Heart Disease Prediction

By Hrithik

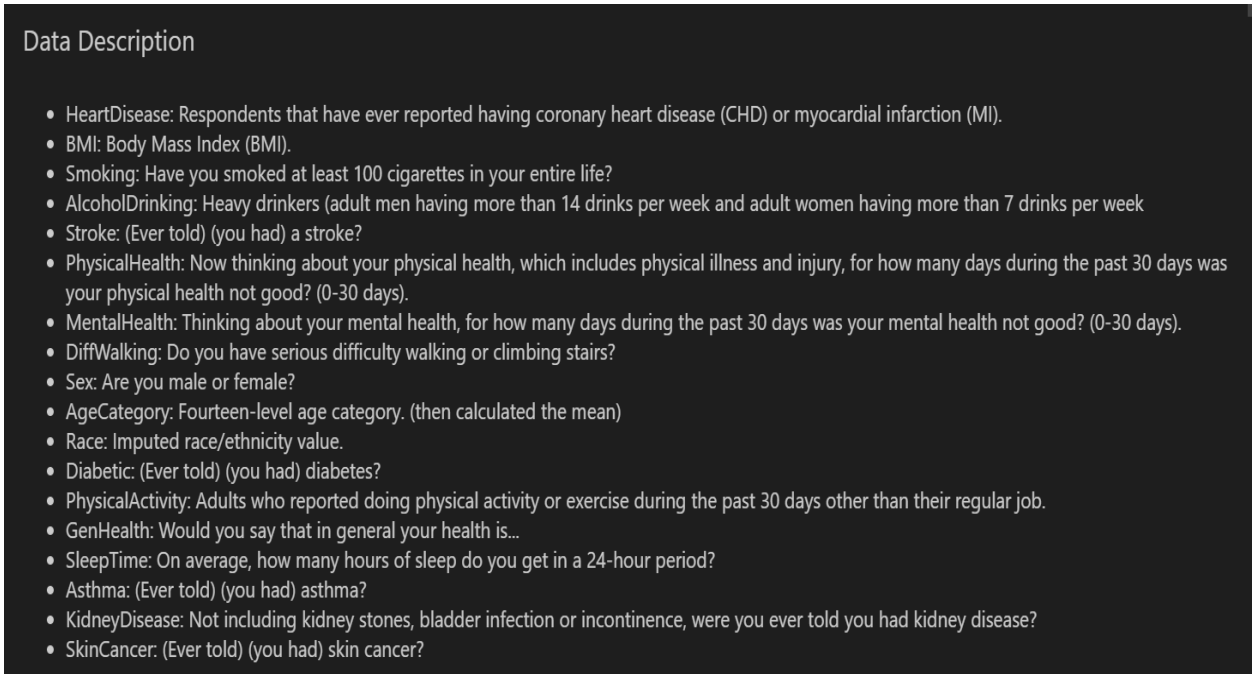
Dataset Source-
https://www.kaggle.com/datasets/kamilpytlak/personal-key-indicators-of-heart-disease

Objective

To predict wether the a Respondents will ever have coronary heart disease (CHD) or myocardial infarction (MI)

Description of the Data Set

According to the CDC, heart disease is one of the leading causes of death for people of most races in the US (African Americans, American Indians and Alaska Natives, and white people). About half of all Americans (47%) have at least 1 of 3 key risk factors for heart disease: high blood pressure, high cholesterol, and smoking. Other key indicator include diabetic status, obesity (high BMI), not getting enough physical activity or drinking too much alcohol. Detecting and preventing the factors that have the greatest impact on heart disease is very important in healthcare. Computational developments, in turn, allow the application of machine learning methods to detect "patterns" from the data that can predict a patient's condition.



Summary of data exploration and actions taken for data cleaning and feature engineering

Data was already preprocessed

```
data.info()
# The data is aldready preprocessed
```

[3] ✓ 0.2s

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 319795 entries, 0 to 319794
Data columns (total 18 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   HeartDisease      319795 non-null  object
 1   BMI               319795 non-null  float64
 2   Smoking           319795 non-null  object
 3   AlcoholDrinking   319795 non-null  object
 4   Stroke            319795 non-null  object
 5   PhysicalHealth    319795 non-null  float64
 6   MentalHealth      319795 non-null  float64
 7   DiffWalking       319795 non-null  object
 8   Sex               319795 non-null  object
 9   AgeCategory       319795 non-null  object
 10  Race              319795 non-null  object
 11  Diabetic          319795 non-null  object
 12  PhysicalActivity  319795 non-null  object
 13  GenHealth         319795 non-null  object
 14  SleepTime         319795 non-null  float64
 15  Asthma            319795 non-null  object
 16  KidneyDisease     319795 non-null  object
 17  SkinCancer        319795 non-null  object
dtypes: float64(4), object(14)
memory usage: 43.9+ MB
```

Label Encoding

In [8]:
```
print("Name \t\t Counts \t Values ")
for col in list(data.columns[data.dtypes==object]):
    print(col , len(data[col].unique()) , list(data[col].unique()) )
```

```
Name             Counts          Values
HeartDisease 2 ['No', 'Yes']
Smoking 2 ['Yes', 'No']
AlcoholDrinking 2 ['No', 'Yes']
Stroke 2 ['No', 'Yes']
DiffWalking 2 ['No', 'Yes']
Sex 2 ['Female', 'Male']
Race 6 ['White', 'Black', 'Asian', 'American Indian/Alaskan Native', 'Other', 'Hispanic']
Diabetic 2 ['Yes', 'No']
PhysicalActivity 2 ['Yes', 'No']
GenHealth 5 ['Very good', 'Fair', 'Good', 'Poor', 'Excellent']
Asthma 2 ['Yes', 'No']
KidneyDisease 2 ['No', 'Yes']
SkinCancer 2 ['Yes', 'No']
```

In [10]:
```
from sklearn.preprocessing import LabelEncoder
for col in data.columns:
        if data[col].dtype == 'O':
            le = LabelEncoder()
            data[col] = le.fit_transform(data[col])
```

```
data.info()
```

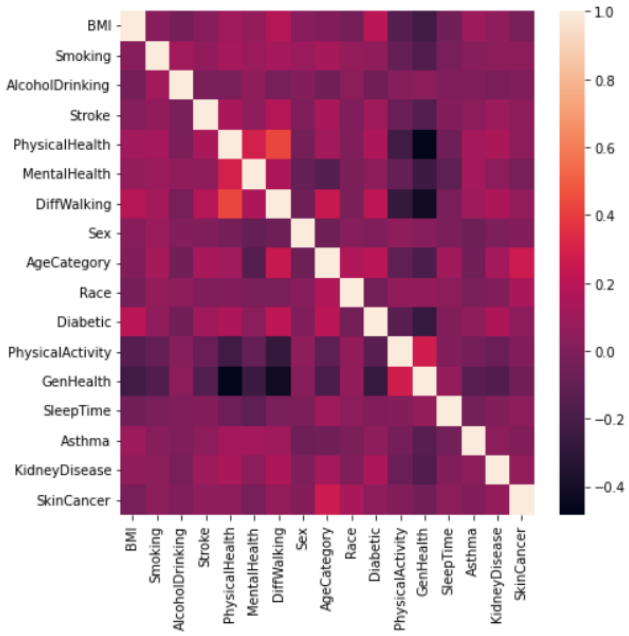
✓ 0.6s

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 319795 entries, 0 to 319794
Data columns (total 18 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   HeartDisease      319795 non-null  int32  
 1   BMI               319795 non-null  float64
 2   Smoking           319795 non-null  int32  
 3   AlcoholDrinking   319795 non-null  int32  
 4   Stroke            319795 non-null  int32  
 5   PhysicalHealth    319795 non-null  float64
 6   MentalHealth      319795 non-null  float64
 7   DiffWalking       319795 non-null  int32  
 8   Sex               319795 non-null  int32  
 9   AgeCategory       319795 non-null  int64  
 10  Race              319795 non-null  int32  
 11  Diabetic          319795 non-null  int32  
 12  PhysicalActivity  319795 non-null  int32  
 13  GenHealth         319795 non-null  int64  
 14  SleepTime         319795 non-null  float64
 15  Asthma            319795 non-null  int32  
 16  KidneyDisease     319795 non-null  int32  
 17  SkinCancer        319795 non-null  int32  
dtypes: float64(4), int32(12), int64(2)
memory usage: 29.3 MB
```

EDA

Correlation matrix

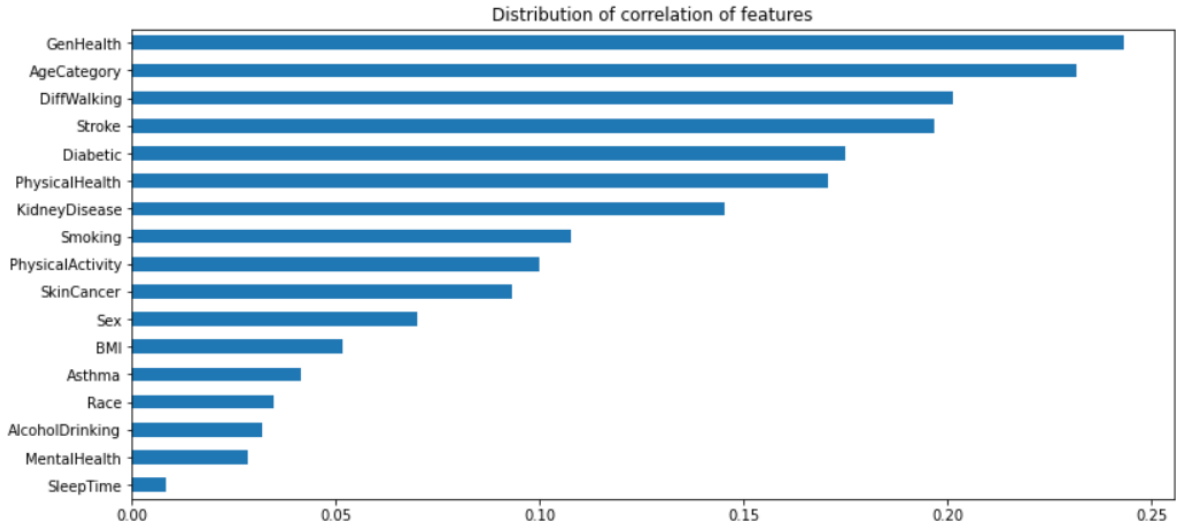
Out[54]: <AxesSubplot:>



We can notice a higher correlation of 0.5 between physical health and difficulty in walking which kinda makes sense

```
plt.figure(figsize = (13,6))
plt.title('Distribution of correlation of features')
abs(data.corr()['HeartDisease']).sort_values()[:-1].plot.barh()
```

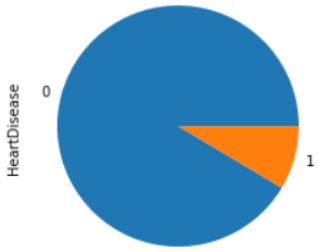
```
<AxesSubplot:title={'center':'Distribution of correlation of features'}>
```



Analysis on Target Variablle

```
ax=data['HeartDisease'].value_counts(normalize=True).plot(kind='pie')
data['HeartDisease'].value_counts(normalize=True)
# We can see that the target variable is skewed and thus we will have to use stratified shuffle split
```

```
0    0.914405
1    0.085595
Name: HeartDisease, dtype: float64
```



Summary of Models Trained

Logistic Regression

```python
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(class_weight={0:1 , 1:20})
lr.fit(X_train,y_train)
y_pred = lr.predict(X_test)
```

```python
from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.metrics import confusion_matrix, accuracy_score, roc_auc_score

confusion_matrix(y_test,y_pred)
```

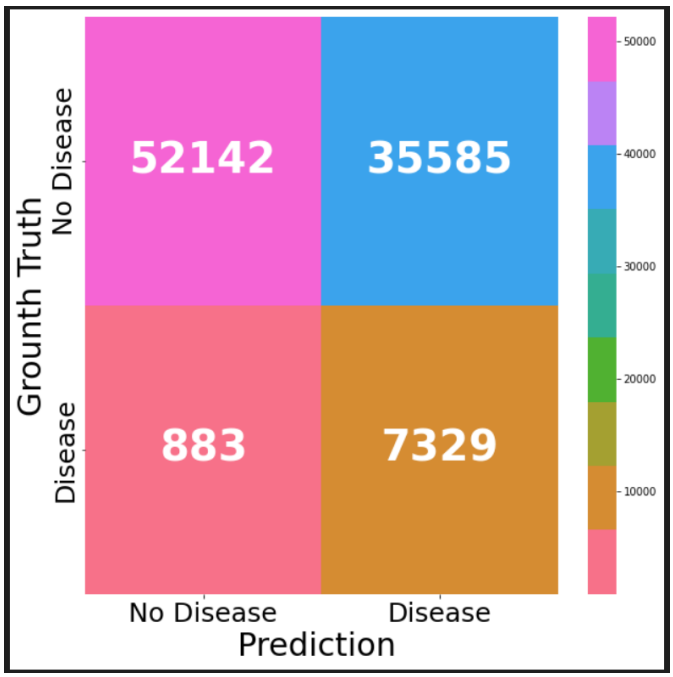
```
array([[52142, 35585],
       [  883,  7329]], dtype=int64)
```

```python
from sklearn.metrics import  classification_report, f1_score
print(classification_report(y_test, y_pred))
print('Accuracy score: ', round(accuracy_score(y_test, y_pred), 2))
print('F1 Score: ', round(f1_score(y_test, y_pred), 2))
```

```
              precision    recall  f1-score   support

           0       0.98      0.59      0.74     87727
           1       0.17      0.89      0.29      8212

    accuracy                           0.62     95939
   macro avg       0.58      0.74      0.51     95939
weighted avg       0.91      0.62      0.70     95939
```



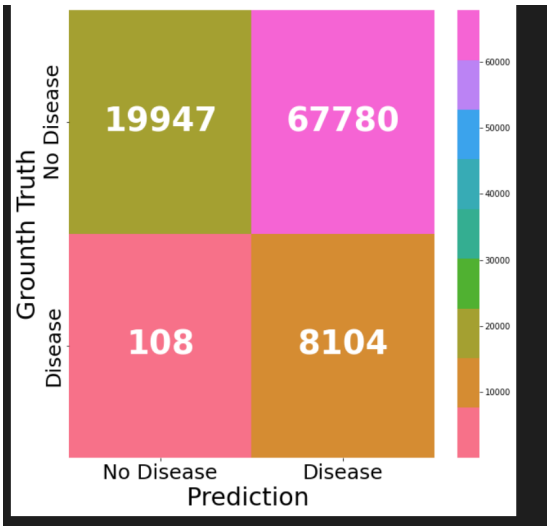
SVM

```
## Linear SVM
from sklearn.svm import LinearSVC
svm = LinearSVC(class_weight={0:1 , 1:10})
svm.fit(X_train,y_train)
svm_pred = svm.predict(X_test)
```

```
D:\Computer science\lib\site-packages\sklearn\svm\_base.py:1206: Convergence
iterations.
  warnings.warn(
```

```
print(classification_report(y_test, svm_pred))
print('Accuracy score: ', round(accuracy_score(y_test, svm_pred), 2))
print('F1 Score: ', round(f1_score(y_test, svm_pred)))
```

	precision	recall	f1-score	support
0	0.99	0.23	0.37	87727
1	0.11	0.99	0.19	8212
accuracy			0.29	95939
macro avg	0.55	0.61	0.28	95939
weighted avg	0.92	0.29	0.35	95939



Random Forest

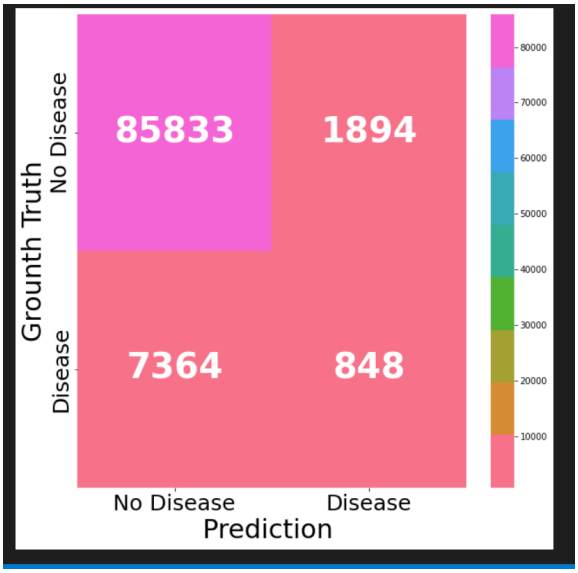
```
from sklearn.ensemble import RandomForestClassifier
RF = RandomForestClassifier(oob_score=True,
                            random_state=42,
                            warm_start=True,
                            n_jobs=-1,
                            class_weight={0:1,1:10} )
RF.fit(X_train,y_train)
```

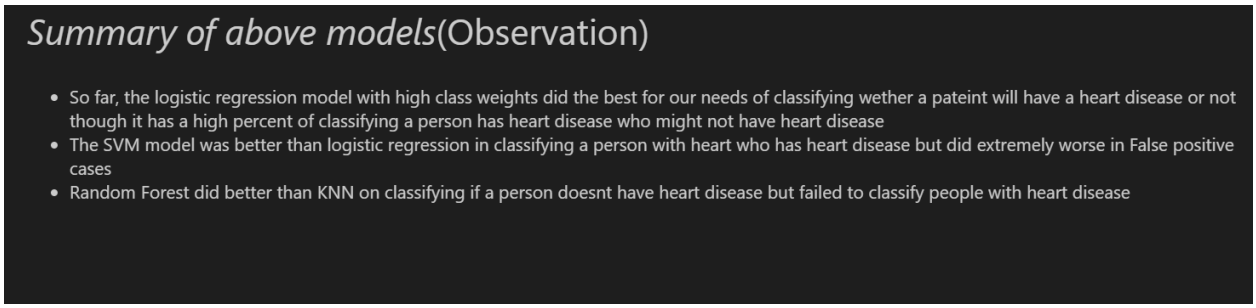
```
RandomForestClassifier(class_weight={0: 1, 1: 10}, n_jobs=-1, oob_score=True,
                       random_state=42, warm_start=True)
```

```
rf_pred = RF.predict(X_test)

print(classification_report(y_test, rf_pred))
print('Accuracy score: ', round(accuracy_score(y_test, rf_pred), 2))
print('F1 Score: ', round(f1_score(y_test, rf_pred)))
```

	precision	recall	f1-score	support
0	0.92	0.98	0.95	87727
1	0.31	0.10	0.15	8212
accuracy			0.90	95939
macro avg	0.62	0.54	0.55	95939
weighted avg	0.87	0.90	0.88	95939





Recommended Model

I recommend the Logistic Regression model since the need to classify a patient who might have heart disease is more important

Key Findings and Insights

It was really suprising to know that nearly 10 percent of patients will have a myocardial infaction
Skin Cancer and Race has higher significance than sleep time in heart disease

Suggestions for next steps

-> PCA
-> Decision Trees
->Feature Selection
->Smote
->VotingClassifiers