

# Minor Project - Heart Disease Prediction using Machine Learning

## Importing the required libraries

```
In [1]: import numpy as np # to work for arrays, Linear algebra, fourier transformation
import pandas as pd # data analysis and manipulation of tabular data
import matplotlib.pyplot as plt # for plotting the graphs
import seaborn as sns # for making statistical graphs

%matplotlib inline

import os
print(os.listdir())

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

```
[ '.ipynb_checkpoints', '2_minor_proj_ppt.pptx', 'archive.zip', 'Decision Tree and random forest.png', 'Decision Tree.png', 'edit1.ipynb', 'edit1.pdf', 'edit2.ipynb', 'edit2.pdf', 'edit3.ipynb', 'edit3.pdf', 'final_minor_report.docx', 'flow chart.jpg', 'Heart-Disease-Prediction-using-Machine-Learning', 'heart-disease-prediction-using-machine-learning-IJERTV9IS04061420200510-84272-1pfgh18-with-cover-page-v2.pdf', 'heart.csv', 'Heart_Disease_Prediction_using_Machine_L.pdf', 'Heart_Disease_Prediction_using_Machine_L_1.pdf', 'Heart_Disease_Prediction_using_Machine_L_2.pdf', 'heart_disease_uci.csv', 'knn.png', 'logistic.jpeg', 'Manish_Bhatt_2451137_ProjectIV.docx', 'Manish_Bhatt_2451137_ProjectIV.pdf', 'Mini_Project_Report_On_Heart_Disease_Pre(1).pdf', 'MINOR PROJECT REPORT.docx', 'MINOR PROJECT REPORT.pdf', 'Minor_Project_Report_2.pdf', 'minor_proj_ppt.pptx', 'MP_1.ipynb', 'mp_1.pdf', 'Naive Bayes.png', 'ProposalHeartDiseasePredictionSystem.pdf', 'Random Forest.png', 'rp2.pdf', 'svm.png', 'XG Boost.png', 'XG Boost.ppm', '~$2_minor_proj_ppt.pptx']
```

## Importing the Dataset

```
In [2]: data = pd.read_csv(r"C:\Users\Asus\Desktop\Rohan\Semester 5\Minor Proj\heart.csv")
```

```
In [3]: type(data)
```

```
Out[3]: pandas.core.frame.DataFrame
```

```
In [4]: data.shape
```

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

```
In [5]: data.head(5)
```

```
Out[5]:
```

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

```
In [6]: data.sample(5)
```

```
Out[6]:
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slo
114	55	1	1	130	262	0	1	155	0	0.0	
247	66	1	1	160	246	0	1	120	1	0.0	
182	61	0	0	130	330	0	0	169	0	0.0	
213	61	0	0	145	307	0	0	146	1	1.0	
83	52	1	3	152	298	1	1	178	0	1.2	

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

```
Out[7]:
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slop
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.646860	0.116138	1.020627	0.000000
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905166	0.339873	1.059601	0.000000
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	0.000000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.000000	0.000000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	0.000000	0.000000	0.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	3.500000	0.000000

```
In [8]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
#   Column      Non-Null Count  Dtype
---  -
0   age         303 non-null   int64
1   sex         303 non-null   int64
2   cp          303 non-null   int64
3   trestbps    303 non-null   int64
4   chol        303 non-null   int64
5   fbs         303 non-null   int64
6   restecg     303 non-null   int64
7   thalach     303 non-null   int64
8   exang       303 non-null   int64
9   oldpeak     303 non-null   float64
10  slope       303 non-null   int64
11  ca          303 non-null   int64
12  thal        303 non-null   int64
13  target      303 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

### Understanding the columns of the dataset

```
In [9]: info = ["age", "1: male, 0: female", "chest pain type, 1: typical angina, 2: atypical angina, 3: non-anginal pain, 4: asymptomatic"]
```

```
for i in range(len(info)):
    print(data.columns[i]+":\t\t\t"+info[i])
```

```
age:          age
sex:          1: male, 0: female
cp:           chest pain type, 1: typical angina, 2: atypical angina,
3: non-anginal pain, 4: asymptomatic
trestbps:     resting blood pressure
chol:         serum cholestoral in mg/dl
fbs:          fasting blood sugar > 120 mg/dl
restecg:      resting electrocardiographic results (values 0,
1,2)
thalach:      maximum heart rate achieved
exang:        exercise induced angina
oldpeak:      oldpeak = ST depression induced by exercise rel
ative to rest
slope:        the slope of the peak exercise ST segment
ca:           number of major vessels (0-3) colored by flourosopy
thal:         thal: 3 = normal; 6 = fixed defect; 7 = reversable defe
ct
```

```
In [10]: data['target'].describe()
```

```
Out[10]: count      303.000000  
mean         0.544554  
std          0.498835  
min          0.000000  
25%          0.000000  
50%          1.000000  
75%          1.000000  
max          1.000000  
Name: target, dtype: float64
```

```
In [11]: data["target"].unique()
```

```
Out[11]: array([1, 0], dtype=int64)
```

**So this is a classification problem with the target variable having values '0' and '1'**

## **Now checking correlation between columns**

```
In [12]: print(data.corr()["target"].abs().sort_values(ascending=False))
```

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

## **Exploratory Data Analysis (EDA)**

**first analysing the target variable**

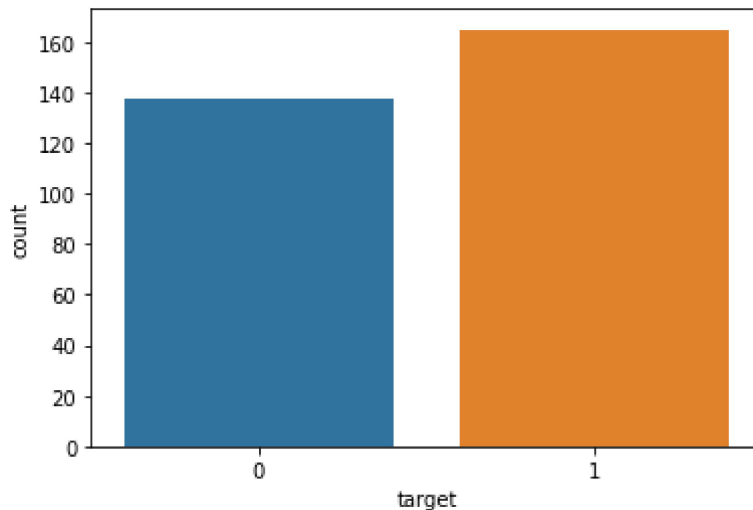
```
In [13]: y = data["target"]

sns.countplot(y)

target_temp = data.target.value_counts()

print(target_temp)
```

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



```
In [14]: print("Percentage of patience without heart problems: "+str(round(target_temp[0]*100,2)))
print("Percentage of patience with heart problems: "+str(round(target_temp[1]*100,2)))
```

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

**Now we will analyse 'sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', and 'thal' features**

**Analysing the 'Sex' feature**

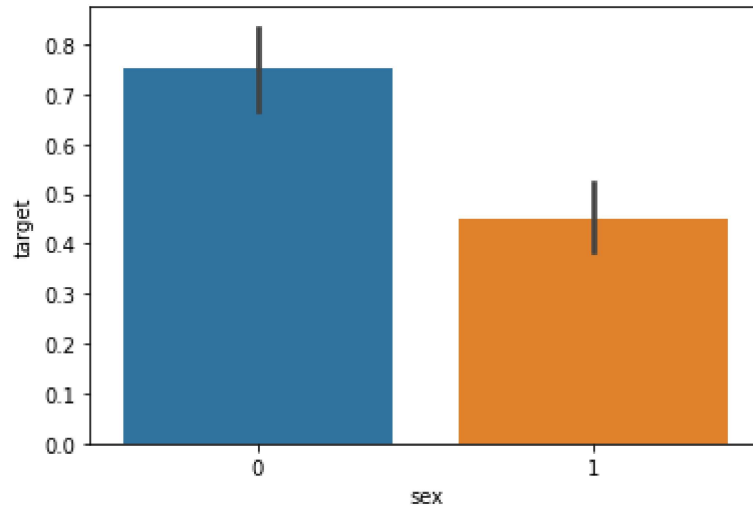
```
In [15]: data["sex"].unique()
```

```
Out[15]: array([1, 0], dtype=int64)
```

As expected, the 'sex' feature has 2 unique features

```
In [16]: # now plotting the sex ratio  
sns.barplot(data["sex"],y)
```

```
Out[16]: <AxesSubplot:xlabel='sex', ylabel='target'>
```



### Analysing the 'Chest Pain Type' feature

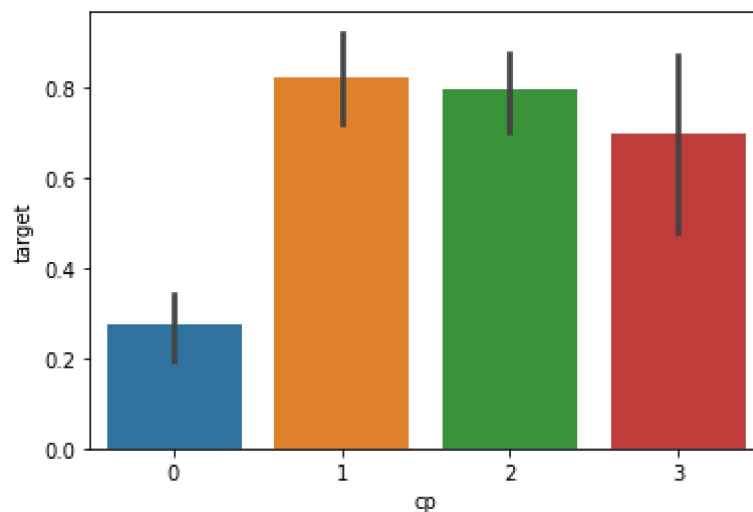
```
In [17]: data["cp"].unique()
```

```
Out[17]: array([3, 2, 1, 0], dtype=int64)
```

```
In [18]: #the cp feature has values from 0 to 3
```

```
In [19]: #plotting the graph  
sns.barplot(data["cp"],y)
```

```
Out[19]: <AxesSubplot:xlabel='cp', ylabel='target'>
```



## Analysing the 'Fasting Blood Sugar (FBS)' feacture

```
In [20]: data["fbs"].describe()
```

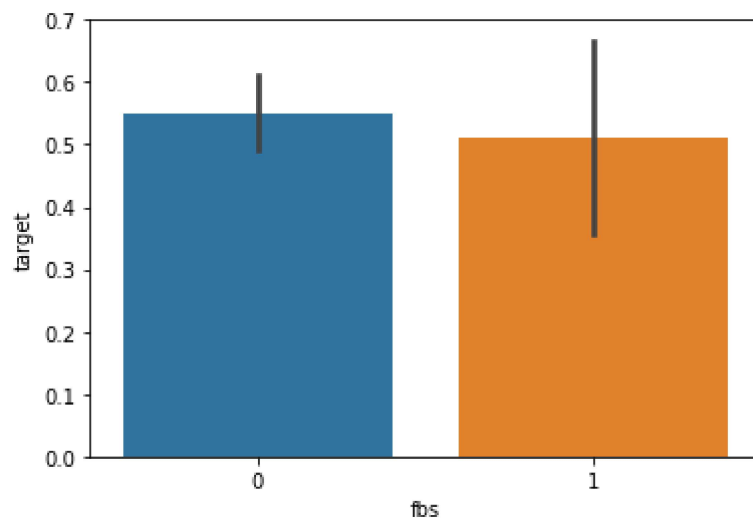
```
Out[20]: count    303.000000  
mean         0.148515  
std          0.356198  
min          0.000000  
25%          0.000000  
50%          0.000000  
75%          0.000000  
max          1.000000  
Name: fbs, dtype: float64
```

```
In [21]: data["fbs"].unique()
```

```
Out[21]: array([1, 0], dtype=int64)
```

```
In [22]: #plotting the graph  
sns.barplot(data["fbs"],y)
```

```
Out[22]: <AxesSubplot:xlabel='fbs', ylabel='target'>
```



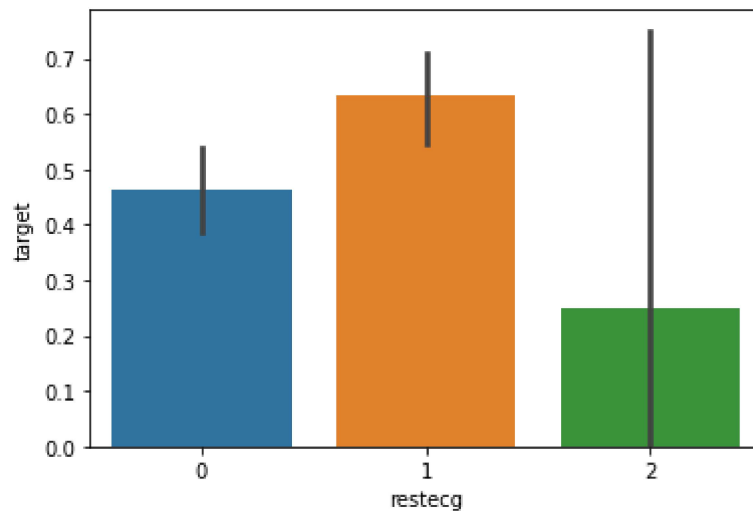
## Analysing the 'Resting Electro Cardiographic Results (restecg)' feacture

```
In [23]: data["restecg"].unique()
```

```
Out[23]: array([0, 1, 2], dtype=int64)
```

```
In [24]: sns.barplot(data["restecg"],y)
```

```
Out[24]: <AxesSubplot:xlabel='restecg', ylabel='target'>
```



```
In [25]: # we find out that the people with the restecg '1' and '0'  
# are much more likely to have a heart disease than with restecg '2'
```

### Analysing the 'Exercise - induced angina (exang)' feature

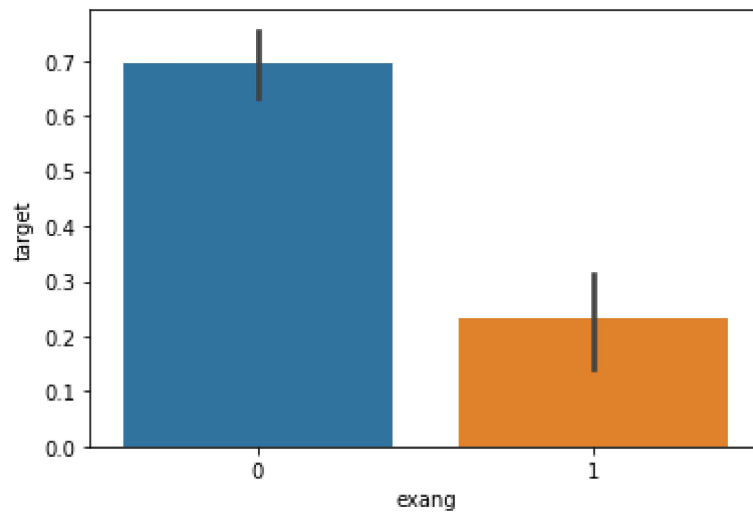
```
In [26]: data["exang"].unique()
```

```
Out[26]: array([0, 1], dtype=int64)
```



```
In [27]: sns.barplot(data["exang"],y)
```

```
Out[27]: <AxesSubplot:xlabel='exang', ylabel='target'>
```



```
In [28]: #people with exang =1 i.e. Exercise included angina are  
# much less likely to have heart problems
```

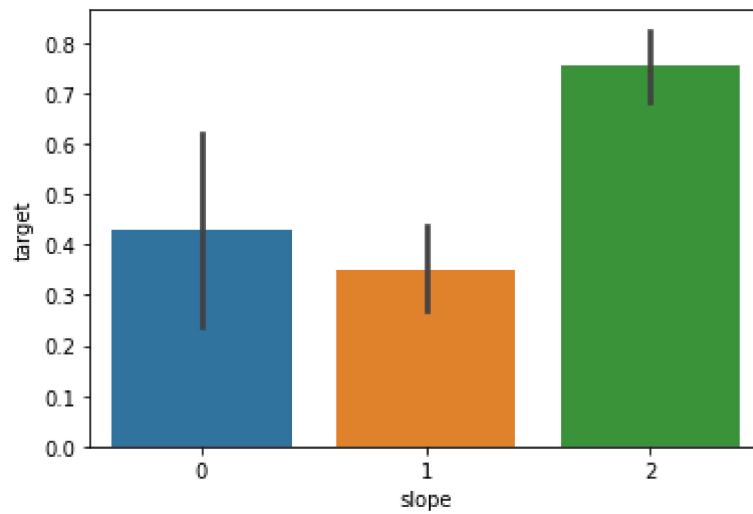
### **Analysing the 'Slope (slope of the peak exercise)' feacture**

```
In [29]: data["slope"].unique()
```

```
Out[29]: array([0, 2, 1], dtype=int64)
```

```
In [30]: sns.barplot(data["slope"],y)
```

```
Out[30]: <AxesSubplot:xlabel='slope', ylabel='target'>
```



```
In [31]: # So, slope '2' causes heart pain much more than  
# slope '0' and '1'
```

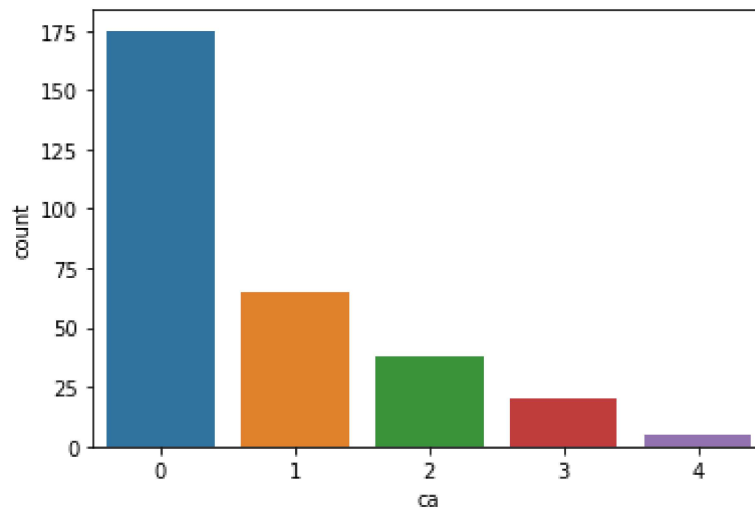
### Analysing the 'ca ( no of major vessels)' feacture

```
In [32]: data["ca"].unique()
```

```
Out[32]: array([0, 2, 1, 3, 4], dtype=int64)
```

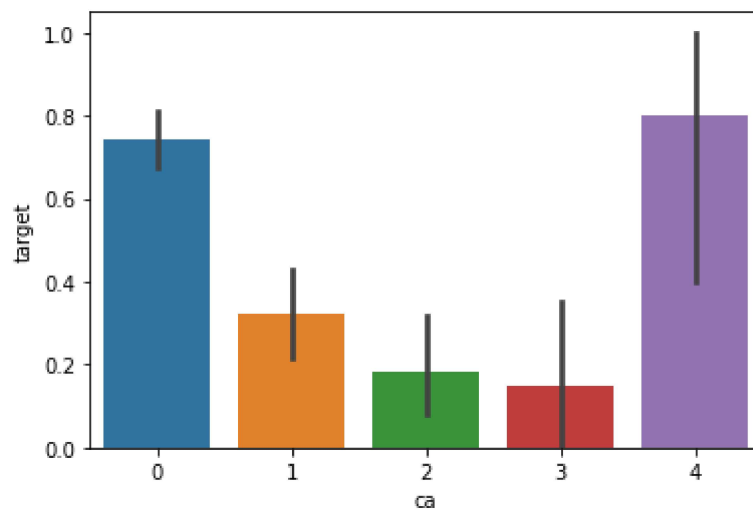
```
In [33]: sns.countplot(data["ca"])
```

```
Out[33]: <AxesSubplot:xlabel='ca', ylabel='count'>
```



```
In [34]: sns.barplot(data["ca"],y)
```

```
Out[34]: <AxesSubplot:xlabel='ca', ylabel='target'>
```



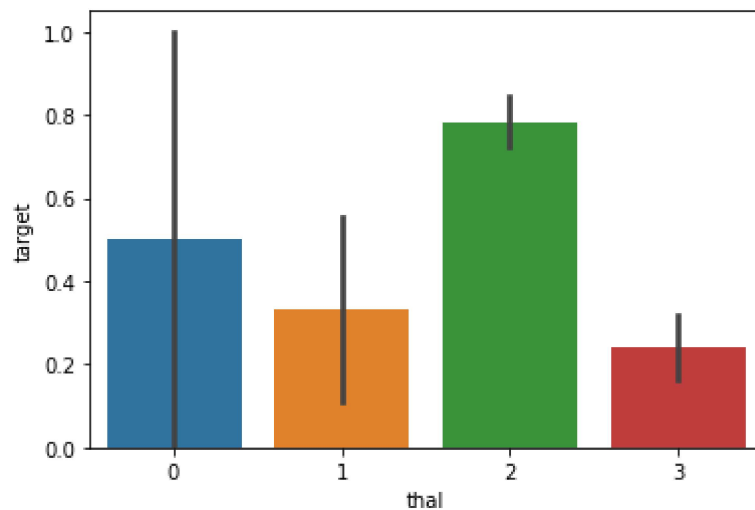
**Analysing the 'thal' feacture**

```
In [35]: data["thal"].unique()
```

```
Out[35]: array([1, 2, 3, 0], dtype=int64)
```

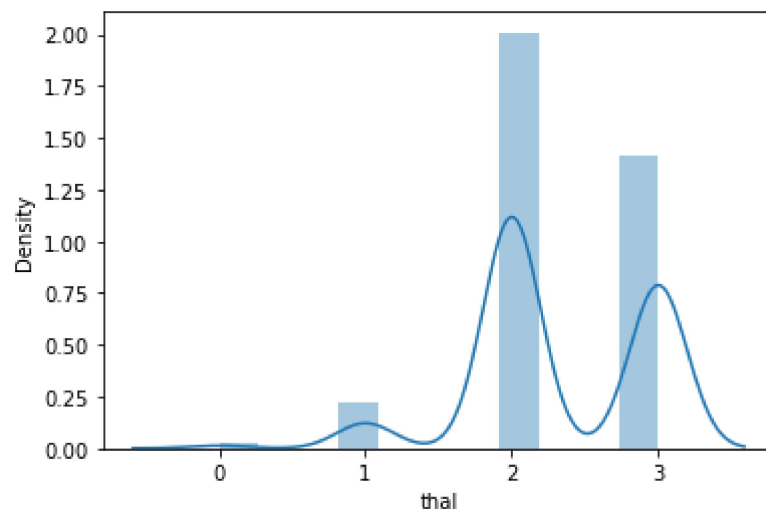
```
In [36]: sns.barplot(data["thal"],y)
```

```
Out[36]: <AxesSubplot:xlabel='thal', ylabel='target'>
```



```
In [37]: sns.distplot(data["thal"])
```

```
Out[37]: <AxesSubplot:xlabel='thal', ylabel='Density'>
```



## Training and Testing our model

```
In [38]: from sklearn.model_selection import train_test_split

predictors = data.drop("target",axis=1)
target = data["target"]

X_train,X_test,Y_train,Y_test = train_test_split(predictors,target,test_size=0.20)
```

```
In [39]: X_train.shape
```

```
Out[39]: (242, 13)
```

```
In [40]: X_test.shape
```

```
Out[40]: (61, 13)
```

```
In [41]: Y_train.shape
```

```
Out[41]: (242,)
```

```
In [42]: Y_test.shape
```

```
Out[42]: (61,)
```

### **V Model fitting**

```
In [43]: from sklearn.metrics import accuracy_score
```

### **Logistic Regression**

```
In [44]: from sklearn.linear_model import LogisticRegression

lr = LogisticRegression()

lr.fit(X_train,Y_train)

Y_pred_lr = lr.predict(X_test)
```

```
In [45]: Y_pred_lr.shape
```

```
Out[45]: (61,)
```

```
In [46]: score_lr = round(accuracy_score(Y_pred_lr,Y_test)*100,2)

print("The accuracy score achieved using Logistic Regression is: "+str(score_lr)+"
```

The accuracy score achieved using Logistic Regression is: 85.25 %

### Naive Bayes

```
In [47]: from sklearn.naive_bayes import GaussianNB

nb = GaussianNB()

nb.fit(X_train,Y_train)

Y_pred_nb = nb.predict(X_test)
```

```
In [48]: Y_pred_nb.shape
```

```
Out[48]: (61,)
```

```
In [49]: score_nb = round(accuracy_score(Y_pred_nb,Y_test)*100,2)

print("The accuracy score achieved using Naive Bayes is: "+str(score_nb)+" %")
```

The accuracy score achieved using Naive Bayes is: 85.25 %

### Support Vector Machine (SVM)

```
In [50]: from sklearn import svm

sv = svm.SVC(kernel='linear')

sv.fit(X_train, Y_train)

Y_pred_svm = sv.predict(X_test)
```

```
In [51]: Y_pred_svm.shape
```

```
Out[51]: (61,)
```

```
In [52]: score_svm = round(accuracy_score(Y_pred_svm,Y_test)*100,2)

print("The accuracy score achieved using Linear SVM is: "+str(score_svm)+" %")
```

The accuracy score achieved using Linear SVM is: 81.97 %

### K Nearest Neighbors (KNN)

```
In [53]: from sklearn.neighbors import KNeighborsClassifier
```

```
knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(X_train,Y_train)
Y_pred_knn=knn.predict(X_test)
```

```
In [54]: Y_pred_knn.shape
```

```
Out[54]: (61,)
```

```
In [55]: score_knn = round(accuracy_score(Y_pred_knn,Y_test)*100,2)

print("The accuracy score achieved using KNN is: "+str(score_knn)+" %")
```

The accuracy score achieved using KNN is: 67.21 %

### Decision Tree

```
In [56]: from sklearn.tree import DecisionTreeClassifier
```

```
max_accuracy = 0
```

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

```
#print(max_accuracy)
#print(best_x)
```

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

```
In [57]: print(Y_pred_dt.shape)
```

```
(61,)
```

```
In [58]: score_dt = round(accuracy_score(Y_pred_dt,Y_test)*100,2)

print("The accuracy score achieved using Decision Tree is: "+str(score_dt)+" %")
```

The accuracy score achieved using Decision Tree is: 81.97 %

## Random Forest

```
In [59]: from sklearn.ensemble import RandomForestClassifier

max_accuracy = 0

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

#print(max_accuracy)
#print(best_x)

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

```
In [60]: Y_pred_rf.shape
```

```
Out[60]: (61,)
```

```
In [61]: score_rf = round(accuracy_score(Y_pred_rf,Y_test)*100,2)

print("The accuracy score achieved using Decision Tree is: "+str(score_rf)+" %")
```

The accuracy score achieved using Decision Tree is: 90.16 %

```
In [65]: scores = [score_lr,score_nb,score_svm,score_knn,score_dt,score_rf]
algorithms = ["Logistic Regression","Naive Bayes","Support Vector Machine","K-Nea

for i in range(len(algorithms)):
    print("The accuracy score achieved using "+algorithms[i]+" is: "+str(scores[i])
```

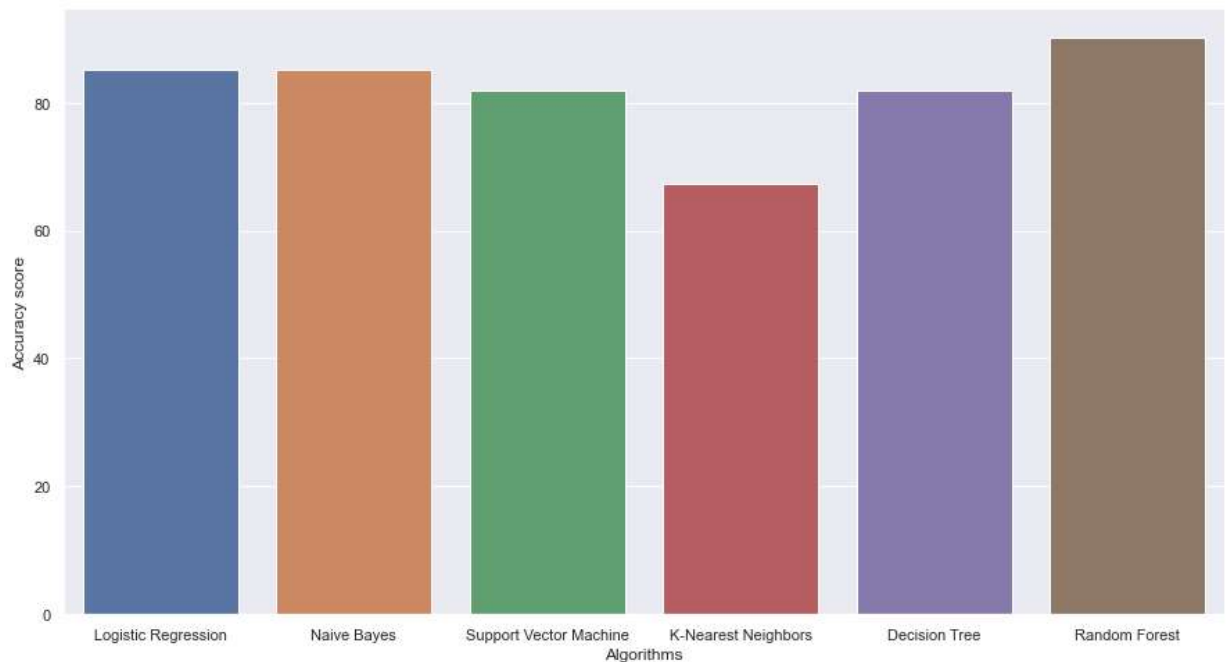
The accuracy score achieved using Logistic Regression is: 85.25 %  
The accuracy score achieved using Naive Bayes is: 85.25 %  
The accuracy score achieved using Support Vector Machine is: 81.97 %  
The accuracy score achieved using K-Nearest Neighbors is: 67.21 %  
The accuracy score achieved using Decision Tree is: 81.97 %  
The accuracy score achieved using Random Forest is: 90.16 %



```
In [66]: sns.set(rc={'figure.figsize':(15,8)})
plt.xlabel("Algorithms")
plt.ylabel("Accuracy score")

sns.barplot(algorithms,scores)
```

Out[66]: <AxesSubplot:xlabel='Algorithms', ylabel='Accuracy score'>



```
In [67]: import pickle
```

```
In [72]: filename='heart_pred_model'
pickle.dump(rf,open(filename,'wb'))
```

```
In [75]: loadedmodel = pickle.load(open(filename,'rb'))
loadedmodel.predict(X_test)
```

Out[75]: array([0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0,  
0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0,  
1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1], dtype=int64)

```
In [ ]:
```

