Name: Naim K.

Mailid: Khannaim33@gmail.com

Logistic Regression:

Probelm Statement:

Create a Classification Model that can predict whether or not a person has presence of heart disease based on physical features of that person (age,sex, cholesterol, etc...)

- Import required libraries

In [198...
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Data load

In [198...
```
df= pd.read_csv(r'C:\Users\Fahim\Downloads\LogisticRegressionWithPython\New Folder\H
print("Data imported successfully")
```

```
Data imported successfully
```

Details:

This dataset has 14 physical attributes based on physical testing of a patient. Blood samples are taken and the patient also conducts a brief exercise test. The "goal" field refers to the presence of heart disease in the patient. It is integer (0 for no presence, 1 for presence). In general, to confirm 100% if a patient has heart disease can be quite an invasive process, so if we can create a model that accurately predicts the likelihood of heart disease, we can help avoid expensive and invasive procedures.

Attribute Information:

- HeartDisease: 0 for no presence of heart disease, 1 for presence of heart disease
- Age:
- Male: Sex
- ChestPainType: chest pain type (4 values)
- BloodPressure: resting blood pressure
- Cholesterol: serum cholestoral in mg/dl
- BloodSugar: fasting blood sugar > 120 mg/dl
- EEG: resting electrocardiographic results (values 0,1,2)
- MaxHR: maximum heart rate achieved
- Angina: exercise induced angina
- OldPeak: ST depression induced by exercise relative to rest
- PeakST: the slope of the peak exercise ST segment
- Flourosopy: number of major vessels (0-3) colored by flourosopy
- Thal: 3 = normal; 6 = fixed defect; 7 = reversable defect

In [198...
```
df.head()
```

Out[198...

	HeartDisease	Age	Male	ChestPainType	BloodPressure	Cholesterol	BloodSugar	EEG	MaxHR
0	1	70	1	4	130	322	0	2	109
1	0	67	0	3	115	564	0	2	160
2	1	57	1	2	124	261	0	0	141
3	0	64	1	4	128	263	0	0	105
4	0	74	0	2	120	269	0	2	121

Data Understanding

In [198...

```
df.shape # The dataset contains 270 records and 14 columns
```

Out[198...

```
(270, 14)
```

In [199...

```
df.isnull().sum() # There is no null present in the given dataset
```

Out[199...

```
HeartDisease     0
Age              0
Male             0
ChestPainType    0
BloodPressure    0
Cholesterol      0
BloodSugar       0
EEG              0
MaxHR            0
Angina           0
OldPeak          0
PeakST           0
Flourosopy       0
Thal             0
dtype: int64
```

In [199...

```
df.info() # There are 13 column with datatype int64 except "OldPeak"  which has data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 270 entries, 0 to 269
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   HeartDisease   270 non-null    int64  
 1   Age            270 non-null    int64  
 2   Male           270 non-null    int64  
 3   ChestPainType  270 non-null    int64  
 4   BloodPressure  270 non-null    int64  
 5   Cholesterol    270 non-null    int64  
 6   BloodSugar     270 non-null    int64  
 7   EEG            270 non-null    int64  
 8   MaxHR          270 non-null    int64  
 9   Angina         270 non-null    int64  
 10  OldPeak        270 non-null    float64
 11  PeakST         270 non-null    int64  
 12  Flourosopy     270 non-null    int64  
 13  Thal           270 non-null    int64  
dtypes: float64(1), int64(13)
memory usage: 29.7 KB
```

In [199...

```
df.describe().transpose() # By using describe function from Pandas we can primary un
```

Out[199...

	count	mean	std	min	25%	50%	75%	max
HeartDisease	270.0	0.444444	0.497827	0.0	0.0	0.0	1.0	1.0

	count	mean	std	min	25%	50%	75%	max
Age	270.0	54.433333	9.109067	29.0	48.0	55.0	61.0	77.0
Male	270.0	0.677778	0.468195	0.0	0.0	1.0	1.0	1.0
ChestPainType	270.0	3.174074	0.950090	1.0	3.0	3.0	4.0	4.0
BloodPressure	270.0	131.344444	17.861608	94.0	120.0	130.0	140.0	200.0
Cholesterol	270.0	249.659259	51.686237	126.0	213.0	245.0	280.0	564.0
BloodSugar	270.0	0.148148	0.355906	0.0	0.0	0.0	0.0	1.0
EEG	270.0	1.022222	0.997891	0.0	0.0	2.0	2.0	2.0
MaxHR	270.0	149.677778	23.165717	71.0	133.0	153.5	166.0	202.0
Angina	270.0	0.329630	0.470952	0.0	0.0	0.0	1.0	1.0
OldPeak	270.0	1.050000	1.145210	0.0	0.0	0.8	1.6	6.2
PeakST	270.0	1.585185	0.614390	1.0	1.0	2.0	2.0	3.0
Flourosopy	270.0	0.670370	0.943896	0.0	0.0	0.0	1.0	3.0
Thal	270.0	4.696296	1.940659	3.0	3.0	3.0	7.0	7.0

Feature Engineering

In [199…
```
# From the dataset, we can see column Male has values both 0 and 1 where we can cons
```

In [199…
```
# So, here we are going to replace Column name 'Male' to 'Sex'

df = df.rename(columns={'Male': 'Sex'})
```

In [199…
```
df.head() # As we can column name Male has been changed from Male to 'Sex' by using
```

Out[199…

	HeartDisease	Age	Sex	ChestPainType	BloodPressure	Cholesterol	BloodSugar	EEG	MaxHR	A
0	1	70	1	4	130	322	0	2	109	
1	0	67	0	3	115	564	0	2	160	
2	1	57	1	2	124	261	0	0	141	
3	0	64	1	4	128	263	0	0	105	
4	0	74	0	2	120	269	0	2	121	

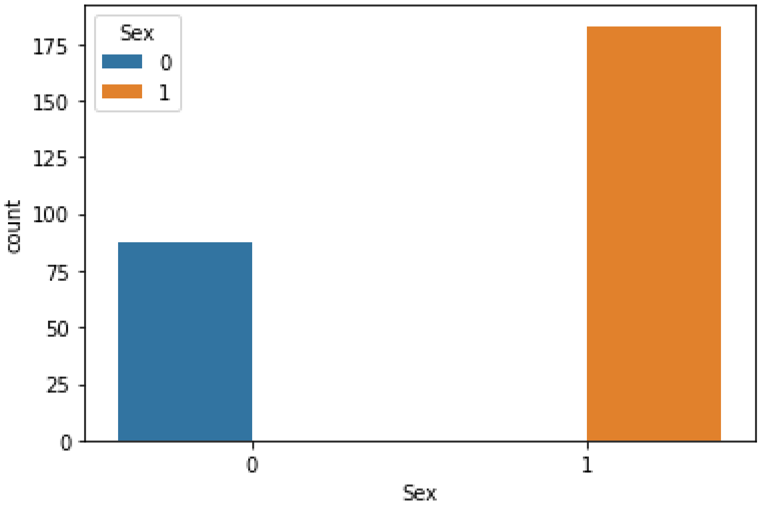
Exploratory Data Analysis (EDA)

- Now, we are going to perform some EDA on the dataset and will put our insights as well on this.

In [199…
```
# Countplot on Sex
```

In [199…
```
sns.countplot(data=df, x = 'Sex', hue='Sex')
```

Out[199…
```
<AxesSubplot:xlabel='Sex', ylabel='count'>
```

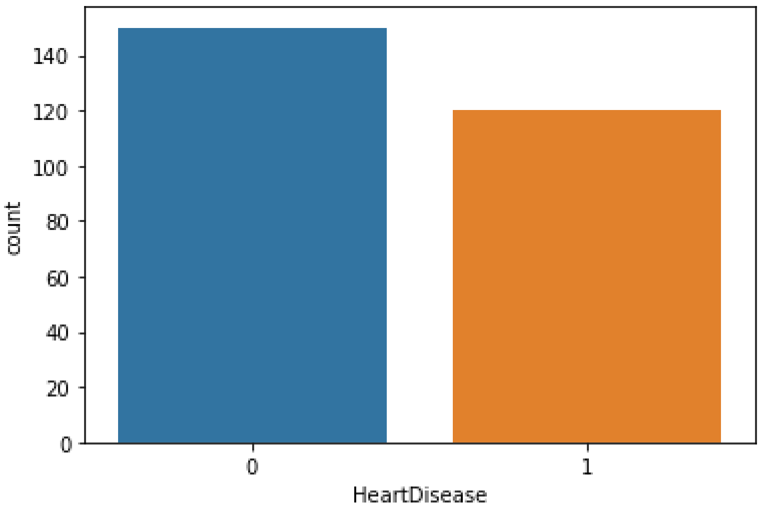


- Insight: As we can see, the number of 'Male' patient is greater in the given dataset than 'Female'

In [199…
```
# Countplot on Heartdisease
```

In [199…
```
sns.countplot(data=df, x = 'HeartDisease')
```

Out[199…
```
<AxesSubplot:xlabel='HeartDisease', ylabel='count'>
```



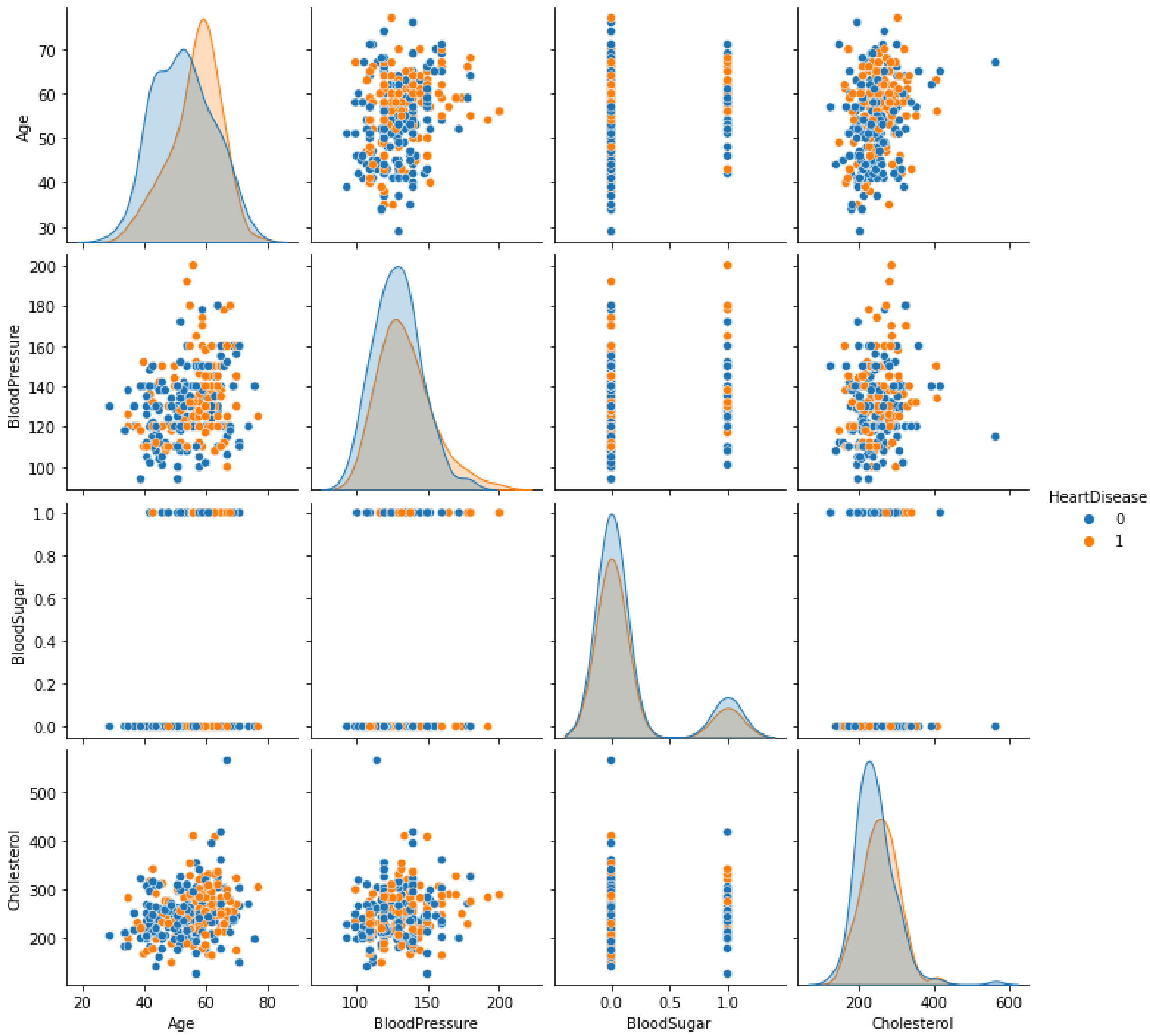
- Insights: Total count of patient who dose not has Heartdisease are greater than number of patietn who has Heartdisease

In [200…
```
# let's draw pairplot to relationship betweem some selected coumn
```

In [200…
```
colums = ['Age','BloodPressure','BloodSugar','Cholesterol','HeartDisease']
```

In [200…
```
sns.pairplot(df[colums], hue='HeartDisease')
```

Out[200…
```
<seaborn.axisgrid.PairGrid at 0x162df51a970>
```



- Insights:
- 1) Based on the above chart, we can see that there is no seperation between who is likely to have heart diseases or not.
- 2) We can se Age, BloodPressure and Cholesterol has dependency on Heartdiseases whereas BloodSugar has not much

In [ ]:

In [200…

```
# Here is the heatmap for dataset to check teh correlation between all columns
```

In [200…

```
df.corr()
```

Out[200…

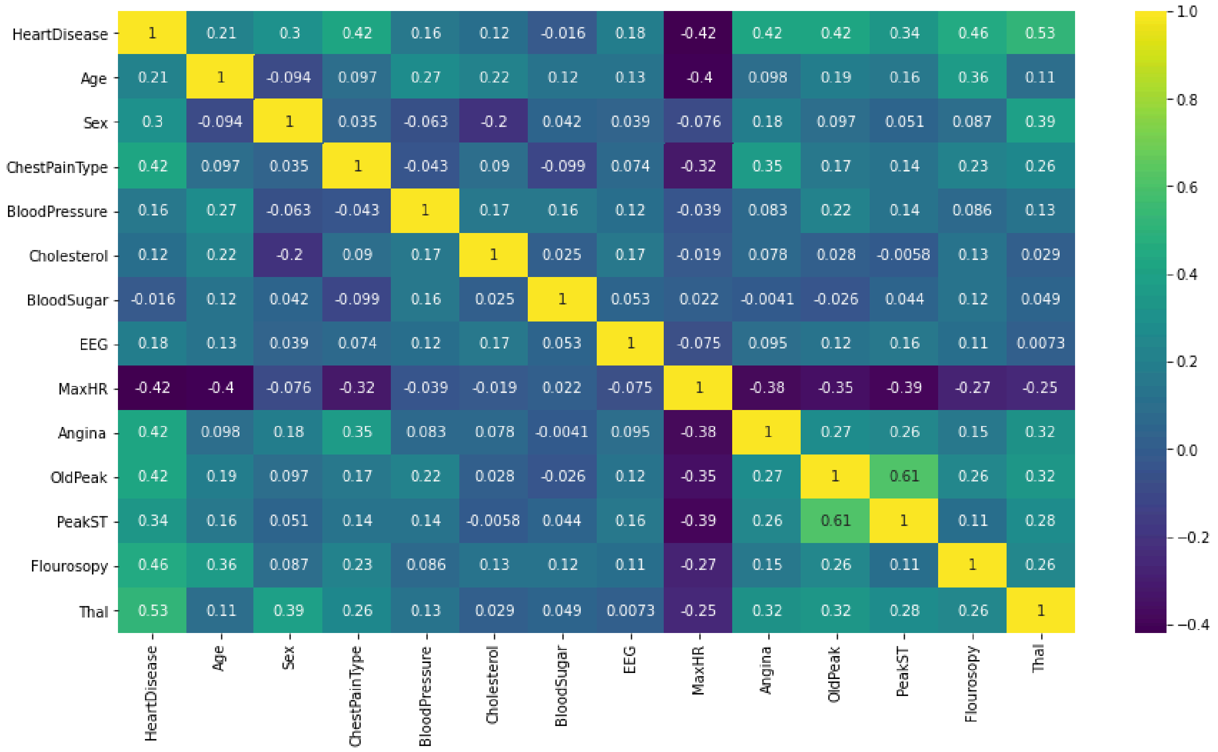
	HeartDisease	Age	Sex	ChestPainType	BloodPressure	Cholesterol	Blood:
HeartDisease	1.000000	0.212322	0.297721	0.417436	0.155383	0.118021	-0.0
Age	0.212322	1.000000	-0.094401	0.096920	0.273053	0.220056	0.1.
Sex	0.297721	-0.094401	1.000000	0.034636	-0.062693	-0.201647	0.0.
ChestPainType	0.417436	0.096920	0.034636	1.000000	-0.043196	0.090465	-0.0
BloodPressure	0.155383	0.273053	-0.062693	-0.043196	1.000000	0.173019	0.1
Cholesterol	0.118021	0.220056	-0.201647	0.090465	0.173019	1.000000	0.0.
BloodSugar	-0.016319	0.123458	0.042140	-0.098537	0.155681	0.025186	1.0

	HeartDisease	Age	Sex	ChestPainType	BloodPressure	Cholesterol	Blood:
EEG	0.182091	0.128171	0.039253	0.074325	0.116157	0.167652	0.0
MaxHR	-0.418514	-0.402215	-0.076101	-0.317682	-0.039136	-0.018739	0.0
Angina	0.419303	0.098297	0.180022	0.353160	0.082793	0.078243	-0.0
OldPeak	0.417967	0.194234	0.097412	0.167244	0.222800	0.027709	-0.0
PeakST	0.337616	0.159774	0.050545	0.136900	0.142472	-0.005755	0.0
Flourosopy	0.455336	0.356081	0.086830	0.225890	0.085697	0.126541	0.1
Thal	0.525020	0.106100	0.391046	0.262659	0.132045	0.028836	0.0

In [200…
```
# Heatmap
```

In [200…
```
plt.figure(figsize=(15,8))
sns.heatmap(df.corr(),annot=True,cmap='viridis')
```

Out[200…
```
&lt;AxesSubplot:&gt;
```



- Insights: Based on the correlation, we can see that chest pain has highest correlation with target.

Data Sampling

In [ ]:
```
```

In [200…
```
from sklearn.model_selection import train_test_split

df_train, df_test = train_test_split(df,test_size=0.2,random_state=123)

df_train_x = df_train.iloc[:,1:]
df_train_y = df_train[['HeartDisease']]
```

```
df_test_x = df_test.iloc[:,1:]
df_test_y = df_test[['HeartDisease']]
```

In [200…

```
print(df_train_x.shape)
print(df_train_y.shape)

print(df_test_x.shape)
print(df_test_y.shape)
```

```
(216, 13)
(216, 1)
(54, 13)
(54, 1)
```

In [200…

```
df_train_x.columns
```

Out[200…

```
Index(['Age', 'Sex', 'ChestPainType', 'BloodPressure', 'Cholesterol',
       'BloodSugar', 'EEG', 'MaxHR', 'Angina', 'OldPeak', 'PeakST',
       'Flourosopy', 'Thal'],
      dtype='object')
```

In [201…

```
df_train_y.columns
```

Out[201…

```
Index(['HeartDisease'], dtype='object')
```

1) Build Logistic Regression

In [201…

```
from sklearn.linear_model import LogisticRegression
```

In [201…

```
logreg = LogisticRegression(class_weight='Balanced', random_state=123)
```

In [201…

```
logreg.fit(df_train_x,df_train_y)
```

```
C:\Users\Fahim\anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConver
sionWarning: A column-vector y was passed when a 1d array was expected. Please change
the shape of y to (n_samples, ), for example using ravel().
  return f(*args, **kwargs)
C:\Users\Fahim\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:763: Con
vergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[201…

```
LogisticRegression(class_weight='Balanced', random_state=123)
```

In [201…

```
# Predict the values based on test dataset
```

In [201…

```
pred_df = logreg.predict(df_test_x)
```

In [201…

```
# Coeficient value
```

In [201…

```
logreg.coef_
```

Out[201…

```
array([[-0.04409515,  0.91781561,  0.57289332,  0.00999822,  0.00544024,
         0.09295322,  0.12429013, -0.03686092,  0.61975884,  0.36288893,
        -0.19602165,  1.12687383,  0.35175873]])
```

In [201…

```
# Compare the coeficient value with train data set
```

In [201…

```
logreg.fit(df_train_x,df_train_y).coef_
```

```
C:\Users\Fahim\anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConver
sionWarning: A column-vector y was passed when a 1d array was expected. Please change
the shape of y to (n_samples, ), for example using ravel().
  return f(*args, **kwargs)
C:\Users\Fahim\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:763: Con
vergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[201…

```
array([[-0.04409515,  0.91781561,  0.57289332,  0.00999822,  0.00544024,
         0.09295322,  0.12429013, -0.03686092,  0.61975884,  0.36288893,
        -0.19602165,  1.12687383,  0.35175873]])
```

In [202…

```
# Calculate the intercept value (slope)
```

In [202…

```
logreg.intercept_
```

Out[202…

```
array([-0.20185871])
```

In [202…

```
# Compare the intercept value with train dataset
```

In [202…

```
logreg.fit(df_train_x,df_train_y).intercept_
```

```
C:\Users\Fahim\anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConver
sionWarning: A column-vector y was passed when a 1d array was expected. Please change
the shape of y to (n_samples, ), for example using ravel().
  return f(*args, **kwargs)
C:\Users\Fahim\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:763: Con
vergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[202…

```
array([-0.20185871])
```

In [202…

```
# Check the paramters applied on the dataset
```

In [202…

```
logreg.get_params()
```

Out[202…

```
{'C': 1.0,
 'class_weight': 'Balanced',
 'dual': False,
 'fit_intercept': True,
 'intercept_scaling': 1,
 'l1_ratio': None,
 'max_iter': 100,
 'multi_class': 'auto',
 'n_jobs': None,
 'penalty': 'l2',
 'random_state': 123,
 'solver': 'lbfgs',
 'tol': 0.0001,
 'verbose': 0,
 'warm_start': False}
```

In [202…

```
# On the basis of Coeficient value of the each field we can judge the relation ship
```

In [202…

```
coef = pd.Series(data=logreg.coef_[0],index = df_train_x.columns)
coef
```

Out[202…

```
Age              -0.044095
Sex               0.917816
ChestPainType     0.572893
BloodPressure     0.009998
Cholesterol       0.005440
BloodSugar        0.092953
EEG               0.124290
MaxHR            -0.036861
Angina            0.619759
OldPeak           0.362889
PeakST           -0.196022
Flourosopy        1.126874
Thal              0.351759
dtype: float64
```

In [202…

```
# Sort the coeficient values in Desc. order
```

In [202…

```
coef = coef.sort_values(ascending=False)
coef
```

Out[202…

```
Flourosopy        1.126874
Sex               0.917816
Angina            0.619759
ChestPainType     0.572893
OldPeak           0.362889
Thal              0.351759
EEG               0.124290
BloodSugar        0.092953
BloodPressure     0.009998
Cholesterol       0.005440
MaxHR            -0.036861
Age              -0.044095
PeakST           -0.196022
dtype: float64
```

In [203…

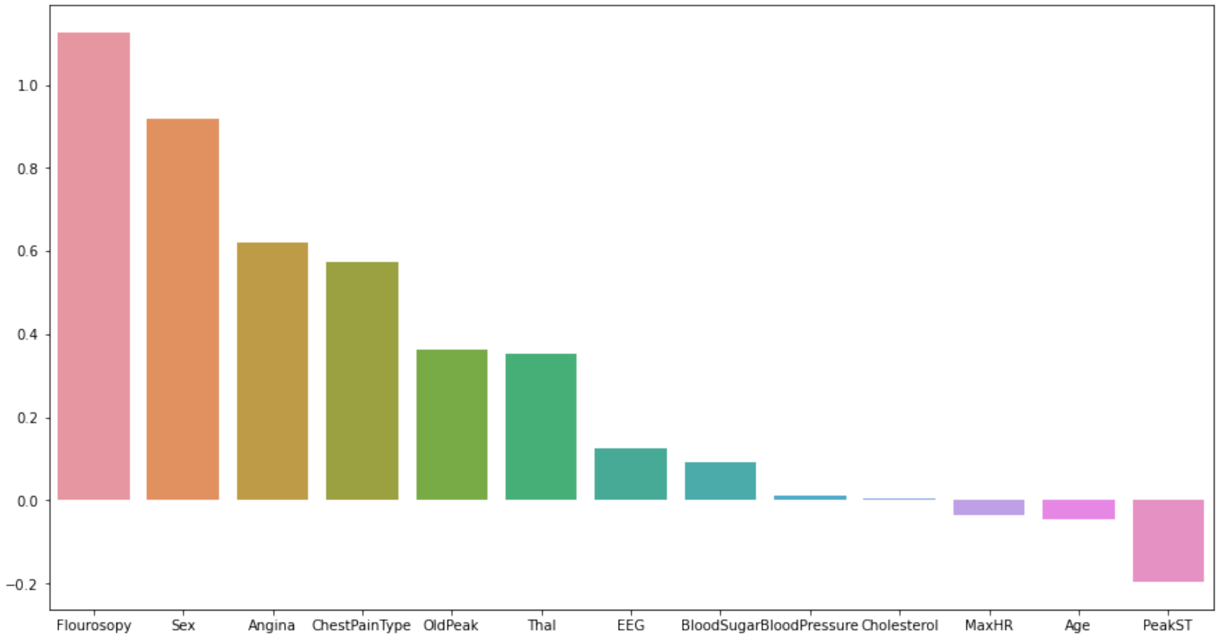
```
# Plot the graph for coeficient values
```

In [203…

```
plt.figure(figsize=(15,8))
sns.barplot(x=coef.index,y=coef.values)
```

Out[203…

```
<AxesSubplot:>
```



- Insights:
- We can see that field Flourosopy, Sex and Angina has strong relation with target column Heartdisease, followed by OldPeak, Sex and Thal
- Whereas PeakST has least correlation with target variable Heartdisease followed by Age and MaxHR.

In [ ]:

```

```

Model Performance Evaluation

Let's now evaluate your model on the remaining 10% of the data, the test set.

Create the following evaluations:

- Confusion Matrix Array
- Confusion Matrix Plot
- Classification Report

In [203…

```
# Imprt confusion matrics library from sklearn.metrics
```

In [203…

```
from sklearn.metrics import confusion_matrix
```

In [203…

```
# Calculate the confusion matrix
```

In [203…

```
conf_matrix = confusion_matrix(pred_df, df_test_y)
conf_matrix
```

Out[203…

```
array([[26,  5],
       [ 4, 19]], dtype=int64)
```

In [203…

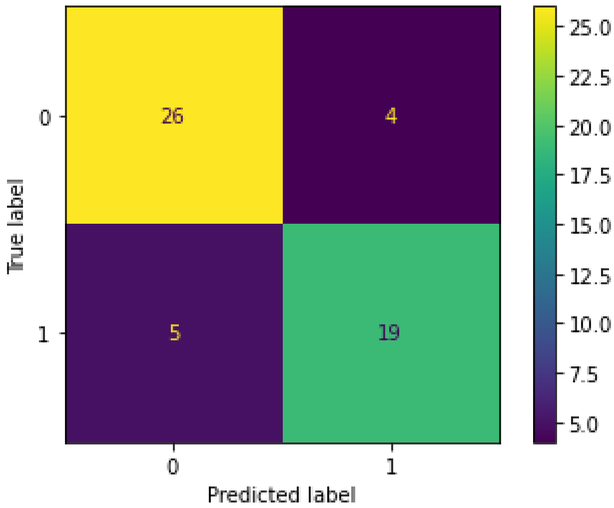
```
# Plot the grapgh for confusion matrix
```

In [203…

```
plt.figure(figsize=(8,8))
plot_confusion_matrix(logreg, df_test_x, df_test_y)
```

Out[203…

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x162e1571bb0>
<Figure size 576x576 with 0 Axes>
```



- Here we can see only 9 records from our testing dataset has wrong assumption, where we got our model 83.33% of accuracy.

In [203…
```
# Print the classification report
```

In [203…
```
print(classification_report(df_test_y, pred_df))
```

```
              precision    recall  f1-score   support

           0       0.84      0.87      0.85        30
           1       0.83      0.79      0.81        24

    accuracy                           0.83        54
   macro avg       0.83      0.83      0.83        54
weighted avg       0.83      0.83      0.83        54
```

In [204…
```
# Verify the Accuracy of the model
```

In [204…
```
Acc = conf_matrix.diagonal().sum() / conf_matrix.sum() * 100
Acc
```

Out[204…
```
83.33333333333334
```

In [ ]:
```

```


- Here we can see only 9 records from our testing dataset has wrong assumption, where we got our model 83.33% of accuracy.

Probability:

- Check for the probability

In [204…
```
pred_prob_test = logreg.predict_proba(df_test_x)
```

In [204…
```
pred_valiue_prob = pd.DataFrame(pred_prob_test)
pred_valiue_prob.head()
```

Out[204…

	0	1
0	0.375536	0.624464
1	0.946424	0.053576

	0	1
2	0.027935	0.972065
3	0.822988	0.177012
4	0.792676	0.207324

Area Under Curve

In [204...
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
```

In [204...
```
log_run_curve = roc_auc_score(pred_df, df_test_y)
log_run_curve
```

Out[204...
```
0.832398316970547
```

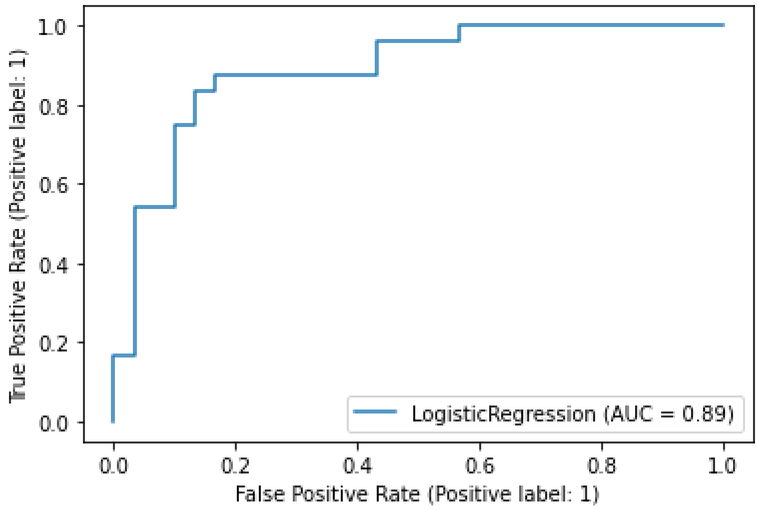
In [ ]:
```

```

In [204...
```
# Plot ROC curve
```

In [204...
```
from sklearn.metrics import plot_roc_curve
```

In [204...
```
plot_roc_curve(logreg, df_test_x, df_test_y);
```



In [ ]:
```

```

Model Improvisation:

Try to imporve your accuracy in this part:

Standardization:

Create a StandardScaler object and normalize the X train and test set feature data. Make sure you only fit to the training data to avoid data leakage (data knowledge leaking from the test set).

In [204...
```
from sklearn.preprocessing import StandardScaler
```

In [205...
```
scalar = StandardScaler()
```

In [205…
```
scaled_x_train = scalar.fit_transform(df_train_x)
scaled_x_test = scalar.transform(df_test_x)
```

In [ ]:

2)Build LogisticregressionCV model

In [205…
```
from sklearn.linear_model import LogisticRegressionCV
```

In [205…
```
logcv_model = LogisticRegressionCV(class_weight='Balanced', random_state=123)
```

In [205…
```
logcv_model.fit(scaled_x_train,df_train_y)
```

```
C:\Users\Fahim\anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConver
sionWarning: A column-vector y was passed when a 1d array was expected. Please change
the shape of y to (n_samples, ), for example using ravel().
  return f(*args, **kwargs)
```

Out[205…
```
LogisticRegressionCV(class_weight='Balanced', random_state=123)
```

In [205…
```
# Check for the C value of the model
```

In [205…
```
logcv_model.C_
```

Out[205…
```
array([2.7825594])
```

In [205…
```
# Check for the parameters by using which our improved dataset is built
```

In [205…
```
logcv_model.get_params()
```

Out[205…
```
{'Cs': 10,
 'class_weight': 'Balanced',
 'cv': None,
 'dual': False,
 'fit_intercept': True,
 'intercept_scaling': 1.0,
 'l1_ratios': None,
 'max_iter': 100,
 'multi_class': 'auto',
 'n_jobs': None,
 'penalty': 'l2',
 'random_state': 123,
 'refit': True,
 'scoring': None,
 'solver': 'lbfgs',
 'tol': 0.0001,
 'verbose': 0}
```

In [205…
```
# Coeficient values
```

In [206…
```
logcv_model.coef_
```

Out[206…
```
array([[-0.06333975,  0.74978547,  0.83158531,  0.36501703,  0.37064021,
        -0.06313544,  0.13153143, -0.528749  ,  0.30053348,  0.33238459,
         0.04351319,  1.10203046,  0.60905311]])
```

In [206…
```
# Check for the intercept values
```

In [206…
```
logcv_model.intercept_
```

Out[206… array([-0.27468955])

In [206…
```
# Comapre the coeficient values wr.r.t. each field by creating dataframe for it
```

In [206…
```
coef_cv = pd.Series(data=logcv_model.coef_[0],index=df_train_x.columns)
coef_cv
```

Out[206…
```
Age              -0.063340
Sex               0.749785
ChestPainType     0.831585
BloodPressure     0.365017
Cholesterol       0.370640
BloodSugar       -0.063135
EEG               0.131531
MaxHR            -0.528749
Angina            0.300533
OldPeak           0.332385
PeakST            0.043513
Flourosopy        1.102030
Thal              0.609053
dtype: float64
```

In [206…
```
# Sort the above coef.dataframe with respect Desc order
```

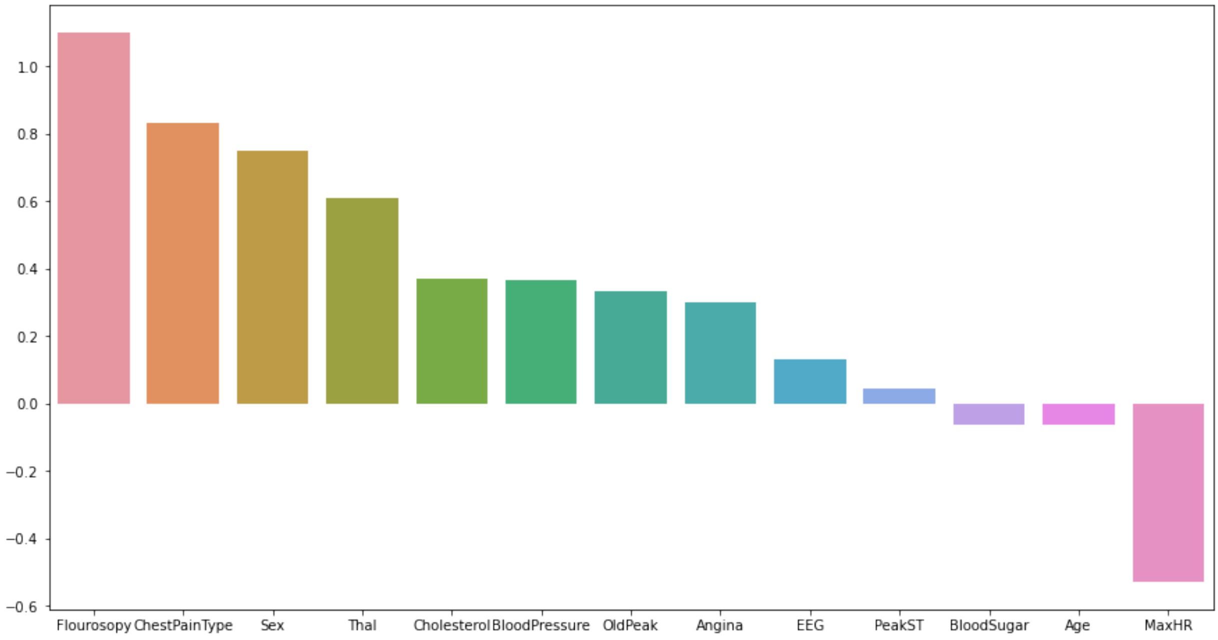
In [206…
```
coef_cv = coef_cv.sort_values(ascending=False)
coef_cv
```

Out[206…
```
Flourosopy        1.102030
ChestPainType     0.831585
Sex               0.749785
Thal              0.609053
Cholesterol       0.370640
BloodPressure     0.365017
OldPeak           0.332385
Angina            0.300533
EEG               0.131531
PeakST            0.043513
BloodSugar       -0.063135
Age              -0.063340
MaxHR            -0.528749
dtype: float64
```

In [206…
```
# Plot the figure for improved coef values
```

In [206…
```
plt.figure(figsize=(15,8))
sns.barplot(x=coef_cv.index,y=coef_cv.values)
```

Out[206… <AxesSubplot:>



- Insights:
- We can see that field Flourosopy, Chestpain and Sex has strong relation with target column Heartdisease, followed by Thal, Chlorestrol and Bloodpressure after model improvisation.
- Whereas MaxHR has least correlation with target variable Heartdisease followed by Age and Bloodsugar.

Model Performance Evaluation

Let's now evaluate your model on the remaining 10% of the data, the test set.

Create the following evaluations:

- Confusion Matrix Array
- Confusion Matrix Plot
- Classification Report

In [206…

```
from sklearn.metrics import confusion_matrix, plot_confusion_matrix, classification_
```

In [207…

```
pred_coef_cv = logcv_model.predict(scaled_x_test)
pred_coef_cv
```

Out[207…

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

In [207…

```
conf_matrix_cv = confusion_matrix(df_test_y,pred_coef_cv)
conf_matrix_cv
```

Out[207…

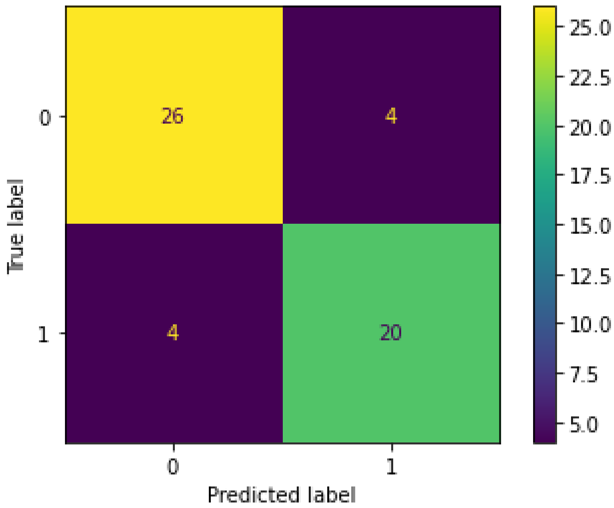
```
array([[26,  4],
       [ 4, 20]], dtype=int64)
```

In [207…

```
plt.figure(figsize=(8,8))
plot_confusion_matrix(logcv_model, scaled_x_test, df_test_y)
```

Out[207…

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x162e176bd30>
<Figure size 576x576 with 0 Axes>
```



In [207…

```
# Print the classification report
```

In [207…

```
print(classification_report(df_test_y, pred_coef_cv))
```

```
              precision    recall  f1-score   support

           0       0.87      0.87      0.87        30
           1       0.83      0.83      0.83        24

    accuracy                           0.85        54
   macro avg       0.85      0.85      0.85        54
weighted avg       0.85      0.85      0.85        54
```

In [207…

```
# Verify the Accuracy of the model
```

In [207…

```
Acc_cv = conf_matrix_cv.diagonal().sum() / conf_matrix_cv.sum() * 100
Acc_cv
```

Out[207…

```
85.18518518518519
```

- Here we can see only 8 records from our testing dataset has wrong assumption, where we got our model 85.18% of accuracy.

Probability:

- Check for the probablity:

In [ ]:

In [207…

```
pred_prob_scaled_test = logcv_model.predict_proba(scaled_x_test)
```

In [207…

```
pred_scaled_value_prob = pd.DataFrame(pred_prob_scaled_test)
pred_scaled_value_prob.head()
```

Out[207…

	0	1
0	0.326915	0.673085
1	0.947272	0.052728
2	0.044356	0.955644
3	0.905360	0.094640

	0	1
4	0.886856	0.113144

In [207…
```
# Apply ROC and A-ROC
```

In [208…
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
```

Area Undre the curve

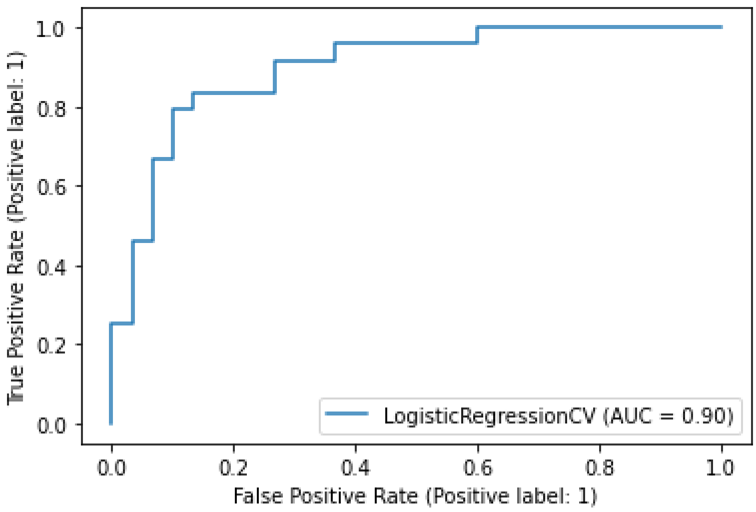
In [208…
```
log_run_curve = roc_auc_score(pred_coef_cv, df_test_y)
log_run_curve
```

Out[208…
```
0.8500000000000001
```

In [208…
```
# Plot ROC curve
```

In [208…
```
from sklearn.metrics import plot_roc_curve
```

In [208…
```
plot_roc_curve(logcv_model, scaled_x_test, df_test_y);
```



In [ ]:
```
```

In [ ]:
```
```

3)Try to boost your accurcay by using SMOTE:

- In both of the above model we got same accuracy with 83.33%. So now we are going try SMOTE method to boost your accuracy.

In [208…
```
from imblearn.over_sampling import SMOTE
```

In [208…
```
log_smote = SMOTE(random_state=123,k_neighbors=7,sampling_strategy='auto', n_jobs=No
```

In [208…
```
smote_x, smote_y = log_smote.fit_resample(df_train_x,df_train_y.values.ravel())
```

In [208…
```
log_sm = logreg.fit(smote_x, smote_y)
log_sm
```

```
C:\Users\Fahim\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:763: Con
vergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[208…

```
LogisticRegression(class_weight='Balanced', random_state=123)
```

In [208…

```
pred_smote = log_sm.predict(df_test_x)
```

In [209…

```
conf_matrix_sm = confusion_matrix(df_test_y,pred_smote)
conf_matrix_sm
```

Out[209…

```
array([[26,  4],
       [ 5, 19]], dtype=int64)
```

In [ ]:

In [209…

```
print(classification_report(df_test_y, pred_smote))
```

```
              precision    recall  f1-score   support

           0       0.84      0.87      0.85        30
           1       0.83      0.79      0.81        24

    accuracy                           0.83        54
   macro avg       0.83      0.83      0.83        54
weighted avg       0.83      0.83      0.83        54
```

In [209…

```
Acc_sm = conf_matrix_sm.diagonal().sum() / conf_matrix_sm.sum() * 100
Acc_sm
```

Out[209…

```
83.33333333333334
```

In [209…

```
# AS we can see accuray decreased after applying smote method, we cant go ahead with
```

In [ ]:

Model testing:

- We are goinf ahead with Logistic Regression CV model after perfoeming Standardization on the dataset.

A patient with the following features has come into the medical office:

- Age 54.0
- Sex 1.0
- ChestPainType 0.0
- BloodPressure 122.0
- Cholesterol 286.0
- BloodSugar 0.0

- EEG 0.0
- MaxHR 116.0
- Angina 1.0
- OldPeak 3.2
- PeakST 1.0
- Flourosopy 2.0
- Thal 2.0

What does your model predict for this patient? Do they have heart disease? How "sure" is your model of this prediction?

For convience, we created an array of the features for the patient above

In [209…
```
patient = [[ 54. ,   1. ,   0. , 122. , 286. ,   0. ,   0. , 116. ,   1. ,
          3.2,   1. ,   2. ,   2. ]]
```

In [209…
```
# EXPECTED PREDICTION
logcv_model.predict(patient)
```

Out[209…
```
array([1], dtype=int64)
```

In [209…
```
# EXPECTED PROBABILITY PER CLASS (Basically model should be extremely sure its in th

logcv_model.predict_proba(patient)
```

Out[209…
```
array([[0., 1.]])
```

- The model predict that the patient belong to target class 1 way more than class 0.

Retrain the model on whole data and predict on the new patient

In [209…
```
scaled_x = scalar.fit_transform(df_train_x)
```

In [209…
```
logcv_model.fit(scaled_x, df_train_y)
```

```
C:\Users\Fahim\anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConver
sionWarning: A column-vector y was passed when a 1d array was expected. Please change
the shape of y to (n_samples, ), for example using ravel().
  return f(*args, **kwargs)
```

Out[209…
```
LogisticRegressionCV(class_weight='Balanced', random_state=123)
```

In [209…
```
# Predict the Heartdisease for the Patient
```

In [210…
```
logcv_model.predict(patient)
```

Out[210…
```
array([1], dtype=int64)
```

In [210…
```
# Predict the probablity
```

In [210…
```
logcv_model.predict_proba(patient)
```

Out[210…
```
array([[0., 1.]])
```

In [ ]:
```

```

- The model predict that the patient is pretty belong the class 1 rather than class 0.

In [ ]:

- Patient-2

In [210…
```
patient2 = [[ 48. ,    1. ,    2. , 130. , 275. ,    0. ,    1. , 139. ,    0. ,
          0.2,    2. ,    0.0 ,    2. ]]
```

In [210…
```
# Predict for Patient2

logcv_model.predict(patient2)
```

Out[210…
```
array([1], dtype=int64)
```

In [210…
```
# Predict the Probablity

logcv_model.predict_proba(patient2)
```

Out[210…
```
array([[0., 1.]])
```

- The model predict that the patient is pretty belong the class 1 rather than class 0.

In [ ]:

Applying Statistics model to build model

In [210…
```
import statsmodels.formula.api as smf    # import statsmodel
```

In [210…
```
# Build statsmodel
```

In [210…
```
stat_model = smf.logit(formula='HeartDisease ~ Age + Sex + ChestPainType + BloodPres
```

In [210…
```
stat_mode_result = stat_model.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.332589
         Iterations 7
```

In [211…
```
print(stat_mode_result.summary())
```

```
                           Logit Regression Results
==============================================================================
Dep. Variable:           HeartDisease   No. Observations:                  270
Model:                          Logit   Df Residuals:                      256
Method:                           MLE   Df Model:                           13
Date:                Mon, 19 Aug 2024   Pseudo R-squ.:                  0.5159
Time:                        01:17:17   Log-Likelihood:                -89.799
converged:                       True   LL-Null:                       -185.48
Covariance Type:            nonrobust   LLR p-value:                 8.075e-34
================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept        -8.4464      3.088     -2.735      0.006     -14.499      -2.394
Age              -0.0175      0.026     -0.680      0.497      -0.068       0.033
Sex               1.5421      0.541      2.852      0.004       0.482       2.602
ChestPainType     0.7009      0.215      3.256      0.001       0.279       1.123
BloodPressure     0.0252      0.011      2.202      0.028       0.003       0.048
Cholesterol       0.0072      0.004      1.773      0.076      -0.001       0.015
BloodSugar       -0.7948      0.575     -1.383      0.167      -1.921       0.332
```

```
MaxHR          -0.0210      0.011     -1.989      0.047      -0.042      -0.000
EEG             0.3017      0.198      1.525      0.127      -0.086       0.689
Angina          0.8294      0.431      1.924      0.054      -0.016       1.674
OldPeak         0.3437      0.227      1.514      0.130      -0.101       0.789
PeakST          0.4423      0.391      1.131      0.258      -0.324       1.209
Flourosopy      1.1653      0.269      4.327      0.000       0.637       1.693
Thal            0.3414      0.106      3.219      0.001       0.133       0.549
==================================================================================
```

- As our model (log-Likelihood model) has score -89.799 whereas baseline model (LL null model) has score -185.48, our model much better than the baseline model

- Confidence intervals plays important role in this statsmodel building, whereas except MaxHR every other fields has confidence interval not equal to 0.00.
- Hence, in this we can try by droping MaxHR field from dataset.

In [211…

```
stat_model_1 = smf.logit(formula='HeartDisease ~ Age + Sex + ChestPainType + BloodPr
```

In [211…

```
stat_mode_result_1 = stat_model_1.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.340161
         Iterations 7
```

In [211…

```
print(stat_mode_result_1.summary())
```

```
                           Logit Regression Results
==============================================================================
Dep. Variable:           HeartDisease   No. Observations:                  270
Model:                          Logit   Df Residuals:                      257
Method:                           MLE   Df Model:                           12
Date:                Mon, 19 Aug 2024   Pseudo R-squ.:                  0.5048
Time:                        01:17:18   Log-Likelihood:                -91.843
converged:                       True   LL-Null:                       -185.48
Covariance Type:            nonrobust   LLR p-value:                 1.367e-33
==================================================================================
                     coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept        -12.4446      2.437     -5.107      0.000     -17.221      -7.668
Age                0.0023      0.023      0.097      0.923      -0.044       0.048
Sex                1.4527      0.533      2.723      0.006       0.407       2.498
ChestPainType      0.7650      0.212      3.609      0.000       0.350       1.180
BloodPressure      0.0217      0.011      1.912      0.056      -0.001       0.044
Cholesterol        0.0060      0.004      1.514      0.130      -0.002       0.014
BloodSugar        -0.8993      0.567     -1.587      0.113      -2.010       0.211
EEG                0.3194      0.195      1.639      0.101      -0.063       0.701
Angina             0.9568      0.420      2.276      0.023       0.133       1.781
OldPeak            0.3973      0.224      1.771      0.077      -0.042       0.837
PeakST             0.5684      0.380      1.495      0.135      -0.177       1.314
Flourosopy         1.1904      0.267      4.461      0.000       0.667       1.713
Thal               0.3541      0.105      3.364      0.001       0.148       0.560
==================================================================================
```

- As our model (log-Likelihood model) has score -91.853 whereas baseline model (LL null model) has score -185.48, our model much better than the baseline model

In [ ]:

Thank you

In [ ]:

In [ ]:

```

```