Problem Statement

To detect whether a person is having Heart Disease or not

Importing libraries

In [1]:

```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report

import seaborn as sns
```

Data Gathering

In [2]:

```
df = pd.read_csv("heart_disease_data.csv")
df.head()
```

Out[2]:

	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

EDA

In [3]:

```
df.columns
```

Out[3]:

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

In [4]:

```
df.info()
```

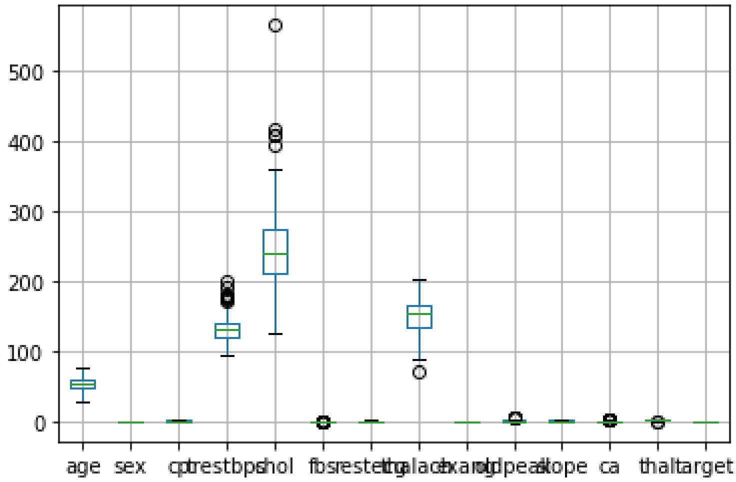
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       303 non-null    int64  
 1   sex       303 non-null    int64  
 2   cp        303 non-null    int64  
 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
```

```
In [5]: df.isna().sum()
```

```
Out[5]: 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
```

```
In [6]: df.boxplot() # we need to work on outliers
```

```
Out[6]: <AxesSubplot:>
```



```
In [7]: df.describe()
```

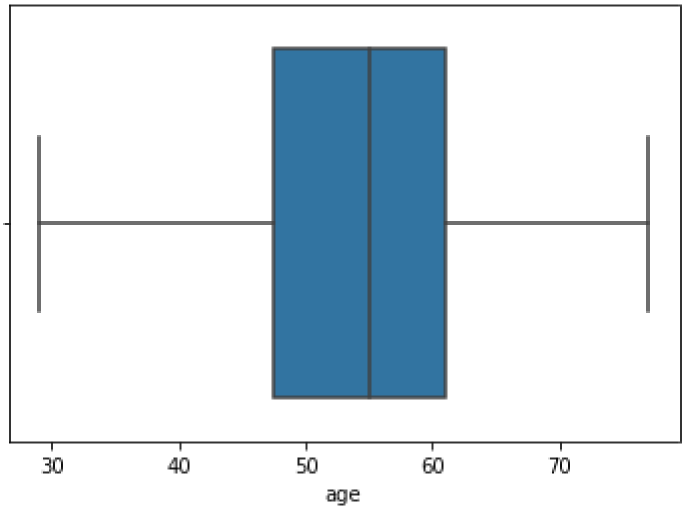
Out[7]:

	age	sex	cp	trestbps	chol	fbs	restecg	tha
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.00
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.64
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.90
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.00
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.50
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.00
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.00
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.00

1) AGE

In [8]:
```
sns.boxplot(df["age"])
```

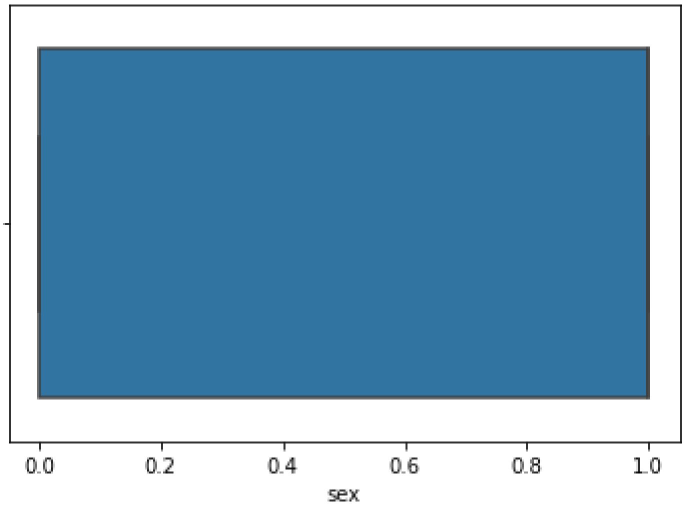
Out[8]:
```
<AxesSubplot:xlabel='age'>
```



2) sex

In [9]:
```
sns.boxplot(df["sex"])
```

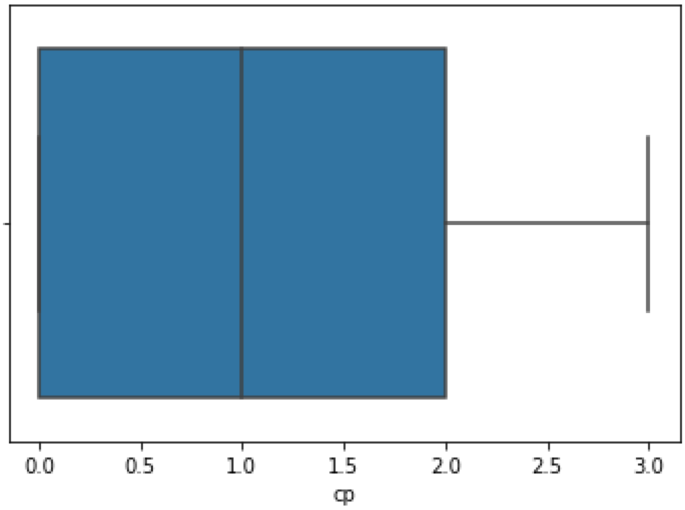
Out[9]:
```
<AxesSubplot:xlabel='sex'>
```



3) cp

```
In [10]: sns.boxplot(df["cp"])
```

```
Out[10]: <AxesSubplot:xlabel='cp'>
```

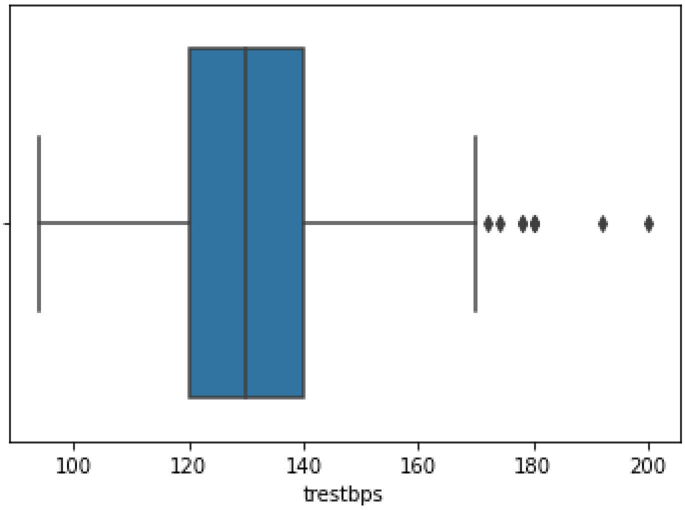


```
In [ ]:
```

4) trestbps

```
In [11]: sns.boxplot(df["trestbps"])  # outliers need to be handled
```

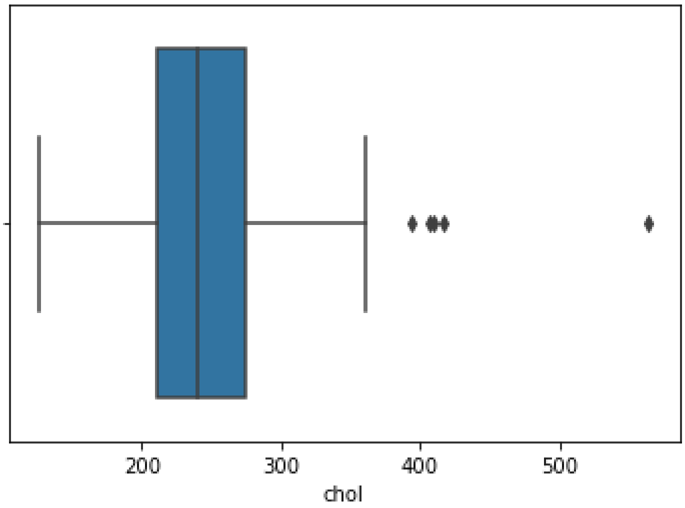
```
Out[11]: <AxesSubplot:xlabel='trestbps'>
```



5) chol

```
In [12]: sns.boxplot(df["chol"]) # outliers need to handled
```

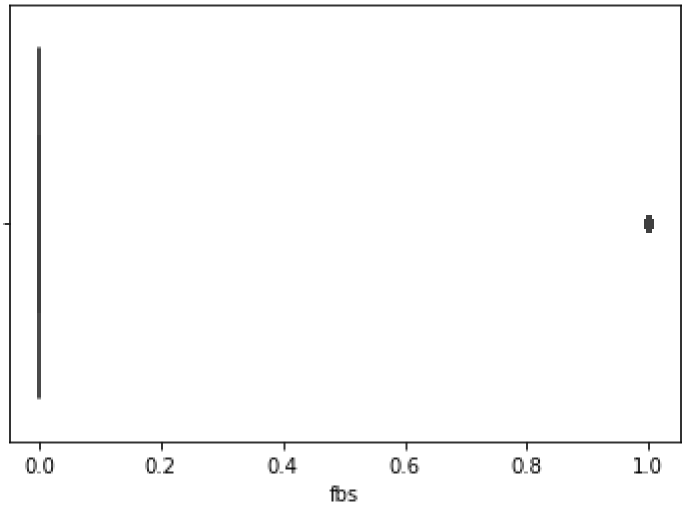
```
Out[12]: <AxesSubplot:xlabel='chol'>
```



6) fbs

```
In [13]: sns.boxplot(df["fbs"])
```

```
Out[13]: <AxesSubplot:xlabel='fbs'>
```



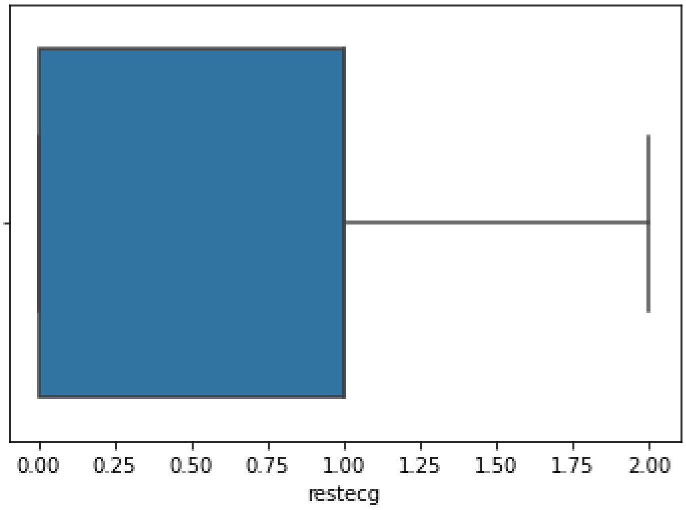
7) restecg

In [14]:

```python
sns.boxplot(df["restecg"])
```

Out[14]:

```
<AxesSubplot:xlabel='restecg'>
```



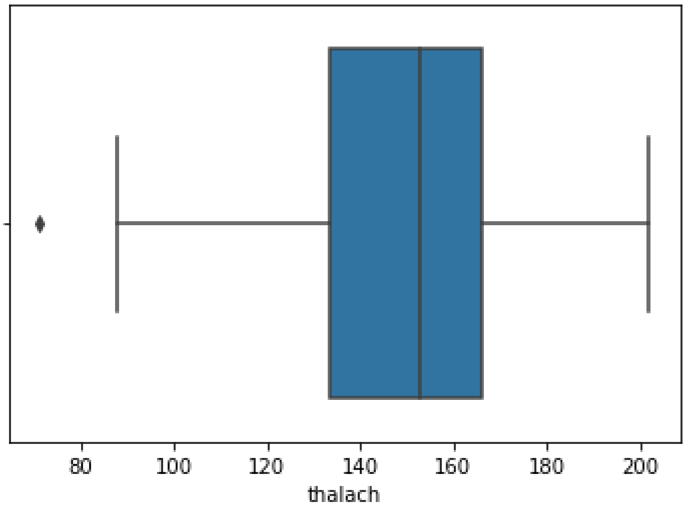
8) thalach

In [15]:

```python
sns.boxplot(df["thalach"])
```

Out[15]:

```
<AxesSubplot:xlabel='thalach'>
```



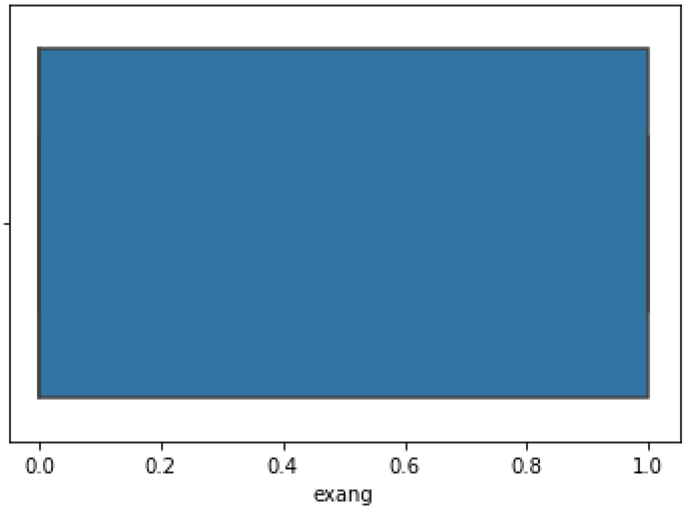
9) exang

In [16]:

```python
sns.boxplot(df["exang"])
```

Out[16]:

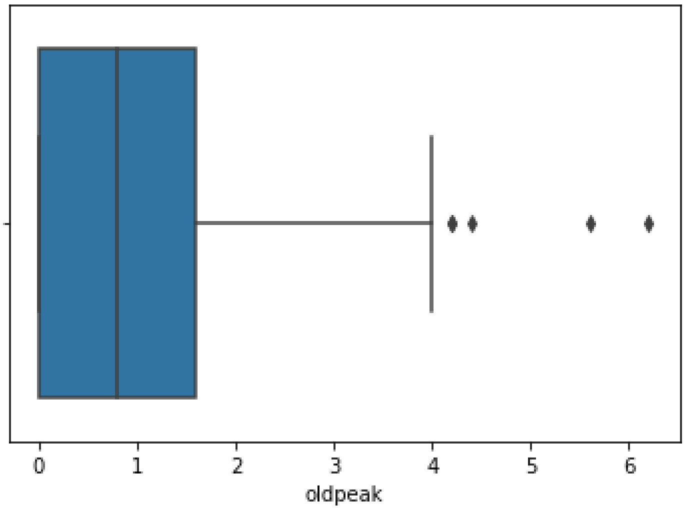
```
<AxesSubplot:xlabel='exang'>
```



10) oldpeak

```
In [17]: sns.boxplot(df["oldpeak"]) # outliers need to handled
```

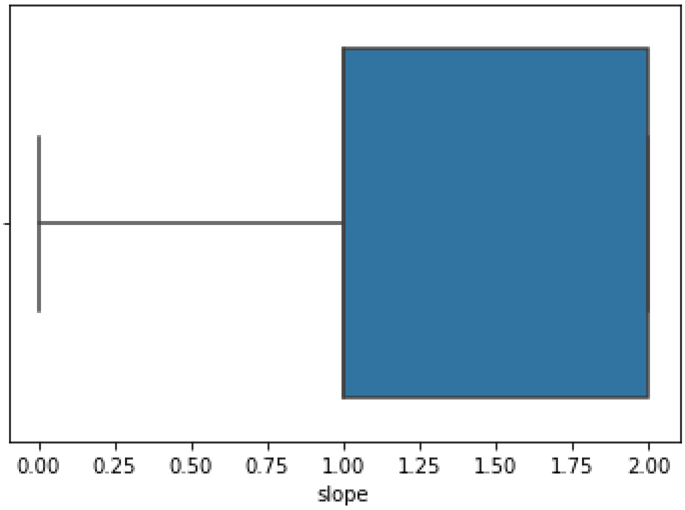
```
Out[17]: <AxesSubplot:xlabel='oldpeak'>
```



11) slope

```
In [18]: sns.boxplot(df["slope"])
```

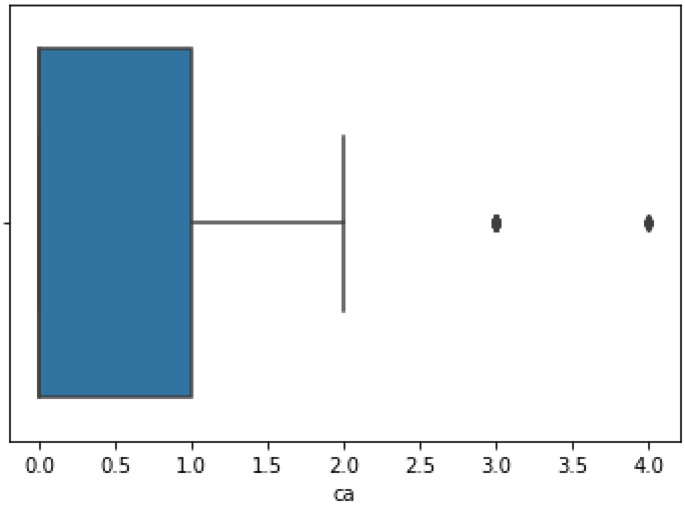
```
Out[18]: <AxesSubplot:xlabel='slope'>
```



12) ca

In [19]:
```
sns.boxplot(df["ca"]) # outliers need to handled
```

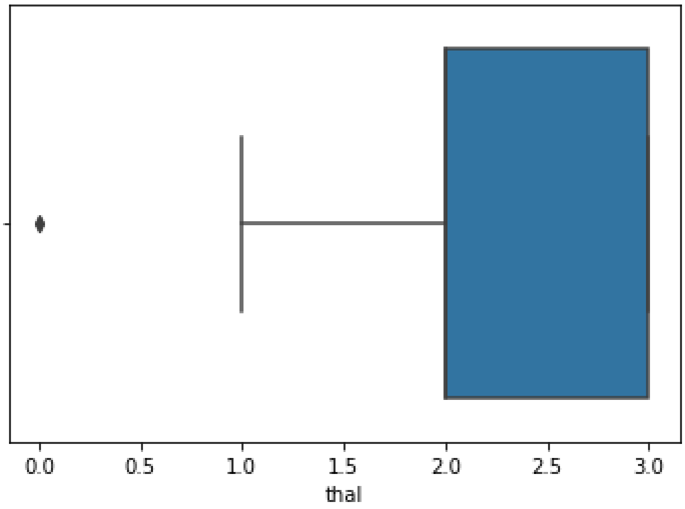
Out[19]:
```
<AxesSubplot:xlabel='ca'>
```



13) thal

In [20]:
```
sns.boxplot(df["thal"]) # outliers need to handled
```

Out[20]:
```
<AxesSubplot:xlabel='thal'>
```

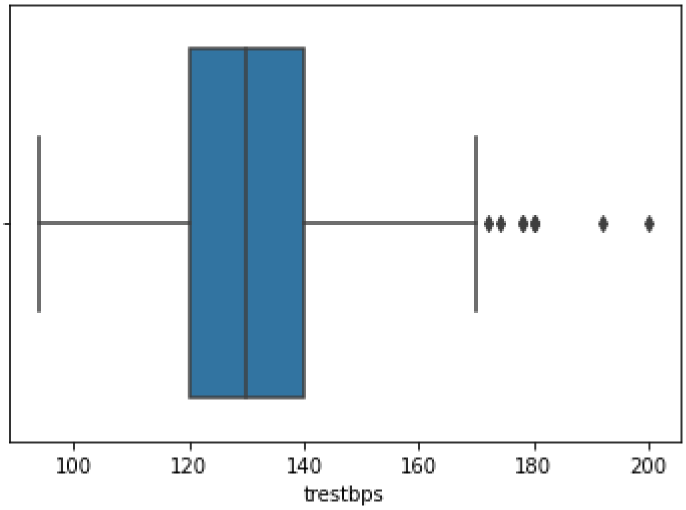


Feature Engineering

4) trestbps

In [21]:
```
sns.boxplot(df["trestbps"])  # outliers need to be handled
```

Out[21]:
```
<AxesSubplot:xlabel='trestbps'>
```



In [22]:
```
# IQR method

q1 = df["trestbps"].quantile(0.25)
q2 = df["trestbps"].quantile(0.50)
q3 = df["trestbps"].quantile(0.75)

IQR = q3-q1

uppertail = q3 + 1.5*IQR
lowertail = q1 - 1.5*IQR
```

In [23]:
```
df.loc[(df["trestbps"]> uppertail) ] # outliers
```

Out[23]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	targe
8	52	1	2	172	199	1	1	162	0	0.5	2	0	3	
101	59	1	3	178	270	0	0	145	0	4.2	0	0	3	
110	64	0	0	180	325	0	1	154	1	0.0	2	0	2	
203	68	1	2	180	274	1	0	150	1	1.6	1	0	3	
223	56	0	0	200	288	1	0	133	1	4.0	0	2	3	
241	59	0	0	174	249	0	1	143	1	0.0	1	0	2	
248	54	1	1	192	283	0	0	195	0	0.0	2	1	3	
260	66	0	0	178	228	1	1	165	1	1.0	1	2	3	
266	55	0	0	180	327	0	2	117	1	3.4	1	0	2	

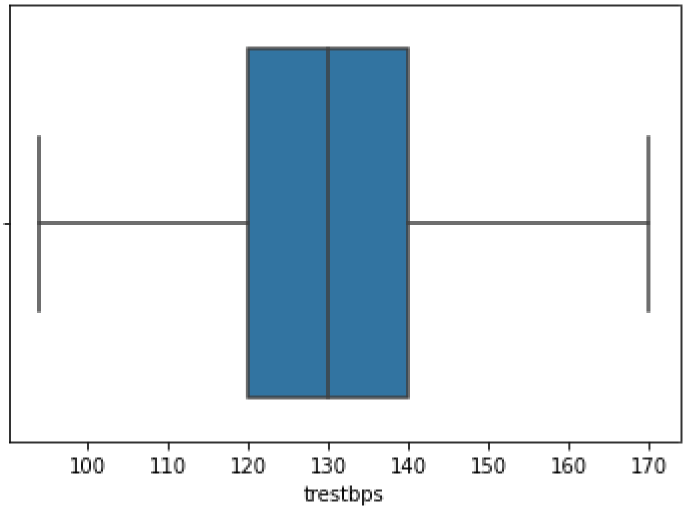
In [24]:
```
trestbps_mean=df.loc[(df["trestbps"]>=lowertail) & (df["trestbps"]<=uppertail),"tre
trestbps_mean
```

Out[24]:
```
130.0952380952381
```

In [25]:
```
df["trestbps"]=np.where(df["trestbps"]>uppertail,trestbps_mean,df["trestbps"])
```

In [26]:
```
sns.boxplot(df["trestbps"])
```

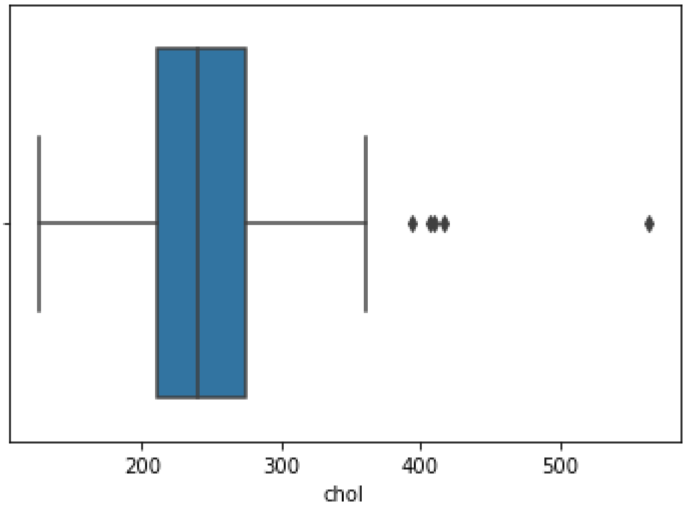
Out[26]:
```
<AxesSubplot:xlabel='trestbps'>
```



5) chol

```
In [27]: sns.boxplot(df["chol"]) # outliers need to handled
```

```
Out[27]: <AxesSubplot:xlabel='chol'>
```



```
In [28]: # IQR method

q1 = df["chol"].quantile(0.25)
q2 = df["chol"].quantile(0.50)
q3 = df["chol"].quantile(0.75)

IQR = q3-q1

uppertail = q3 + 1.5*IQR
lowertail = q1 - 1.5*IQR
```

```
In [29]: df["chol"].value_counts()
```

Out[29]:
```
204    6
197    6
234    6
269    5
254    5
      ..
284    1
224    1
167    1
276    1
131    1
Name: chol, Length: 152, dtype: int64
```

In [30]:
```
df.loc[df["chol"]>uppertail]
```

Out[30]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	targe
28	65	0	2	140.0	417	1	0	157	0	0.8	2	1	2	
85	67	0	2	115.0	564	0	0	160	0	1.6	1	0	3	
96	62	0	0	140.0	394	0	0	157	0	1.2	1	0	2	
220	63	0	0	150.0	407	0	0	154	0	4.0	1	3	3	
246	56	0	0	134.0	409	0	0	150	1	1.9	1	2	3	

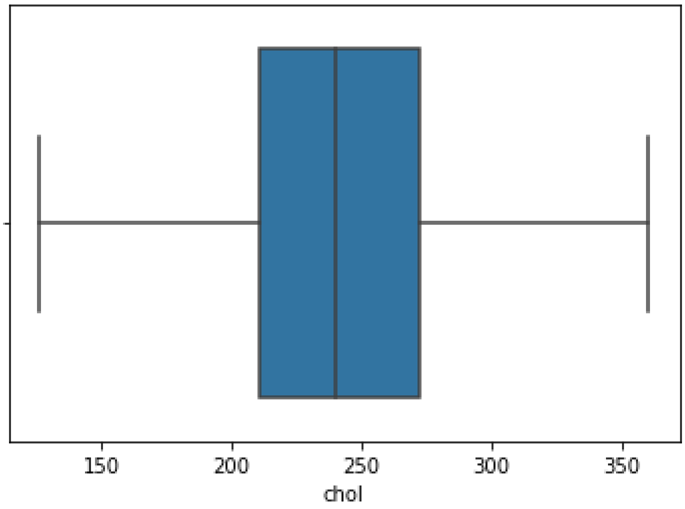
In [31]:
```
chol_mean = df.loc[df["chol"]<=uppertail,"chol"].mean()
chol_mean
```

Out[31]:
```
243.04362416107384
```

In [32]:
```
df["chol"]=np.where(df["chol"]>uppertail,chol_mean,df["chol"])
```

In [33]:
```
sns.boxplot(df["chol"])
```

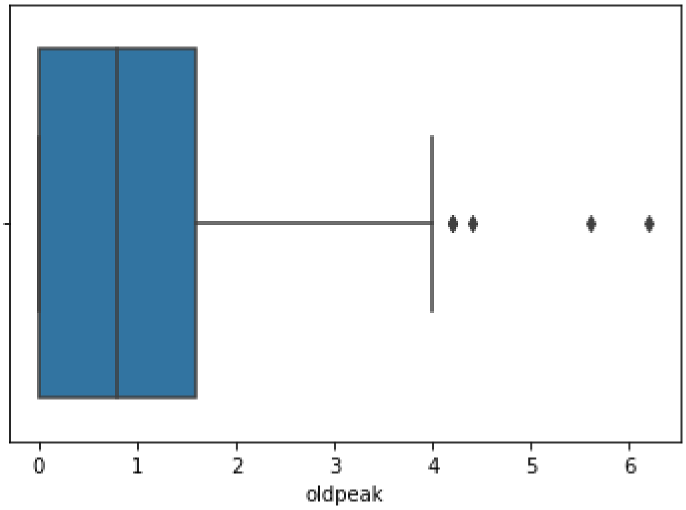
Out[33]:
```
<AxesSubplot:xlabel='chol'>
```



10) oldpeak

In [34]:
```
sns.boxplot(df["oldpeak"]) # outliers need to handled
```

Out[34]:
```
<AxesSubplot:xlabel='oldpeak'>
```



In [35]:

```
# IQR method

q1 = df["oldpeak"].quantile(0.25)
q2 = df["oldpeak"].quantile(0.50)
q3 = df["oldpeak"].quantile(0.75)

IQR = q3-q1

uppertail = q3 + 1.5*IQR
lowertail = q1 - 1.5*IQR
```

In [36]:

```
df.loc[df["oldpeak"]>uppertail]
```

Out[36]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	ta
101	59	1	3	130.095238	270.0	0	0	145	0	4.2	0	0	3	
204	62	0	0	160.000000	164.0	0	0	145	0	6.2	0	3	3	
221	55	1	0	140.000000	217.0	0	1	111	1	5.6	0	0	3	
250	51	1	0	140.000000	298.0	0	1	122	1	4.2	1	3	3	
291	58	1	0	114.000000	318.0	0	2	140	0	4.4	0	3	1	

In [37]:

```
oldpeak_mean = df.loc[df["oldpeak"]<=uppertail,"oldpeak"].mean()
oldpeak_mean
```

Out[37]:

```
0.9744966442953017
```

In [38]:

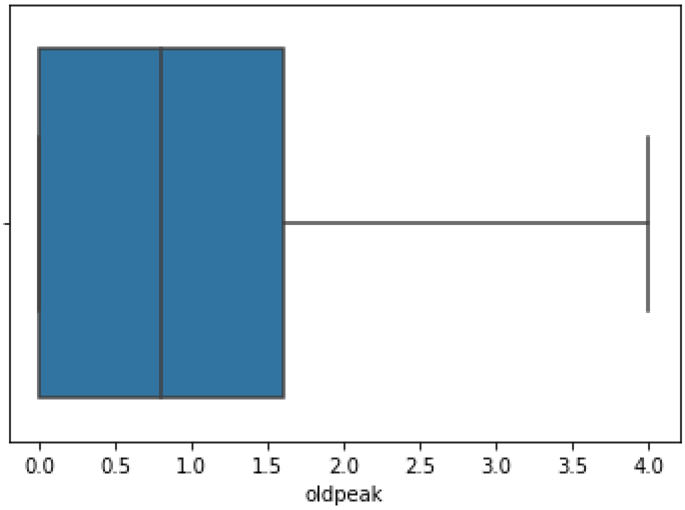
```
df["oldpeak"]=np.where(df["oldpeak"]>uppertail,oldpeak_mean,df["oldpeak"])
```

In [39]:

```
sns.boxplot(df["oldpeak"])
```

Out[39]:

```
<AxesSubplot:xlabel='oldpeak'>
```

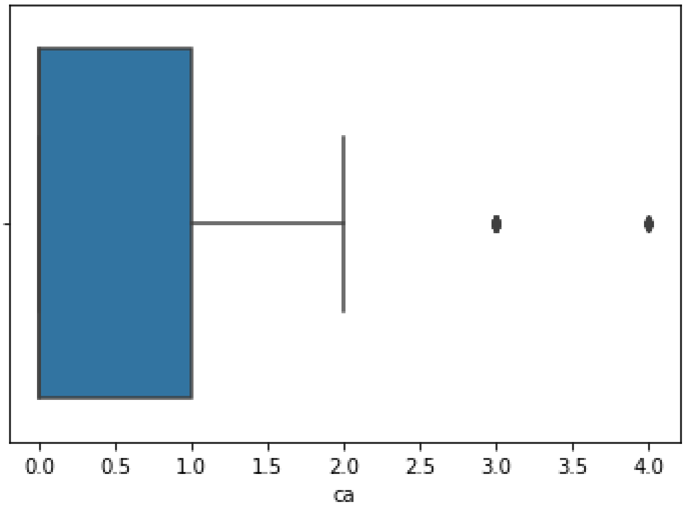


```
In [ ]:
```

12) ca

```
In [40]: sns.boxplot(df["ca"]) # outliers need to handled
```

```
Out[40]: <AxesSubplot:xlabel='ca'>
```



```
In [41]: # IQR method

q1 = df["ca"].quantile(0.25)
q2 = df["ca"].quantile(0.50)
q3 = df["ca"].quantile(0.75)

IQR = q3-q1

uppertail = q3 + 1.5*IQR
lowertail = q1 - 1.5*IQR
```

```
In [42]: df.loc[df["ca"]>uppertail]
```

Out[42]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
52	62	1	2	130.0	231.000000	0	1	146	0	1.800000	1	3	3
92	52	1	2	138.0	223.000000	0	1	169	0	0.000000	2	4	2
97	52	1	0	108.0	233.000000	1	1	147	0	0.100000	2	3	3
99	53	1	2	130.0	246.000000	1	0	173	0	0.000000	2	3	2
158	58	1	1	125.0	220.000000	0	1	144	0	0.400000	1	4	3
163	38	1	2	138.0	175.000000	0	1	173	0	0.000000	2	4	2
164	38	1	2	138.0	175.000000	0	1	173	0	0.000000	2	4	2
165	67	1	0	160.0	286.000000	0	0	108	1	1.500000	1	3	2
181	65	0	0	150.0	225.000000	0	0	114	0	1.000000	1	3	3
191	58	1	0	128.0	216.000000	0	0	131	1	2.200000	1	3	3
204	62	0	0	160.0	164.000000	0	0	145	0	0.974497	0	3	3
208	49	1	2	120.0	188.000000	0	1	139	0	2.000000	1	3	3
217	63	1	0	130.0	330.000000	1	0	132	1	1.800000	2	3	3
220	63	0	0	150.0	243.043624	0	0	154	0	4.000000	1	3	3
231	57	1	0	165.0	289.000000	1	0	124	0	1.000000	1	3	3
234	70	1	0	130.0	322.000000	0	0	109	0	2.400000	1	3	2
238	77	1	0	125.0	304.000000	0	0	162	1	0.000000	2	3	2
247	66	1	1	160.0	246.000000	0	1	120	1	0.000000	1	3	1
249	69	1	2	140.0	254.000000	0	0	146	0	2.000000	1	3	3
250	51	1	0	140.0	298.000000	0	1	122	1	0.974497	1	3	3
251	43	1	0	132.0	247.000000	1	0	143	1	0.100000	1	4	3
252	62	0	0	138.0	294.000000	1	1	106	0	1.900000	1	3	2
255	45	1	0	142.0	309.000000	0	0	147	1	0.000000	1	3	3
267	49	1	2	118.0	149.000000	0	0	126	0	0.800000	2	3	2
291	58	1	0	114.0	318.000000	0	2	140	0	0.974497	0	3	1

In [43]:

```
ca_mean = df.loc[df["ca"]<=uppertail,"ca"].mean()
ca_mean
```

Out[43]:

```
0.5071942446043165
```

In [44]:

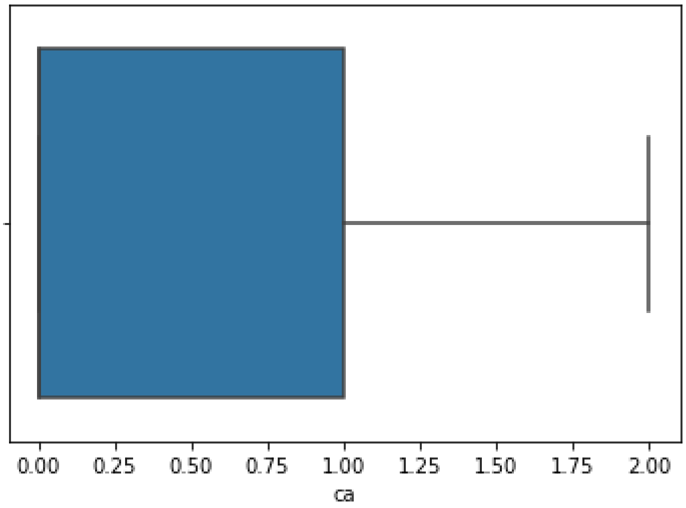
```
df["ca"]=np.where(df["ca"]>uppertail,ca_mean,df["ca"])
```

In [45]:

```
sns.boxplot(df["ca"])
```

Out[45]:

```
<AxesSubplot:xlabel='ca'>
```



In [ ]:

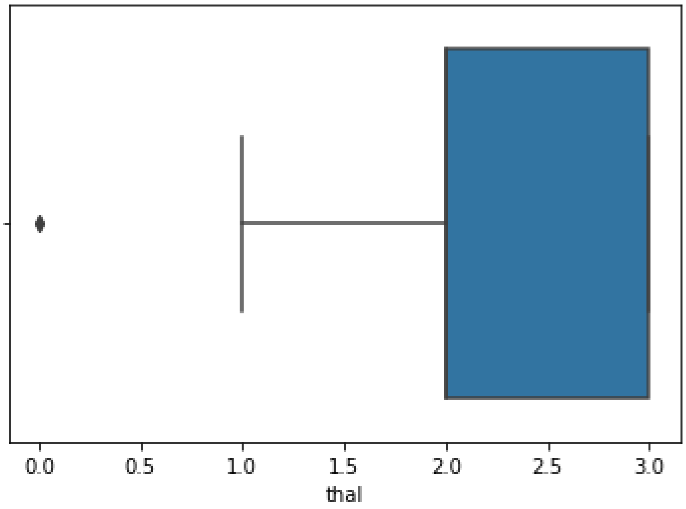
13) thal

In [46]:

```
sns.boxplot(df["thal"]) # outliers need to handled
```

Out[46]:

```
<AxesSubplot:xlabel='thal'>
```



In [47]:

```
# IQR method

q1 = df["thal"].quantile(0.25)
q2 = df["thal"].quantile(0.50)
q3 = df["thal"].quantile(0.75)

IQR = q3-q1

uppertail = q3 + 1.5*IQR
lowertail = q1 - 1.5*IQR
```

In [48]:

```
df.loc[df["thal"]>uppertail]
```

Out[48]:

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target

In [49]:

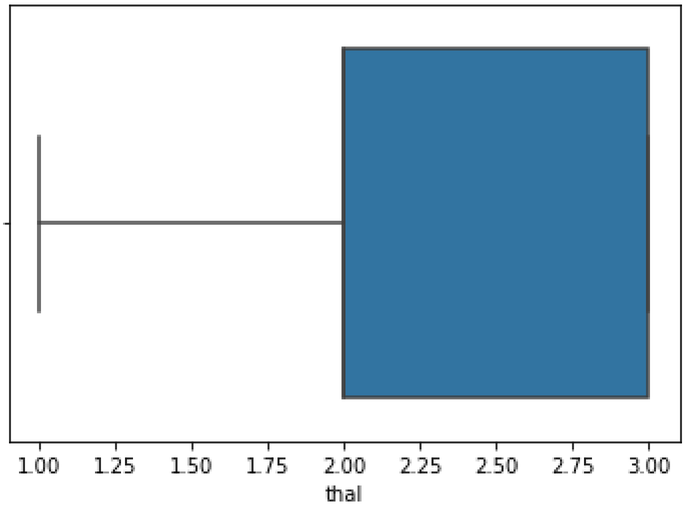
```
thal_mean = df.loc[(df["thal"]>=lowertail)&(df["thal"]<=uppertail),"thal"].mean()
thal_mean
```

Out[49]:
```
2.3289036544850497
```

In [50]:
```
df["thal"]=np.where(df["thal"]<lowertail,thal_mean,df["thal"])
```

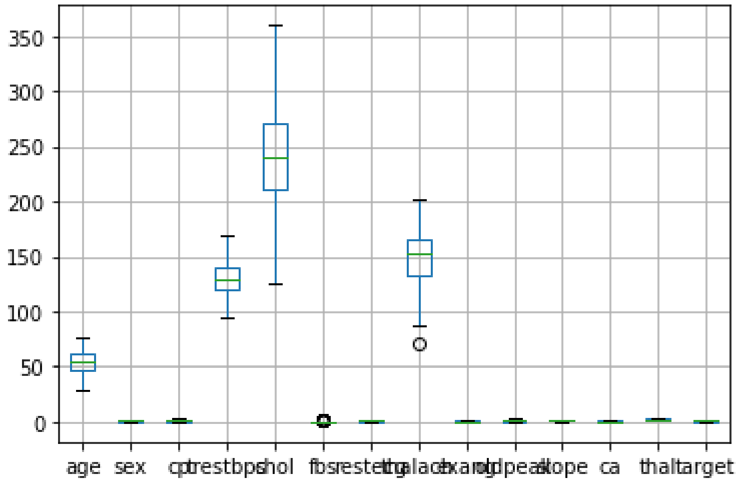
In [51]:
```
sns.boxplot(df["thal"])
```

Out[51]:
```
<AxesSubplot:xlabel='thal'>
```



In [52]:
```
df.boxplot()
```

Out[52]:
```
<AxesSubplot:>
```



In [53]:
```
df.columns
```

Out[53]:
```
Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
      dtype='object')
```

In [54]:
```
df.dtypes
```

Out[54]:

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

In [55]:

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

Out[55]:

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

Train_Test_Split

In [56]:

```
x=df.drop("target",axis=1)
y=df["target"]
```

In [57]:

```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=4
```

Model Evaluation (Logistic regression)

In [58]:

```
lg_model = LogisticRegression()
```

In [59]:

```
lg_model.fit(x_train,y_train)
```

Out[59]:

```
▾ LogisticRegression
LogisticRegression()
```

training and testing

In [60]:

```
# training

y_pred_train = lg_model.predict(x_train)

cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix\n",cnf_matrix)

Accuracy = accuracy_score(y_train,y_pred_train)
print("Accuracy",Accuracy)

clf_report = classification_report(y_train,y_pred_train)
print("Classification report\n",clf_report)
```

```
Confusion Matrix
 [[ 84  19]
 [  7 117]]
Accuracy 0.8854625550660793
Classification report
               precision    recall  f1-score   support

           0       0.92      0.82      0.87       103
           1       0.86      0.94      0.90       124

    accuracy                           0.89       227
   macro avg       0.89      0.88      0.88       227
weighted avg       0.89      0.89      0.88       227
```

In [61]:

```
# testing

y_pred_test = lg_model.predict(x_test)

cnf_matrix = confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix\n",cnf_matrix)

Accuracy = accuracy_score(y_test,y_pred_test)
print("Accuracy",Accuracy)

clf_report = classification_report(y_test,y_pred_test)
print("Classification report\n",clf_report)
```

```
Confusion Matrix
 [[22 13]
 [ 2 39]]
Accuracy 0.8026315789473685
Classification report
               precision    recall  f1-score   support

           0       0.92      0.63      0.75        35
           1       0.75      0.95      0.84        41

    accuracy                           0.80        76
   macro avg       0.83      0.79      0.79        76
weighted avg       0.83      0.80      0.80        76
```

Decision tree Model

In [62]:

```
# now lets make another model using decision tree
```

In [ ]:

```

```

In [63]:

```
from sklearn.tree import DecisionTreeClassifier,plot_tree
from sklearn.model_selection import train_test_split,GridSearchCV,RandomizedSearch
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score
```

In [64]:

```
df = pd.read_csv("heart_disease_data.csv")
df.head()
```

Out[64]:

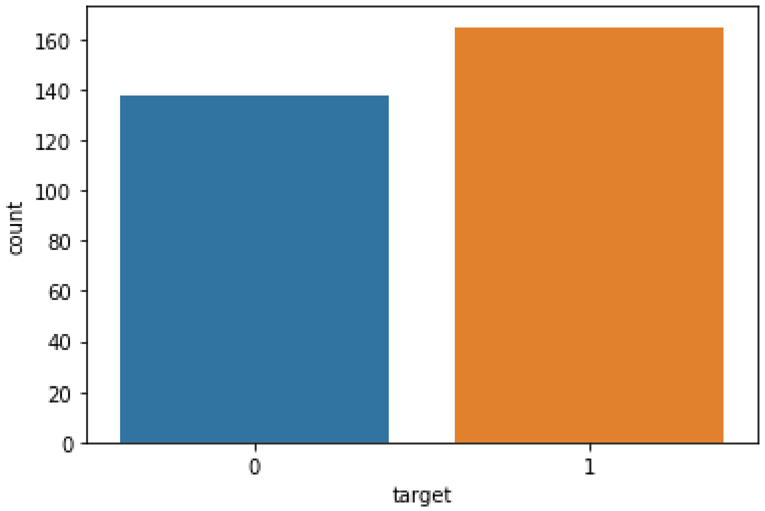
	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

In [65]:

```
sns.countplot(df["target"])
```

Out[65]:

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



In [66]:

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

Out[66]:

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

In [67]:

```
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
```

In [68]:
```
df.isna().sum()
```

Out[68]:
```
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
```

train test split

In [69]:
```
x = df.drop("target",axis=1)
y = df["target"]
x_train,x_test,y_train,y_test = train_test_split(x,y,train_size=0.8,random_state=4
```

In [ ]:
```
```

Model Selection

In [70]:
```
dt_clf = DecisionTreeClassifier()
dt_clf.fit(x_train,y_train)
```

Out[70]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

Model Evaluation

In [71]:
```
# Training
y_pred_train  = dt_clf.predict(x_train)
cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("confusion metrics\n",cnf_matrix)

accuracy = accuracy_score(y_train,y_pred_train)
print("accuracy\n",accuracy)

clf_report = classification_report(y_train,y_pred_train)
print("classification report\n",clf_report)
```

```
confusion metrics
 [[110   0]
 [  0 132]]
accuracy
 1.0
classification report
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       110
           1       1.00      1.00      1.00       132

    accuracy                           1.00       242
   macro avg       1.00      1.00      1.00       242
weighted avg       1.00      1.00      1.00       242
```

In [72]:

```
# Testing
y_pred_test  = dt_clf.predict(x_test)
cnf_matrix = confusion_matrix(y_test,y_pred_test)
print("confusion metrics\n",cnf_matrix)

accuracy = accuracy_score(y_test,y_pred_test)
print("accuracy\n",accuracy)

clf_report = classification_report(y_test,y_pred_test)
print("classification report\n",clf_report)
```

```
confusion metrics
 [[18 10]
 [ 7 26]]
accuracy
 0.7213114754098361
classification report
               precision    recall  f1-score   support

           0       0.72      0.64      0.68        28
           1       0.72      0.79      0.75        33

    accuracy                           0.72        61
   macro avg       0.72      0.72      0.72        61
weighted avg       0.72      0.72      0.72        61
```

In [ ]:

Lets check accuracy with Hyper parameter

In [75]:

```
dt_model = DecisionTreeClassifier()
hyper_para = {"criterion" :['gini',"entropy"],
              "max_depth":np.arange(2,8),
        "min_samples_split":np.arange(3,20),
        "min_samples_leaf":np.arange(3,15),
             }
gscv_dt_clf = GridSearchCV(dt_model,hyper_para,cv=5)
gscv_dt_clf.fit(x_train,y_train)
```

Out[75]:

```
▸              GridSearchCV
▸ estimator: DecisionTreeClassifier
      ▸ DecisionTreeClassifier
```

In [ ]:

In [76]:

```
gscv_dt_clf.best_estimator_
```

Out[76]:

```
▾                     DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', max_depth=7, min_samples_leaf
=4,
                       min_samples_split=7)
```

In [77]:

```
dt_clf = DecisionTreeClassifier(criterion='entropy', max_depth=7, min_samples_leaf=
                       min_samples_split=7)
dt_clf.fit(x_train,y_train)
```

Out[77]:

```
▾                     DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', max_depth=7, min_samples_leaf
=4,
                       min_samples_split=7)
```

Training and Testing

In [78]:

```
# Training
y_pred_train  = dt_clf.predict(x_train)
cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("confusion metrics\n",cnf_matrix)

accuracy = accuracy_score(y_train,y_pred_train)
print("accuracy\n",accuracy)

clf_report = classification_report(y_train,y_pred_train)
print("classification report\n",clf_report)
```

```
confusion metrics
 [[100  10]
 [  9 123]]
accuracy
 0.9214876033057852
classification report
               precision    recall  f1-score   support

           0       0.92      0.91      0.91       110
           1       0.92      0.93      0.93       132

    accuracy                           0.92       242
   macro avg       0.92      0.92      0.92       242
weighted avg       0.92      0.92      0.92       242
```

In [79]:

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

Out[79]:

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

In [80]:

```
# Testing
y_pred_test  = dt_clf.predict(x_test)
cnf_matrix = confusion_matrix(y_test,y_pred_test)
print("confusion metrics\n",cnf_matrix)
```

```
accuracy = accuracy_score(y_test,y_pred_test)
print("accuracy\n",accuracy)

clf_report = classification_report(y_test,y_pred_test)
print("classification report\n",clf_report)
```

```
confusion metrics
 [[17 11]
 [ 4 29]]
accuracy
 0.7540983606557377
classification report
               precision    recall  f1-score   support

           0       0.81      0.61      0.69        28
           1       0.72      0.88      0.79        33

    accuracy                           0.75        61
   macro avg       0.77      0.74      0.74        61
weighted avg       0.76      0.75      0.75        61
```

Also we will check accyarcy with pre-pruning and post pruning

In [ ]:

Pruning

In [81]:

```
d_tree_model = DecisionTreeClassifier(random_state=45,ccp_alpha=0.0)
d_tree_model.fit(x_train,y_train)
```

Out[81]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=45)
```

In [82]:

```
#training

y_pred_train = d_tree_model.predict(x_train)

cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("confusion matrix\n",cnf_matrix)

accuracy = accuracy_score(y_train,y_pred_train)
print("accuracy\n",accuracy)

clf_report = classification_report(y_train,y_pred_train)
print("classification report\n",clf_report)
```

```
confusion matrix
 [[110   0]
 [  0 132]]
accuracy
 1.0
classification report
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       110
           1       1.00      1.00      1.00       132

    accuracy                           1.00       242
   macro avg       1.00      1.00      1.00       242
weighted avg       1.00      1.00      1.00       242
```

In [ ]:

```

```

In [83]:

```
# Testing
y_pred_test  = d_tree_model.predict(x_test)
cnf_matrix = confusion_matrix(y_test,y_pred_test)
print("confusion metrics\n",cnf_matrix)

accuracy = accuracy_score(y_test,y_pred_test)
print("accuracy\n",accuracy)

clf_report = classification_report(y_test,y_pred_test)
print("classification report\n",clf_report)
```

```
confusion metrics
 [[16 12]
 [ 5 28]]
accuracy
 0.7213114754098361
classification report
               precision    recall  f1-score   support

           0       0.76      0.57      0.65        28
           1       0.70      0.85      0.77        33

    accuracy                           0.72        61
   macro avg       0.73      0.71      0.71        61
weighted avg       0.73      0.72      0.71        61
```

Post Pruning method

In [84]:

```
dict_result = d_tree_model.cost_complexity_pruning_path(x_train,y_train)
ccp_alphas_list = dict_result["ccp_alphas"]
ccp_alphas_list
```

Out[84]:

```
array([0.        , 0.00385675, 0.00404431, 0.00407056, 0.0050632 ,
       0.00522877, 0.00550964, 0.00661157, 0.00688705, 0.00688705,
       0.0072314 , 0.00768603, 0.00782949, 0.00991736, 0.00991736,
       0.01056015, 0.01114265, 0.01115702, 0.01126972, 0.01398368,
       0.01496458, 0.02568847, 0.0377135 , 0.04855589, 0.1419503 ])
```

In [85]:

```
train_accuracy_list = []
test_accuracy_list = []
for ccp_alpha_v in ccp_alphas_list:
    dt_clf_1 = DecisionTreeClassifier(random_state=45,ccp_alpha=ccp_alpha_v)
    dt_clf_1.fit(x_train,y_train)
    train_accuracy_list.append(dt_clf_1.score(x_train,y_train))
    test_accuracy_list.append(dt_clf_1.score(x_test,y_test))
train_accuracy_list
```

Out[85]:

```
[1.0,
 0.9958677685950413,
 0.9917355371900827,
 0.987603305785124,
 0.9793388429752066,
 0.9710743801652892,
 0.9628099173553719,
 0.9586776859504132,
 0.9504132231404959,
 0.9504132231404959,
 0.9462809917355371,
 0.9380165289256198,
 0.9338842975206612,
 0.9256198347107438,
 0.9132231404958677,
 0.8884297520661157,
 0.8884297520661157,
 0.8842975206611571,
 0.8636363636363636,
 0.859504132231405,
 0.8347107438016529,
 0.8347107438016529,
 0.7768595041322314,
 0.768595041322314,
 0.5454545454545454]
```

In [86]:

```
test_accuracy_list
```

Out[86]:

```
[0.7213114754098361,
 0.7213114754098361,
 0.7213114754098361,
 0.7213114754098361,
 0.7049180327868853,
 0.7377049180327869,
 0.7377049180327869,
 0.7377049180327869,
 0.7377049180327869,
 0.7377049180327869,
 0.7377049180327869,
 0.7377049180327869,
 0.7377049180327869,
 0.7377049180327869,
 0.7377049180327869,
 0.7540983606557377,
 0.7540983606557377,
 0.7704918032786885,
 0.7704918032786885,
 0.7868852459016393,
 0.7868852459016393,
 0.7868852459016393,
 0.7377049180327869,
 0.7213114754098361,
 0.5409836065573771]
```

In [87]:

```
np.where(test_accuracy_list == np.max(test_accuracy_list))
```

Out[87]:

```
(array([19, 20, 21], dtype=int64),)
```

In [88]:

```
test_accuracy_list[19]
```

Out[88]:
```
0.7868852459016393
```

In [89]:
```
test_accuracy_list[20]
```

Out[89]:
```
0.7868852459016393
```

In [90]:
```
test_accuracy_list[21]
```

Out[90]:
```
0.7868852459016393
```

Lets check results with Random Forest

In [91]:
```
from sklearn.ensemble import RandomForestClassifier
```

Train Test Split

In [92]:
```
x = df.drop("target",axis=1)
y = df["target"]
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=42
```

Model Training

In [93]:
```
rf_model = RandomForestClassifier()
rf_model.fit(x_train,y_train)
```

Out[93]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [94]:
```
#Training
y_pred_train = rf_model.predict(x_train)

cnf_metrics = confusion_matrix(y_train,y_pred_train)
print("confusion metrics\n",cnf_metrics)

accuracy = accuracy_score(y_train,y_pred_train)
print("accuracy",accuracy)
clf_report = classification_report(y_train,y_pred_train)
print("clf_report\n",clf_report)
```

```
confusion metrics
 [[110   0]
 [  0 132]]
accuracy 1.0
clf_report
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       110
           1       1.00      1.00      1.00       132

    accuracy                           1.00       242
   macro avg       1.00      1.00      1.00       242
weighted avg       1.00      1.00      1.00       242
```

In [95]:
```
#Testing
y_pred_test = rf_model.predict(x_test)
```

```
cnf_metrics = confusion_matrix(y_test,y_pred_test)
print("confusion metrics\n",cnf_metrics)

accuracy = accuracy_score(y_test,y_pred_test)
print("accuracy",accuracy)
clf_report = classification_report(y_test,y_pred_test)
print("clf_report\n",clf_report)
```

```
confusion metrics
 [[19  9]
 [ 2 31]]
accuracy 0.819672131147541
clf_report
               precision    recall  f1-score   support

           0       0.90      0.68      0.78        28
           1       0.78      0.94      0.85        33

    accuracy                           0.82        61
   macro avg       0.84      0.81      0.81        61
weighted avg       0.83      0.82      0.82        61
```

HyperParamter Tuning

In [96]:

```
rf_model = RandomForestClassifier()
hyperparamter = {"n_estimators":np.arange(10,20),
                "criterion":["gini","entropy"],
                "max_depth" :np.arange(4,10),
                "min_samples_split":np.arange(3,10),
                "min_samples_leaf":np.arange(3,10),
                "max_features":["sqrt", "log2"],
                "random_state":[41,42,43,44,45],
                "oob_score":[True]}
rdscv = RandomizedSearchCV(rf_model,hyperparamter,cv=4)
rdscv.fit(x_train,y_train)
```

Out[96]:

```
▸        RandomizedSearchCV
▸ estimator: RandomForestClassifier
     ▸ RandomForestClassifier
```

In [97]:

```
rf_model = rdscv.best_estimator_
```

In [98]:

```
rf_model.fit(x_train,y_train)
```

Out[98]:

```
▾                    RandomForestClassifier
RandomForestClassifier(max_depth=8, min_samples_leaf=6, min_samples_split
=5,
                         n_estimators=14, oob_score=True, random_state=44)
```

In [99]:

```
#Training
y_pred_train = rf_model.predict(x_train)

cnf_metrics = confusion_matrix(y_train,y_pred_train)
print("confusion metrics\n",cnf_metrics)
```

```
accuracy = accuracy_score(y_train,y_pred_train)
print("accuracy",accuracy)
clf_report = classification_report(y_train,y_pred_train)
print("clf_report\n",clf_report)
```

```
confusion metrics
 [[ 92  18]
 [ 10 122]]
accuracy 0.8842975206611571
clf_report
               precision    recall  f1-score   support

           0       0.90      0.84      0.87       110
           1       0.87      0.92      0.90       132

    accuracy                           0.88       242
   macro avg       0.89      0.88      0.88       242
weighted avg       0.89      0.88      0.88       242
```

In [100…

```
#Testing
y_pred_test = rf_model.predict(x_test)

cnf_metrics = confusion_matrix(y_test,y_pred_test)
print("confusion metrics\n",cnf_metrics)

accuracy = accuracy_score(y_test,y_pred_test)
print("accuracy",accuracy)
clf_report = classification_report(y_test,y_pred_test)
print("clf_report\n",clf_report)
```

```
confusion metrics
 [[19  9]
 [ 1 32]]
accuracy 0.8360655737704918
clf_report
               precision    recall  f1-score   support

           0       0.95      0.68      0.79        28
           1       0.78      0.97      0.86        33

    accuracy                           0.84        61
   macro avg       0.87      0.82      0.83        61
weighted avg       0.86      0.84      0.83        61
```

SVM

In [101…

```
from sklearn.svm import SVC

from sklearn.model_selection import train_test_split,GridSearchCV,RandomizedSearchC
from sklearn.preprocessing import MinMaxScaler,StandardScaler
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
import seaborn as sns
import matplotlib.pyplot as plt
```

In [102…

```
df.head()
```

Out[102]:

	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

Train Test Split

In [103…

```
x = df.drop("target",axis=1)
y = df["target"]
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=42
```

Model Training

In [104…

```
svc_model = SVC()
svc_model.fit(x_train,y_train)
```

Out[104]:

```
▾ SVC
SVC()
```

Training and Testing

In [105…

```
#training

y_pred_train = svc_model.predict(x_train)

cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix\n",cnf_matrix)

Accuracy = accuracy_score(y_train,y_pred_train)
print("ACCURACY",Accuracy)

clf_report = classification_report(y_train,y_pred_train)
print("Classification Report\n",clf_report)
```

```
Confusion Matrix
 [[ 51  59]
 [ 25 107]]
ACCURACY 0.6528925619834711
Classification Report
               precision    recall  f1-score   support

           0       0.67      0.46      0.55       110
           1       0.64      0.81      0.72       132

    accuracy                           0.65       242
   macro avg       0.66      0.64      0.63       242
weighted avg       0.66      0.65      0.64       242
```

In [106…

```
#testing
```

```
y_pred_test = svc_model.predict(x_test)

cnf_matrix = confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix\n",cnf_matrix)

Accuracy = accuracy_score(y_test,y_pred_test)
print("ACCURACY",Accuracy)

clf_report = classification_report(y_test,y_pred_test)
print("Classification Report\n",clf_report)
```

```
Confusion Matrix
 [[14 14]
 [ 7 26]]
ACCURACY 0.6557377049180327
Classification Report
               precision    recall  f1-score   support

           0       0.67      0.50      0.57        28
           1       0.65      0.79      0.71        33

    accuracy                           0.66        61
   macro avg       0.66      0.64      0.64        61
weighted avg       0.66      0.66      0.65        61
```

Lets check result with scaling

In [126…

```
df.head()
```

Out[126]:

	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

In [127…

```
x_df = df.drop("target",axis=1)
y = df["target"]
```

In [128…

```
normal = MinMaxScaler()
array = normal.fit_transform(x_df)
x_normal_df = pd.DataFrame(array,columns=x_df.columns)
x_normal_df
```

Out[128]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope
0	0.708333	1.0	1.000000	0.481132	0.244292	1.0	0.0	0.603053	0.0	0.370968	0.0
1	0.166667	1.0	0.666667	0.339623	0.283105	0.0	0.5	0.885496	0.0	0.564516	0.0
2	0.250000	0.0	0.333333	0.339623	0.178082	0.0	0.0	0.770992	0.0	0.225806	1.0
3	0.562500	1.0	0.333333	0.245283	0.251142	0.0	0.5	0.816794	0.0	0.129032	1.0
4	0.583333	0.0	0.000000	0.245283	0.520548	0.0	0.5	0.702290	1.0	0.096774	1.0
...	...	...	...	...	...	...	...	...	...	...	...
298	0.583333	0.0	0.000000	0.433962	0.262557	0.0	0.5	0.396947	1.0	0.032258	0.5
299	0.333333	1.0	1.000000	0.150943	0.315068	0.0	0.5	0.465649	0.0	0.193548	0.5
300	0.812500	1.0	0.000000	0.471698	0.152968	1.0	0.5	0.534351	0.0	0.548387	0.5
301	0.583333	1.0	0.000000	0.339623	0.011416	0.0	0.5	0.335878	1.0	0.193548	0.5
302	0.583333	0.0	0.333333	0.339623	0.251142	0.0	0.0	0.786260	0.0	0.000000	0.5

303 rows × 13 columns

In [129…

```
x = x_normal_df.copy()
y = df["target"]
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=4
```

Model Training

In [130…

```
svc_model = SVC()
svc_model.fit(x_train,y_train)
```

Out[130]:

```
▾ SVC
SVC()
```

Training and Testing

In [131…

```
#training

y_pred_train = svc_model.predict(x_train)

cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix\n",cnf_matrix)

Accuracy = accuracy_score(y_train,y_pred_train)
print("ACCURACY",Accuracy)

clf_report = classification_report(y_train,y_pred_train)
print("Classification Report\n",clf_report)
```

```
Confusion Matrix
 [[ 86  17]
 [  7 117]]
ACCURACY 0.8942731277533039
Classification Report
               precision    recall  f1-score   support

           0       0.92      0.83      0.88       103
           1       0.87      0.94      0.91       124

    accuracy                           0.89       227
   macro avg       0.90      0.89      0.89       227
weighted avg       0.90      0.89      0.89       227
```

In [132…

```python
#testing

y_pred_test = svc_model.predict(x_test)

cnf_matrix = confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix\n",cnf_matrix)

Accuracy = accuracy_score(y_test,y_pred_test)
print("ACCURACY",Accuracy)

clf_report = classification_report(y_test,y_pred_test)
print("Classification Report\n",clf_report)
```

```
Confusion Matrix
 [[22 13]
 [ 4 37]]
ACCURACY 0.7763157894736842
Classification Report
               precision    recall  f1-score   support

           0       0.85      0.63      0.72        35
           1       0.74      0.90      0.81        41

    accuracy                           0.78        76
   macro avg       0.79      0.77      0.77        76
weighted avg       0.79      0.78      0.77        76
```

SVM with Hyperparameter

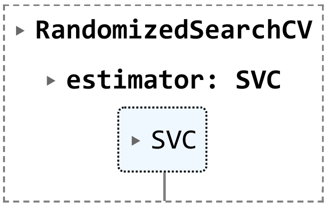
In [146…

```python
svc_model = SVC()
```

In [147…

```python
hyperparameter = {"kernel":["linear","poly","sigmoid","rbf"],
                 "C":np.arange(1,100)}
rscv = RandomizedSearchCV(svc_model,hyperparameter,cv=5)
rscv.fit(x_train,y_train)
```

Out[147]:



▸ RandomizedSearchCV

▸ estimator: SVC

▸ SVC

In [148…

```python
rscv.best_estimator_
```

Out[148]:

```
▾           SVC
SVC(C=76, kernel='linear')
```

In [149…

```
svc_model_1 = SVC(C=76, kernel='linear')
svc_model_1.fit(x_train,y_train)
```

Out[149]:

```
▾           SVC
SVC(C=76, kernel='linear')
```

Training and Testing

In [150…

```
#Training Data
y_pred_train = svc_model_1.predict(x_train)
cnf_metrix = confusion_matrix(y_train,y_pred_train)
print("confusion matrix\n",cnf_metrix)
accuracy = accuracy_score(y_train,y_pred_train)
print("accuarcy",accuracy)
clf_report = classification_report(y_train,y_pred_train)
print("classification report",clf_report)
```

```
confusion matrix
 [[ 80  23]
 [ 10 114]]
accuarcy 0.8546255506607929
classification report               precision    recall  f1-score   support

           0       0.89      0.78      0.83       103
           1       0.83      0.92      0.87       124

    accuracy                           0.85       227
   macro avg       0.86      0.85      0.85       227
weighted avg       0.86      0.85      0.85       227
```

In [151…

```
#Testing
y_pred = svc_model_1.predict(x_test)
cnf_metrix = confusion_matrix(y_test,y_pred)
print("confusion matrix\n",cnf_metrix)
accuracy = accuracy_score(y_test,y_pred)
print("accuarcy",accuracy)
clf_report = classification_report(y_test,y_pred)
print("classification report",clf_report)
```

```
confusion matrix
 [[20 15]
 [ 2 39]]
accuarcy 0.7763157894736842
classification report               precision    recall  f1-score   support

           0       0.91      0.57      0.70        35
           1       0.72      0.95      0.82        41

    accuracy                           0.78        76
   macro avg       0.82      0.76      0.76        76
weighted avg       0.81      0.78      0.77        76
```

In [ ]:

Lets see the accuracy we've got by the models

In [152…

```
df1 = pd.DataFrame({"MODEL":["Logistic Regression","Decision tree","Decision tree
                             "Random Forest","Random Forest with Hyperparameter","S
                    "Training Accuracy(%)":[88.5,100,92.1,100,85.9,100,88.4,65.2,89
                    "Testing Accuracy(%)":[80.2,72.1,75.4,72.1,78.6,81.9,83.6,65.5,
df1
```

Out[152]:

	MODEL	Training Accuracy(%)	Testing Accuracy(%)
0	Logistic Regression	88.5	80.2
1	Decision tree	100.0	72.1
2	Decision tree with Hyperparameter	92.1	75.4
3	Pruning	100.0	72.1
4	Post Pruning	85.9	78.6
5	Random Forest	100.0	81.9
6	Random Forest with Hyperparameter	88.4	83.6
7	SVM	65.2	65.5
8	SVM with Scaling	89.4	77.6
9	SVM with Hyperparameter	85.4	77.6

In [ ]:

```
Here we got the best accuracy by SVM with Hyperparameter >>svc_model_1
Training = 85.9%
Testing = 83.6%
```

In [ ]:

User Input Function

In [159…

```
#User input function

input_data = (44,0,2,118,242,0,1,149,0,0.3,1,1,2)

# change input data to numpy array
input_data_as_numpy_array = np.asarray(input_data)

# reshaping the numpy array
input_data_reshape = input_data_as_numpy_array.reshape(1,-1)

prediction = lg_model.predict(input_data_reshape)
print(prediction)

if (prediction[0]==0):
    print("Person is not having Heart Disease")
else:
    print("Person is having Heart Disease")
```

```
[1]
Person is having Heart Disease
```

In [ ]: