Heart_Attack_Project_Notebook

December 7, 2023

1 Imports

[1]:
```
# !pip install catboost
# !pip install xgboost
```

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier
from catboost import CatBoostClassifier

# Misc
from sklearn.metrics import accuracy_score, roc_auc_score, f1_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import warnings

warnings.filterwarnings("ignore")
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
```

2 Introduction to the Data

[3]:
```
df = pd.read_csv("heart_attack.csv")
```

[4]:
```
df.shape
```

[4]:
```
(8763, 26)
```

[5]:
```
df.head()
```

[5]:
```
  Patient ID  Age     Sex  Cholesterol Blood Pressure  Heart Rate  Diabetes  \
0    BMW7812   67    Male          208         158/88          72         0
1    CZE1114   21    Male          389         165/93          98         1
2    BNI9906   21  Female          324         174/99          72         1
3    JLN3497   84    Male          383        163/100          73         1
4    GFO8847   66    Male          318          91/88          93         1

   Family History  Smoking  Obesity  Alcohol Consumption  \
0               0        1        0                    0
1               1        1        1                    1
2               0        0        0                    0
3               1        1        0                    1
4               1        1        1                    0

   Exercise Hours Per Week       Diet  Previous Heart Problems  \
0                 4.168189    Average                        0
1                 1.813242  Unhealthy                        1
2                 2.078353    Healthy                        1
3                 9.828130    Average                        1
4                 5.804299  Unhealthy                        1

   Medication Use  Stress Level  Sedentary Hours Per Day  Income        BMI  \
0               0             9                 6.615001  261404  31.251233
1               0             1                 4.963459  285768  27.194973
2               1             9                 9.463426  235282  28.176571
3               0             9                 7.648981  125640  36.464704
4               0             6                 1.514821  160555  21.809144

   Triglycerides  Physical Activity Days Per Week  Sleep Hours Per Day  \
0            286                                0                    6
1            235                                1                    7
2            587                                4                    4
3            378                                3                    4
4            231                                1                    5

     Country      Continent           Hemisphere  Heart Attack Risk
0  Argentina  South America  Southern Hemisphere                  0
1     Canada  North America  Northern Hemisphere                  0
2     France         Europe  Northern Hemisphere                  0
3     Canada  North America  Northern Hemisphere                  0
4   Thailand           Asia  Northern Hemisphere                  0
```

[6]:
```
df.describe()
```

[6]:

```
               Age  Cholesterol   Heart Rate     Diabetes  Family History  \
count  8763.000000  8763.000000  8763.000000  8763.000000     8763.000000
mean     53.707977   259.877211    75.021682     0.652288        0.492982
std      21.249509    80.863276    20.550948     0.476271        0.499979
min      18.000000   120.000000    40.000000     0.000000        0.000000
25%      35.000000   192.000000    57.000000     0.000000        0.000000
50%      54.000000   259.000000    75.000000     1.000000        0.000000
75%      72.000000   330.000000    93.000000     1.000000        1.000000
max      90.000000   400.000000   110.000000     1.000000        1.000000

           Smoking      Obesity  Alcohol Consumption  Exercise Hours Per Week  \
count  8763.000000  8763.000000          8763.000000              8763.000000
mean      0.896839     0.501426             0.598083                10.014284
std       0.304186     0.500026             0.490313                 5.783745
min       0.000000     0.000000             0.000000                 0.002442
25%       1.000000     0.000000             0.000000                 4.981579
50%       1.000000     1.000000             1.000000                10.069559
75%       1.000000     1.000000             1.000000                15.050018
max       1.000000     1.000000             1.000000                19.998709

       Previous Heart Problems  Medication Use  Stress Level  \
count              8763.000000     8763.000000   8763.000000
mean                  0.495835        0.498345      5.469702
std                   0.500011        0.500026      2.859622
min                   0.000000        0.000000      1.000000
25%                   0.000000        0.000000      3.000000
50%                   0.000000        0.000000      5.000000
75%                   1.000000        1.000000      8.000000
max                   1.000000        1.000000     10.000000

       Sedentary Hours Per Day         Income          BMI  Triglycerides  \
count              8763.000000    8763.000000  8763.000000    8763.000000
mean                  5.993690  158263.181901    28.891446     417.677051
std                   3.466359   80575.190806     6.319181     223.748137
min                   0.001263   20062.000000    18.002337      30.000000
25%                   2.998794   88310.000000    23.422985     225.500000
50%                   5.933622  157866.000000    28.768999     417.000000
75%                   9.019124  227749.000000    34.324594     612.000000
max                  11.999313  299954.000000    39.997211     800.000000

       Physical Activity Days Per Week  Sleep Hours Per Day  Heart Attack Risk
count                      8763.000000          8763.000000        8763.000000
mean                          3.489672             7.023508           0.358211
std                           2.282687             1.988473           0.479502
min                           0.000000             4.000000           0.000000
25%                           2.000000             5.000000           0.000000
50%                           3.000000             7.000000           0.000000
```

```
75%                     5.000000          9.000000          1.000000
max                     7.000000         10.000000          1.000000
```

[7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8763 entries, 0 to 8762
Data columns (total 26 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   Patient ID                       8763 non-null   object 
 1   Age                              8763 non-null   int64  
 2   Sex                              8763 non-null   object 
 3   Cholesterol                      8763 non-null   int64  
 4   Blood Pressure                   8763 non-null   object 
 5   Heart Rate                       8763 non-null   int64  
 6   Diabetes                         8763 non-null   int64  
 7   Family History                   8763 non-null   int64  
 8   Smoking                          8763 non-null   int64  
 9   Obesity                          8763 non-null   int64  
 10  Alcohol Consumption              8763 non-null   int64  
 11  Exercise Hours Per Week          8763 non-null   float64
 12  Diet                             8763 non-null   object 
 13  Previous Heart Problems          8763 non-null   int64  
 14  Medication Use                   8763 non-null   int64  
 15  Stress Level                     8763 non-null   int64  
 16  Sedentary Hours Per Day          8763 non-null   float64
 17  Income                           8763 non-null   int64  
 18  BMI                              8763 non-null   float64
 19  Triglycerides                    8763 non-null   int64  
 20  Physical Activity Days Per Week  8763 non-null   int64  
 21  Sleep Hours Per Day              8763 non-null   int64  
 22  Country                          8763 non-null   object 
 23  Continent                        8763 non-null   object 
 24  Hemisphere                       8763 non-null   object 
 25  Heart Attack Risk                8763 non-null   int64  
dtypes: float64(3), int64(16), object(7)
memory usage: 1.7+ MB
```

2.0.1 It is first apparent here that the data doesnt contain any missing values

[8]:
```
df["Heart Attack Risk"].value_counts()
```

[8]:
```
Heart Attack Risk
0    5624
1    3139
Name: count, dtype: int64
```

3 Initial Cleaning

3.0.1 To get the maximum values out of my plot, I would like to first convert the existing categorical columns into numeric ones that can be visualized.

categorical_columns = "Patient ID", "Sex", "Blood Pressure", "Diet", "Country", "Continent,"Hemisphere"

[10]:
```
df["Patient ID"].str[:3].value_counts() # Mostly unique, dropping the column
```

[10]:
```
Patient ID
MPX    6
BGV    5
OMJ    5
RLR    5
VAA    4
      ..
AWA    1
SUP    1
MQX    1
MVX    1
XKA    1
Name: count, Length: 6866, dtype: int64
```

[11]:
```
df2 = df.drop(["Patient ID"],axis=1) #Patient ID
```

[12]:
```
df.Sex.value_counts();
```

[13]:
```
#Sex [One-Hot Encoding]
df2["Male"] = df.Sex.apply(lambda x: 1 if x == "Male" else 0)
df3 = df2.drop(["Sex"], axis=1)
```

[14]:
```
# Blood Pressure
df3["Blood Pressure"]
split = pd.DataFrame(df3['Blood Pressure'].str.split('/').to_list(), columns =␣
↪['Systolic', 'Diastolic'])
df4 = pd.concat([df3, split], axis=1)
df4.Systolic = df4.Systolic.astype(np.int32)
df4.Diastolic = df4.Diastolic.astype(np.int32)
df5 = df4.drop(['Blood Pressure'], axis = 1)
```

[15]:
```
# Diet [Ordinal Encoding]
def encode_diet(x):
    if x == 'Healthy':
        return 0
    elif x == 'Average':
        return 1
    else:
```

```
        return 2

df5['Bad_Diet'] = df5['Diet'].apply(lambda x: encode_diet(x))
df6 = df5.drop(["Diet"], axis = 1)
```

One-Hot Encoding : "Country", "Continent", "Hemisphere", would result in too many columns that contain information that is barely if at all to "Heart Attack Risk". That is why I'm deciding to drop them.

[16]:
```
df7 = df6.drop(["Country", "Continent", "Hemisphere"],axis = 1)
```

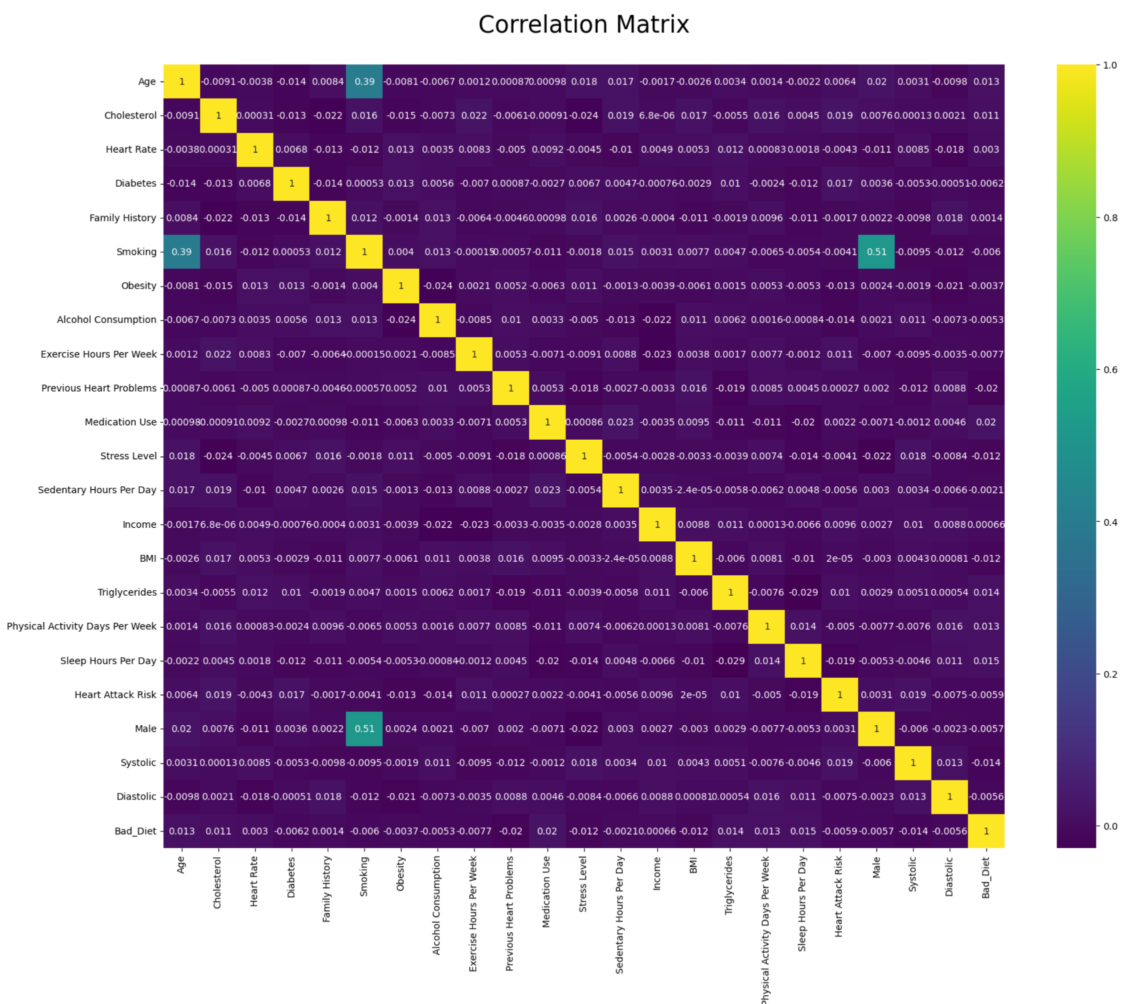
[17]:
```
df7.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8763 entries, 0 to 8762
Data columns (total 23 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   Age                              8763 non-null   int64  
 1   Cholesterol                      8763 non-null   int64  
 2   Heart Rate                       8763 non-null   int64  
 3   Diabetes                         8763 non-null   int64  
 4   Family History                   8763 non-null   int64  
 5   Smoking                          8763 non-null   int64  
 6   Obesity                          8763 non-null   int64  
 7   Alcohol Consumption              8763 non-null   int64  
 8   Exercise Hours Per Week          8763 non-null   float64
 9   Previous Heart Problems          8763 non-null   int64  
 10  Medication Use                   8763 non-null   int64  
 11  Stress Level                     8763 non-null   int64  
 12  Sedentary Hours Per Day          8763 non-null   float64
 13  Income                           8763 non-null   int64  
 14  BMI                              8763 non-null   float64
 15  Triglycerides                    8763 non-null   int64  
 16  Physical Activity Days Per Week  8763 non-null   int64  
 17  Sleep Hours Per Day              8763 non-null   int64  
 18  Heart Attack Risk                8763 non-null   int64  
 19  Male                             8763 non-null   int64  
 20  Systolic                         8763 non-null   int32  
 21  Diastolic                        8763 non-null   int32  
 22  Bad_Diet                         8763 non-null   int64  
dtypes: float64(3), int32(2), int64(18)
memory usage: 1.5 MB
```

4 Exploratory Data Analysis

[18]:
```python
corr = df7.corr()
```

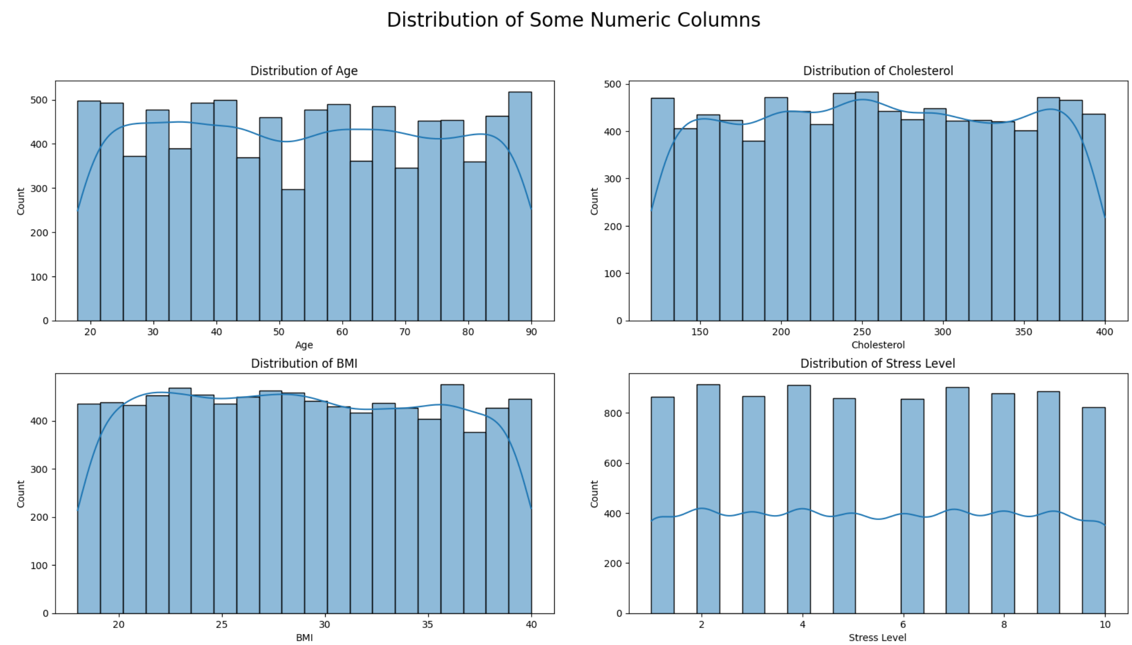
[19]:
```python
cmap = sns.color_palette("viridis", as_cmap=True)
fig,ax = plt.subplots(figsize=(20,15))
ax = sns.heatmap(corr,annot=True,cmap=cmap)
ax.set_title("Correlation Matrix\n",fontsize=25)
plt.show()
```



4.0.1 From the Heatmap we can see that there is only a clear relation between 2 columns:

Findings: - Smoking and Age, which makes sense & Smoking and Men. - Heart Attack risk has highest correlation with Diabetes, Cholestrol and Exercise Hours Per Weak - Heart attack Risk is not much dependent on Sedentary Hours Per Day

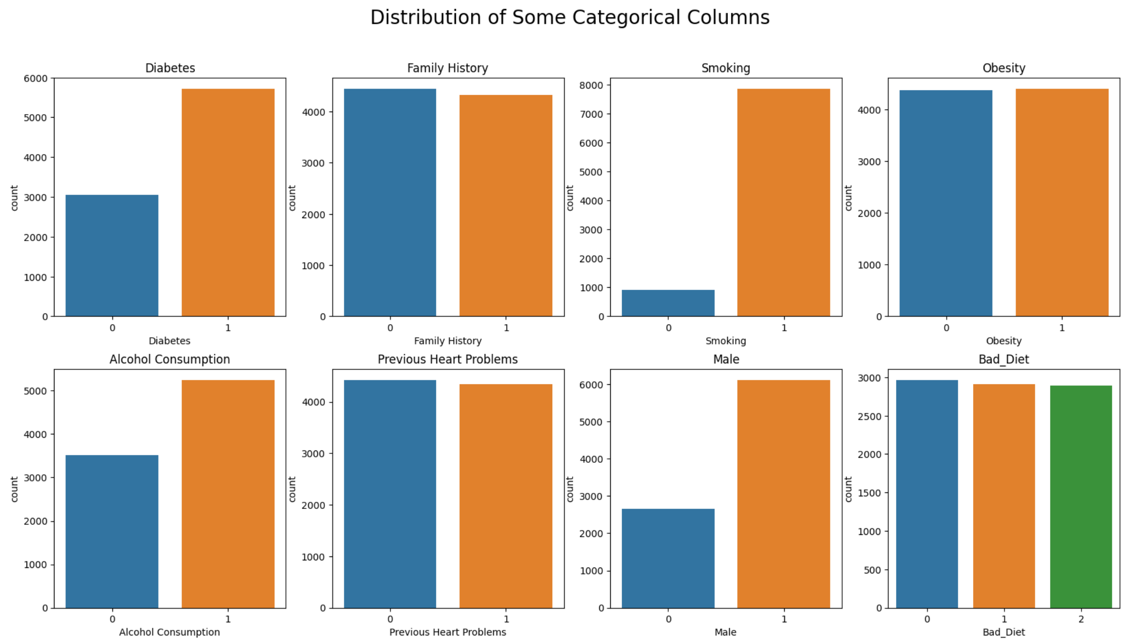
[20]:
```
# Distribution of Age
fig, ax = plt.subplots(2,2,figsize=(20,10))
fig.suptitle('Distribution of Some Numeric Columns',fontsize=20)
fig.subplots_adjust(hspace=0.22, wspace=0.15)
sns.histplot(ax=ax[0,0], data=df7["Age"],bins=20, kde=True).
  ↪set(title='Distribution of Age')
sns.histplot(ax=ax[0,1], data=df7["Cholesterol"],bins=20, kde=True).
  ↪set(title='Distribution of Cholesterol')
sns.histplot(ax=ax[1,0], data=df7["BMI"],bins=20, kde=True).
  ↪set(title='Distribution of BMI')
sns.histplot(ax=ax[1,1], data=df7["Stress Level"],bins=20, kde=True).
  ↪set(title='Distribution of Stress Level')
plt.show()
```



4.0.2 Now lets take a look at some of the divisions between the binary features

[21]:
```
fig, ax = plt.subplots(2,4,figsize=(20,10))
fig.suptitle('Distribution of Some Categorical Columns',fontsize=20)
fig.subplots_adjust(hspace=0.22, wspace=0.2)
sns.countplot(ax=ax[0,0], data=df7,x ='Diabetes').set(title='Diabetes')
sns.countplot(ax=ax[0,1], data=df7,x ='Family History').set(title='Family␣
  ↪History')
sns.countplot(ax=ax[0,2], data=df7,x ="Smoking").set(title='Smoking')
sns.countplot(ax=ax[0,3], data=df7,x ="Obesity").set(title='Obesity')
```

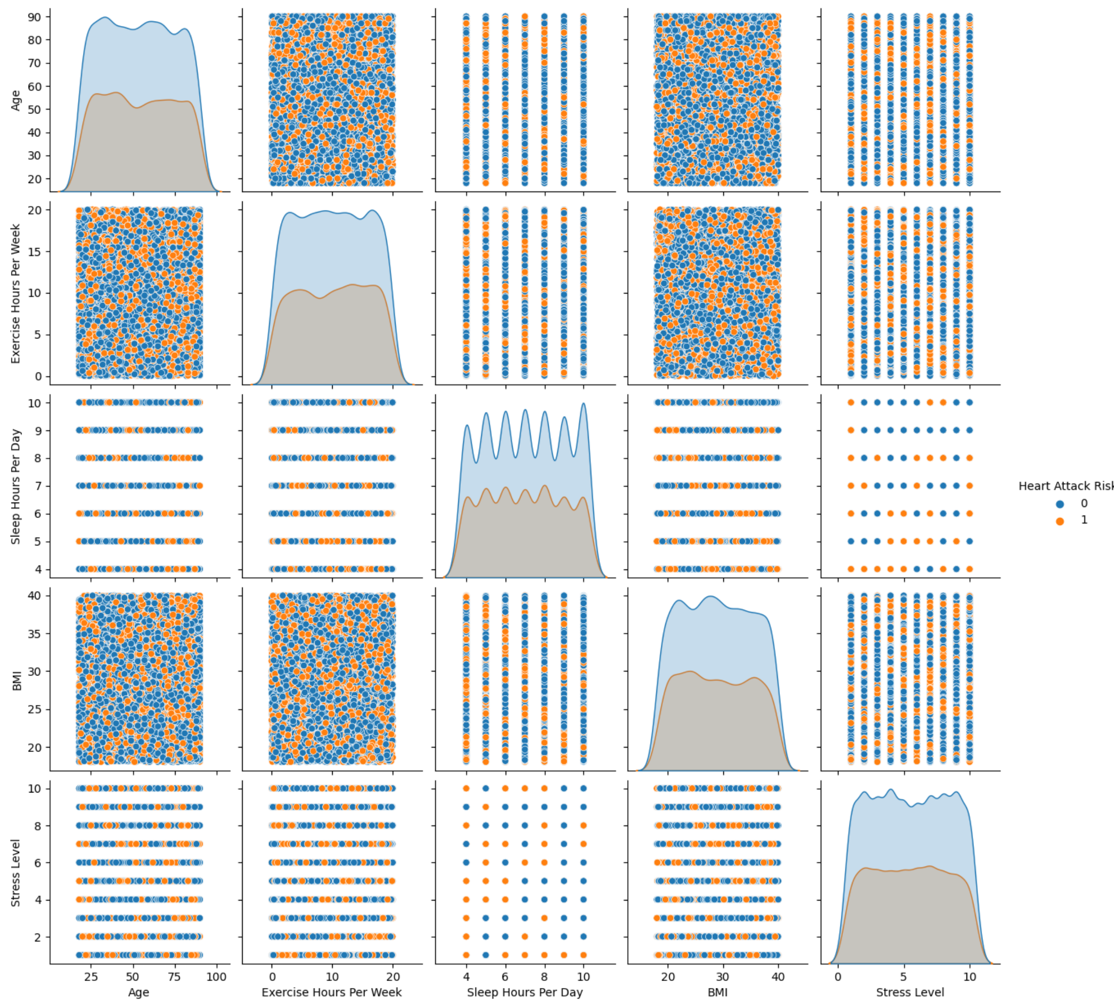
```
sns.countplot(ax=ax[1,0], data=df7,x ="Alcohol Consumption").set(title='Alcohol␣
↪Consumption')
sns.countplot(ax=ax[1,1], data=df7,x ="Previous Heart Problems").
↪set(title='Previous Heart Problems')
sns.countplot(ax=ax[1,2], data=df7,x ="Male").set(title='Male')
sns.countplot(ax=ax[1,3], data=df7,x ="Bad_Diet").set(title='Bad_Diet')
plt.show()
```



4.0.3 Since there is hardly any correlation in the data, scatter plots probably won't be very useful. However,the EDA that we can still do is look through come of the columns and compare the different labels

[22]:
```
plt.figure(figsize=(10,10))
sns.pairplot(data=df7, vars=['Age','Exercise Hours Per Week', 'Sleep Hours Per␣
↪Day', 'BMI', 'Stress Level'], hue='Heart Attack Risk', diag_kind='kde')
plt.show()
```

```
<Figure size 1000x1000 with 0 Axes>
```



4.0.4 We can see thet the data is very uniformly distributed, whether or not the person is at risk of a heart disease

4.1 Detecting outliers

[23]:
```
for i in df7.columns:
    Q1 = df7[i].quantile(0.25)
    Q3 = df7[i].quantile(0.75)
    IQR = Q3 - Q1
    threshold = 1.5
    outliers = df7[(df7[i] < Q1 - threshold * IQR) | (df7[i] > Q3 + threshold *␣
 ↪IQR)]
    print(f"{i:<35}Outliers : {outliers.shape[0]}")
```

```
Age                                Outliers : 0
Cholesterol                        Outliers : 0
```

```
Heart Rate                          Outliers : 0
Diabetes                            Outliers : 0
Family History                      Outliers : 0
Smoking                             Outliers : 904
Obesity                             Outliers : 0
Alcohol Consumption                 Outliers : 0
Exercise Hours Per Week             Outliers : 0
Previous Heart Problems             Outliers : 0
Medication Use                      Outliers : 0
Stress Level                        Outliers : 0
Sedentary Hours Per Day             Outliers : 0
Income                              Outliers : 0
BMI                                 Outliers : 0
Triglycerides                       Outliers : 0
Physical Activity Days Per Week     Outliers : 0
Sleep Hours Per Day                 Outliers : 0
Heart Attack Risk                   Outliers : 0
Male                                Outliers : 0
Systolic                            Outliers : 0
Diastolic                           Outliers : 0
Bad_Diet                            Outliers : 0
```

[24]:
```
df7.Smoking.value_counts() # Not really outliers
```

[24]:
```
Smoking
1    7859
0     904
Name: count, dtype: int64
```

5 Data Preparation

[25]:
```
X = df7.drop(["Heart Attack Risk"],axis = 1)
y = df7["Heart Attack Risk"]
```

[26]:
```
X.shape
```

[26]:
```
(8763, 22)
```

[27]:
```
y.shape
```

[27]:
```
(8763,)
```

5.1 Scaling

Although not useful for every algorithm, it works for some and doesn't hurt the others. Since our data, is not heavy skewed on either side, just using sklearn's StandardScaler should be fine.

[28]:
```
sc = StandardScaler()
X_scaled = sc.fit_transform(X)
X2 = pd.DataFrame(X_scaled,columns=X.columns,index = X.index)
```

[29]:
```
X2.describe(); # Mean at 0, std = 1
```

5.2 Train test Split

[30]:
```
X_train,X_test,y_train,y_test = train_test_split(X2,y,test_size=0.
 ↪3,shuffle=True,random_state=0)
```

[31]:
```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(6134, 22)
(2629, 22)
(6134,)
(2629,)
```

6 Model Selection

[32]:
```
models = {'LogisticRegression' : LogisticRegression(),
          'DecisionTreeClassifier' : DecisionTreeClassifier(),
          'RandomForestClassifier' : RandomForestClassifier(),
          'GradientBoostingClassifier' : GradientBoostingClassifier(),
          'CatBoostClassifier' : CatBoostClassifier(verbose=0)}
```

6.0.1 Baseline Models

[33]:
```
def run_models(X_train,X_test,y_train,y_test):
    resultsdf = pd.DataFrame(columns =␣
 ↪['Model','Train_Accuracy',"Test_Accuracy","F1_Score","Roc_Auc"])
    for name, model in models.items():
        model.fit(X_train, y_train)
        print(f"{name} trained.")
        y_pred_train = model.predict(X_train)
        y_pred = model.predict(X_test)

        train_accuracy = accuracy_score(y_train, y_pred_train)
        test_accuracy = accuracy_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred)
        roc_auc = roc_auc_score(y_test,y_pred)
```

```
        results = {'Model': name, 'Train_Accuracy':train_accuracy,␣
↪'Test_Accuracy': test_accuracy, 'F1_Score': f1, 'Roc_Auc': roc_auc}
        resultsdf.loc[len(resultsdf)] = results
    return resultsdf

baseline = run_models(X_train,X_test,y_train,y_test)
```

```
LogisticRegression trained.
DecisionTreeClassifier trained.
RandomForestClassifier trained.
GradientBoostingClassifier trained.
CatBoostClassifier trained.
```

[34]:
```
baseline.sort_values("F1_Score",ascending=False)
```

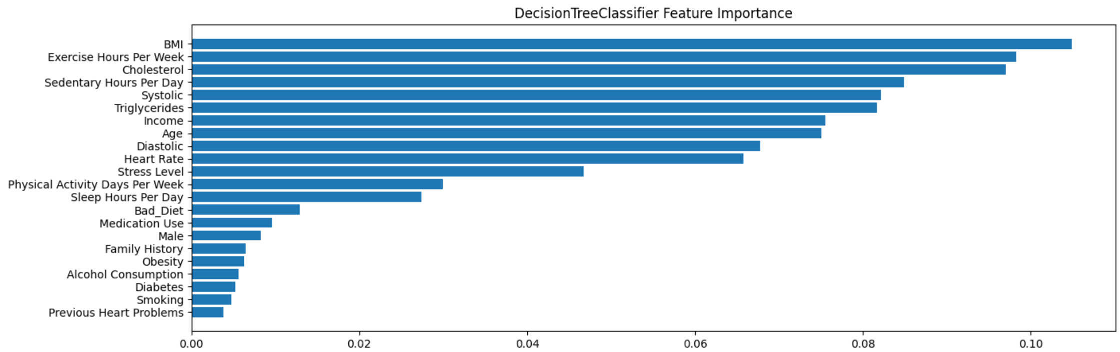
[34]:
```
                        Model  Train_Accuracy  Test_Accuracy  F1_Score  \
1      DecisionTreeClassifier        1.000000       0.546215  0.382185
4          CatBoostClassifier        0.828171       0.634081  0.099251
2      RandomForestClassifier        1.000000       0.638266  0.066732
3  GradientBoostingClassifier        0.664493       0.635983  0.030395
0          LogisticRegression        0.643300       0.638266  0.000000

    Roc_Auc
1  0.511944
4  0.508795
2  0.507745
3  0.501629
0  0.500000
```

Even though all these algorithms hav decent accuracy allround, an F1 score near 0 shoes that it really isn't predicting anything.

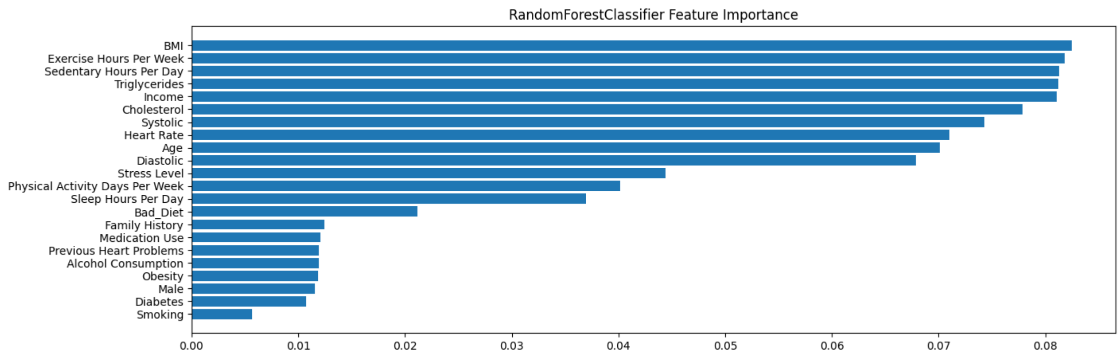
7 Feature Selection

[35]:
```
for name, model in models.items():
    try:
        importances = model.feature_importances_
        indices = np.argsort(importances)[::-1]
        names = [X.columns[i] for i in indices]
        plt.figure(figsize=(15, 5))
        plt.title(f"{name} Feature Importance")
        plt.barh(range(X.shape[1]), importances[indices])
        plt.yticks(range(X.shape[1]), names)
        plt.gca().invert_yaxis()
        plt.show()
    except:
```

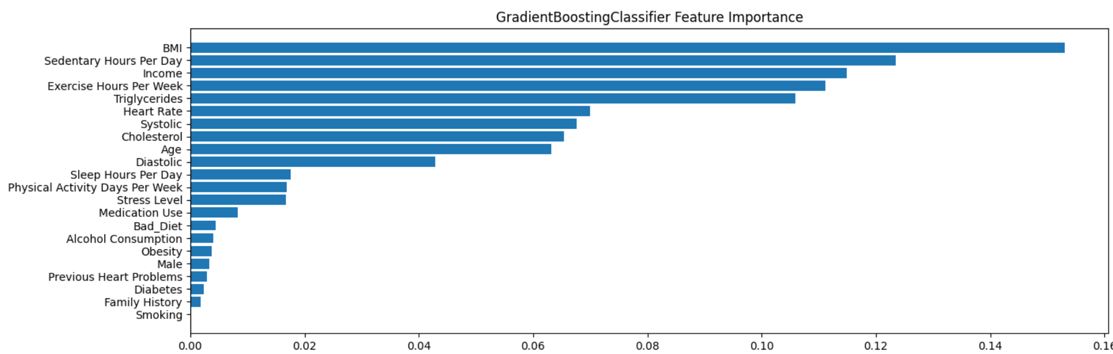
```
pass
```



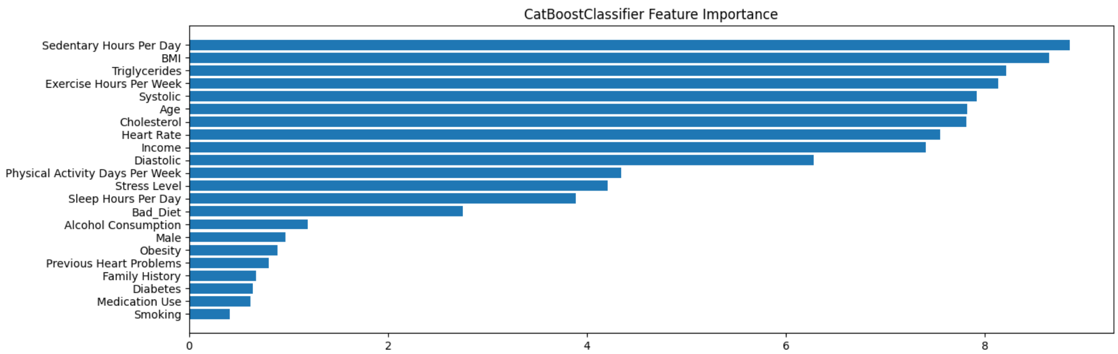
DecisionTreeClassifier Feature Importance
BMI
Exercise Hours Per Week
Cholesterol
Sedentary Hours Per Day
Systolic
Triglycerides
Income
Age
Diastolic
Heart Rate
Stress Level
Physical Activity Days Per Week
Sleep Hours Per Day
Bad_Diet
Medication Use
Male
Family History
Obesity
Alcohol Consumption
Diabetes
Smoking
Previous Heart Problems
0.00
0.02
0.04
0.06
0.08
0.10



RandomForestClassifier Feature Importance
BMI
Exercise Hours Per Week
Sedentary Hours Per Day
Triglycerides
Income
Cholesterol
Systolic
Heart Rate
Age
Diastolic
Stress Level
Physical Activity Days Per Week
Sleep Hours Per Day
Bad_Diet
Family History
Medication Use
Previous Heart Problems
Alcohol Consumption
Obesity
Male
Diabetes
Smoking
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08



GradientBoostingClassifier Feature Importance
BMI
Sedentary Hours Per Day
Income
Exercise Hours Per Week
Triglycerides
Heart Rate
Systolic
Cholesterol
Age
Diastolic
Sleep Hours Per Day
Physical Activity Days Per Week
Stress Level
Medication Use
Bad_Diet
Alcohol Consumption
Obesity
Male
Previous Heart Problems
Diabetes
Family History
Smoking
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16



7.0.1 Findings:

Most Important Features: - BMI - Exercise Hours Per Week - Triglycerides

Least Important Features: - Smoking - Diabetes - Previous Heart Problems - Family History

Lets take these features out and try again.

[36]:
```
X_select = X2.drop(["Smoking","Diabetes","Previous Heart Problems", "Family␣
↪History","Medication Use"],axis=1)
```

[37]:
```
X_train_select,X_test_select,y_train_select,y_test_select =␣
↪train_test_split(X_select,y,test_size=0.3,shuffle=True,random_state=0)
```

[38]:
```
feature_selection = run_models(X_train_select,X_test_select,y_train,y_test)
```

```
LogisticRegression trained.
DecisionTreeClassifier trained.
RandomForestClassifier trained.
GradientBoostingClassifier trained.
CatBoostClassifier trained.
```

[39]:
```
feature_selection.sort_values(by="F1_Score",ascending=False)
```

[39]:
```
                        Model  Train_Accuracy  Test_Accuracy  F1_Score  \
1      DecisionTreeClassifier        1.000000       0.552301  0.387936
4          CatBoostClassifier        0.829638       0.627235  0.095941
2      RandomForestClassifier        1.000000       0.628376  0.059673
3  GradientBoostingClassifier        0.664656       0.635223  0.026396
0          LogisticRegression        0.643300       0.638266  0.000000

    Roc_Auc
1  0.517623
4  0.503204
2  0.499314
```

```
3   0.500577
0   0.500000
```

Little Improvement

8 Removing Imbalance

[40]:
```
y.value_counts()
```

[40]:
```
Heart Attack Risk
0    5624
1    3139
Name: count, dtype: int64
```

There is a clear imbalance between 0s and 1s, in the target column making it so that a model can be ~63% accurate by just saying 0 everytime

[41]:
```
5624 - 3139
```

[41]:
```
2485
```

[42]:
```
to_drop = y.where(lambda x: x==0).dropna().sample(2485,random_state = 99).index
  #Not the best practice.
```

[43]:
```
X_dropped = X_select.drop(to_drop,axis=0)
```

[44]:
```
y_dropped = y.drop(to_drop)
```

[45]:
```
X_train_dropped,X_test_dropped,y_train_dropped,y_test_dropped =
  train_test_split(X_dropped,y_dropped,test_size=0.
  3,shuffle=True,random_state=0)
```

[46]:
```
dropped =
  run_models(X_train_dropped,X_test_dropped,y_train_dropped,y_test_dropped)
```

```
LogisticRegression trained.
DecisionTreeClassifier trained.
RandomForestClassifier trained.
GradientBoostingClassifier trained.
CatBoostClassifier trained.
```

[47]:
```
dropped
```

[47]:
```
                      Model  Train_Accuracy  Test_Accuracy  F1_Score  \
0        LogisticRegression        0.521848       0.507431  0.493450
1    DecisionTreeClassifier        1.000000       0.496815  0.495208
```

```
2      RandomForestClassifier        1.000000       0.500531  0.486634
3  GradientBoostingClassifier        0.708921       0.501592  0.492707
4          CatBoostClassifier        0.945380       0.499469  0.505506

    Roc_Auc
0  0.507592
1  0.496846
2  0.500689
3  0.501699
4  0.499418
```

This helped the F1 Score come up for every model by a significant margin.

9 Correcting Overfitting [HyperParameter Tuning]

[48]:
```
X_train_final = X_train_dropped
X_test_final = X_test_dropped
y_train_final = y_train_dropped
y_test_final = y_test_dropped
```

From this point on I will just be focusing on 3 models. - Decision Tree Classifier - Random Forest Classifier - Catgorical Boost Classifier

[49]:
```
def test_model(model):
    resultsdf = pd.DataFrame(columns =
 ↪['Train_Accuracy',"Test_Accuracy","F1_Score","Roc_Auc"])
    model.fit(X_train_final, y_train_final)
    y_pred_train = model.predict(X_train_final)
    y_pred = model.predict(X_test_final)
    train_accuracy = accuracy_score(y_train_final, y_pred_train)
    test_accuracy = accuracy_score(y_test_final, y_pred)
    f1 = f1_score(y_test_final, y_pred)
    roc_auc = roc_auc_score(y_test_final,y_pred)
    results = {'Train_Accuracy':train_accuracy, 'Test_Accuracy': test_accuracy,
 ↪'F1_Score': f1, 'Roc_Auc': roc_auc}
    resultsdf.loc[0] = results
    return resultsdf
```

9.0.1 Decision Tree Classifier

[50]:
```
dt = DecisionTreeClassifier()
```

[51]:
```
dt_results = test_model(dt)
dt_results
```

[51]:

	Train_Accuracy	Test_Accuracy	F1_Score	Roc_Auc
0	1.0	0.501062	0.504219	0.501042

[52]:
```
# dt_params = {"max_depth" : [3,5,7,9,11],
#             "criterion" : ["gini", "entropy", "log_loss"],
#             "min_samples_split" : [2,4,6,8]
#            }

# tuned_dt =
 ↪GridSearchCV(dt,dt_params,verbose=0,cv=5,return_train_score=True,scoring='f1')
# tuned_dt.fit(X_train,y_train)
# tuned_dt.best_params_
```

[53]:
```
best_dt = DecisionTreeClassifier(criterion='gini', max_depth = 11,
 ↪min_samples_split =2) #Parameters from GridSearchCV above
dt_results = test_model(best_dt)
dt_results
```

[53]:

	Train_Accuracy	Test_Accuracy	F1_Score	Roc_Auc
0	0.63746	0.500531	0.355921	0.501737

Didn't really work

9.0.2 Random Forest Classifier

[54]:
```
rf = RandomForestClassifier()
```

[55]:
```
rf_results = test_model(rf)
rf_results
```

[55]:

	Train_Accuracy	Test_Accuracy	F1_Score	Roc_Auc
0	1.0	0.485669	0.479871	0.485742

[56]:
```
# rf_params = {'n_estimators' : [10,20,30,50,100],
#               "max_depth" : [2,4,6,8]}

# tuned_rf =
 ↪GridSearchCV(rf,rf_params,verbose=0,cv=5,return_train_score=False,scoring='f1')
# tuned_rf.fit(X_train,y_train)
# tuned_rf.best_params_
```

[57]:
```
best_rf = RandomForestClassifier(max_depth = 8,n_estimators = 10) #Parameters
 ↪from GridSearchCV above
rf_results = test_model(best_rf)
rf_results
```

[57]:

	Train_Accuracy	Test_Accuracy	F1_Score	Roc_Auc
0	0.742831	0.503185	0.497854	0.503255

Worked a bit. Probably resulted in better model.

9.0.3 Categorical Boost Classifier

[58]:
```
cb = CatBoostClassifier(verbose=0)
```

[59]:
```
cb_results = test_model(cb)
cb_results
```

[59]:

	Train_Accuracy	Test_Accuracy	F1_Score	Roc_Auc
0	0.94538	0.499469	0.505506	0.499418

[60]:
```
# cb_params ={"depth" : [4,8,10],
#             'learning_rate' : [0.5,0.75],
#             'iterations' : [20,30,50],
#             "random_strength" :[2,5,10]
#          }

# tuned_cb =␣
 ↪GridSearchCV(cb,cb_params,verbose=0,cv=5,return_train_score=False,scoring='f1')
# tuned_cb.fit(X_train,y_train)
# tuned_cb.best_params_
```

[61]:
```
best_cb = CatBoostClassifier(depth = 8,iterations = 30,learning_rate=0.5,␣
 ↪random_strength=5,verbose=0) #Parameters from GridSearchCV above
cb_results = test_model(best_cb)
cb_results
```

[61]:

	Train_Accuracy	Test_Accuracy	F1_Score	Roc_Auc
0	0.840237	0.518047	0.515475	0.518089

The best accuracy and f1 score of all the models.

Despite my best efforts to avoid overfitting, the models still tended to do it. When limiting max depth too much it cam at a high cost of accuracy. Each of the GridSearchCVs done on the models aimed to maximize their f1_score. Even though it did improve it, the difference was very minute.

10 Conclusion

Given the data that I was, which mostly comprised of superficial attributes of a person, I couldn't predict the risk of a heart attack for a given person. Maybe if the features were more scientific, like the division of Cholesterol into HDL and LDL would have helped. Something that could have improved the model more would be correctly balancing the labelled data, by not just removing a bunch of data. Furthermore, none of these methods used neural networks/deep learning models. This could be an interesting avenue to go down next time. As it stands, it is best to say that we shouldn't use this model to predict a person's risk of having a heart attack.