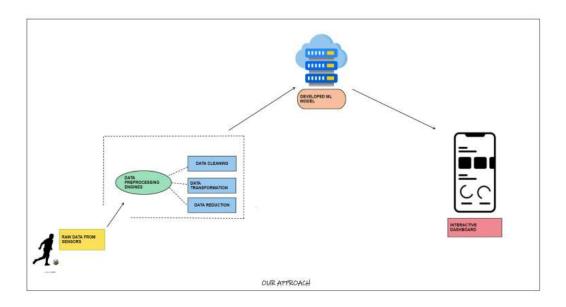
## TEAM ID: IBM-Project-25390-1659961381

#### **Heart Disease Prediction**

Machine learning is used to diagnose, detect, and forecast many disorders in the medical industry. The primary purpose of this study is to give clinicians a tool to detect cardiac problems at an early stage. As a result, it will be easier to deliver appropriate treatment to patients while avoiding serious effects. In the system of the human heart, the heart's electrical activity is recorded by ECG with various wave forms through skin. electrodes. Our approach begins with acquiring raw data through various sensors attached to the human body, let's say a fitness tracker watch, the raw data is sent to the preprocessing engine where the data is structured and ready for further processing. The processed data is sent to the developed model for prediction, after which the results are displayed in a interactive dashboard where the users can keep track of their body status.

In this machine learning project, I have collected the dataset from Kaggle (https://www.kaggle.com/ronitf/heart-disease-uci) and I will be using Machine Learning to predict whether any person is suffering from heart disease



### Import libraries

```
from matplotlib.cm import rainbow
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

Here we will be experimenting with 3 algorithms 1. KNeighborsClassifier 2. DecisionTreeClassifier 3. RandomForestClassifier

```
In [5]: from sklearn.neighbors import KNeighborsClassifier
    from sklearn.tree import DecisionTreeClassifier
    from sklearn.ensemble import RandomForestClassifier
```

#### Import dataset

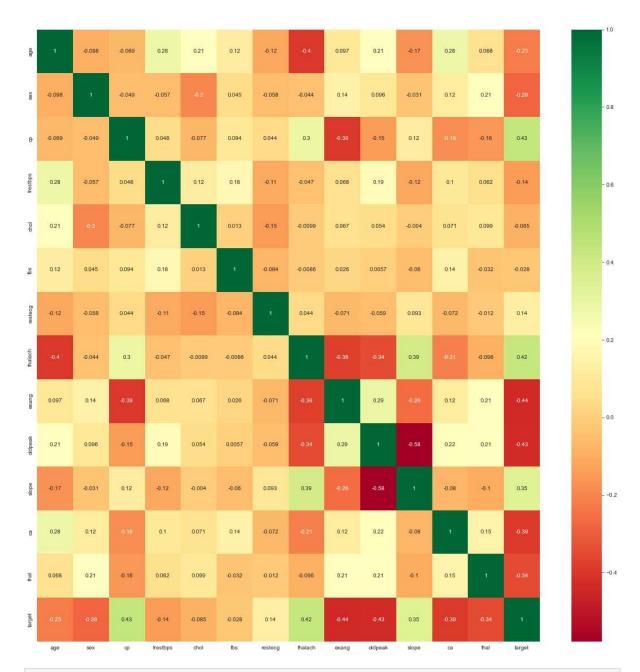
Now that we have all the libraries we will need, we can import the dataset and take a look at it. The dataset is stored in the file dataset.csv. We'll use the pandas read\_csv method to read the dataset.

```
df = pd.read_csv('dataset.csv')
In [6]:
       df.info()
In [7]:
       <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 303 entries, 0 to 302
       Data columns (total 14 columns):
            Column
                    Non-Null Count Dtype
           ----
                     -----
        0
                    303 non-null
                                   int64
            age
        1
           sex
                    303 non-null int64
                   303 non-null int64
        2
           ср
           trestbps 303 non-null int64
        3
                    303 non-null
                                  int64
        4
           chol
        5
           fbs
                   303 non-null int64
        6 restecg 303 non-null int64
        7
          thalach 303 non-null int64
                    303 non-null int64
        8 exang
           oldpeak
                    303 non-null float64
        9
        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
       df.describe()
In [8]:
```

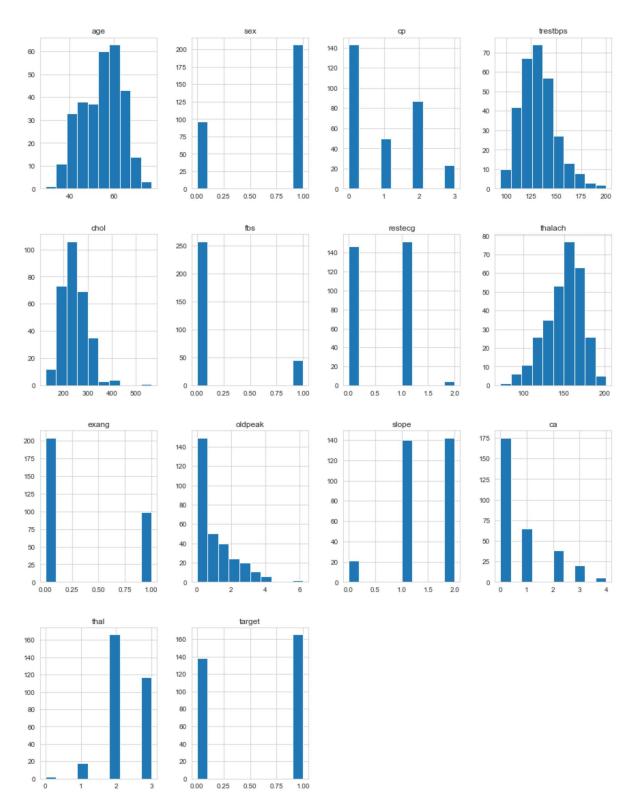
]:	age	sex	ср	trestbps	chol	fbs	restecg	th
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.00
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.64
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.90
min	29.000000	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
	mean std min 25% 50% 75%	count       303.000000         mean       54.366337         std       9.082101         min       29.000000         25%       47.500000         50%       55.000000         75%       61.000000	count         303.000000         303.000000           mean         54.366337         0.683168           std         9.082101         0.466011           min         29.000000         0.000000           25%         47.500000         0.000000           50%         55.000000         1.000000           75%         61.000000         1.000000	count         303.000000         303.000000         303.000000           mean         54.366337         0.683168         0.966997           std         9.082101         0.466011         1.032052           min         29.000000         0.000000         0.000000           25%         47.500000         0.000000         0.000000           50%         55.000000         1.000000         2.000000           75%         61.000000         1.000000         2.000000	count         303.000000         303.000000         303.000000         303.000000           mean         54.366337         0.683168         0.966997         131.623762           std         9.082101         0.466011         1.032052         17.538143           min         29.000000         0.000000         0.000000         94.000000           25%         47.500000         0.000000         0.000000         120.000000           50%         55.000000         1.000000         1.000000         140.000000           75%         61.000000         1.000000         2.000000         140.000000	count         303.000000         303.000000         303.000000         303.000000         303.000000         303.000000           mean         54.366337         0.683168         0.966997         131.623762         246.264026           std         9.082101         0.466011         1.032052         17.538143         51.830751           min         29.000000         0.000000         0.000000         94.000000         126.000000           25%         47.500000         0.000000         1.000000         130.000000         240.000000           50%         55.000000         1.000000         2.000000         140.000000         274.500000	count         303.000000         300.00000 <th>count         303.000000<!--</th--></th>	count         303.000000 </th

## **Feature Selection**

```
import seaborn as sns
#get correlations of each features in dataset
corrmat = df.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(20,20))
#plot heat map
g=sns.heatmap(df[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```

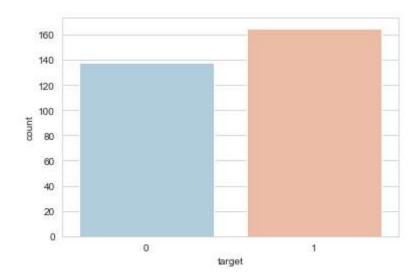


```
df.hist(figsize = (15,20))
In [28]:
          array([[<AxesSubplot:title={'center':'age'}>,
Out[28]:
                   <AxesSubplot:title={'center':'sex'}>,
                   <AxesSubplot:title={'center':'cp'}>,
                   <AxesSubplot:title={'center':'trestbps'}>],
                  [<AxesSubplot:title={'center':'chol'}>,
                   <AxesSubplot:title={'center':'fbs'}>,
                   <AxesSubplot:title={'center':'restecg'}>,
<AxesSubplot:title={'center':'thalach'}>],
                  [<AxesSubplot:title={'center':'exang'}>,
                   <AxesSubplot:title={'center':'oldpeak'}>,
                   <AxesSubplot:title={'center':'slope'}>,
                   <AxesSubplot:title={'center':'ca'}>],
                  [<AxesSubplot:title={'center':'thal'}>,
                   <AxesSubplot:title={'center':'target'}>, <AxesSubplot:>,
                   <AxesSubplot:>]], dtype=object)
```



It's always a good practice to work with a dataset where the target classes are of approximately equal size. Thus, let's check for the same.

```
In [11]: sns.set_style('whitegrid')
    sns.countplot(x='target',data=df,palette='RdBu_r')
Out[11]: <AxesSubplot:xlabel='target', ylabel='count'>
```



# **#Data Processing**

After exploring the dataset, I observed that I need to convert some categorical variables into dummy variables and scale all the values before training the Machine Learning models. First, I'll use the get\_dummies method to create dummy columns for categorical variables.

```
dataset = pd.get_dummies(df, columns = ['sex', 'cp', 'fbs', 'restecg', 'exang', 's
In [12]:
In [13]:
          from sklearn.model selection import train test split
          from sklearn.preprocessing import StandardScaler
          standardScaler = StandardScaler()
          columns_to_scale = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
          dataset[columns_to_scale] = standardScaler.fit_transform(dataset[columns_to_scale]
In [14]:
          dataset.head()
Out[14]:
                  age
                       trestbps
                                    chol
                                           thalach
                                                    oldpeak target sex_0 sex_1
                                                                                cp_0 cp_1 ... slop
            0.952197
                       0.763956 -0.256334
                                         0.015443
                                                   1.087338
                                                                                   0
                                                                                         0
                                                                       0
          1 -1.915313 -0.092738
                                 0.072199 1.633471
                                                   2.122573
                                                                 1
                                                                       0
                                                                                   0
                                                                                         0
          2 -1.474158 -0.092738
                                -0.816773 0.977514
                                                   0.310912
                                                                 1
                                                                       1
                                                                             0
                                                                                   0
                                                                                         1 ...
            0.180175 -0.663867 -0.198357 1.239897
                                                  -0.206705
                                                                       0
                                                                                   0
             0.290464 -0.663867
                                 2.082050 0.583939 -0.379244
                                                                             0
                                                                                   1
                                                                       1
                                                                                         0
```

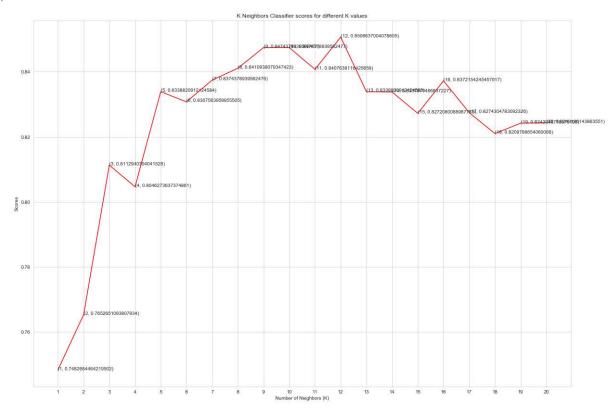
5 rows × 31 columns

```
In [15]: y = dataset['target']
X = dataset.drop(['target'], axis = 1)

In [16]: from sklearn.model_selection import cross_val_score
knn_scores = []
for k in range(1,21):
    knn_classifier = KNeighborsClassifier(n_neighbors = k)
    score=cross_val_score(knn_classifier,X,y,cv=10)
    knn_scores.append(score.mean())
```

```
In [26]: plt.plot([k for k in range(1, 21)], knn_scores, color = 'red')
for i in range(1,21):
    plt.text(i, knn_scores[i-1], (i, knn_scores[i-1]))
plt.xticks([i for i in range(1, 21)])
plt.xlabel('Number of Neighbors (K)')
plt.ylabel('Scores')
plt.title('K Neighbors Classifier scores for different K values')
```

Out[26]: Text(0.5, 1.0, 'K Neighbors Classifier scores for different K values')



```
In [17]: knn_classifier = KNeighborsClassifier(n_neighbors = 12)
    score=cross_val_score(knn_classifier,X,y,cv=10)

In [18]: score.mean()
Out[18]: 0.8448387096774195
```

#### **Random Forest Classifier**