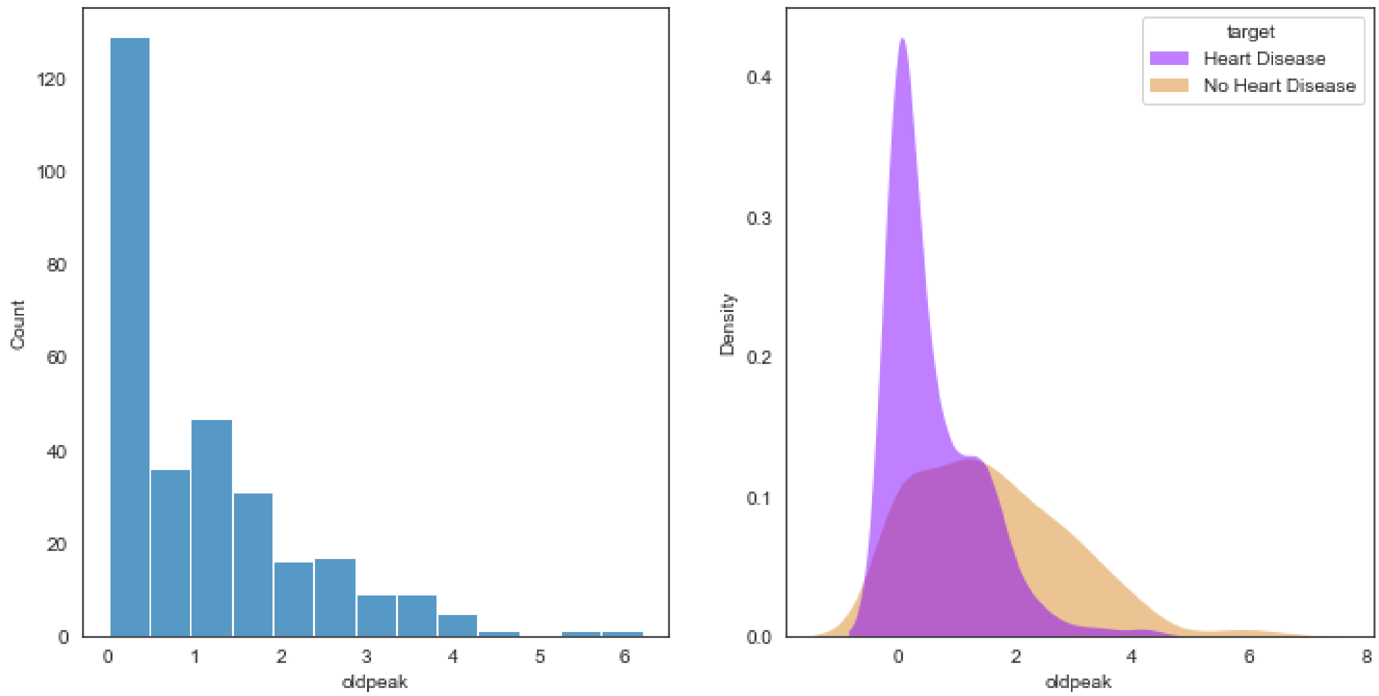
Out[157]:

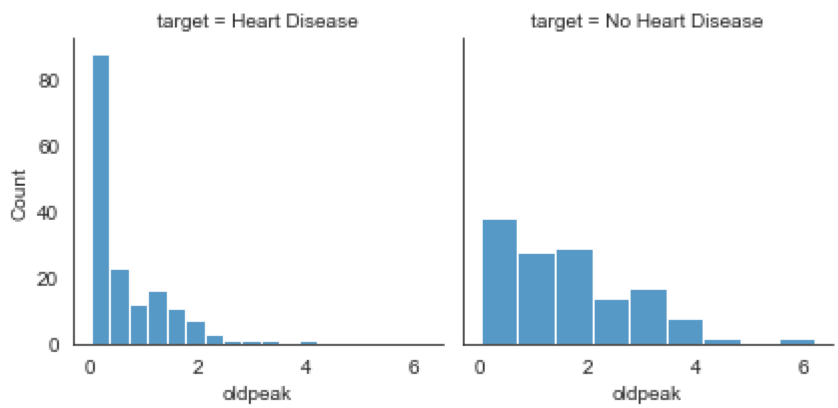
```
oldpeak
(-0.0062, 1.24]     0.666667
(1.24, 2.48]        0.437500
(2.48, 3.72]        0.096774
(3.72, 4.96]        0.142857
(4.96, 6.2]         0.000000
Name: target, dtype: float64
```

In [158…

```
fig, axes = plt.subplots(1,2, figsize=(12, 6))

sns.histplot(df["oldpeak"], ax=axes[0])
sns.kdeplot(ax=axes[1], data=df1, x =df.oldpeak,hue="target", fill=True,palette=["#8000f


g = sns.FacetGrid(data=df1, col='target', col_wrap=2)
#add histograms to each plot
g.map(sns.histplot, 'oldpeak')
```

Out[158]: <seaborn.axisgrid.FacetGrid at 0x1c533174c40>

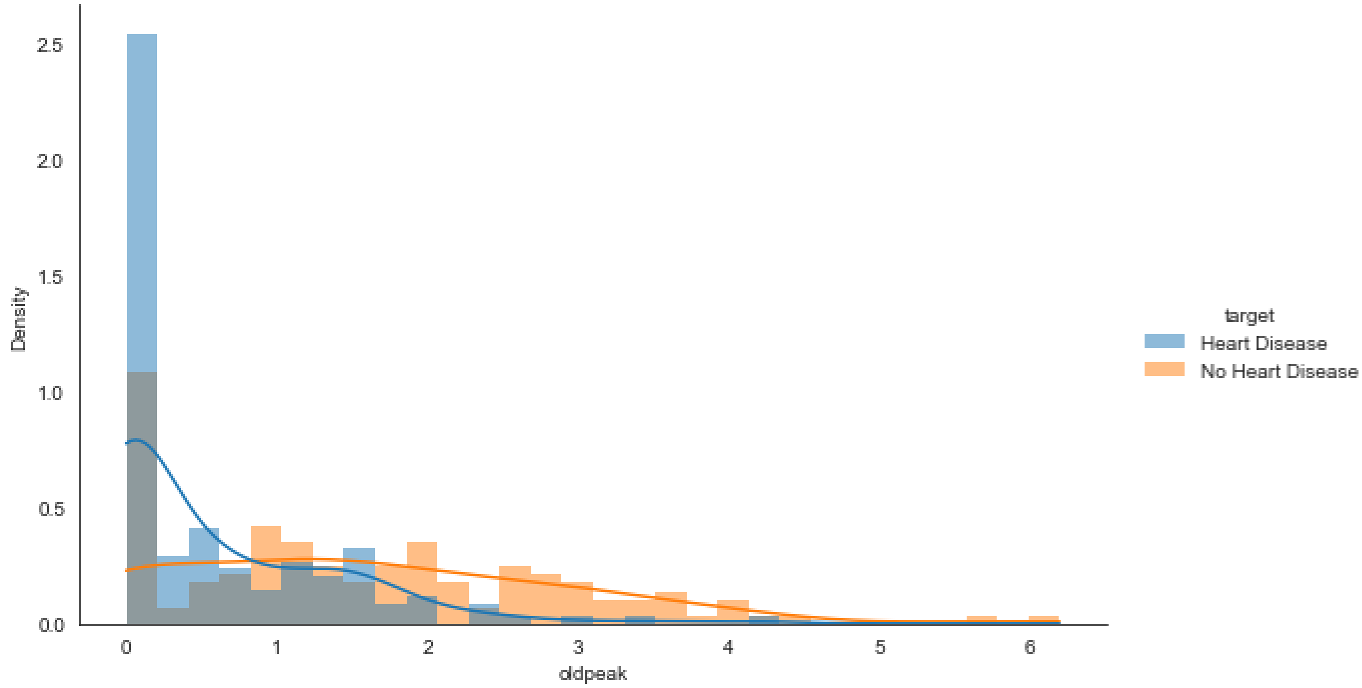




In [159…

```
sns.displot(
    df1, x='oldpeak', hue='target',
    bins=30, linewidth=0, kde=True,
    stat="density", common_norm=False,
    height=5, aspect=1.6
)
```

Out[159]: <seaborn.axisgrid.FacetGrid at 0x1c532d57df0>

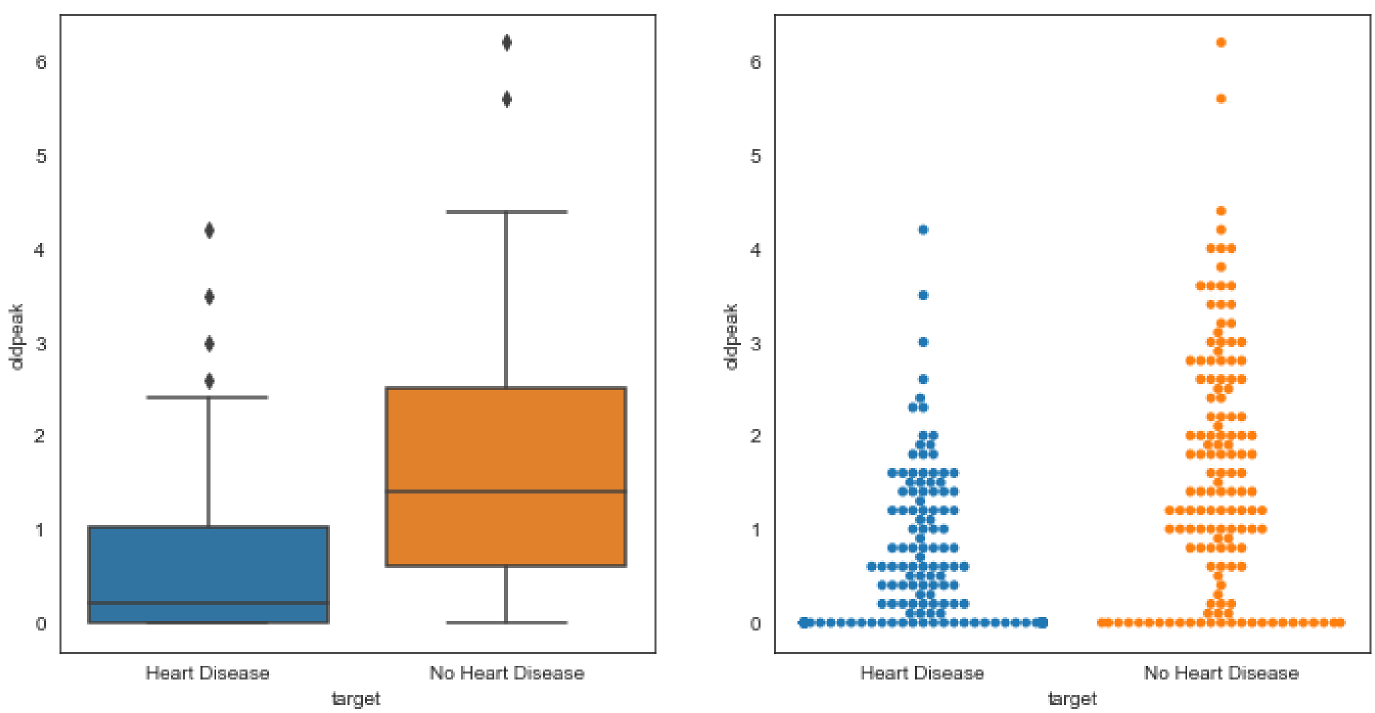


In [160…

```
fig, axes = plt.subplots(1,2, figsize=(12, 6))

sns.boxplot(x='target',y='oldpeak',ax=axes[0],data=df1)
sns.swarmplot(x='target',y='oldpeak',ax=axes[1],data=df1)
```

Out[160]:

```
<AxesSubplot:xlabel='target', ylabel='oldpeak'>
```

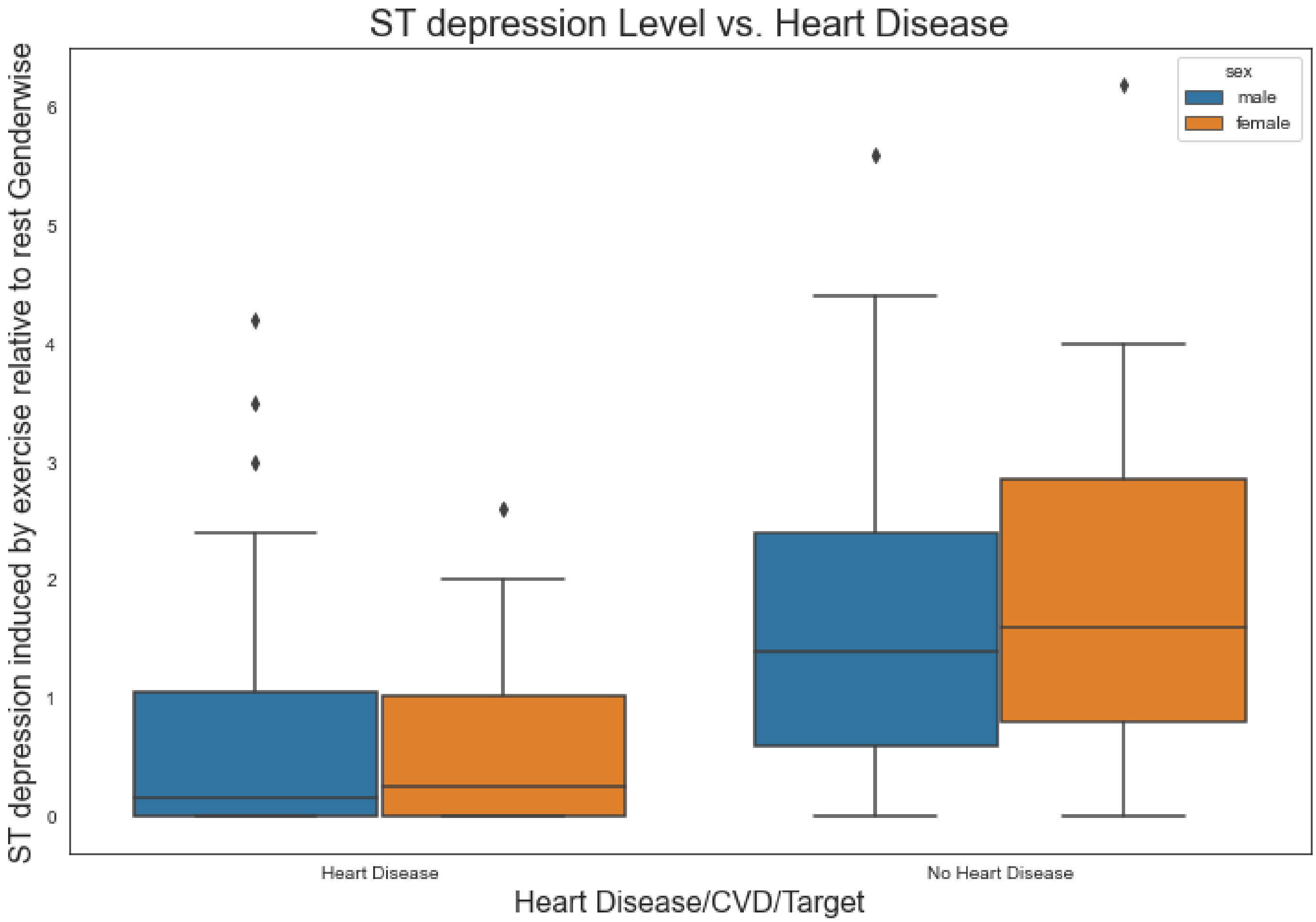


In [161…

```
plt.figure(figsize=(12,8))
sns.boxplot(x= 'target', y= 'oldpeak',hue="sex", data=df1 )
plt.title("ST depression Level vs. Heart Disease", fontsize=20)
plt.xlabel("Heart Disease/CVD/Target",fontsize=16)
plt.ylabel("ST depression induced by exercise relative to rest Genderwise", fontsize=16)
```

Out[161]:

```
Text(0, 0.5, 'ST depression induced by exercise relative to rest Genderwise')
```

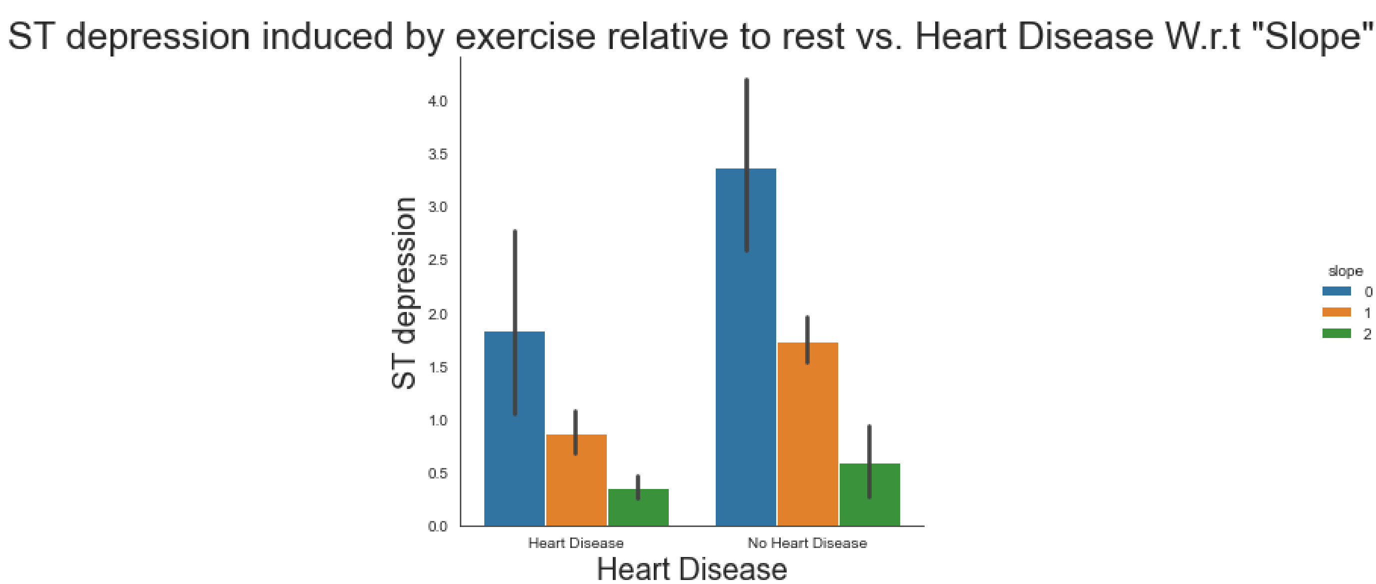


In [162…

```
sns.catplot(x="target", y="oldpeak", hue="slope", kind="bar", data=df1);

plt.title('ST depression induced by exercise relative to rest vs. Heart Disease W.r.t "S
plt.xlabel('Heart Disease',size=20)
plt.ylabel('ST depression',size=20)
```

Out[162]:

```
Text(24.980000000000001, 0.5, 'ST depression')
```



Analysis

- There is a high negative corelation existing between old peak and target columns. Resting ST-segment depression is a risk marker of adverse cardiac prognosis. ST segment depression occurs because when the ventricle is at rest and therefore repolarized. If the trace in the ST segment is abnormally low below the baseline, this can lead to this Heart Disease.

- The “slope” hue, refers to the peak exercise ST segment, with values: 0: upsloping , 1: flat , 2: downsloping). Both positive & negative heart disease patients exhibit equal distributions of the 3 slope categories.
- There are some outliers in data
- Negetaive CVD patients exhibit a heightened median for ST depression level, while Positive patients have lower levels. In addition, we don’t see many differences between male & female target outcomes, expect for the fact that female have slightly larger ranges of ST Depression.
- Oldpeak ST depression induced by exercise relative to rest looks at stress of heart during excercise unhealthy heart will stress more

h. Check if thalassemia is a major cause of CVD

In [163…
```
df[['target','thal']].corr()
```

Out[163]:

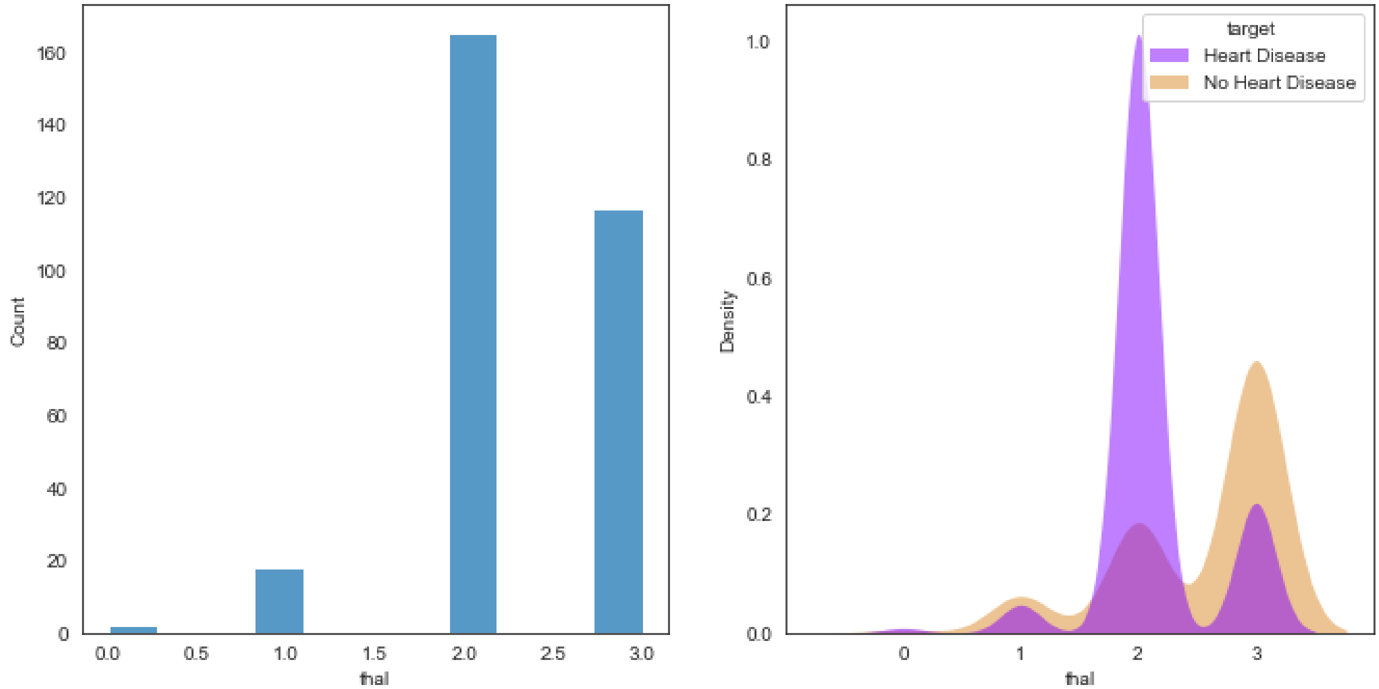
	target	thal
target	1.000000	-0.343101
thal	-0.343101	1.000000

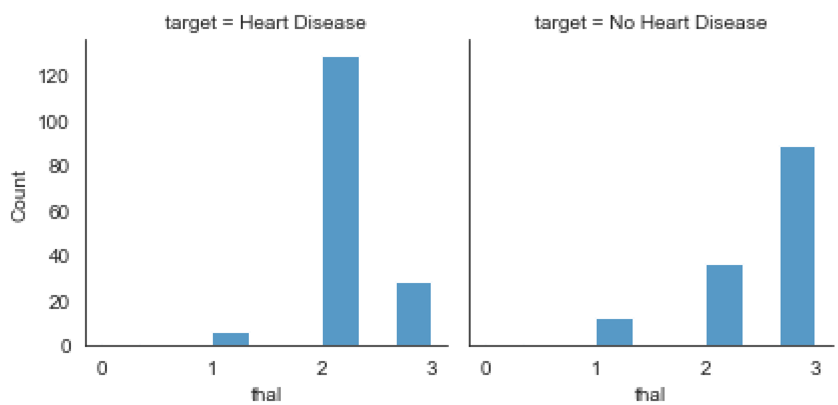
In [164…
```
df.groupby([pd.cut(df['thal'],5)])['target'].mean()
```

Out[164]:
```
thal
(-0.003, 0.6]    0.500000
(0.6, 1.2]       0.333333
(1.2, 1.8]            NaN
(1.8, 2.4]       0.781818
(2.4, 3.0]       0.239316
Name: target, dtype: float64
```

In [165…
```
fig, axes = plt.subplots(1,2, figsize=(12, 6))

sns.histplot(df["thal"], ax=axes[0])
sns.kdeplot(ax=axes[1], data=df1, x =df.thal,hue="target", fill=True,palette=["#8000ff",


g = sns.FacetGrid(data=df1, col='target', col_wrap=2)
#add histograms to each plot
g.map(sns.histplot, 'thal')
```

Out[165]: <seaborn.axisgrid.FacetGrid at 0x1c535647700>



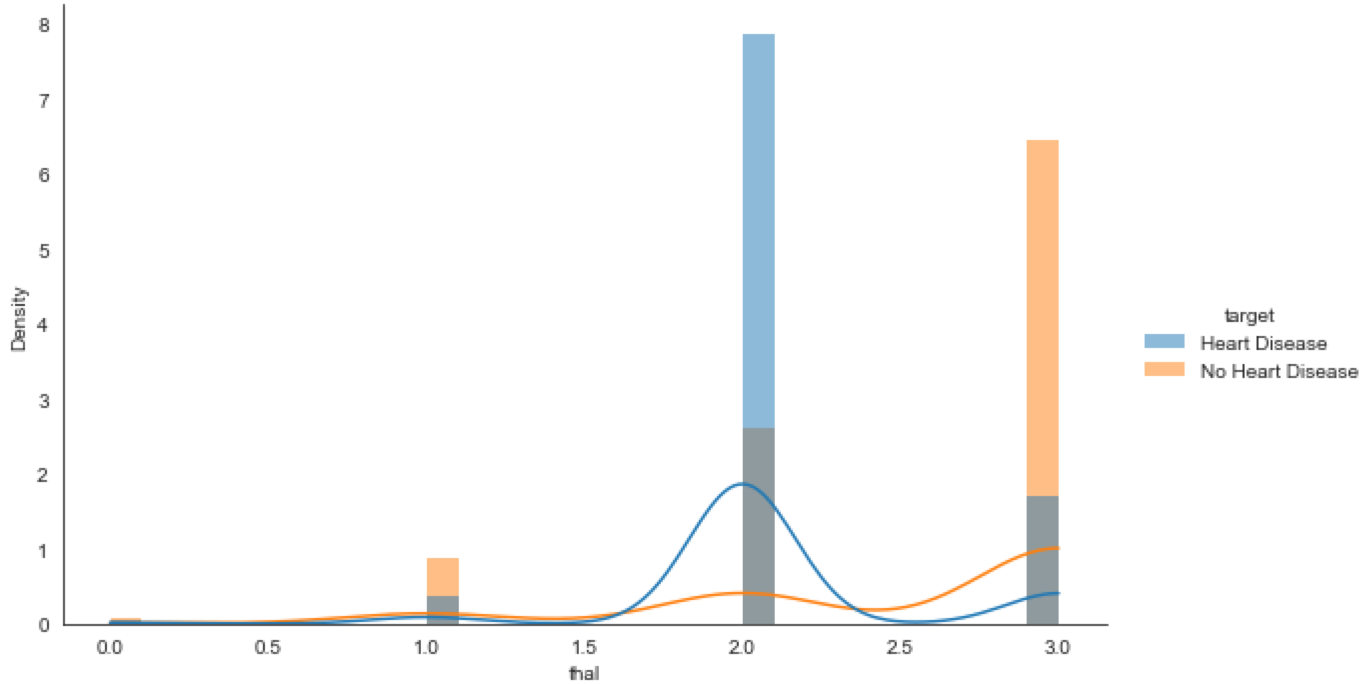


In [166…

```
sns.displot(
    df1, x='thal', hue='target',
    bins=30, linewidth=0, kde=True,
    stat="density", common_norm=False,
    height=5, aspect=1.6
)
```

Out[166]:

```
<seaborn.axisgrid.FacetGrid at 0x1c52dc708b0>
```

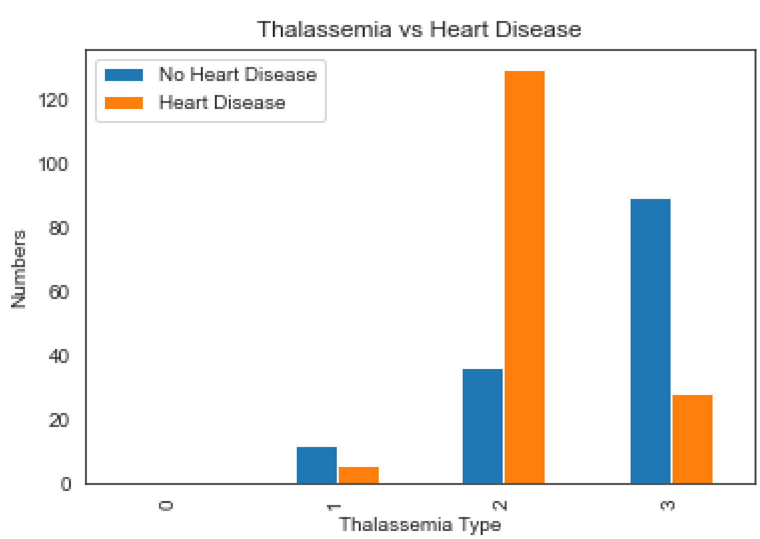


In [167…
```
a = pd.crosstab(df['thal'],df['target'])
a
```

Out[167]:

target	0	1
thal		
0	1	1
1	12	6
2	36	129
3	89	28

In [168…
```
a.plot(kind ='bar')
plt.title('Thalassemia vs Heart Disease')
plt.xlabel('Thalassemia Type')
plt.ylabel('Numbers')
plt.legend(['No Heart Disease', 'Heart Disease'])
plt.show()
```



Analysis

- There is a high negative corelation existing between thal(Thalassemia) and the occurrence of a heart attack
- People with Thalassemia Type = 2 is having more chances of Heart Disease

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

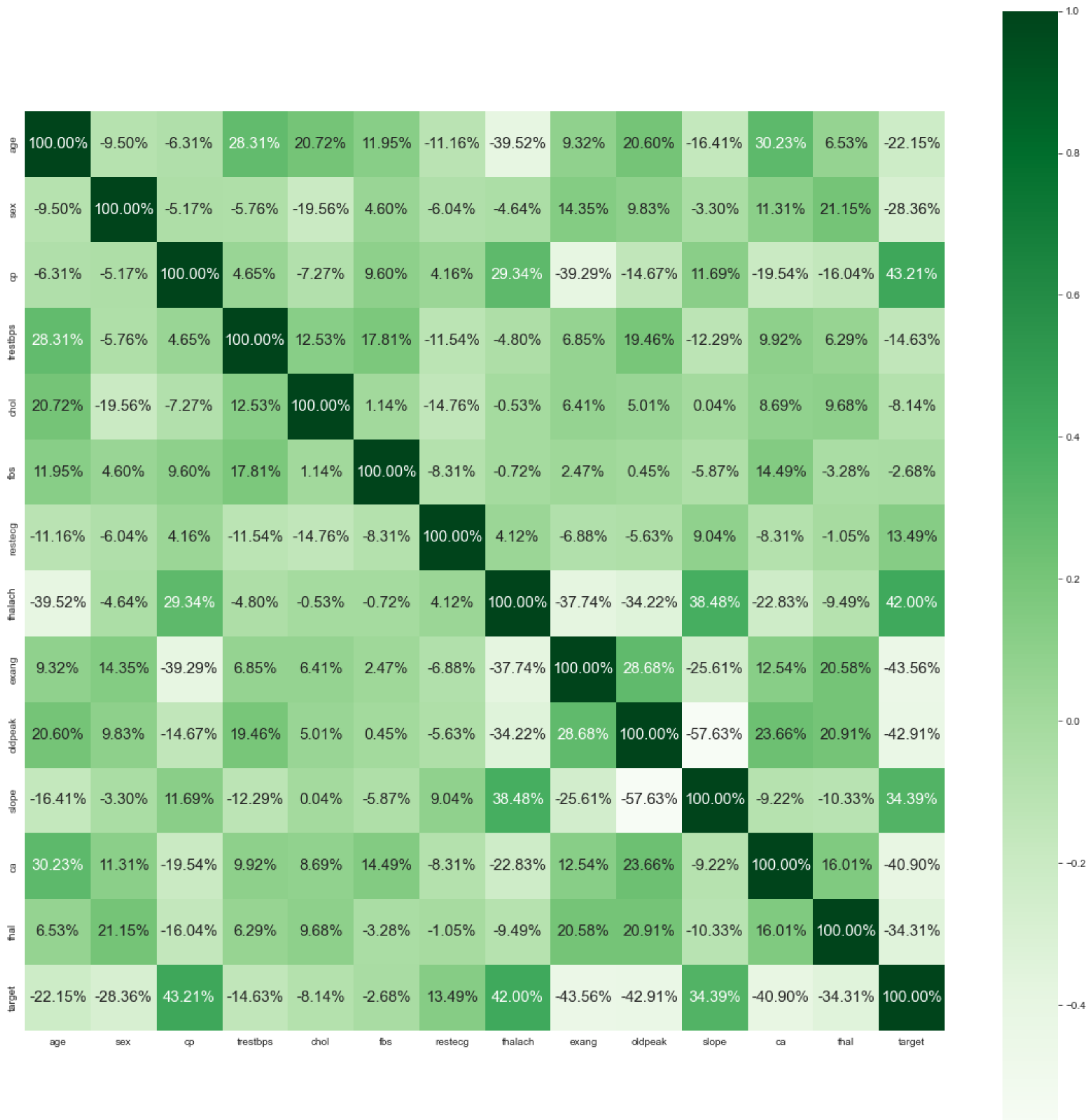
Using Pearson Coff

In [169…

```
corr = df.corr()
plt.figure(figsize=(20,20))
sns.heatmap(corr, cbar=True, square= True, fmt = '.2%' , annot=True, annot_kws={'size':1
```

Out[169]:

```
<AxesSubplot:>
```



In [170…

```
#print the column names which have threshold ≥ 0.3 or ≤ -0.3 with 'target':
```

```
var= corr['target'][((corr['target'] >=0.3) | (corr['target'] <= -0.3)) & (corr['target'
var
```

Out[170]:

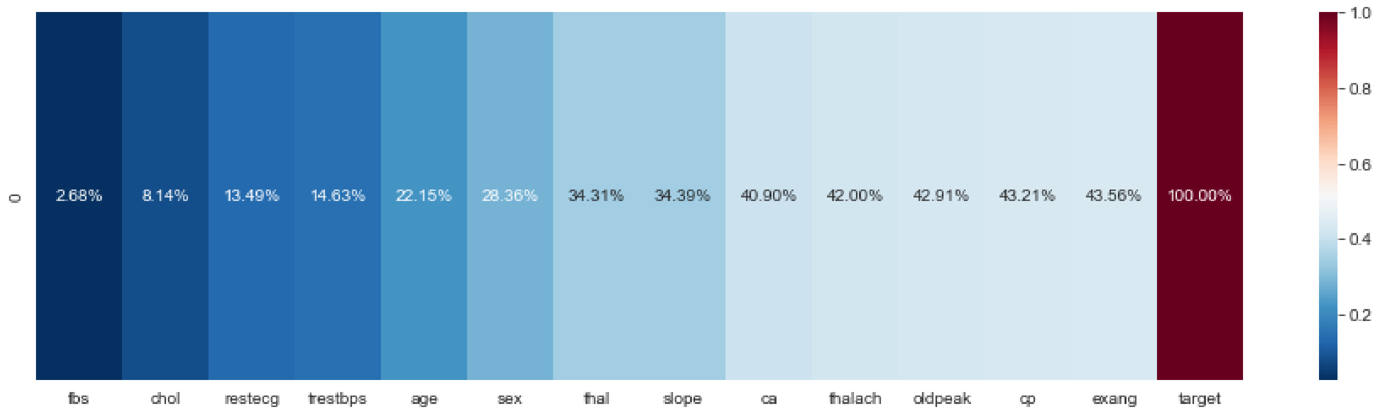
```
['cp', 'thalach', 'exang', 'oldpeak', 'slope', 'ca', 'thal']
```

In [171…

```
# Visualizing correlation of features with prediction column `target`

corr_with_target = df.corrwith(df['target'])

plt.figure(figsize = (16, 4))
sns.heatmap([np.abs(corr_with_target).sort_values()], cmap = 'RdBu_r', annot = True, fmt
```

Out[171]:

```
<AxesSubplot:>
```



In [172…

```
# Feature Importances by Correlation Matrix

corr_with_target[:-1].abs().sort_values(ascending = False)
```

Out[172]:

```
exang       0.435601
cp          0.432080
oldpeak     0.429146
thalach     0.419955
ca          0.408992
slope       0.343940
thal        0.343101
sex         0.283609
age         0.221476
trestbps    0.146269
restecg     0.134874
chol        0.081437
fbs         0.026826
dtype: float64
```

Using ExtraTreesClassifier

In [173…

```
from sklearn.ensemble import ExtraTreesClassifier


# To know the feature Importances using ExtraTreesClassifier
y = df['target'].values
extra_tree_forest = ExtraTreesClassifier(n_estimators=5, criterion = 'entropy', random_s
extra_tree_forest.fit(df.iloc[:, :-1].values, df['target'])

print("Percentage Importance of each features with respect to Target : ")
important_features = pd.Series(extra_tree_forest.feature_importances_*100, index = df.co
important_features.sort_values(ascending = False)
```

Out[173]:

```
Percentage Importance of each features with respect to Target :
oldpeak     12.860611
ca          11.499608
exang       10.730463
```

```
age           9.986715
thalach       9.241941
thal          8.288959
cp            8.250057
chol          6.591516
slope         5.886851
trestbps      5.831797
sex           4.710882
restecg       4.163261
fbs           1.957339
dtype: float64
```

Analysis

The above two methods 1.Pearson Coff and 2. ExtraTreesClassifier :

- 'fbs' (fasting blood sugar) have very less inverse correlation with Target variable and 'fbs' seems least important feature.
- Cholestrol levels and target variable have a small inverse correlation.

The features cp, thalach, exang, oldpeak and ca have strong correlation with the target value.

- exang (Exercise induced angina) and oldpeak (ST depression induced by exercise relative to rest) have strong inverse corelation wit target. This makes sense because when you excercise, your heart requires more blood, but narrowed arteries slow down blood flow.

- cp (Chest pain type) is positively co-related to target (predictor) , chest pain is major symptoms of heart attack. the greater amount of chest pain results in a greater chance of having heart disease

- thalach (Maximum heart rate achieved) is also a major sympton of heart attack

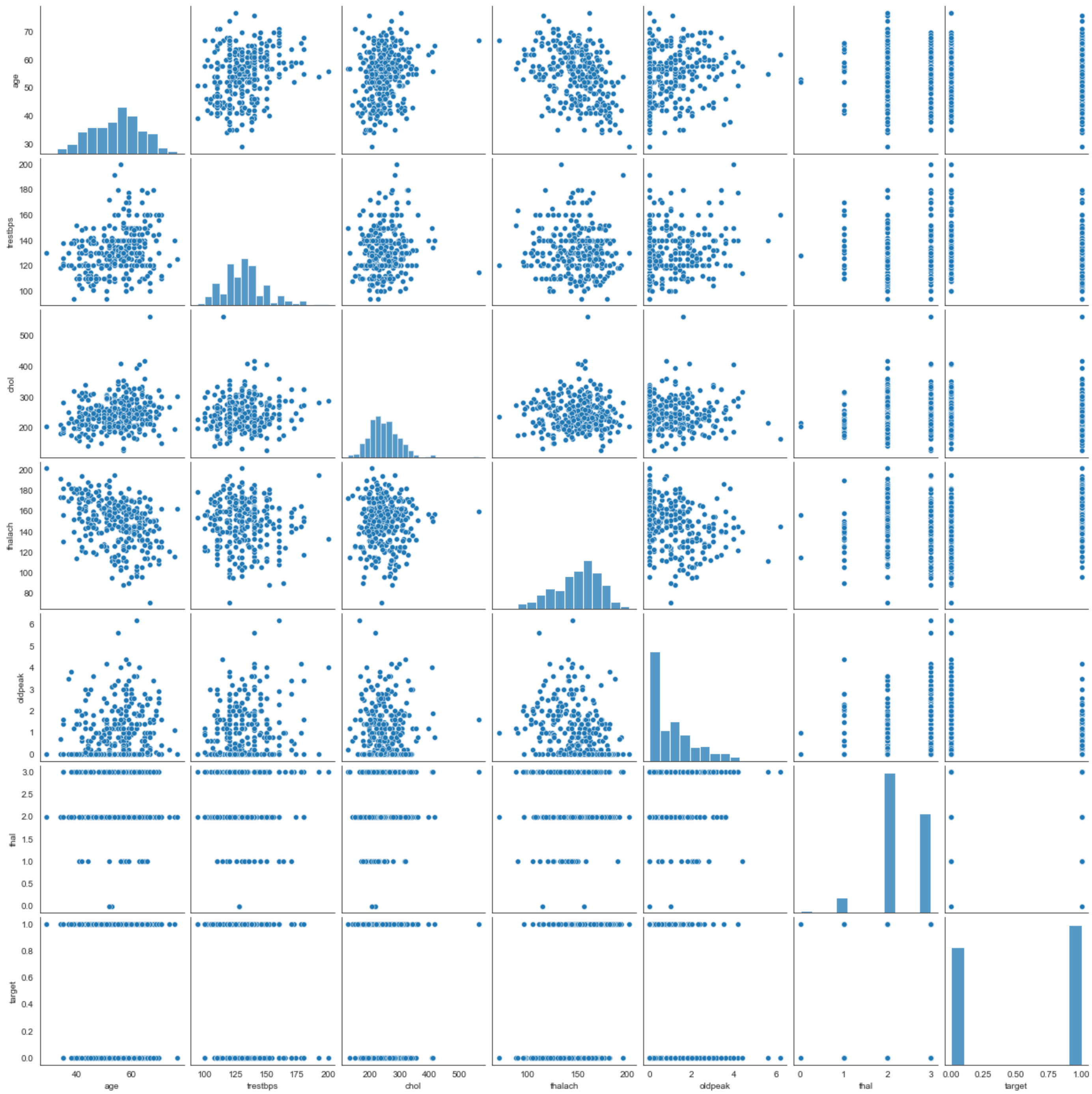
- thalassemia is highly correlated with Heart diseases.

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

It make sence to use plot only for continuous columns from data, because with so many features, it can be difficult to see each one. So only continuous features are used for pairplot

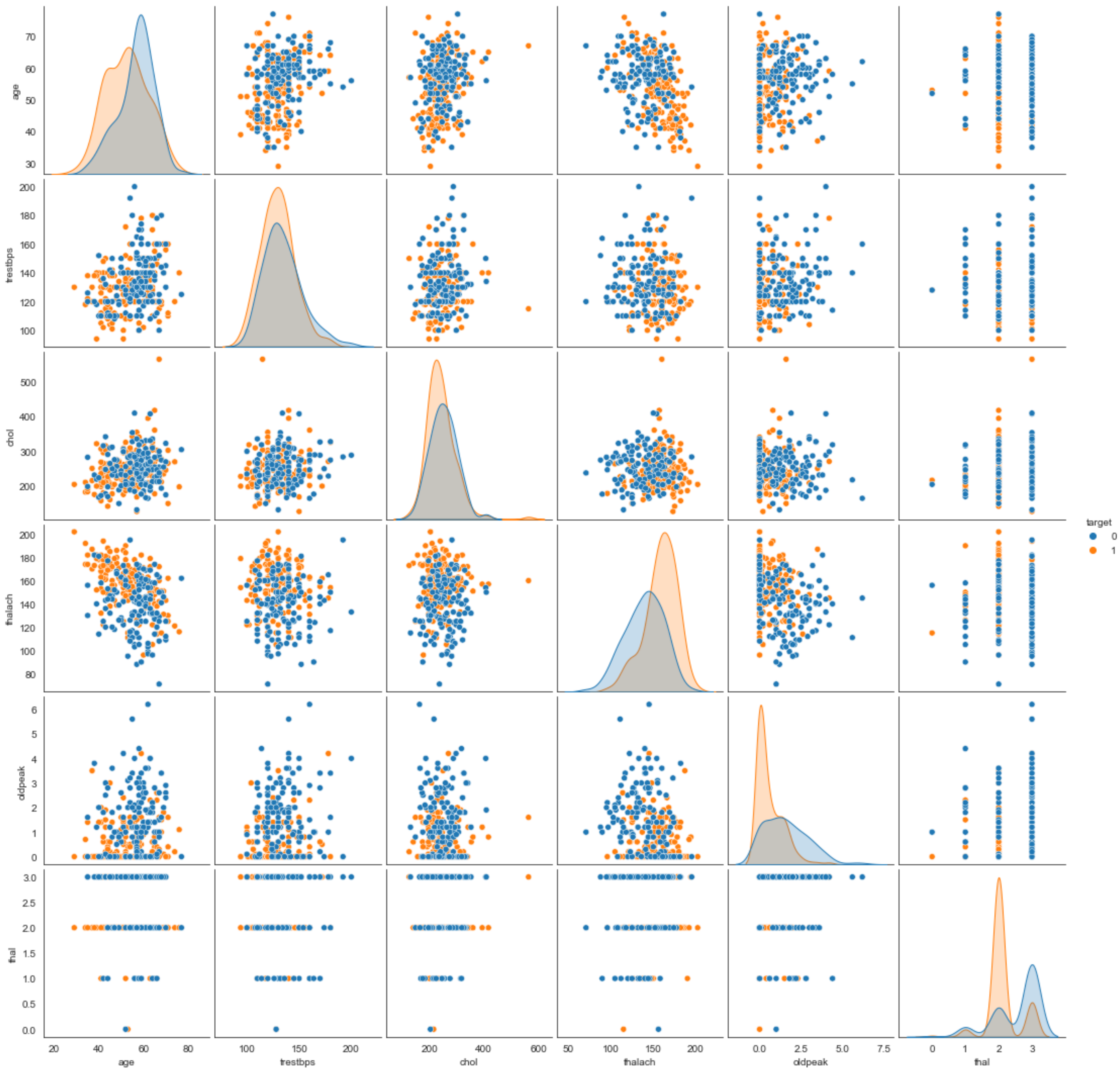
In [174…
```
# Pairplotfor continious features and Target

sns.pairplot(df[['age', 'trestbps', 'chol', 'thalach', 'oldpeak','thal','target']])
```

Out[174]:
```
<seaborn.axisgrid.PairGrid at 0x1c532df1c70>
```




```
In [175…  sns.pairplot(df[['age', 'trestbps', 'chol', 'thalach', 'oldpeak','thal','target']],hue='
```

```
Out[175]: <seaborn.axisgrid.PairGrid at 0x1c5330696d0>
```



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

Prepare Data for Moeling

Assign

In [176…
```
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
```

Split

In [177…
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.2, random_state =
```

In [178…
```
print("X_train : {} \n X_test : {} \n y_train : {} \n y_test : {}".format(X_train.shape,
```

```
X_train : (241, 13)
 X_test : (61, 13)
 y_train : (241,)
 y_test : (61,)
```

Normaliz

In [179…
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Data Modelling

Implement 2 models on dataset:

- Logistic Regression
- Random forest

We will also use State models of Logistic Regression for feature selection

We will be using three search algorithms for each :

- GridSearchCV
- RandomSearchCV

Base Model

1. Logistic Regression

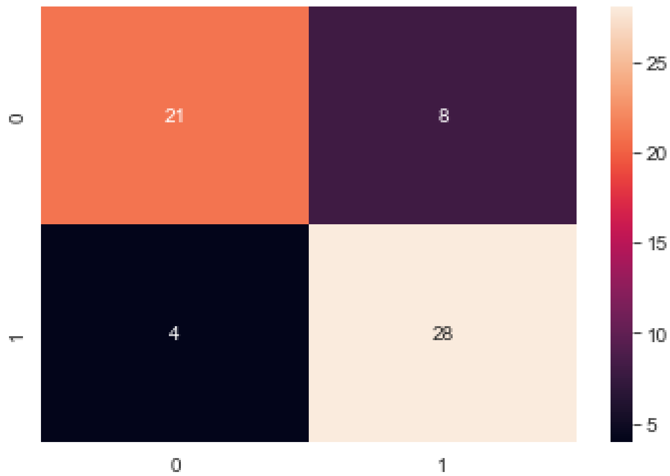
In [180…
```
model1 = 'Logistic Regression'
lr = LogisticRegression()
model_lr = lr.fit(X_train, y_train)
lr_y_predict = lr.predict(X_test)
lr_conf_matrix = confusion_matrix(y_test, lr_y_predict)
lr_acc_score = accuracy_score(y_test, lr_y_predict)

print("Accuracy of Logistic Regression:",lr_acc_score*100,'\n')
print(classification_report(y_test,lr_y_predict))
print("\n")
print("confussion matrix")
print(lr_conf_matrix)
sns.heatmap(lr_conf_matrix,annot=True)
```

```
Accuracy of Logistic Regression: 80.32786885245902

              precision    recall  f1-score   support

           0       0.84      0.72      0.78        29
           1       0.78      0.88      0.82        32

    accuracy                           0.80        61
   macro avg       0.81      0.80      0.80        61
```

```
weighted avg       0.81      0.80      0.80        61



confussion matrix
[[21  8]
 [ 4 28]]
```

Out[180]:

```
<AxesSubplot:>
```



In [181…

```python
actual = []
predcition = []

for i,j in zip(y_test,lr_y_predict):
  actual.append(i)
  predcition.append(j)

dic = {'Actual':actual,
       'Prediction':predcition
       }
```

In [182…

```python
result  = pd.DataFrame(dic)
result
```

Out[182]:

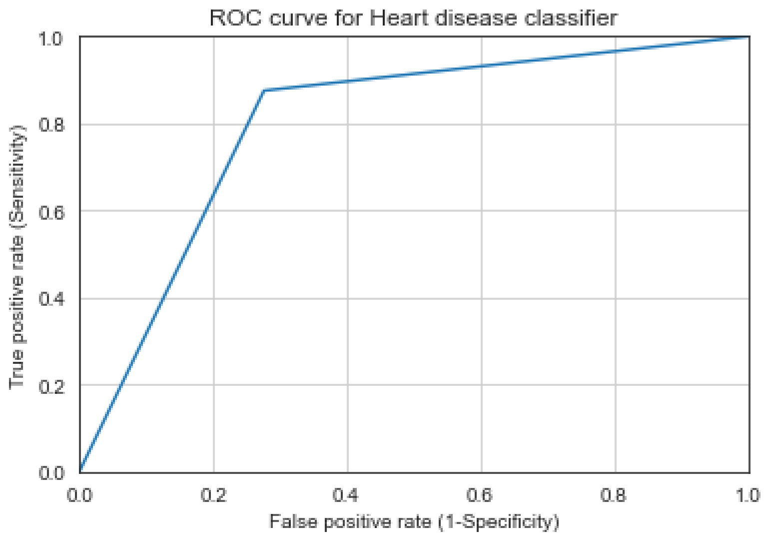
	Actual	Prediction
0	0	0
1	1	1
2	1	0
3	0	0
4	1	1
...	...	...
56	0	1
57	1	1
58	0	0
59	0	0
60	0	0

61 rows × 2 columns

ROC Curve

In [183…

```
fpr, tpr, thresholds = roc_curve(y_test, lr_y_predict)
plt.plot(fpr,tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.title('ROC curve for Heart disease classifier')
plt.xlabel('False positive rate (1-Specificity)')
plt.ylabel('True positive rate (Sensitivity)')
plt.grid(True)
```



In [184…

```
roc_auc_score(y_test,lr_y_predict)
```

Out[184]:

```
0.7995689655172414
```

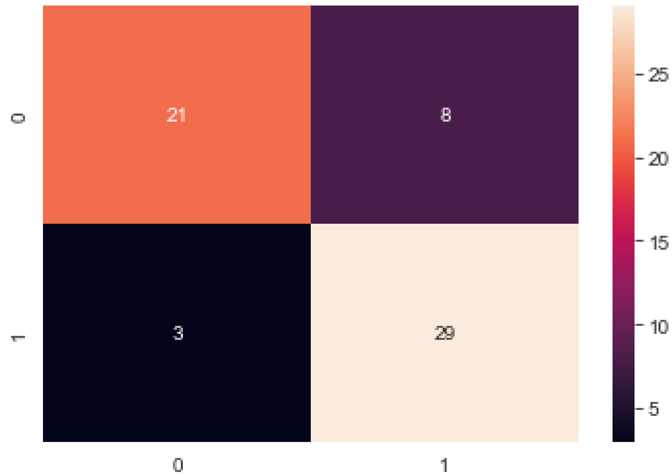
2. Random Forest Classfier

In [185…

```
model2 = 'Random Forest Classfier'
rf = RandomForestClassifier(n_estimators=20, random_state=12,max_depth=5)
model_rf = rf.fit(X_train,y_train)
rf_y_predicted = rf.predict(X_test)
rf_conf_matrix = confusion_matrix(y_test, rf_y_predicted)
rf_acc_score = accuracy_score(y_test, rf_y_predicted)

print("Accuracy of Random Forest Classfier:",rf_acc_score*100,'\n')
print(classification_report(y_test,rf_y_predicted))
print("\n")
print("confussion matrix")
print(rf_conf_matrix)
sns.heatmap(rf_conf_matrix,annot=True)
```

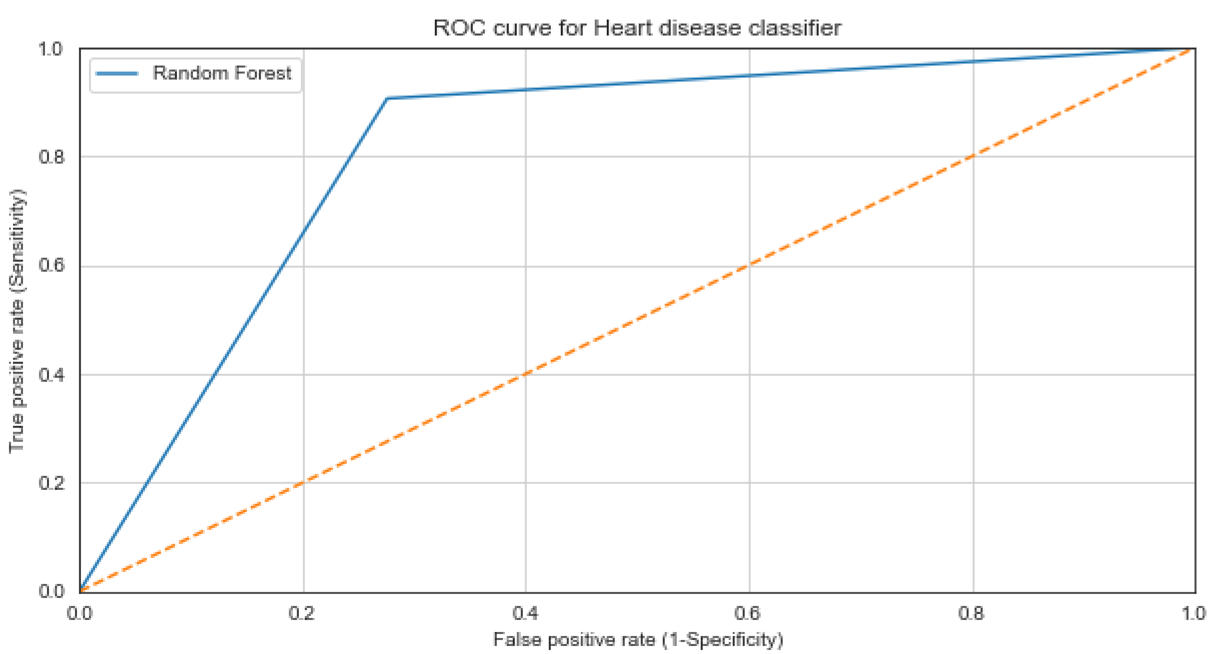
```
Accuracy of Random Forest Classfier: 81.9672131147541 

              precision    recall  f1-score   support

           0       0.88      0.72      0.79        29
           1       0.78      0.91      0.84        32

    accuracy                           0.82        61
   macro avg       0.83      0.82      0.82        61
weighted avg       0.83      0.82      0.82        61



confussion matrix
[[21  8]
 [ 3 29]]
```

Out[185]: <AxesSubplot:>



In [186…

```
plt.figure(figsize=(10,5))
plt.title('ROC curve for Heart disease classifier')
sns.set_style('whitegrid')
rf_false_positive_rate,rf_true_positive_rate,rf_threshold = roc_curve(y_test, rf_y_predi
plt.plot(rf_false_positive_rate,rf_true_positive_rate,label='Random Forest')

plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.title('ROC curve for Heart disease classifier')
plt.xlabel('False positive rate (1-Specificity)')
plt.ylabel('True positive rate (Sensitivity)')
plt.plot([0,1],ls='--')
plt.plot([0,0],[1,0],c='.5')
plt.plot([1,1],c='.5')
plt.grid(True)
plt.legend()
plt.show()
```



Model Evaluation

In [187…

```
model_ev = pd.DataFrame({'Model': ['Logistic Regression','Random Forest'], 'Accuracy': [
model_ev
```

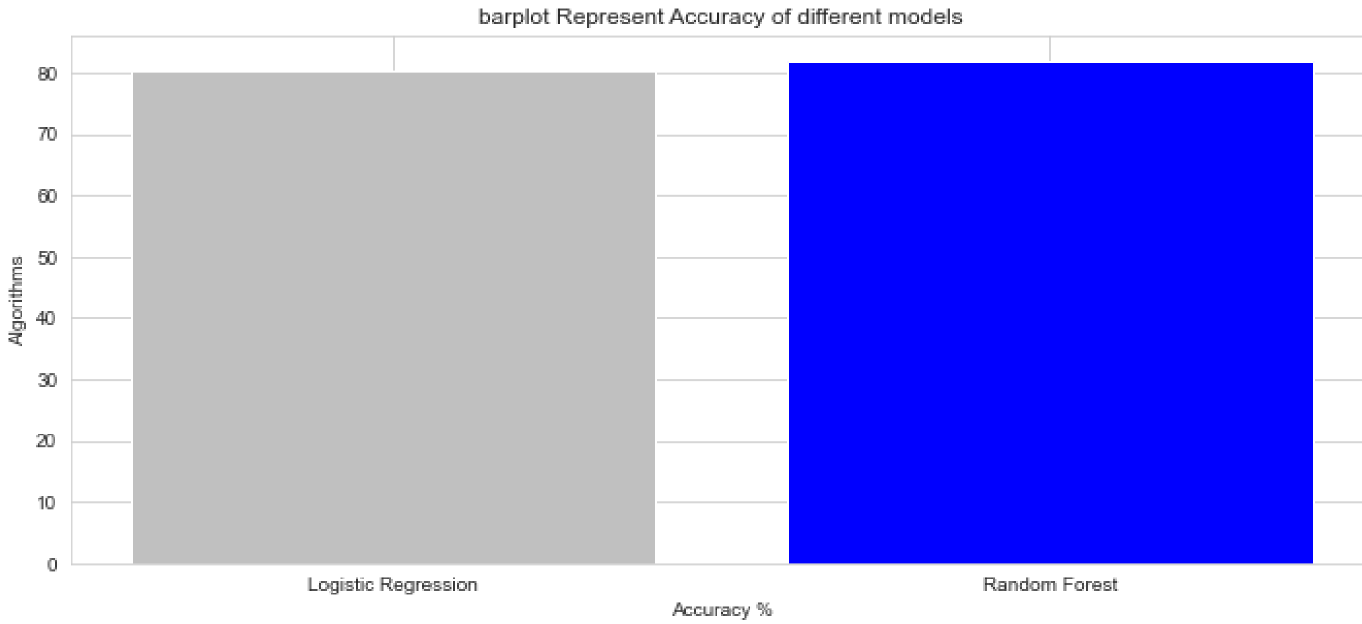
Out[187]:

	Model	Accuracy

0	Logistic Regression	80.327869
1	Random Forest	81.967213

In [188...

```
colors = ['silver','blue']
plt.figure(figsize=(12,5))
plt.title("barplot Represent Accuracy of different models")
plt.xlabel("Accuracy %")
plt.ylabel("Algorithms")
plt.bar(model_ev['Model'],model_ev['Accuracy'],color = colors)
plt.show()
```



leveraging standard error and p-values from statsmodels for Feature Selection and re-build the Random Forest Model and Logistic Regression Model

In [189...

```
Xtrain = df.drop('target', axis=1)
ytrain = df['target']
```

In [190...

```
log_reg = sm.Logit(ytrain,Xtrain).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.351033
         Iterations 7
```

In [191...

```
print(log_reg.summary())
```

```
                           Logit Regression Results
==============================================================================
Dep. Variable:                 target   No. Observations:                  302
Model:                          Logit   Df Residuals:                      289
Method:                           MLE   Df Model:                           12
Date:                Fri, 30 Sep 2022   Pseudo R-squ.:                  0.4908
Time:                        23:20:09   Log-Likelihood:                -106.01
converged:                       True   LL-Null:                       -208.21
Covariance Type:            nonrobust   LLR p-value:                 4.033e-37
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
age            0.0156      0.019      0.811      0.417      -0.022       0.053
sex           -1.6352      0.451     -3.622      0.000      -2.520      -0.750
```

```
cp            0.8357      0.184      4.535      0.000       0.475       1.197
trestbps     -0.0163      0.010     -1.651      0.099      -0.036       0.003
chol         -0.0035      0.004     -0.917      0.359      -0.011       0.004
fbs           0.0316      0.529      0.060      0.952      -1.005       1.068
restecg       0.5225      0.342      1.526      0.127      -0.149       1.194
thalach       0.0314      0.008      3.731      0.000       0.015       0.048
exang        -0.8971      0.403     -2.226      0.026      -1.687      -0.107
oldpeak      -0.4829      0.210     -2.298      0.022      -0.895      -0.071
slope         0.6180      0.346      1.785      0.074      -0.061       1.297
ca           -0.8310      0.201     -4.129      0.000      -1.225      -0.437
thal         -0.8325      0.288     -2.891      0.004      -1.397      -0.268
==============================================================================
```

Explanation of some of the terms in the summary table:

- std dev : Features age, trestbps, chol and thalach have low standard deviation of coefficient which is not looking too good.
- coef : the coefficients of the independent variables in the equation. Features sex, cp, exang, ca and thal have high coefficient values, it is the measurement of how change in that variable affects the independent variable. Features trestbps, age, chol, fbs and thalach are having low coefficient values, we may have to remove some of them taking into account the result of correlation analysis, standard error and p value.
- Pseudo R-squ. : a substitute for the R-squared value in Least Squares linear regression. It is the ratio of the log-likelihood of the null model to that of the full model. We see that we get a Pseudo R-squared of 0.49 which means the model explains 49% of the target variable.

Six Features are greater than the conventional limit of 0.05 for p-values.

We will eliminate the feature chol, fbs,age,restecg on basis of correlation analysis, coefficient value and p-value. We can also eliminate other features but for now we use them and not deleting other features to void underfitting.

REDEFINE Features

In [192…

```
# Define Feature and labels:

X_train_fs = df.drop(['chol','fbs','age','restecg','target'], axis=1)
y_train_fs = df['target']
X_train_fs.head()
```

Out[192]:

	sex	cp	trestbps	thalach	exang	oldpeak	slope	ca	thal
0	1	3	145	150	0	2.3	0	0	1
1	1	2	130	187	0	3.5	0	0	2
2	0	1	130	172	0	1.4	2	0	2
3	1	1	120	178	0	0.8	2	0	2
4	0	0	120	163	1	0.6	2	0	2

Train Test Split

In [193…

```
#Split
X_train, X_test, y_train, y_test = train_test_split(X_train_fs,y_train_fs,test_size = 0.

print(X_train.shape)
print(X_test.shape)
```

```
print(y_train.shape)
print(y_test.shape)
```

```
(241, 9)
(61, 9)
(241,)
(61,)
```

Normaliz

In [194…

```
#Normaliz

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Parameter Grid

In [195…

```
# use this structure if you want to try multiple algorithms (with hyper parameter tuning)

model_params = {

   'random-forest' : {

        'model' : RandomForestClassifier(),
        'params' : {
             "n_estimators": [50, 100, 200, 300, 500],
             "max_depth": [3, 5, 7, 9, 11, 13],
            # "min_samples_split" : np.arange(2,20,2),
            # "min_samples_leaf" : np.arange(1,20,2)

         }
    },
    'Logistic Regression' :{
        'model' :  LogisticRegression(),
        'params' : {'penalty': ['l1','l2'], 'C': [0.001,0.01,0.1,1,10,100,1000],'solver'
                   }
    }

}
```

In [196…

```
model_params.items()
```

Out[196]:

```
dict_items([('random-forest', {'model': RandomForestClassifier(), 'params': {'n_estimato
rs': [50, 100, 200, 300, 500], 'max_depth': [3, 5, 7, 9, 11, 13]}}), ('Logistic Regressi
on', {'model': LogisticRegression(), 'params': {'penalty': ['l1', 'l2'], 'C': [0.001, 0.
01, 0.1, 1, 10, 100, 1000], 'solver': ['liblinear']}})])
```

RandomizedSearchCV

In [197…

```
model_scores = {}

for model_name ,mp in model_params.items():

    print('model_name :',model_name,' mp: ', mp,'\n\n')

    if model_name == 'random-forest':
        clf = RandomizedSearchCV(mp['model'],mp['params'],  cv = 5,verbose=3, n_iter=20)

        clf.fit(X_train,y_train)

        model_scores[model_name]={'best_score' : clf.best_score_,
                                  'best_params' : clf.best_params_}
```

```python
    elif model_name == 'Logistic Regression':
        clf = RandomizedSearchCV(mp['model'],mp['params'],  cv=10, scoring='accuracy', r

        clf.fit(X_train,y_train)

        model_scores[model_name]={'best_score' : clf.best_score_,
                                  'best_params' : clf.best_params_}
```

```
model_name : random-forest  mp:  {'model': RandomForestClassifier(), 'params': {'n_estim
ators': [50, 100, 200, 300, 500], 'max_depth': [3, 5, 7, 9, 11, 13]}}


Fitting 5 folds for each of 20 candidates, totalling 100 fits
[CV 1/5] END .....max_depth=3, n_estimators=300;, score=0.796 total time=   0.3s
[CV 2/5] END .....max_depth=3, n_estimators=300;, score=0.812 total time=   0.3s
[CV 3/5] END .....max_depth=3, n_estimators=300;, score=0.792 total time=   0.2s
[CV 4/5] END .....max_depth=3, n_estimators=300;, score=0.938 total time=   0.3s
[CV 5/5] END .....max_depth=3, n_estimators=300;, score=0.896 total time=   0.3s
[CV 1/5] END .....max_depth=9, n_estimators=300;, score=0.735 total time=   0.3s
[CV 2/5] END .....max_depth=9, n_estimators=300;, score=0.792 total time=   0.3s
[CV 3/5] END .....max_depth=9, n_estimators=300;, score=0.771 total time=   0.4s
[CV 4/5] END .....max_depth=9, n_estimators=300;, score=0.958 total time=   0.5s
[CV 5/5] END .....max_depth=9, n_estimators=300;, score=0.875 total time=   0.3s
[CV 1/5] END .....max_depth=3, n_estimators=100;, score=0.776 total time=   0.0s
[CV 2/5] END .....max_depth=3, n_estimators=100;, score=0.792 total time=   0.0s
[CV 3/5] END .....max_depth=3, n_estimators=100;, score=0.792 total time=   0.0s
[CV 4/5] END .....max_depth=3, n_estimators=100;, score=0.938 total time=   0.0s
[CV 5/5] END .....max_depth=3, n_estimators=100;, score=0.896 total time=   0.0s
[CV 1/5] END .....max_depth=7, n_estimators=300;, score=0.755 total time=   0.3s
[CV 2/5] END .....max_depth=7, n_estimators=300;, score=0.792 total time=   0.3s
[CV 3/5] END .....max_depth=7, n_estimators=300;, score=0.771 total time=   0.3s
[CV 4/5] END .....max_depth=7, n_estimators=300;, score=0.938 total time=   0.3s
[CV 5/5] END .....max_depth=7, n_estimators=300;, score=0.854 total time=   0.3s
[CV 1/5] END .....max_depth=7, n_estimators=100;, score=0.776 total time=   0.0s
[CV 2/5] END .....max_depth=7, n_estimators=100;, score=0.792 total time=   0.0s
[CV 3/5] END .....max_depth=7, n_estimators=100;, score=0.792 total time=   0.0s
[CV 4/5] END .....max_depth=7, n_estimators=100;, score=0.938 total time=   0.0s
[CV 5/5] END .....max_depth=7, n_estimators=100;, score=0.896 total time=   0.0s
[CV 1/5] END ......max_depth=9, n_estimators=50;, score=0.755 total time=   0.0s
[CV 2/5] END ......max_depth=9, n_estimators=50;, score=0.792 total time=   0.0s
[CV 3/5] END ......max_depth=9, n_estimators=50;, score=0.792 total time=   0.0s
[CV 4/5] END ......max_depth=9, n_estimators=50;, score=0.958 total time=   0.0s
[CV 5/5] END ......max_depth=9, n_estimators=50;, score=0.896 total time=   0.0s
[CV 1/5] END ......max_depth=3, n_estimators=50;, score=0.776 total time=   0.0s
[CV 2/5] END ......max_depth=3, n_estimators=50;, score=0.812 total time=   0.0s
[CV 3/5] END ......max_depth=3, n_estimators=50;, score=0.771 total time=   0.0s
[CV 4/5] END ......max_depth=3, n_estimators=50;, score=0.938 total time=   0.0s
[CV 5/5] END ......max_depth=3, n_estimators=50;, score=0.896 total time=   0.0s
[CV 1/5] END ......max_depth=7, n_estimators=50;, score=0.755 total time=   0.0s
[CV 2/5] END ......max_depth=7, n_estimators=50;, score=0.812 total time=   0.0s
[CV 3/5] END ......max_depth=7, n_estimators=50;, score=0.750 total time=   0.0s
[CV 4/5] END ......max_depth=7, n_estimators=50;, score=0.958 total time=   0.0s
[CV 5/5] END ......max_depth=7, n_estimators=50;, score=0.896 total time=   0.0s
[CV 1/5] END ....max_depth=11, n_estimators=500;, score=0.755 total time=   0.6s
[CV 2/5] END ....max_depth=11, n_estimators=500;, score=0.792 total time=   0.5s
[CV 3/5] END ....max_depth=11, n_estimators=500;, score=0.771 total time=   0.5s
[CV 4/5] END ....max_depth=11, n_estimators=500;, score=0.917 total time=   0.6s
[CV 5/5] END ....max_depth=11, n_estimators=500;, score=0.854 total time=   0.8s
[CV 1/5] END ....max_depth=11, n_estimators=200;, score=0.735 total time=   0.2s
[CV 2/5] END ....max_depth=11, n_estimators=200;, score=0.771 total time=   0.2s
[CV 3/5] END ....max_depth=11, n_estimators=200;, score=0.792 total time=   0.2s
[CV 4/5] END ....max_depth=11, n_estimators=200;, score=0.938 total time=   0.2s
[CV 5/5] END ....max_depth=11, n_estimators=200;, score=0.854 total time=   0.2s
[CV 1/5] END .....max_depth=7, n_estimators=200;, score=0.776 total time=   0.2s
[CV 2/5] END .....max_depth=7, n_estimators=200;, score=0.792 total time=   0.2s
```

```
[CV 3/5] END .....max_depth=7, n_estimators=200;, score=0.792 total time=   0.2s
[CV 4/5] END .....max_depth=7, n_estimators=200;, score=0.958 total time=   0.2s
[CV 5/5] END .....max_depth=7, n_estimators=200;, score=0.875 total time=   0.3s
[CV 1/5] END ....max_depth=11, n_estimators=300;, score=0.735 total time=   0.4s
[CV 2/5] END ....max_depth=11, n_estimators=300;, score=0.792 total time=   0.4s
[CV 3/5] END ....max_depth=11, n_estimators=300;, score=0.771 total time=   0.3s
[CV 4/5] END ....max_depth=11, n_estimators=300;, score=0.917 total time=   0.3s
[CV 5/5] END ....max_depth=11, n_estimators=300;, score=0.896 total time=   0.3s
[CV 1/5] END ....max_depth=13, n_estimators=200;, score=0.755 total time=   0.2s
[CV 2/5] END ....max_depth=13, n_estimators=200;, score=0.792 total time=   0.2s
[CV 3/5] END ....max_depth=13, n_estimators=200;, score=0.792 total time=   0.2s
[CV 4/5] END ....max_depth=13, n_estimators=200;, score=0.938 total time=   0.2s
[CV 5/5] END ....max_depth=13, n_estimators=200;, score=0.896 total time=   0.2s
[CV 1/5] END .....max_depth=9, n_estimators=200;, score=0.755 total time=   0.2s
[CV 2/5] END .....max_depth=9, n_estimators=200;, score=0.792 total time=   0.1s
[CV 3/5] END .....max_depth=9, n_estimators=200;, score=0.792 total time=   0.2s
[CV 4/5] END .....max_depth=9, n_estimators=200;, score=0.938 total time=   0.2s
[CV 5/5] END .....max_depth=9, n_estimators=200;, score=0.875 total time=   0.2s
[CV 1/5] END ....max_depth=13, n_estimators=300;, score=0.755 total time=   0.3s
[CV 2/5] END ....max_depth=13, n_estimators=300;, score=0.792 total time=   0.4s
[CV 3/5] END ....max_depth=13, n_estimators=300;, score=0.750 total time=   0.3s
[CV 4/5] END ....max_depth=13, n_estimators=300;, score=0.958 total time=   0.3s
[CV 5/5] END ....max_depth=13, n_estimators=300;, score=0.875 total time=   0.3s
[CV 1/5] END ....max_depth=11, n_estimators=100;, score=0.714 total time=   0.0s
[CV 2/5] END ....max_depth=11, n_estimators=100;, score=0.792 total time=   0.0s
[CV 3/5] END ....max_depth=11, n_estimators=100;, score=0.750 total time=   0.0s
[CV 4/5] END ....max_depth=11, n_estimators=100;, score=0.917 total time=   0.1s
[CV 5/5] END ....max_depth=11, n_estimators=100;, score=0.875 total time=   0.0s
[CV 1/5] END .....max_depth=5, n_estimators=100;, score=0.755 total time=   0.0s
[CV 2/5] END .....max_depth=5, n_estimators=100;, score=0.792 total time=   0.0s
[CV 3/5] END .....max_depth=5, n_estimators=100;, score=0.792 total time=   0.0s
[CV 4/5] END .....max_depth=5, n_estimators=100;, score=0.958 total time=   0.0s
[CV 5/5] END .....max_depth=5, n_estimators=100;, score=0.896 total time=   0.1s
[CV 1/5] END .....max_depth=3, n_estimators=200;, score=0.755 total time=   0.2s
[CV 2/5] END .....max_depth=3, n_estimators=200;, score=0.812 total time=   0.2s
[CV 3/5] END .....max_depth=3, n_estimators=200;, score=0.792 total time=   0.1s
[CV 4/5] END .....max_depth=3, n_estimators=200;, score=0.938 total time=   0.2s
[CV 5/5] END .....max_depth=3, n_estimators=200;, score=0.896 total time=   0.2s
[CV 1/5] END ......max_depth=5, n_estimators=50;, score=0.735 total time=   0.0s
[CV 2/5] END ......max_depth=5, n_estimators=50;, score=0.812 total time=   0.0s
[CV 3/5] END ......max_depth=5, n_estimators=50;, score=0.792 total time=   0.0s
[CV 4/5] END ......max_depth=5, n_estimators=50;, score=0.938 total time=   0.0s
[CV 5/5] END ......max_depth=5, n_estimators=50;, score=0.875 total time=   0.0s
[CV 1/5] END .....max_depth=9, n_estimators=100;, score=0.755 total time=   0.0s
[CV 2/5] END .....max_depth=9, n_estimators=100;, score=0.771 total time=   0.0s
[CV 3/5] END .....max_depth=9, n_estimators=100;, score=0.812 total time=   0.0s
[CV 4/5] END .....max_depth=9, n_estimators=100;, score=0.938 total time=   0.1s
[CV 5/5] END .....max_depth=9, n_estimators=100;, score=0.875 total time=   0.0s
model_name : Logistic Regression  mp:  {'model': LogisticRegression(), 'params': {'penal
ty': ['l1', 'l2'], 'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000], 'solver': ['liblinear']}}


Fitting 10 folds for each of 10 candidates, totalling 100 fits
[CV 1/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.750 total time=   0.0s
[CV 7/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.958 total time=   0.0s
[CV 8/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 1/10] END C=100, penalty=l1, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=100, penalty=l1, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=100, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
```

```
[CV 4/10] END C=100, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=100, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=100, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=100, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=100, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=100, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=100, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.440 total time=   0.0s
[CV 2/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.417 total time=   0.0s
[CV 3/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 4/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 5/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 6/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 7/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 8/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 9/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 10/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 1/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.440 total time=   0.0s
[CV 2/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.417 total time=   0.0s
[CV 3/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 4/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 5/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 6/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 7/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 8/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 9/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 10/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 1/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.708 total time=   0.0s
[CV 3/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.792 total time=   0.0s
[CV 7/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.880 total time=   0.0s
[CV 2/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 4/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.750 total time=   0.0s
[CV 7/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.958 total time=   0.0s
[CV 8/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 1/10] END C=1000, penalty=l2, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=1000, penalty=l2, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=1000, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=1000, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=1000, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=1000, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=1000, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=1000, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=1000, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=1000, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=1000, penalty=l1, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=1000, penalty=l1, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=1000, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=1000, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=1000, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=1000, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=1000, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=1000, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=1000, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
```

```
[CV 10/10] END C=1000, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=10, penalty=l1, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=10, penalty=l1, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=10, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=10, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=10, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=10, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=10, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=10, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=10, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=10, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=10, penalty=l2, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=10, penalty=l2, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=10, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=10, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=10, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=10, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=10, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=10, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=10, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=10, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
```

In [198…

```
model_scores
```

Out[198]:

```
{'random-forest': {'best_score': 0.8466836734693878,
  'best_params': {'n_estimators': 300, 'max_depth': 3}},
 'Logistic Regression': {'best_score': 0.8505,
  'best_params': {'solver': 'liblinear', 'penalty': 'l2', 'C': 0.01}}}
```

GridSearchCV

In [199…

```
model_scores = {}

for model_name ,mp in model_params.items():

    print('model_name :',model_name,' mp: ', mp,'\n\n')


    if model_name == 'random-forest':
        clf = GridSearchCV(mp['model'],mp['params'],  cv = 3,verbose=3)

        clf.fit(X_train,y_train)

        model_scores[model_name]={'best_score' : clf.best_score_,
                                  'best_params' : clf.best_params_}

    elif model_name == 'Logistic Regression':
        clf = GridSearchCV(mp['model'],mp['params'],  cv=10, scoring='accuracy', return_

        clf.fit(X_train,y_train)

        model_scores[model_name]={'best_score' : clf.best_score_,
                                  'best_params' : clf.best_params_}
```

```
model_name : random-forest  mp:  {'model': RandomForestClassifier(), 'params': {'n_estim
ators': [50, 100, 200, 300, 500], 'max_depth': [3, 5, 7, 9, 11, 13]}}


Fitting 3 folds for each of 30 candidates, totalling 90 fits
[CV 1/3] END ......max_depth=3, n_estimators=50;, score=0.753 total time=   0.0s
[CV 2/3] END ......max_depth=3, n_estimators=50;, score=0.825 total time=   0.0s
[CV 3/3] END ......max_depth=3, n_estimators=50;, score=0.912 total time=   0.0s
[CV 1/3] END .....max_depth=3, n_estimators=100;, score=0.753 total time=   0.0s
[CV 2/3] END .....max_depth=3, n_estimators=100;, score=0.825 total time=   0.0s
[CV 3/3] END .....max_depth=3, n_estimators=100;, score=0.912 total time=   0.0s
```

```
[CV 1/3] END .....max_depth=3, n_estimators=200;, score=0.753 total time=   0.2s
[CV 2/3] END .....max_depth=3, n_estimators=200;, score=0.812 total time=   0.2s
[CV 3/3] END .....max_depth=3, n_estimators=200;, score=0.938 total time=   0.2s
[CV 1/3] END .....max_depth=3, n_estimators=300;, score=0.741 total time=   0.3s
[CV 2/3] END .....max_depth=3, n_estimators=300;, score=0.812 total time=   0.5s
[CV 3/3] END .....max_depth=3, n_estimators=300;, score=0.925 total time=   0.4s
[CV 1/3] END .....max_depth=3, n_estimators=500;, score=0.741 total time=   0.8s
[CV 2/3] END .....max_depth=3, n_estimators=500;, score=0.825 total time=   0.7s
[CV 3/3] END .....max_depth=3, n_estimators=500;, score=0.925 total time=   0.6s
[CV 1/3] END ......max_depth=5, n_estimators=50;, score=0.741 total time=   0.0s
[CV 2/3] END ......max_depth=5, n_estimators=50;, score=0.825 total time=   0.0s
[CV 3/3] END ......max_depth=5, n_estimators=50;, score=0.912 total time=   0.0s
[CV 1/3] END .....max_depth=5, n_estimators=100;, score=0.753 total time=   0.0s
[CV 2/3] END .....max_depth=5, n_estimators=100;, score=0.812 total time=   0.0s
[CV 3/3] END .....max_depth=5, n_estimators=100;, score=0.912 total time=   0.0s
[CV 1/3] END .....max_depth=5, n_estimators=200;, score=0.753 total time=   0.2s
[CV 2/3] END .....max_depth=5, n_estimators=200;, score=0.825 total time=   0.3s
[CV 3/3] END .....max_depth=5, n_estimators=200;, score=0.912 total time=   0.1s
[CV 1/3] END .....max_depth=5, n_estimators=300;, score=0.741 total time=   0.3s
[CV 2/3] END .....max_depth=5, n_estimators=300;, score=0.812 total time=   0.3s
[CV 3/3] END .....max_depth=5, n_estimators=300;, score=0.925 total time=   0.4s
[CV 1/3] END .....max_depth=5, n_estimators=500;, score=0.741 total time=   0.6s
[CV 2/3] END .....max_depth=5, n_estimators=500;, score=0.800 total time=   0.6s
[CV 3/3] END .....max_depth=5, n_estimators=500;, score=0.925 total time=   0.6s
[CV 1/3] END ......max_depth=7, n_estimators=50;, score=0.741 total time=   0.0s
[CV 2/3] END ......max_depth=7, n_estimators=50;, score=0.800 total time=   0.0s
[CV 3/3] END ......max_depth=7, n_estimators=50;, score=0.875 total time=   0.0s
[CV 1/3] END .....max_depth=7, n_estimators=100;, score=0.728 total time=   0.0s
[CV 2/3] END .....max_depth=7, n_estimators=100;, score=0.800 total time=   0.0s
[CV 3/3] END .....max_depth=7, n_estimators=100;, score=0.875 total time=   0.0s
[CV 1/3] END .....max_depth=7, n_estimators=200;, score=0.741 total time=   0.2s
[CV 2/3] END .....max_depth=7, n_estimators=200;, score=0.787 total time=   0.2s
[CV 3/3] END .....max_depth=7, n_estimators=200;, score=0.887 total time=   0.2s
[CV 1/3] END .....max_depth=7, n_estimators=300;, score=0.753 total time=   0.3s
[CV 2/3] END .....max_depth=7, n_estimators=300;, score=0.800 total time=   0.3s
[CV 3/3] END .....max_depth=7, n_estimators=300;, score=0.887 total time=   0.3s
[CV 1/3] END .....max_depth=7, n_estimators=500;, score=0.741 total time=   0.6s
[CV 2/3] END .....max_depth=7, n_estimators=500;, score=0.812 total time=   0.9s
[CV 3/3] END .....max_depth=7, n_estimators=500;, score=0.887 total time=   0.8s
[CV 1/3] END ......max_depth=9, n_estimators=50;, score=0.753 total time=   0.0s
[CV 2/3] END ......max_depth=9, n_estimators=50;, score=0.787 total time=   0.0s
[CV 3/3] END ......max_depth=9, n_estimators=50;, score=0.887 total time=   0.0s
[CV 1/3] END .....max_depth=9, n_estimators=100;, score=0.741 total time=   0.1s
[CV 2/3] END .....max_depth=9, n_estimators=100;, score=0.787 total time=   0.1s
[CV 3/3] END .....max_depth=9, n_estimators=100;, score=0.900 total time=   0.1s
[CV 1/3] END .....max_depth=9, n_estimators=200;, score=0.741 total time=   0.2s
[CV 2/3] END .....max_depth=9, n_estimators=200;, score=0.812 total time=   0.2s
[CV 3/3] END .....max_depth=9, n_estimators=200;, score=0.912 total time=   0.2s
[CV 1/3] END .....max_depth=9, n_estimators=300;, score=0.753 total time=   0.3s
[CV 2/3] END .....max_depth=9, n_estimators=300;, score=0.800 total time=   0.3s
[CV 3/3] END .....max_depth=9, n_estimators=300;, score=0.887 total time=   0.4s
[CV 1/3] END .....max_depth=9, n_estimators=500;, score=0.741 total time=   0.8s
[CV 2/3] END .....max_depth=9, n_estimators=500;, score=0.812 total time=   0.7s
[CV 3/3] END .....max_depth=9, n_estimators=500;, score=0.875 total time=   0.7s
[CV 1/3] END .....max_depth=11, n_estimators=50;, score=0.728 total time=   0.0s
[CV 2/3] END .....max_depth=11, n_estimators=50;, score=0.787 total time=   0.0s
[CV 3/3] END .....max_depth=11, n_estimators=50;, score=0.887 total time=   0.0s
[CV 1/3] END ....max_depth=11, n_estimators=100;, score=0.753 total time=   0.0s
[CV 2/3] END ....max_depth=11, n_estimators=100;, score=0.812 total time=   0.0s
[CV 3/3] END ....max_depth=11, n_estimators=100;, score=0.863 total time=   0.0s
[CV 1/3] END ....max_depth=11, n_estimators=200;, score=0.753 total time=   0.2s
[CV 2/3] END ....max_depth=11, n_estimators=200;, score=0.812 total time=   0.2s
[CV 3/3] END ....max_depth=11, n_estimators=200;, score=0.900 total time=   0.2s
[CV 1/3] END ....max_depth=11, n_estimators=300;, score=0.741 total time=   0.3s
[CV 2/3] END ....max_depth=11, n_estimators=300;, score=0.800 total time=   0.3s
[CV 3/3] END ....max_depth=11, n_estimators=300;, score=0.887 total time=   0.3s
```

```
[CV 1/3] END ....max_depth=11, n_estimators=500;, score=0.728 total time=   0.6s
[CV 2/3] END ....max_depth=11, n_estimators=500;, score=0.800 total time=   0.5s
[CV 3/3] END ....max_depth=11, n_estimators=500;, score=0.900 total time=   0.6s
[CV 1/3] END .....max_depth=13, n_estimators=50;, score=0.728 total time=   0.0s
[CV 2/3] END .....max_depth=13, n_estimators=50;, score=0.775 total time=   0.0s
[CV 3/3] END .....max_depth=13, n_estimators=50;, score=0.887 total time=   0.0s
[CV 1/3] END ....max_depth=13, n_estimators=100;, score=0.765 total time=   0.0s
[CV 2/3] END ....max_depth=13, n_estimators=100;, score=0.800 total time=   0.0s
[CV 3/3] END ....max_depth=13, n_estimators=100;, score=0.887 total time=   0.1s
[CV 1/3] END ....max_depth=13, n_estimators=200;, score=0.741 total time=   0.1s
[CV 2/3] END ....max_depth=13, n_estimators=200;, score=0.800 total time=   0.1s
[CV 3/3] END ....max_depth=13, n_estimators=200;, score=0.887 total time=   0.1s
[CV 1/3] END ....max_depth=13, n_estimators=300;, score=0.728 total time=   0.4s
[CV 2/3] END ....max_depth=13, n_estimators=300;, score=0.812 total time=   0.5s
[CV 3/3] END ....max_depth=13, n_estimators=300;, score=0.863 total time=   0.4s
[CV 1/3] END ....max_depth=13, n_estimators=500;, score=0.741 total time=   0.8s
[CV 2/3] END ....max_depth=13, n_estimators=500;, score=0.800 total time=   0.7s
[CV 3/3] END ....max_depth=13, n_estimators=500;, score=0.875 total time=   0.6s
model_name : Logistic Regression  mp:  {'model': LogisticRegression(), 'params': {'penal
ty': ['l1', 'l2'], 'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000], 'solver': ['liblinear']}}


Fitting 10 folds for each of 14 candidates, totalling 140 fits
[CV 1/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.440 total time=   0.0s
[CV 2/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.417 total time=   0.0s
[CV 3/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 4/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 5/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 6/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 7/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 8/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 9/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 10/10] END C=0.001, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 1/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.750 total time=   0.0s
[CV 7/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.958 total time=   0.0s
[CV 8/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=0.001, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 1/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.440 total time=   0.0s
[CV 2/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.417 total time=   0.0s
[CV 3/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 4/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 5/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 6/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 7/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 8/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 9/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 10/10] END C=0.01, penalty=l1, solver=liblinear;, score=0.458 total time=   0.0s
[CV 1/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.880 total time=   0.0s
[CV 2/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 4/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.750 total time=   0.0s
[CV 7/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.958 total time=   0.0s
[CV 8/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=0.01, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 1/10] END C=0.1, penalty=l1, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=0.1, penalty=l1, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=0.1, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
```

```
[CV 4/10] END C=0.1, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=0.1, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=0.1, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=0.1, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=0.1, penalty=l1, solver=liblinear;, score=0.958 total time=   0.0s
[CV 9/10] END C=0.1, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=0.1, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 1/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.708 total time=   0.0s
[CV 3/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.792 total time=   0.0s
[CV 7/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=0.1, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=1, penalty=l1, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=1, penalty=l1, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=1, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=1, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=1, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=1, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=1, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=1, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=1, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=1, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=1, penalty=l2, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=1, penalty=l2, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=1, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=1, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=1, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=1, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=1, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=1, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=1, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=1, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=10, penalty=l1, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=10, penalty=l1, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=10, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=10, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=10, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
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[CV 6/10] END C=10, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=10, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=10, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
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[CV 10/10] END C=10, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=100, penalty=l1, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=100, penalty=l1, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=100, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=100, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=100, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
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[CV 7/10] END C=100, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=100, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=100, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
```

```
[CV 10/10] END C=100, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=100, penalty=l2, solver=liblinear;, score=0.840 total time=   0.0s
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[CV 3/10] END C=100, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=100, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
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[CV 2/10] END C=1000, penalty=l1, solver=liblinear;, score=0.667 total time=   0.0s
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[CV 4/10] END C=1000, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=1000, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=1000, penalty=l1, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=1000, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=1000, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=1000, penalty=l1, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=1000, penalty=l1, solver=liblinear;, score=0.875 total time=   0.0s
[CV 1/10] END C=1000, penalty=l2, solver=liblinear;, score=0.840 total time=   0.0s
[CV 2/10] END C=1000, penalty=l2, solver=liblinear;, score=0.667 total time=   0.0s
[CV 3/10] END C=1000, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 4/10] END C=1000, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 5/10] END C=1000, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 6/10] END C=1000, penalty=l2, solver=liblinear;, score=0.833 total time=   0.0s
[CV 7/10] END C=1000, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 8/10] END C=1000, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
[CV 9/10] END C=1000, penalty=l2, solver=liblinear;, score=0.917 total time=   0.0s
[CV 10/10] END C=1000, penalty=l2, solver=liblinear;, score=0.875 total time=   0.0s
```

In [200…

```
model_scores
```

Out[200]:

```
{'random-forest': {'best_score': 0.8343621399176954,
  'best_params': {'max_depth': 3, 'n_estimators': 200}},
 'Logistic Regression': {'best_score': 0.8505,
  'best_params': {'C': 0.01, 'penalty': 'l2', 'solver': 'liblinear'}}}
```

Prediction using best estimators

Logistic Regression

In [201…

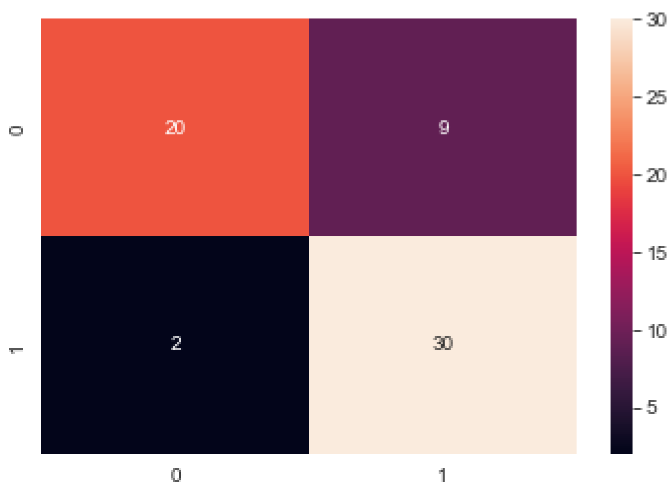
```
#Train Data Accuracy

model_LogisticReg = LogisticRegression(C= model_scores['Logistic Regression']['best_para

model_LogisticReg.fit(X_train, y_train)

y_test_Log_pred=model_LogisticReg.predict(X_test)

LogisticReg_TrainData_Score = model_LogisticReg.score(X_train, y_train)
LogisticReg_TestData_Score = model_LogisticReg.score(X_test, y_test)
LogisticReg_accuracy_score = accuracy_score(y_test, y_test_Log_pred)
LogisticReg_conf_matrix = confusion_matrix(y_test, y_test_Log_pred)


print("Score for our training dataset with tuning is : {:.2f}%".format(LogisticReg_Train
print("Score for our training dataset with tuning is : {:.2f}%".format(LogisticReg_TestD

print("\n")
print("Model Accuracy after tuning is : {:.2f}%".format(LogisticReg_accuracy_score *100)
print("\n")
```

```
print("classification report")
print(classification_report(y_test,y_test_Log_pred))
print("\n")
print("confussion matrix")
print(LogisticReg_conf_matrix)
sns.heatmap(LogisticReg_conf_matrix,annot=True)
```

```
Score for our training dataset with tuning is : 86.31%
Score for our training dataset with tuning is : 81.97%


Model Accuracy after tuning is : 81.97%


classification report
              precision    recall  f1-score   support

           0       0.91      0.69      0.78        29
           1       0.77      0.94      0.85        32

    accuracy                           0.82        61
   macro avg       0.84      0.81      0.81        61
weighted avg       0.84      0.82      0.82        61



confussion matrix
[[20  9]
 [ 2 30]]
```

Out[201]:

```
<AxesSubplot:>
```



Random Forest

In [202…

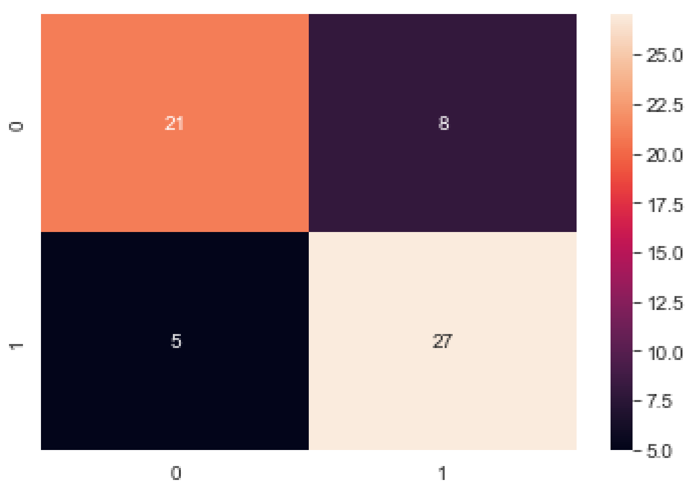
```
#Train Data Accuracy

model_RandomForest = RandomForestClassifier(n_estimators= model_scores['random-forest'][

model_RandomForest.fit(X_train, y_train)

y_test_RF_pred=model_RandomForest.predict(X_test)

RF_TrainData_Score = model_RandomForest.score(X_train, y_train)
RF_TestData_Score = model_RandomForest.score(X_test, y_test)
rf_accuracy_score = accuracy_score(y_test, y_test_RF_pred)
rf_conf_matrix = confusion_matrix(y_test, y_test_RF_pred)


print("Score for our training dataset with tuning is : {:.2f}%".format(RF_TrainData_Scor
```

```
print("Score for our testing dataset with tuning is : {:.2f}%".format(RF_TestData_Score
print("\n")
print("Model Accuracy after tuning is : {:.2f}%".format(rf_accuracy_score *100) )
print("\n")
print("classification report")
print(classification_report(y_test,y_test_RF_pred))
print("\n")
print("confussion matrix")
print(rf_conf_matrix)
sns.heatmap(rf_conf_matrix,annot=True)
```

```
Score for our training dataset with tuning is : 87.14%
Score for our testing dataset with tuning is : 78.69%


Model Accuracy after tuning is : 78.69%


classification report
              precision    recall  f1-score   support

           0       0.81      0.72      0.76        29
           1       0.77      0.84      0.81        32

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



confussion matrix
[[21  8]
 [ 5 27]]
```

Out[202]:

```
<AxesSubplot:>
```



Model Evaluation

In [203…

```
model_ev_fs = pd.DataFrame({'Model': ['Logistic Regression','Random Forest'],'Train Data
model_ev_fs
```

Out[203]:

	Model	Train Data Accuracy	Test Data Accuracy
0	Logistic Regression	86.307054	81.967213
1	Random Forest	87.136929	78.688525

Evaluating our tuned Machine Learning model classifier beyond accuracy

ROC curve and AUC score

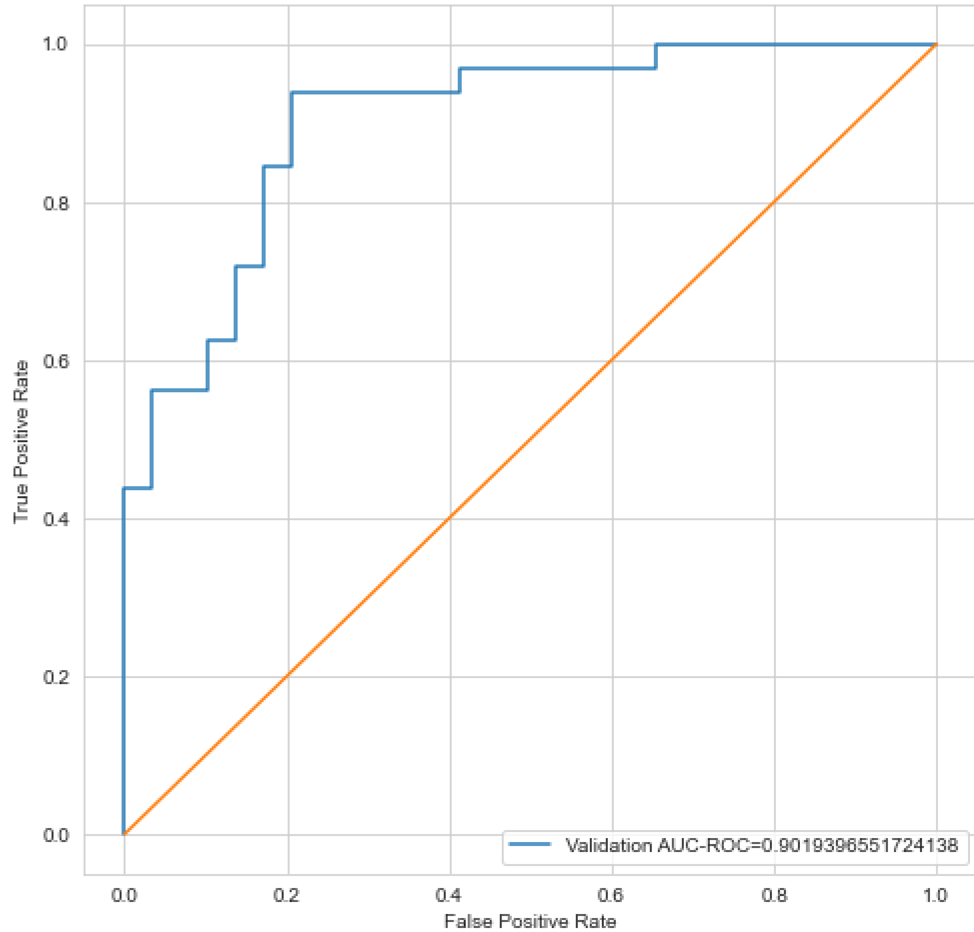
In [204…
```
y_pred_LogREg_probability = model_LogisticReg.predict_proba(X_test)[:,1]
pd.DataFrame({"Actual":y_test, "Predicted":y_pred_LogREg_probability})
```

Out[204]:

	Actual	Predicted
174	0	0.168300
88	1	0.727068
163	1	0.525272
243	0	0.167810
110	1	0.557762
...	...	...
194	0	0.552402
78	1	0.732899
248	0	0.587972
220	0	0.238127
235	0	0.404056

61 rows × 2 columns

In [205…
```
fpr, tpr, _ = roc_curve(y_test,y_pred_LogREg_probability)
auc = roc_auc_score(y_test, y_pred_LogREg_probability)
plt.figure(figsize=(8,8))
plt.plot(fpr,tpr,label="Validation AUC-ROC="+str(auc))
x = np.linspace(0, 1, 1000)
plt.plot(x, x, linestyle='-')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc=4)
plt.show()
```



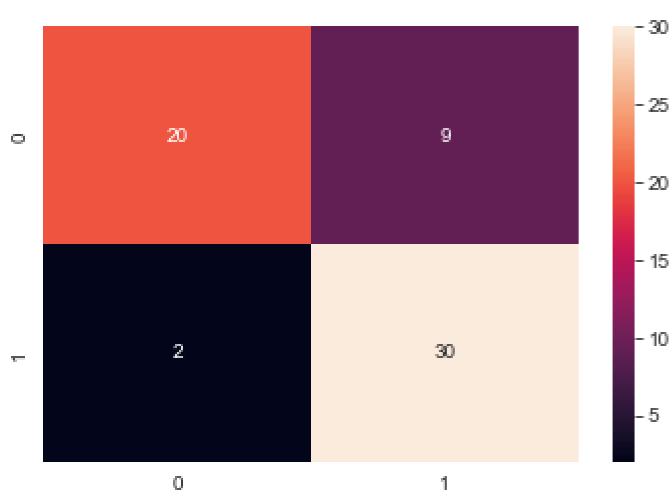
In [206…
```
auc = roc_auc_score(y_test, y_pred_LogREg_probability)
print("Auc score for RF is : ", auc)
```

```
Auc score for RF is :  0.9019396551724138
```

In [207…
```
print("confussion matrix")
print(LogisticReg_conf_matrix)
sns.heatmap(LogisticReg_conf_matrix,annot=True)
```

```
confussion matrix
[[20  9]
 [ 2 30]]
```

Out[207]:
```
<AxesSubplot:>
```



In [208…
```
print("classification report")
print(classification_report(y_test,y_test_Log_pred))
print("\n")
```

```
classification report
              precision    recall  f1-score   support

           0       0.91      0.69      0.78        29
           1       0.77      0.94      0.85        32

    accuracy                           0.82        61
   macro avg       0.84      0.81      0.81        61
weighted avg       0.84      0.82      0.82        61
```

Conclusion :

1. Logistic Regression is better Model for the given Dataset for predection because its more stable than Random forest with Train data Accuracy = 86.307054 and Test Data Accuracy = 81.967213
2. AUC score is .88 which is above .50 which is very good
3. The male sex carries a higher risk for heart attacks and therefore medical screenings should be more targeted to that gender in order to help pick cases more easily.
4. Chest pain in most cases are the first warning signs, more patients should be sensitized on the need to mention that pain during visits to the doctor, even when they dont feel it severely at every hour of the day.
5. Resting ECG,especially Value 2 which represents probable or definite left ventricular hypertrophy by Estes' criteria is also a high risk therefore it is advised that annual ECG tests to detect any ECG abnormalities ,especially when other risk factors are present, are carried out.
6. Increased fasting blood sugar is also an identified risk, thus measures to control fasting blood sugar such as regular exercises, treatment of diabetes mellitus if present and dietary restrictions of sugars are advised.