Heart attack predictions

Objective

Performing the Exploratory Data Analysis & regressive machine learning on this dataset

Handling the dataset

Before getting into the EDA, It's important to mine the data for increasing the efficiency in EDA.

About Dataset(heart.csv)

Age : Age of the patient

Sex : Sex of the patient

exang: exercise induced angina (1 = yes; 0 = no)

ca: number of major vessels (0-3)

cp : Chest Pain type chest pain type

Value 1: typical angina

Value 2: atypical angina

Value 3: non-anginal pain

Value 4: asymptomatic

trtbps : resting blood pressure (in mm Hg)

chol : cholestoral in mg/dl fetched via BMI sensor

fbs : (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)

rest_ecg : resting electrocardiographic results

Value 0: normal

Value 1: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV)

Value 2: showing probable or definite left ventricular hypertrophy by Estes' criteria

thalach : maximum heart rate achieved

target : 0= less chance of heart attack 1= more chance of heart attack

Questions about the dataset

Analysis-1: What is the maximum age count of the heart patients? What is the % of male and female patients?

Analysis-2: What is the maximum blood pressure, cholesterol and heart rate count of the patients?

Analysis-3: Does blood pressure, maximum heart rate and cholesterol vary with increase in the age of the patients?

Analysis-4: Does cholesterol incerases the chance of causing heart attack?

Analysis-5: Does max heart rate & blood pressure incerases the chance of causing heart attack?

Analysis-6: When patients suffers from chest pain, is it due to high pulse rate?

Analysis-7: Does blood pressure,max pulse rate & cholesterol vary with the gender?

```
import numpy as np

import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

import plotly.express as px

df= pd.read_csv('heart.csv')

print(df.head())

#
```

	age	sex	cp	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	caa	thall	output
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

```
#Data wrangling


df.info()

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   trtbps    303 non-null    int64
 4   chol      303 non-null    int64
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    int64
 7   thalachh  303 non-null    int64
 8   exng      303 non-null    int64
 9   oldpeak   303 non-null    float64
 10  slp       303 non-null    int64
```

```
 11  caa       303 non-null    int64
 12  thall     303 non-null    int64
 13  output    303 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

df.isnull().sum()

```
age         0
sex         0
cp          0
trtbps      0
chol        0
fbs         0
restecg     0
thalachh    0
exng        0
oldpeak     0
slp         0
caa         0
thall       0
output      0
dtype: int64
```

train_df=df['sex'].replace([0,1],['Female','Male'], inplace=False)

train_df

```
0        Male
1        Male
2      Female
3        Male
4      Female
       ...
298    Female
299      Male
300      Male
301      Male
302    Female
Name: sex, Length: 303, dtype: object
```

df.duplicated().sum()

```
1
```

df.drop_duplicates(keep='first')

#Checking the outlier

	age	sex	cp	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	caa	thall	output
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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
298	57	0	0	140	241	0	1	123	1	0.2	1	0	3	0
299	45	1	3	110	264	0	1	132	0	1.2	1	0	3	0
300	68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
301	57	1	0	130	131	0	1	115	1	1.2	1	1	3	0
302	57	0	1	130	236	0	0	174	0	0.0	1	1	2	0

302 rows × 14 columns

q1= df.quantile(0.25)

q3= df.quantile(0.75)

IQR= q3-q1

upper_outlier= q3+IQR*1.5

lower_outlier= q1-IQR*1.5

upper_dict=dict(upper_outlier)

lower_dict= dict(lower_outlier)

```
for a,b in df.items():
    b_col = b[( b<= lower_dict[a]) | (b >= upper_dict[a])]
    perc = np.shape(b_col)[0] * 100.0 / np.shape(df)[0]
    print("Column {} outliers = {} => {}%".format(a,len(b_col),round((perc),2)))
```

Column age outliers = 0 => 0.0%
Column sex outliers = 0 => 0.0%
Column cp outliers = 0 => 0.0%
Column trtbps outliers = 13 => 4.29%
Column chol outliers = 5 => 1.65%
Column fbs outliers = 303 => 100.0%
Column restecg outliers = 0 => 0.0%
Column thalachh outliers = 1 => 0.33%
Column exng outliers = 0 => 0.0%
Column oldpeak outliers = 8 => 2.64%
Column slp outliers = 0 => 0.0%
Column caa outliers = 25 => 8.25%
Column thall outliers = 2 => 0.66%
Column output outliers = 0 => 0.0%

#transformation of outliers

```
df["fbs"]= np.log(df.age)

df["trtbps"]= np.log(df.trtbps)

df["chol"]= np.log(df.chol)

df["thalachh"]= np.log(df.thalachh)

print("---Log Transform of outliers performed---")
```

---Log Transform of outliers performed---

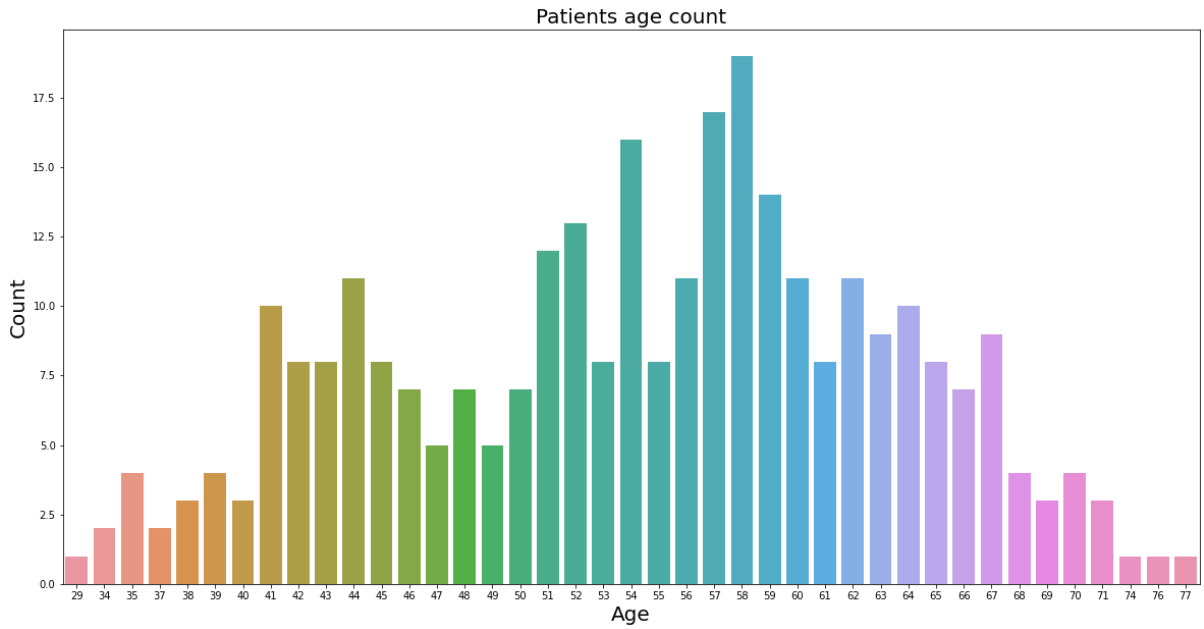
#Exploratory Data Analysis

#Analysis-1

```
plt.figure(figsize=(20,10))

sns.countplot(x=df["age"])

plt.title('Patients age count',fontsize=20)

plt.xlabel('Age',fontsize=20)
```

plt.ylabel('Count',fontsize=20)

plt.show()



s=df["sex"].value_counts().reset_index()
px.pie(s,names="index",values="sex",title='percentage of male & female patients')

#Observation:

#Maximum age count of the heart patients is 58

#Percentage of male patients is 68.3% and female patients is 31.7%

#Analysis-2

#Analysis-3

#Analysis-4

#Analysis-5

#Analysis6

#Analysis-7

#Basics of Machine learning

```
# droping the column 'drop' as it's unecessary for the predictions
X= df.drop('output', axis=1)
y= df['output']

#importing sklearn libraries
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn import metrics

#Fitting & transforming the data
scaler=StandardScaler()
```

X= pd.DataFrame(scaler.fit_transform(X))

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=0)

knn=KNeighborsClassifier(n_neighbors=5)

knn.fit(X_train,y_train)

y_pred=knn.predict(X_test)

print(metrics.classification_report(y_test,y_pred))

	precision	recall	f1-score	support
0	0.83	0.70	0.76	27
1	0.79	0.88	0.83	34
accuracy			0.80	61
macro avg	0.81	0.79	0.80	61
weighted avg	0.81	0.80	0.80	61

df.head()

	age	sex	cp	trtbps	chol	fbs	restecg	thalach	exng	oldpeak	slp	caa	thall	output
0	63	1	3	4.976734	5.451038	4.143135	0	5.010635	0	2.3	0	0	1	1
1	37	1	2	4.867534	5.521461	3.610918	1	5.231109	0	3.5	0	0	2	1
2	41	0	1	4.867534	5.318120	3.713572	0	5.147494	0	1.4	2	0	2	1
3	56	1	1	4.787492	5.463832	4.025352	1	5.181784	0	0.8	2	0	2	1
4	57	0	0	4.787492	5.869297	4.043051	1	5.093750	1	0.6	2	0	2	1

#checking the accuracy of the model

model= RandomForestClassifier()

```
model.fit(X_train,y_train)

predict_df=model.predict(X_test)

metrics.accuracy_score(y_test,predict_df)
```

0.8852459016393442