PROBLEM STATEMENT

- The leading cause of death in the developed world is heart disease. Therefore there needs to be work done to help prevent the risks of having a heart attack or stroke.
- Use this dataset to predict which patients are most likely to suffer from a heart disease in the near future using the features given.
- The "target" field refers to the presence of heart disease in the patient. It is integer valued from 0 (no presence) and 1.

CONTENT

- Attribute Information:
- age
- sex
- chest pain type (4 values)
- resting blood pressure
- serum cholesterol in mg/dl
- fasting blood sugar > 120 mg/dl
- resting electrocardiographic results (values 0,1,2)
- maximum heart rate achieved
- exercise induced angina
- oldpeak = ST depression induced by exercise relative to rest
- the slope of the peak exercise ST segment
- number of major vessels (0-3) colored by flourosopy
- thal: 3 = normal; 6 = fixed defect; 7 = reversable defect

DEFINITION AND WORKING

- Unlike regression where we predict a continuous number, we use classification to predict a category.
- Example:
  1. To identify customer segment
  2. To identify if a kid will pass or fail in examination
- Types of classification algorithms:
  - Linear models
    - Logistics Regression
    - Support Vector machines
  - Non-linear Models
    - K-nearest Neighbours(KNN)
    - Kernel SVM
    - Naïve Bayes

LOGISTIC REGRESSION:

- Logistic regression is one of the most popular Machine Learning algorithms, which comes under the Supervised Learning technique. It is used for predicting the categorical dependent variable using a given set of independent variables.
- Logistic regression predicts the output of a categorical dependent variable. Therefore the outcome must be a categorical or discrete value. It can be either Yes or No, 0 or 1, true or False, etc. but instead of giving the exact value as 0 and 1, **it gives the probabilistic values which lie between 0 and 1**.
- Logistic Regression is much similar to the Linear Regression except that how they are used. Linear Regression is used for solving Regression problems, whereas **Logistic regression is used for solving the classification problems**.

SUPPORT VECTOR MACHINE:

- A support vector machine (SVM) is a supervised machine learning model that uses classification algorithms for two-group classification problems.
- After giving an SVM model sets of labeled training data for each category, they're able to categorize new text.
- Applications:
  - **Face detection** – SVM classify parts of the image as a face and non-face and create a square boundary around the face.
  - **Handwriting recognition** – We use SVM to recognize handwritten characters used widely

STEP 1:IMPORT ALL THE NECESSARY LIBRARIES

- 1) numpy: To work with arrays
- 2) pandas: To work with csv files and data frames
- 3) matplotlib: To create charts using pyplot, define parameters using rcParams and color them with cm.rainbow
- 4) warnings: To ignore all warnings which might be showing up in the notebook due to past/future depreciation of a feature
- 5) train_test_split: To split the dataset into training and testing data
- 6) StandardScaler: To scale all the features, so that the Machine Learning model better adapts to the dataset.
- Import all the necessary Machine Learning algorithms.

```python
#impotring necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import rcParams
from matplotlib.cm import rainbow
import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
from sklearn.model_selection import  RandomizedSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

STEP 2: READ AND LOAD THE DATASET

```
#load the heart price prediction dataset
dataset = pd.read_csv("C:\ML and AI notes\heart_disease_predictor (1).csv")
```

```
#printing the dataset
dataset
```

	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	0.0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0.0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0.0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0.0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0.0	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
298	57	0	0	140	241	0	1	123	1	0.2	1	0.0	3	0
299	45	1	3	110	264	0	1	132	0	1.2	1	0.0	3	0
300	68	1	0	144	193	1	1	141	0	3.4	1	2.0	3	0
301	57	1	0	130	131	0	1	115	1	1.2	1	1.0	3	0
302	57	0	1	130	236	0	0	174	0	0.0	1	1.0	2	0

303 rows × 14 columns

STEP 3:DATA ANALYSIS

BRIEF INFO OF DATASET

```
#brief information about the dataset
dataset.info()
```

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

UNIQUE VALUES IN DATASET

```
#print number of unique values per column
dataset.nunique()
```

```
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
```

CHECKING NULL VALUES

```
#checking null values in the dataset
dataset.isnull().sum()
```

```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          1
thal        0
target      0
dtype: int64
```

From the above results it is seen that the 'ca' column is having 1 null value.Hence it is filled with the most occuring data (mode) in the 'ca' column

```
#handling missing data in ca
dataset['ca'] = dataset['ca'].fillna(dataset['ca'].mode())
```

CHECKING SKEWNESS

```
#checking skewness of the dataset
dataset.skew(axis=0,skipna=True)
```

```
age        -0.202463
sex        -0.791335
cp          0.484732
trestbps    0.713768
chol        1.143401
fbs         1.986652
restecg     0.162522
thalach    -0.537410
exang       0.742532
oldpeak     1.269720
slope      -0.508316
ca          1.326101
thal       -0.476722
target     -0.179821
dtype: float64
```

COMPLETE DATASET DESCRIPTION

Here the complete description like count , mean , standard deviation , minimum , qurtile ranges , maximum values are calculated

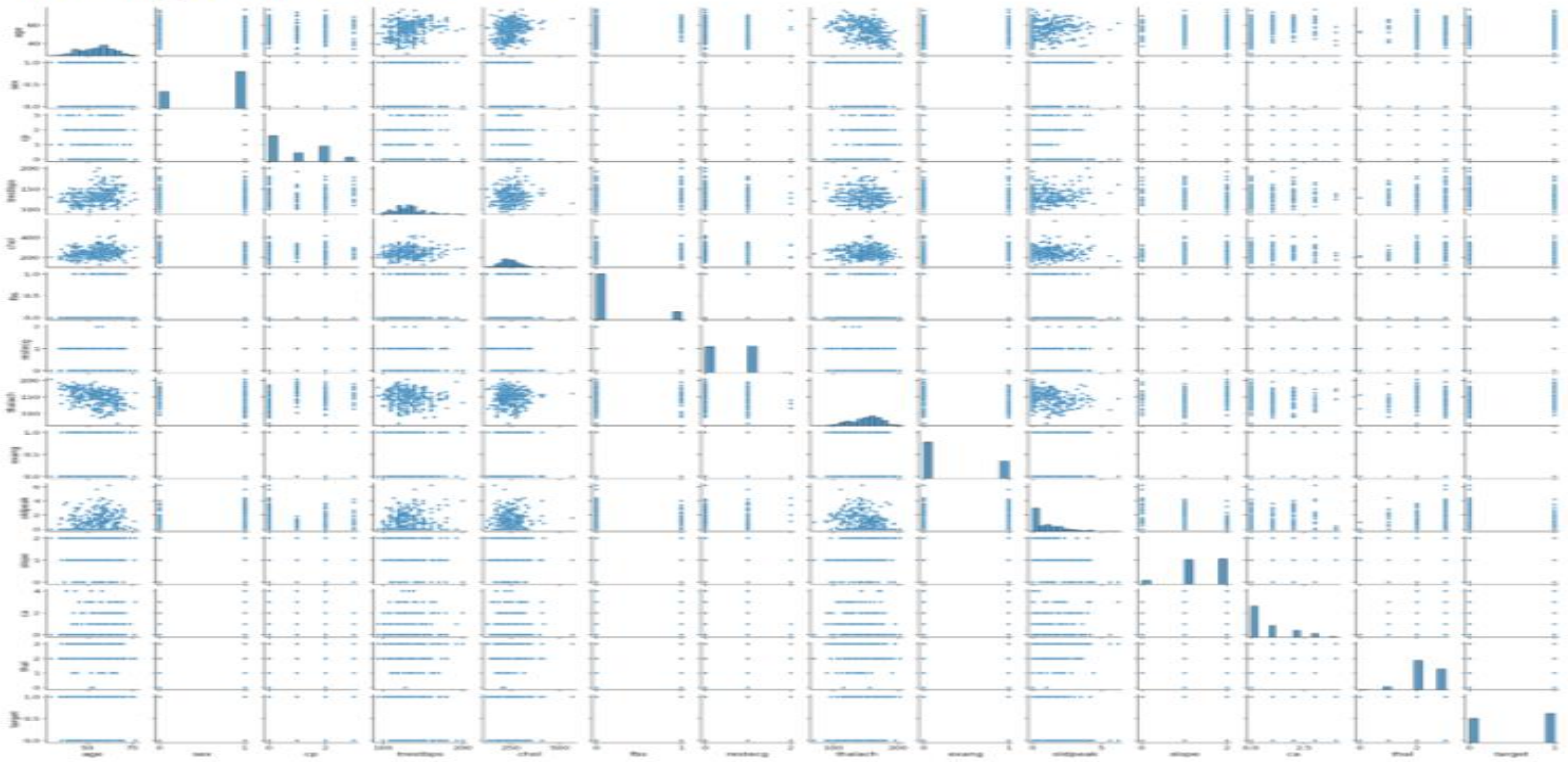
```
#complete desciption of the dataset
dataset.describe()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	302.000000	303.000000	303.000000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.646865	0.326733	1.039604	1.399340	0.721854	2.313531	0.544554
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469794	1.161075	0.616226	1.015880	0.612277	0.498835
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	1.000000	0.000000	2.000000	0.000000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.800000	1.000000	0.000000	2.000000	1.000000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.600000	2.000000	1.000000	3.000000	1.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000	4.000000	3.000000	1.000000

PAIRPLOT FOR THE COMPLETE DATASET

```
#pairplot for complete dataset
sns.pairplot(dataset)
```

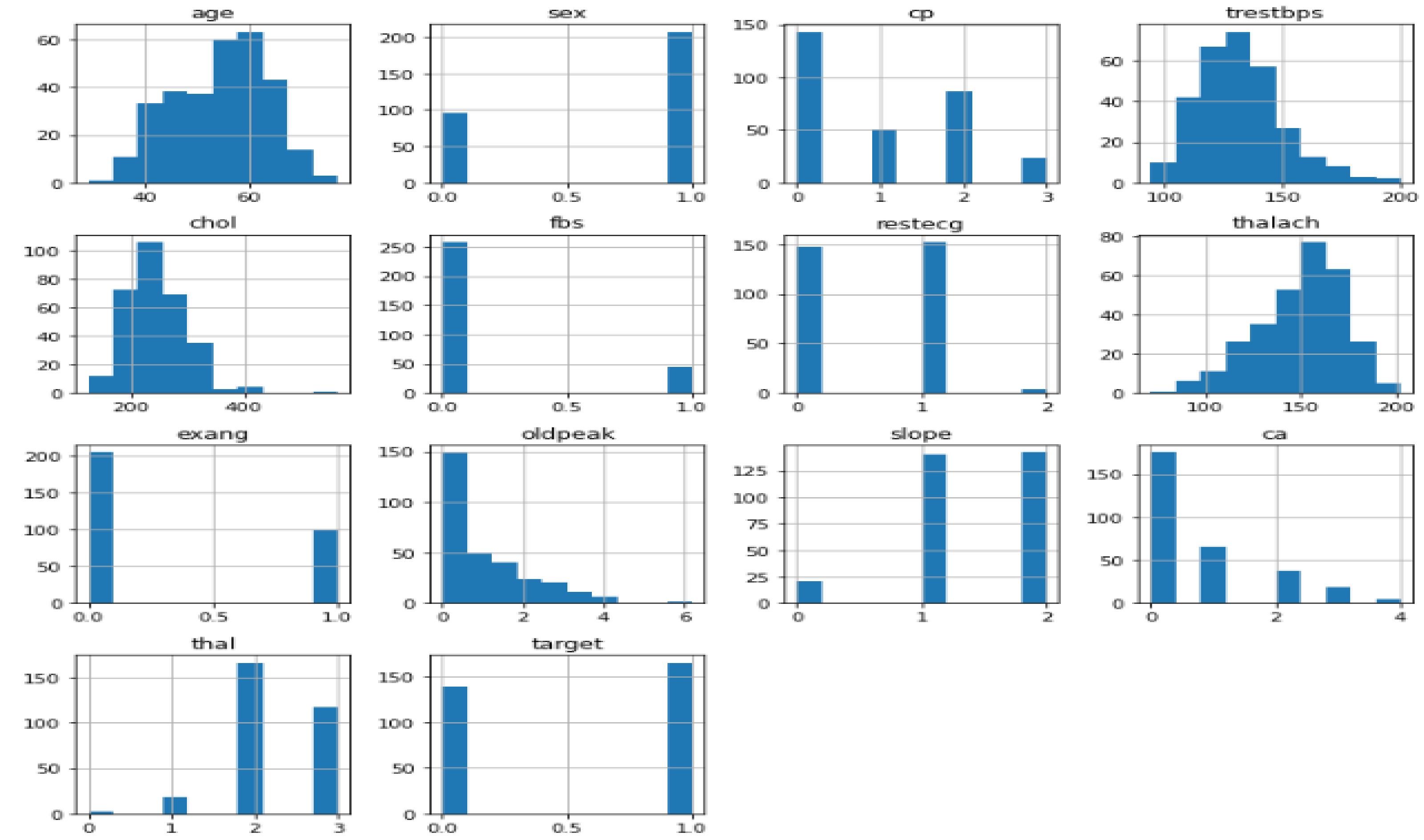
```
<seaborn.axisgrid.PairGrid at 0x24615e55610>
```



HISTOGRAM PLOT FOR THE DATASET

Here a Histogram for all columns in plotted. It shows how each feature and label is distributed along different ranges, which further confirms the need for scaling. Next, wherever you see discrete bars, it basically means that each of these is actually a categorical variable. We will need to handle these categorical variables before applying Machine Learning. Our target labels have two classes, 0 for no disease and 1 for disease.

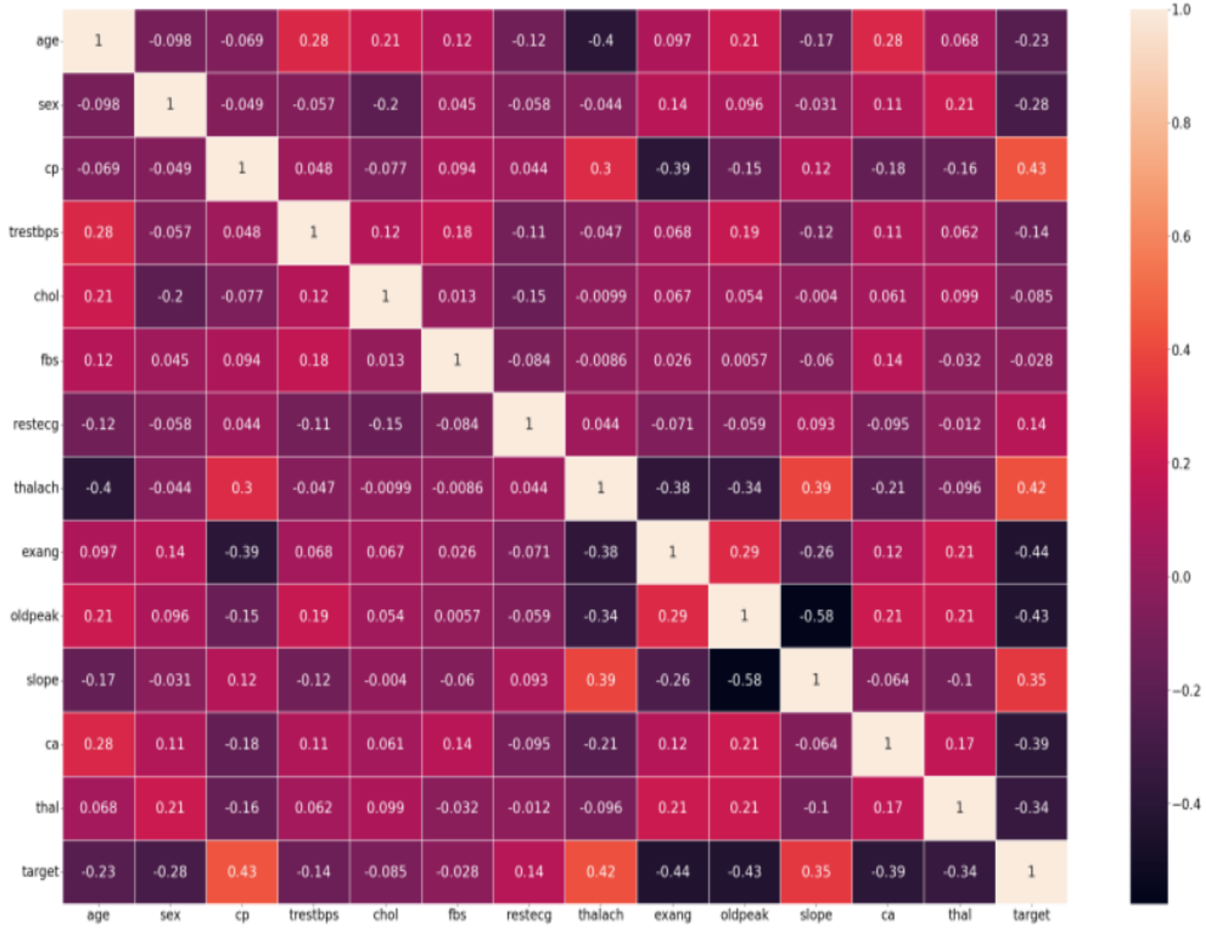
```
#histogram for the dataset
rcParams['figure.figsize'] = 10,10
dataset.hist()
plt.tight_layout()
```



HEATMAP FOR THE DATASET

Here a correlation between the features is analysed through a heat map.This tells us which feature is negatively correlated and which is positively correlated.

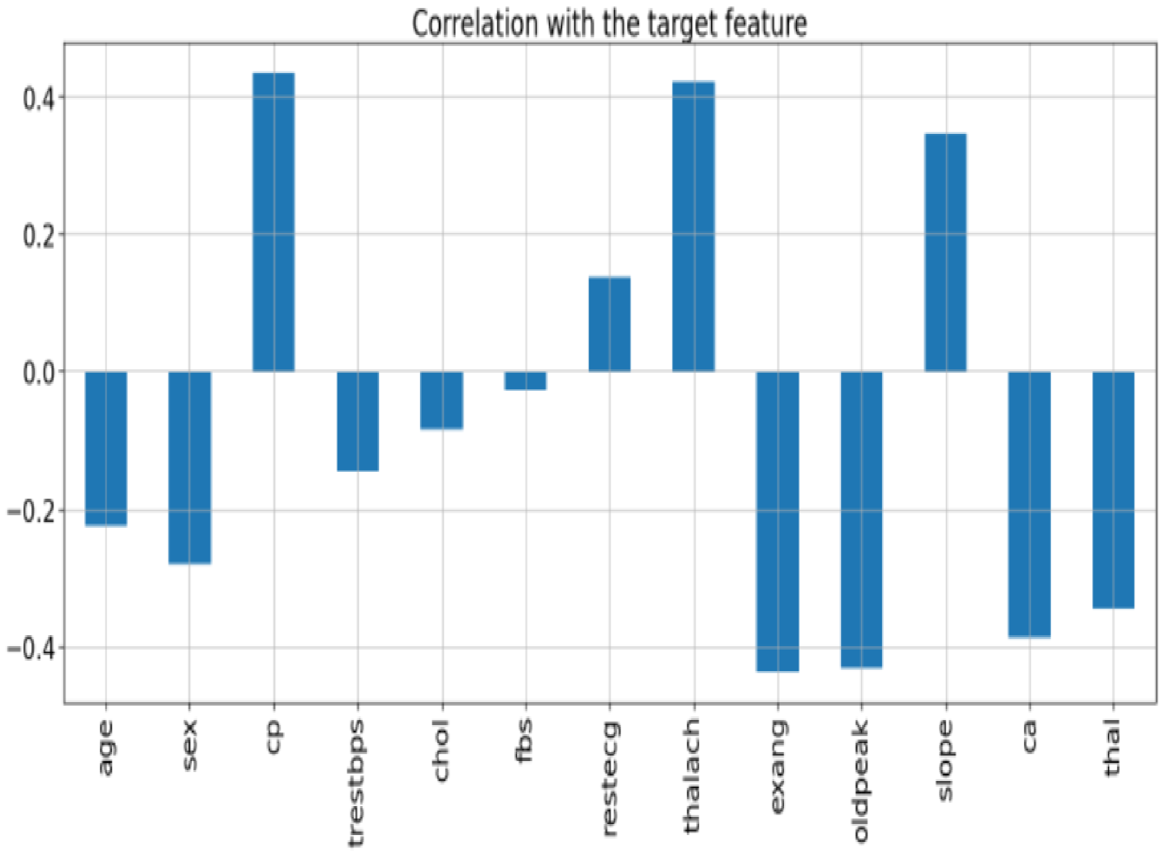
```
#heat map for the complete dataset
plt.figure(figsize=(50,30))
sns.set_context('notebook', font_scale = 3)
sns.heatmap(dataset.corr(),annot = True, linewidth = 2)
plt.tight_layout()
```



CORRELATION BETWEEN TARGET AND OTHER PARAMETERS

Here a correlation between the target and other features is analysed.This tells us which feature is negatively correlated and which is positively correlated.

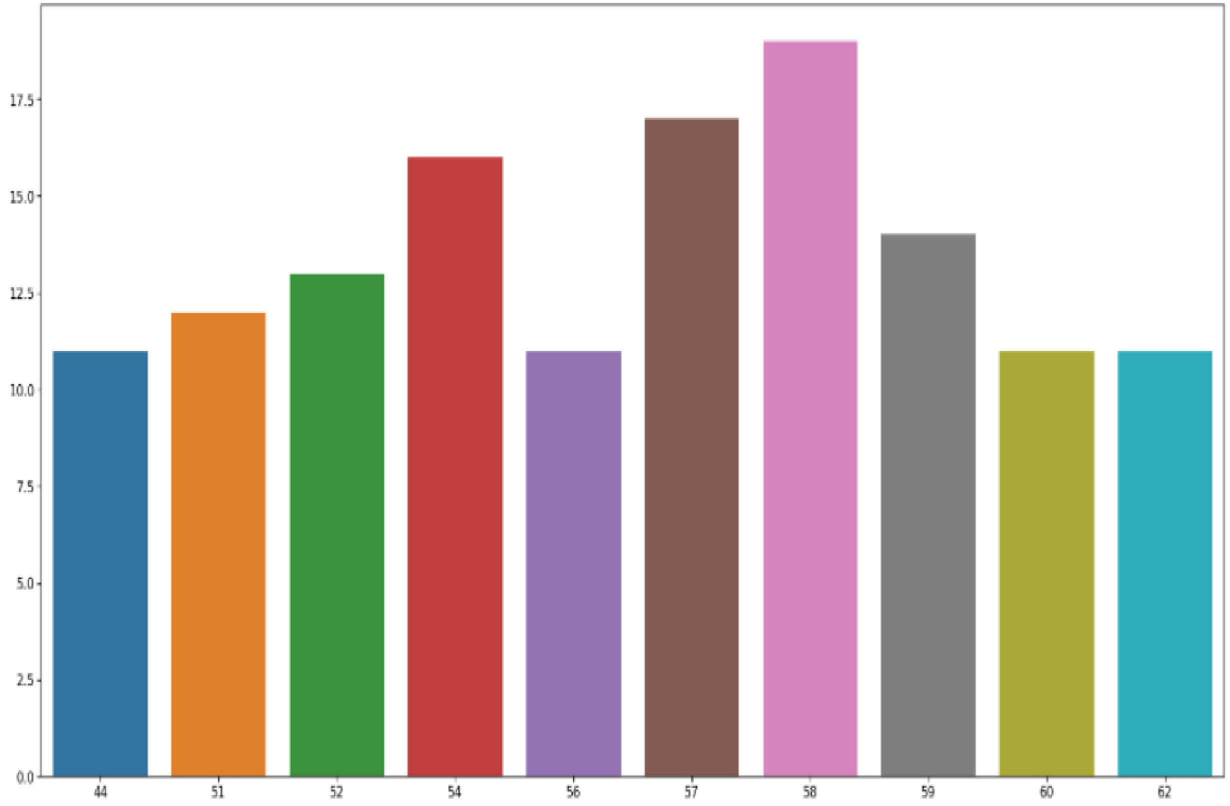
```
#correlation plot with target feature
sns.set_context('notebook',font_scale = 2.3)
dataset.drop('target', axis=1).corrwith(dataset.target).plot(kind='bar', grid=True, figsize=(20, 10),
                                                   title="Correlation with the target feature")
plt.tight_layout()
```



BAR GRAPH FOR 10 DIFFERENT AGE COUNT

Here a bar graph for 10 age counts are plotted.Here we can see that the 58 age column has the highest frequency.

```
##bar graph for 10 different age values
plt.figure(figsize=(25,12))
sns.set_context('notebook',font_scale = 1.5)
sns.barplot(x=dataset.age.value_counts()[:10].index,y=dataset.age.value_counts()[:10].values)
plt.tight_layout()
```



MAXIMUM, MINIMUM AND MEAN AGE

Here minimum,maximum and mean age is determined

```
#determining the maximum, minimum and mean age
minAge=min(dataset.age)
maxAge=max(dataset.age)
meanAge=dataset.age.mean()
print('Min Age :',minAge)
print('Max Age :',maxAge)
print('Mean Age :',meanAge)
```

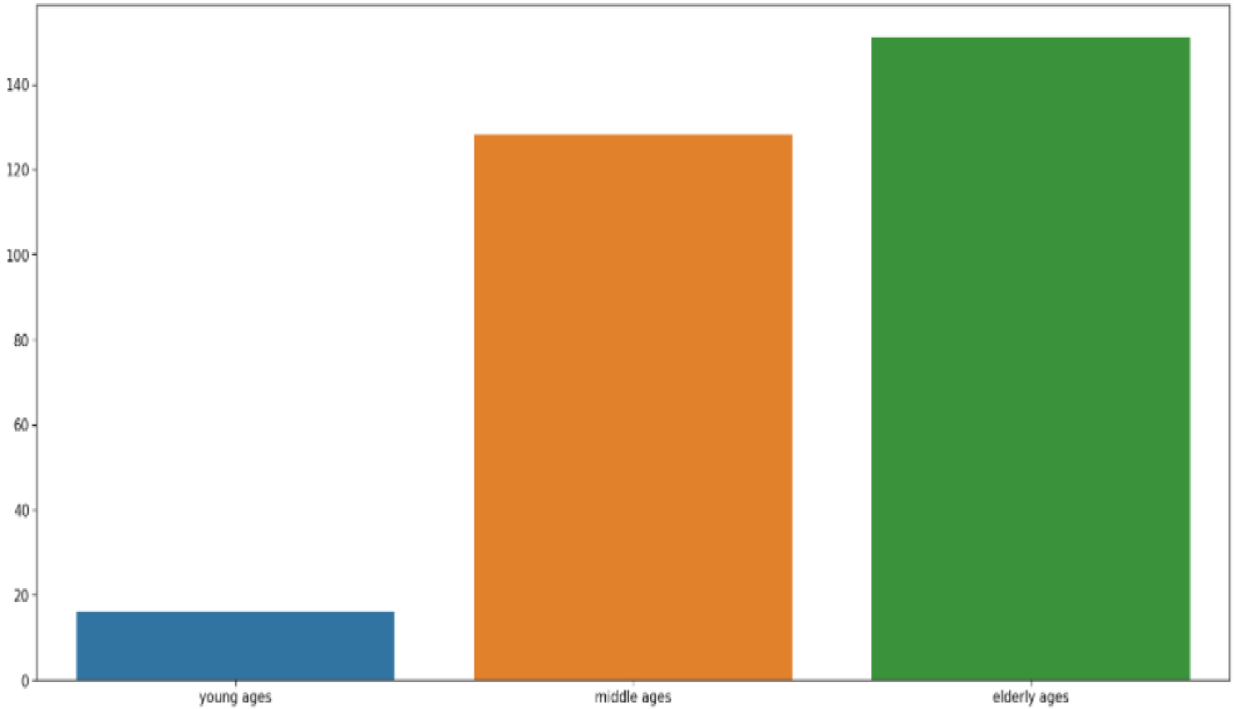
```
Min Age : 29
Max Age : 77
Mean Age : 54.366336633663366
```

DIVIDING AGE IN TO THREE CATEGORY AND ITS ANALYSIS

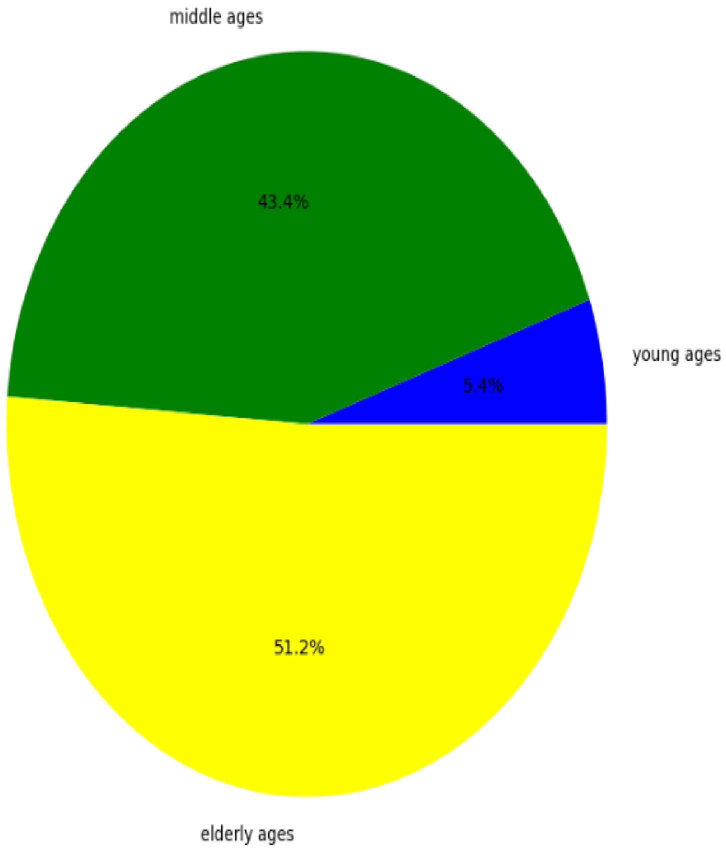
The age is divided into three category- "young" , "middle" , "elder". Here we can see that elder people are the most affected by heart disease and young ones are the least affected.

```
#bar graph for dividing age into young , middle and elder category
Young = dataset[(dataset.age>=29)&(dataset.age<40)]
Middle = dataset[(dataset.age>=40)&(dataset.age<55)]
Elder = dataset[(dataset.age>55)]

plt.figure(figsize=(23,10))
sns.set_context('notebook',font_scale = 1.5)
sns.barplot(x=['young ages','middle ages','elderly ages'],y=[len(Young),len(Middle),len(Elder)])
plt.tight_layout()
```



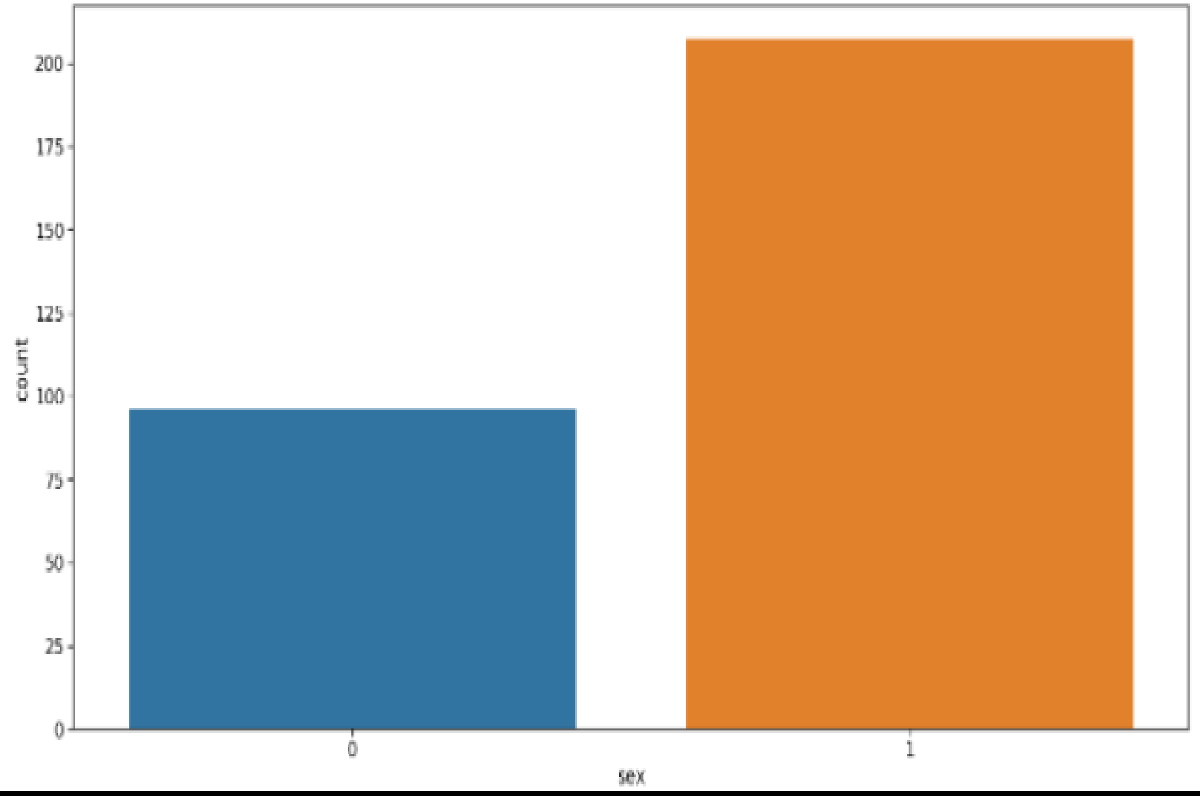

```
#pie chart for the young, middle and elder age category
colors = ['blue','green','yellow']
explode = [0,0,0.1]
plt.figure(figsize=(10,10))
sns.set_context('notebook',font_scale = 1.2)
plt.pie([len(Young),len(Middle),len(Elder)],labels=['young ages','middle ages','elderly ages'],colors=colors, autopct='%1.1f%%')
plt.tight_layout()
```



BAR GRAPH ANALYSIS FOR RATIO OF MALE VS FEMALE AND SLOPE ANALYSIS

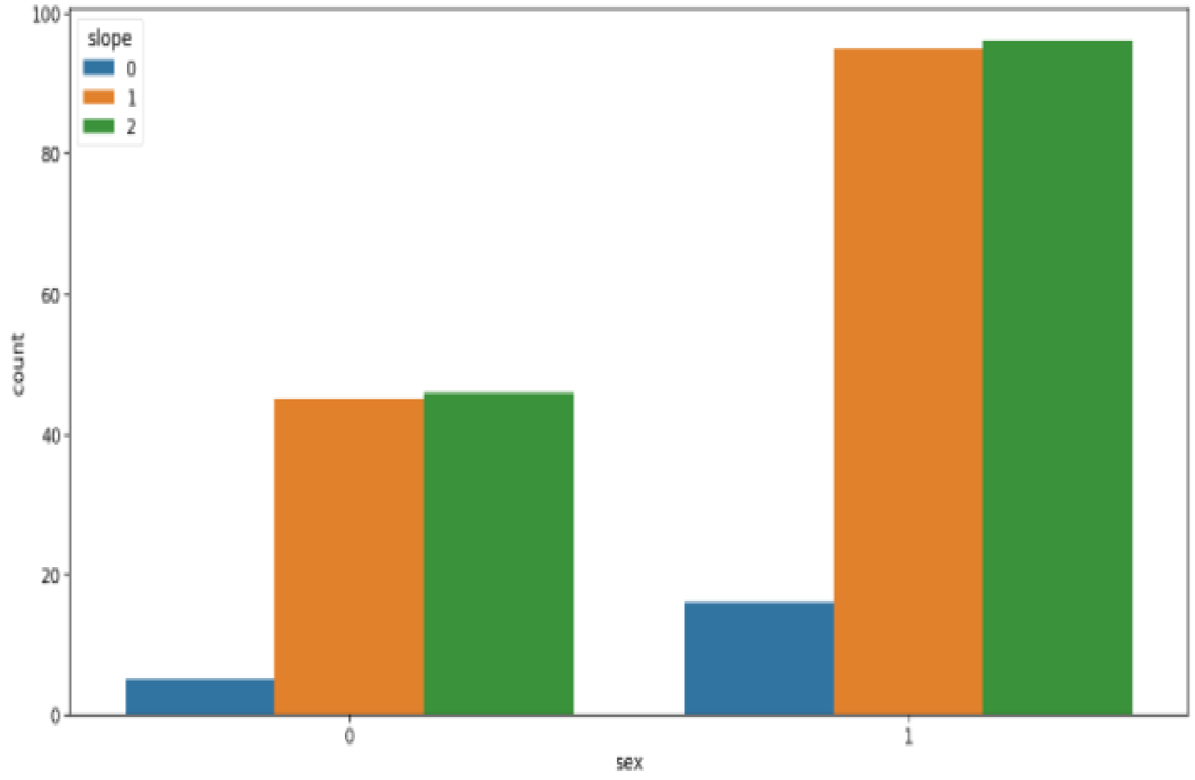
Sex feature analysis.Here it is clearly visible that, Ratio of Male to Female is approx 2:1.

```
#bar graph for number of males anf females (sex)
plt. figure(figsize=(18,9))
sns.set_context('notebook' , font_scale=1.5)
sns.countplot(dataset['sex'])
plt.tight_layout()
```



Relation between sex and slope.Here it is clearly visible that the slope value is higher in the case of males(1).

```
#bar graph relation between sex and slope
plt.figure(figsize=(18,9))
sns.set_context('notebook',font_scale = 1.5)
sns.countplot(dataset['sex'],hue=dataset["slope"])
plt.tight_layout()
```

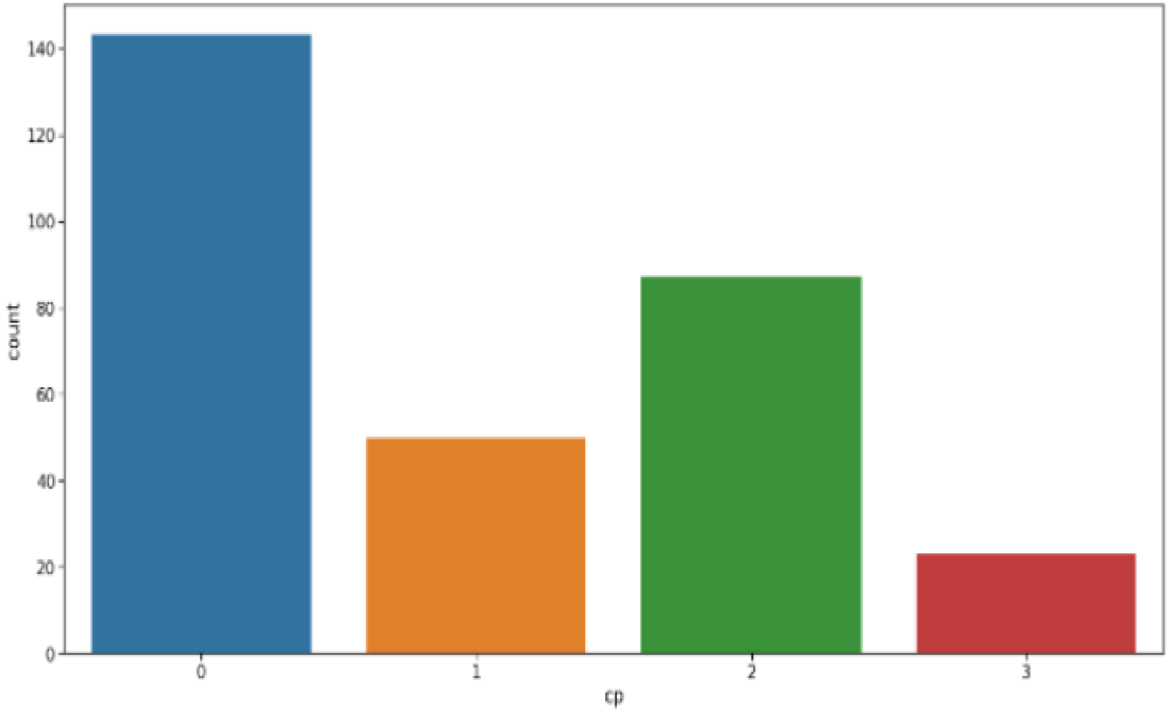


CHEST PAIN ANALYSIS AND BAR GRAPH FOR CHEST PAIN AND TARGET

Chest pain analysis ("cp").

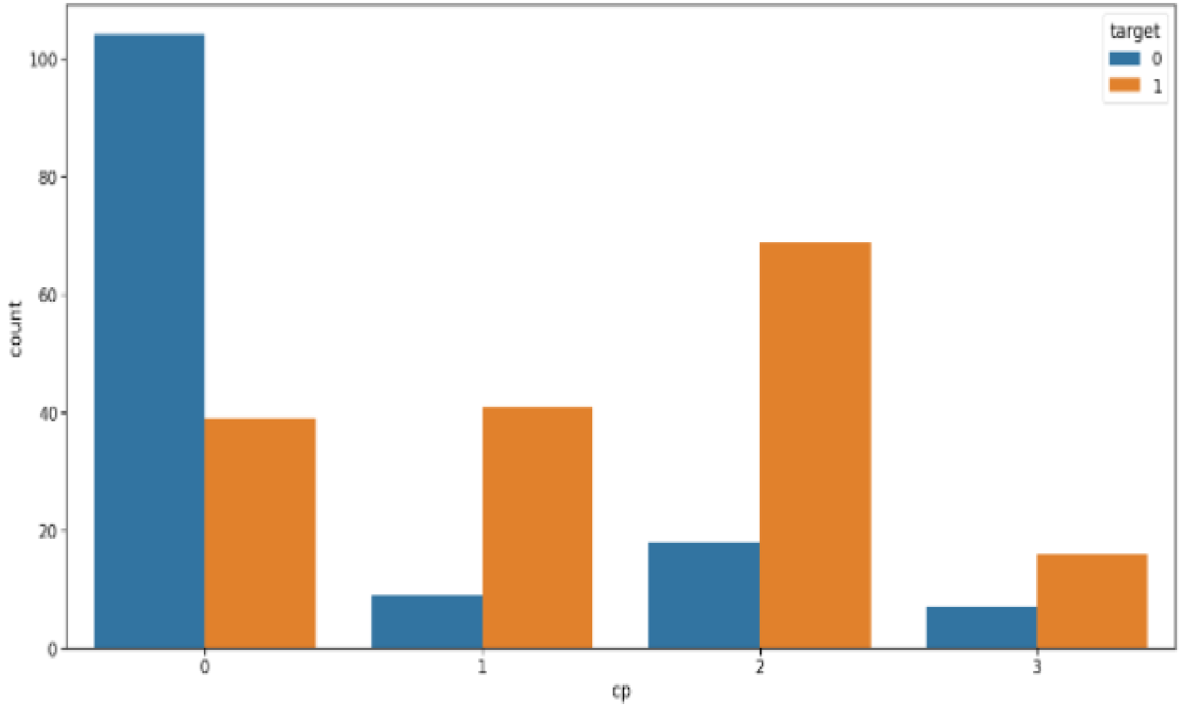
As seen, there are 4 types of chest pain status at least, condition slightly distressed, condition medium problem, condition too bad.

```
#nar graph analysis for chest pain (cp)
plt.figure(figsize=(18,9))
sns.set_context('notebook',font_scale = 1.5)
sns.countplot(dataset['cp'])
plt.tight_layout()
```



Analyzing cp vs target column

```
#bar graph relation between vhest pain and target
plt.figure(figsize=(18,9))
sns.set_context('notebook',font_scale = 1.5)
sns.countplot(dataset['cp'],hue=dataset["target"])
plt.tight_layout()
```

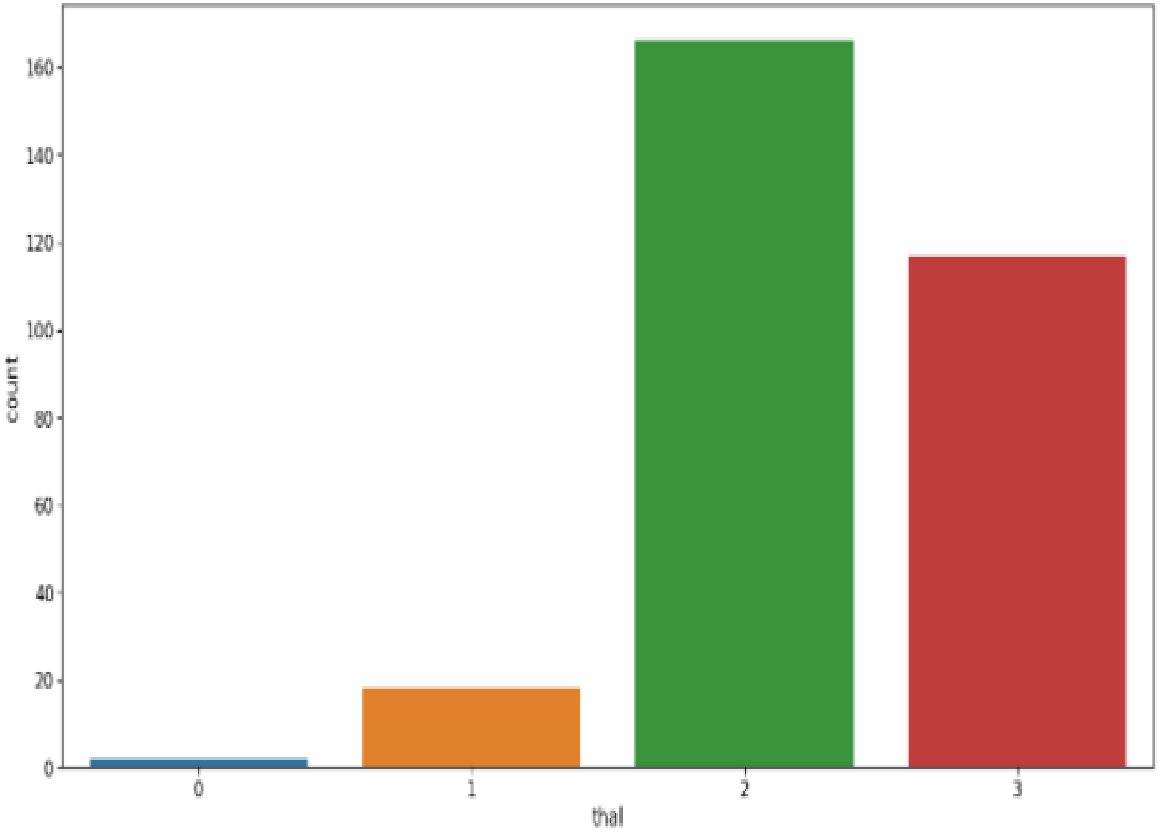


From the above graph we can make some inferences, People having the least chest pain are not likely to have heart disease. People having severe chest pain are likely to have heart disease. Elderly people are more likely to have chest pain.

BAR GRAPH FOR THAL

Thal Analysis

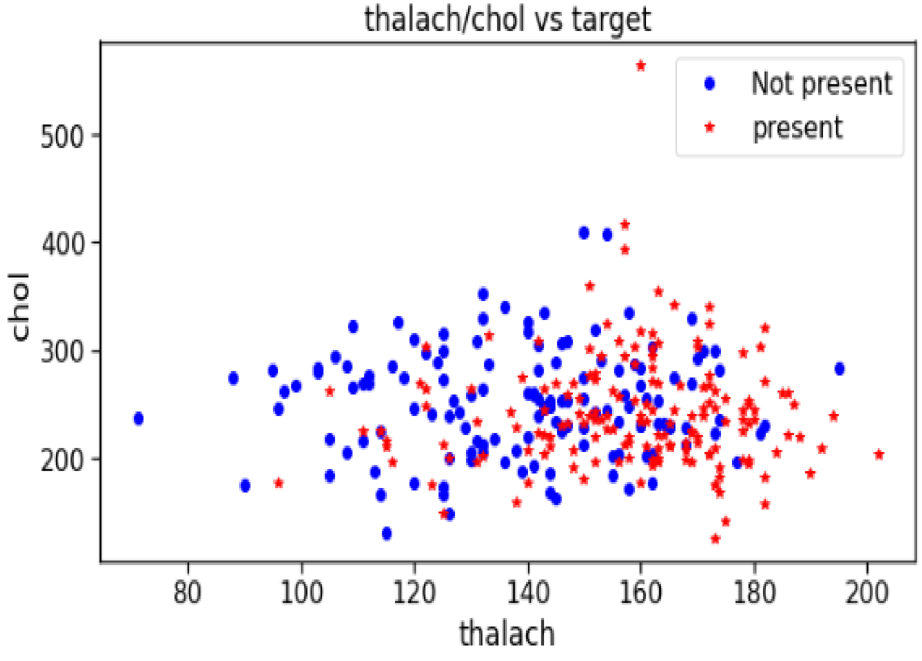
```
# bar graph analysis for thal
plt.figure(figsize=(18,9))
sns.set_context('notebook',font_scale = 1.5)
sns.countplot(dataset['thal'])
plt.tight_layout()
```



SCATTER PLOT BETWEEN THALACH AND CHOL

Here a scatter plot between thalach and chol with target as a parameter is plotted

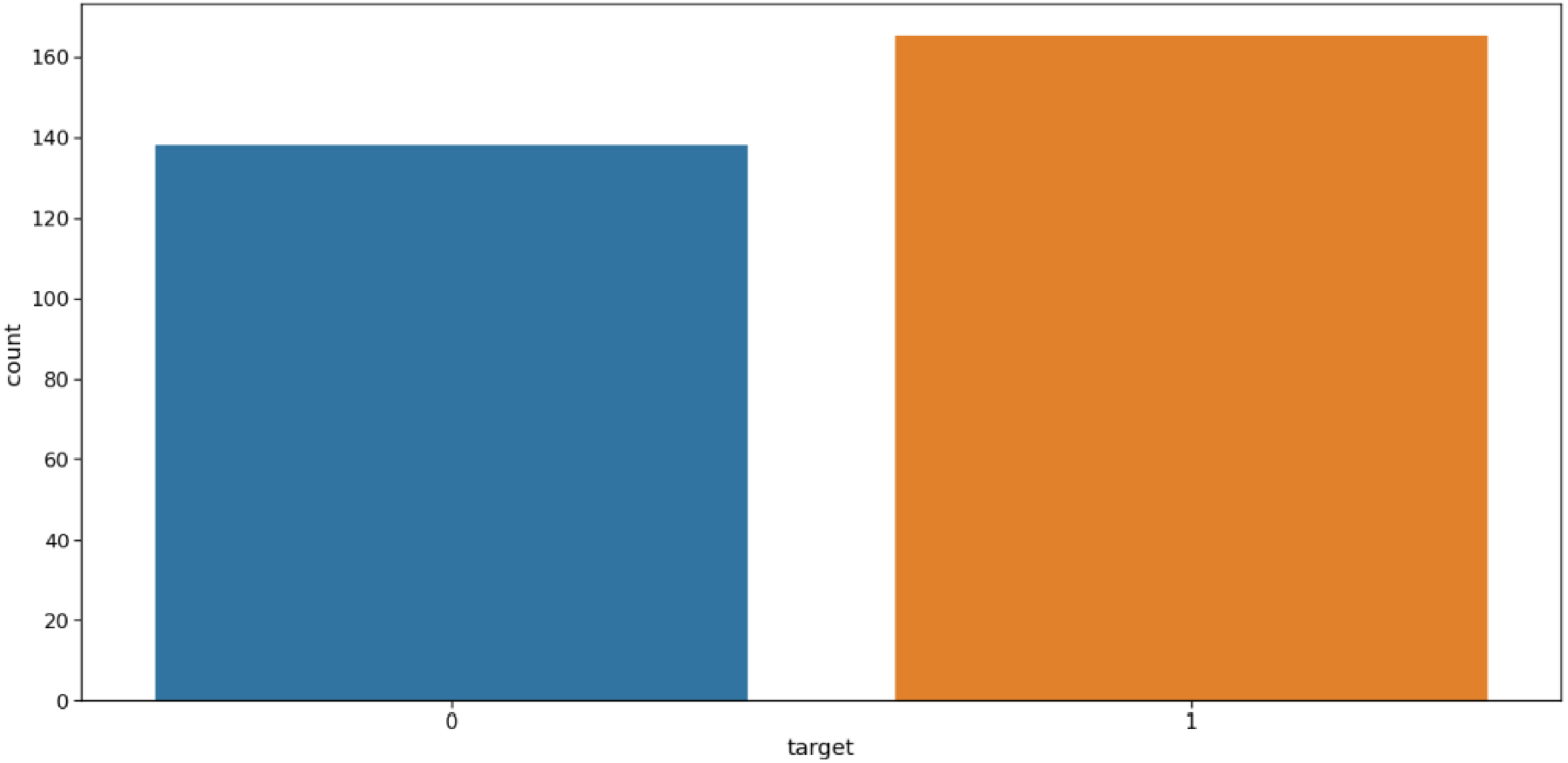
```
#scatter plot between thalach and age
abc_zero=dataset[dataset['target']==0].index
abc_one=dataset[dataset['target']==1].index
plt.figure(figsize=(10,5))
plt.title('thalach/chol vs target')
plt.plot(dataset['thalach'][abc_zero],dataset['chol'][abc_zero] , 'bo' , label='Not present')
plt.plot(dataset['thalach'][abc_one],dataset['chol'][abc_one] , 'r*' , label='present')
plt.xlabel('thalach')
plt.ylabel('chol')
plt.legend()
plt.show()
```



BAR GRAPH FOR TARGET PARAMETER

Target analysis

```
#bar graph analysis for target
plt. figure(figsize=(18,9))
sns.set_context('notebook' , font_scale=1.5)
sns.countplot(dataset['target'])
plt.tight_layout()
```



The ratio between 1 and 0 is much less than 1.5 which indicates that the target feature is not imbalanced. So for a balanced dataset, we can use accuracy_score as evaluation metrics for our model.

COMPLETE DESCRIPTION OF CONTINUOUS AND CATEGORICAL DATA

Now we will see the complete description of the continuous data as well as the categorical data

```python
#complete description about continuous and categorical data
categorical_val = []
continous_val = []
for column in dataset.columns:
    print("--------------------")
    print(f"{column} : {dataset[column].unique()}")
    if len(dataset[column].unique()) <= 10:
        categorical_val.append(column)
    else:
        continous_val.append(column)
```

```
--------------------
age : [63 37 41 56 57 44 52 54 48 49 64 58 50 66 43 69 59 42 61 40 71 51 65 53
 46 45 39 47 62 34 35 29 55 60 67 68 74 76 70 38 77]
--------------------
sex : [1 0]
--------------------
cp : [3 2 1 0]
--------------------
trestbps : [145 130 120 140 172 150 110 135 160 105 125 142 155 104 138 128 108 134
 122 115 118 100 124  94 112 102 152 101 132 148 178 129 180 136 126 106
 156 170 146 117 200 165 174 192 144 123 154 114 164]
--------------------
chol : [233 250 204 236 354 192 294 263 199 168 239 275 266 211 283 219 340 226
 247 234 243 302 212 175 417 197 198 177 273 213 304 232 269 360 308 245
 208 264 321 325 235 257 216 256 231 141 252 201 222 260 182 303 265 309
 186 203 183 220 209 258 227 261 221 205 240 318 298 564 277 214 248 255
 207 223 288 160 394 315 246 244 270 195 196 254 126 313 262 215 193 271
 268 267 210 295 306 178 242 180 228 149 278 253 342 157 286 229 284 224
 206 167 230 335 276 353 225 330 290 172 305 188 282 185 326 274 164 307
 249 341 407 217 174 281 289 322 299 300 293 184 409 259 200 327 237 218
 319 166 311 169 187 176 241 131]
--------------------
fbs : [1 0]
--------------------
restecg : [0 1 2]
--------------------
thalach : [150 187 172 178 163 148 153 173 162 174 160 139 171 144 158 114 151 161
 179 137 157 123 152 168 140 188 125 170 165 142 180 143 182 156 115 149
 146 175 186 185 159 130 190 132 147 154 202 166 164 184 122 169 138 111
 145 194 131 133 155 167 192 121  96 126 105 181 116 108 129 120 112 128
 109 113  99 177 141 136  97 127 103 124  88 195 106  95 117  71 118 134
  90]
--------------------
exang : [0 1]
--------------------
oldpeak : [2.3 3.5 1.4 0.8 0.6 0.4 1.3 0.  0.5 1.6 1.2 0.2 1.8 1.  2.6 1.5 3.  2.4
 0.1 1.9 4.2 1.1 2.  0.7 0.3 0.9 3.6 3.1 3.2 2.5 2.2 2.8 3.4 6.2 4.  5.6
 2.9 2.1 3.8 4.4]
--------------------
slope : [0 2 1]
--------------------
ca : [ 0.  2.  1.  3.  4. nan]
--------------------
thal : [1 2 3 0]
--------------------
target : [1 0]
```

STEP 4:APPLYING PD.GET_DUMMIES() FUNCTION AND DECLARING X AND Y VALUES FOR TRAINING MODEL

To work with categorical variables, we should break each categorical column into dummy columns with 1s and 0s.To get this done, we use the get_dummies() method from pandas. Next, we need to scale the dataset for which we will use the StandardScaler. The fit_transform() method of the scaler scales the data and we update the columns.

```
#scaling the dataset
dataset = pd.get_dummies(dataset, columns = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal'])
standardScaler = StandardScaler()
columns_to_scale = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
dataset[columns_to_scale] = standardScaler.fit_transform(dataset[columns_to_scale])
```

The dataset is now ready. We can begin with training our models.The next step is to assign X and y valuse for splittinf the dataset

```
#declaring the X and y values
X = dataset.drop('target' , axis=1)
y = dataset.target
```

STEP 5: SPLITTING OF DATA INTO TRAINING AND TEST SUBSET

The dataset is now ready. We can begin with training our models.The next step is to assign X and y valuse for splittinf the dataset

```
#declaring the X and y values
X = dataset.drop('target' , axis=1)
y = dataset.target
```

```
#printing X
X
```

	age	trestbps	chol	thalach	oldpeak	sex_0	sex_1	cp_0	cp_1	cp_2	...	slope_2	ca_0.0	ca_1.0	ca_2.0	ca_3.0	ca_4.0	thal_0	thal_1	thal_2	thal_3
0	0.952197	0.763956	-0.256334	0.015443	1.087338	0	1	0	0	0	...	0	1	0	0	0	0	0	1	0	0
1	-1.915313	-0.092738	0.072199	1.633471	2.122573	0	1	0	0	1	...	0	1	0	0	0	0	0	0	1	0
2	-1.474158	-0.092738	-0.816773	0.977514	0.310912	1	0	0	1	0	...	1	1	0	0	0	0	0	0	1	0
3	0.180175	-0.663867	-0.198357	1.239897	-0.206705	0	1	0	1	0	...	1	1	0	0	0	0	0	0	1	0
4	0.290464	-0.663867	2.082050	0.583939	-0.379244	1	0	1	0	0	...	1	1	0	0	0	0	0	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
298	0.290464	0.478391	-0.101730	-1.165281	-0.724323	1	0	1	0	0	...	0	1	0	0	0	0	0	0	0	1
299	-1.033002	-1.234996	0.342756	-0.771706	0.138373	0	1	0	0	0	...	0	1	0	0	0	0	0	0	0	1
300	1.503641	0.706843	-1.029353	-0.378132	2.036303	0	1	1	0	0	...	0	0	0	1	0	0	0	0	0	1
301	0.290464	-0.092738	-2.227533	-1.515125	0.138373	0	1	1	0	0	...	0	0	1	0	0	0	0	0	0	1
302	0.290464	-0.092738	-0.198357	1.064975	-0.896862	1	0	0	1	0	...	0	0	1	0	0	0	0	0	1	0

303 rows × 30 columns

```
#printing y
y
```

```
0      1
1      1
2      1
3      1
4      1
      ..
298    0
299    0
300    0
301    0
302    0
Name: target, Length: 303, dtype: int64
```

In this project the data is split into 20% for training data and 80% for testing data.

```
#splitting data for testing and training
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

printing X_train values

STEP 6: MODEL DEVELOPMENT

SVM: THIS CLASSIFIER AIMS AT FORMING A HYPERPLANE THAT CAN SEPARATE THE CLASSES AS MUCH AS POSSIBLE BY ADJUSTING THE DISTANCE BETWEEN THE DATA POINTS AND THE HYPERPLANE. THERE ARE SEVERAL KERNELS BASED ON WHICH THE HYPERPLANE IS DECIDED. I TRIED FOUR KERNELS NAMELY, LINEAR, POLY, RBF, AND SIGMOID.

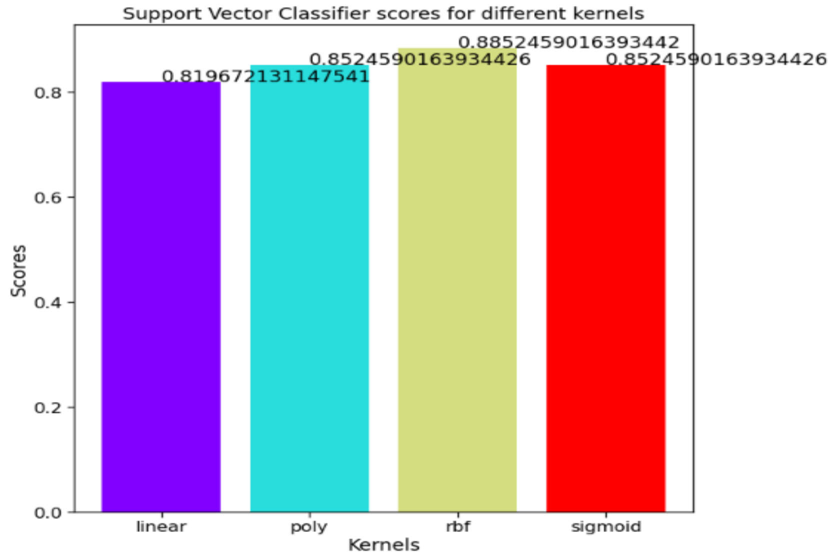
SVM modes for different kernels

```
svc_scores = []
kernels = ['linear', 'poly', 'rbf', 'sigmoid']
for i in range(len(kernels)):
    svc_classifier = SVC(kernel = kernels[i])
    svc_classifier.fit(X_train, y_train)
    svc_scores.append(svc_classifier.score(X_test, y_test))
```

Bar graph for accuracy scores for different SVM kernels

```
colors = rainbow(np.linspace(0, 1, len(kernels)))
plt.bar(kernels, svc_scores, color = colors)
for i in range(len(kernels)):
    plt.text(i, svc_scores[i], svc_scores[i])
plt.xlabel('Kernels')
plt.ylabel('Scores')
plt.title('Support Vector Classifier scores for different kernels')
```

```
Text(0.5, 1.0, 'Support Vector Classifier scores for different kernels')
```



As can be seen from the plot above, the RBF kernel performed the best for this dataset and achieved a score of 88.52%.

APPLYING LOGISTIC REGRESSION FOR THE SAME MODEL AND PRINTING THE CONFUSION MATRIX

Similarly Logistic regression algorithm is applied for the dataset and accuracy scores is calculated

```
from sklearn.linear_model import LogisticRegression
lin_reg = LogisticRegression()
lin_reg.fit(X_train,y_train)
y_pred=lin_reg.predict(X_test)
y_pred=svc.predict(X_test)
print('Accuracy Score:')
print(metrics.accuracy_score(y_test,y_pred))
```

```
Accuracy Score:
0.8524590163934426
```

As we can see that from logstic regression an accuracy score of 85.25% is achieved.

For the above logistic regression a confusion matrix is plotted and accuracy is calculated

```
from sklearn import metrics
cm = metrics.confusion_matrix(y_test,y_pred)
print('Confusion matrix', cm)
```

```
Confusion matrix [[22  5]
 [ 4 30]]
```

From the above confusion matrix we can see that 22 are predicted as true positive(TP), 5 are predicted as false positive(FP), 4 are predicted as false negative(FN) and 30 are predicted as true negative(TN).

From this the accuracy is calculated as = (22+30)/(22+5+4+30). Therefore the final accuracy score is 85.25%.

STEP 7:MODEL EVALUATION

- PREDICTIONS ON TEST DATA:
- A test dataset is a dataset that is independent of the training dataset but that follows the same probability distribution as the training data set. A test dataset is therefore a set of examples used only to assess the performance of a fully specified classifier. To do this the final model is used to predict classifications of examples in the test set. Those predictions are compared to the examples true classifications to assess the model accuracy.

```
y_pred
```

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

```
y_test
```

```
225    0
152    1
228    0
201    0
52     1
      ..
146    1
302    0
26     1
108    1
89     1
Name: target, Length: 61, dtype: int64
```

The above image shows the predicted values by the machine learning algorithm used and the actual values. By these predictions the accuracy of the model can be evaluated.

The accuracy of a model can be calculated based on the prediction values or confusion matrix.

To validate a model we need to check few parameters of SVM and logistic regression:

A support vector machine (SVM) is a supervised machine learning model that uses classification algorithms for two-group classification problems.

Logistic regression is used for predicting the categorical dependent variable using a given set of independent variables.

As these condition are applicable to the given dataset, Hence SVM and logistic regression algorithms are used and accuracy of the model is calculated

STEP 8: CONCLUSION

- For the given dataset i.e. for heart disease prediction SVM and Logistic regression algorithm are used and evaluated for the model accuracy based on the prediction output by the ML algorithm .
- The accuracy scores of different kernels of SVM are as follows:
- RBF : 88.52%
- Linear : 81.96%
- Polynomial : 85.24%
- Sigmoid : 85.24%

As can be seen from the above scores , the RBF kernel performed the best for this dataset and achieved a score of 88.52%.

Similarly Logistic regression algorithm is applied for the dataset and accuracy scores is calculated.

As we can see that from logistic regression an accuracy score of 85.25% is achieved.

- For the logistic regression a confusion matrix was calculated .From confusion matrix we can see that 22 are predicted as true positive(TP), 5 are predicted as false positive(FP), 4 are predicted as false negative(FN) and 30 are predicted as true negative(TN).
- From this the accuracy is calculated as = (22+30)/(22+5+4+30).Therefore the final accuracy score is 85.25%.