Diabetes Predictor: A Machine Learning Approach

Context

One of the most common chronic diseases in the US, diabetes affects millions of people annually and costs the country's economy a lot of money. Diabetes is a significant chronic condition that impairs a person's capacity to control blood glucose levels, which can shorten life expectancy and lower quality of life. Sugars from various foods are converted during digestion and subsequently released into the bloodstream. The pancreas is prompted to secrete insulin as a result. Insulin assists in making it possible for body cells to use the carbohydrates in the bloodstream as fuel. Either the body doesn't produce enough insulin or it can't use the insulin that is produced as efficiently in those with diabetes.

For those with diabetes, the persistently high amounts of sugar that remain in the bloodstream are linked to complications like heart disease, vision loss, lower limb amputation, and kidney illness. Despite the fact that there is no cure for diabetes, many patients can lessen the negative effects of the condition by using measures including decreasing weight, eating a healthy diet, exercising, and receiving medical care. Predictive models for diabetes risk are valuable tools for the general population and public health officials as early diagnosis can result in lifestyle changes and more effective treatment.

Important risk factors for diabetes :

(blood pressure (high) , cholesterol (high) , smoking , diabetes , obesity , age , sex , race , diet , exercise , alcohol consumption , BMI , Household Income , Marital Status , Sleep , Time since last checkup , Education , Health care coverage , Mental Health)

About Columns :

Diabetes_binary : you have diabetes (0,1)

HighBP : Adults who have been notified by a doctor, nurse, or other healthcare provider that they have high blood pressure (0,1)

HighChol : Have you EVER been informed that you have high blood cholesterol by a doctor, nurse, or other healthcare provider? (0,1)

CholCheck : Cholesterol check within past five years (0,1)

BMI : Body Mass Index (BMI)

Smoker : Have you smoked at least 100 cigarettes in your entire life? [Note: 5 packs = 100 cigarettes] (0,1)

Stroke : (Ever told) you had a stroke. (0,1)

HeartDiseaseorAttack : Respondents that have ever reported having coronary heart disease (CHD) or myocardial infarction (MI) (0,1)

PhysActivity : Adults who reported doing physical activity or exercise during the past 30 days other than their regular job (0,1)

Fruits : Consume Fruit 1 or more times per day (0,1)

Veggies : Consume Vegetables 1 or more times per day (0,1)

HvyAlcoholConsump : Heavy drinkers (adult men having more than 14 drinks per week and adult women having more than 7 drinks per week)(0,1)

AnyHealthcare : Do you have any kind of health care coverage, including health insurance, prepaid plans such as HMOs, or government plans such as Medicare, or Indian Health Service? (0,1)

NoDocbcCost : Was there a time in the past 12 months when you needed to see a doctor but could not because of cost? (0,1)

GenHlth : Would you say that in general your health is: rate (1 ~ 5)

MentHlth : Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good? (0 ~ 30)

PhysHlth : Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 days was your physical health not good? (0 ~ 30)

DiffWalk : Do you have serious difficulty walking or climbing stairs? (0,1)

Sex : Indicate sex of respondent (0,1) (Female or Male)

Age : Fourteen-level age category (1 ~ 14)

Education : What is the highest grade or year of school you completed? (1 ~ 6)

Income : Is your annual household income from all sources: (If respondent refuses at any income level, code "Refused.") (1 ~ 8)

Import Libraries

In [49]:
```
import math
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from pandas.api.types import is_numeric_dtype

from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.datasets import make_classification
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE

from sklearn.metrics import confusion_matrix,plot_roc_curve, classification
from sklearn.metrics import mean_absolute_error , mean_absolute_percentage_
from mlxtend.plotting import plot_confusion_matrix
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
```

Exploratory Data Analysis

In [50]:
```
Orginal_data = pd.read_csv("diabetes_binary_health_indicators_BRFSS2015.csv
```

In [51]:
```
df = pd.read_csv("diabetes_binary_health_indicators_BRFSS2015.csv", sep=","
```

Dataset Report

In [52]:
```
df.head()
```

Out[52]:

	Diabetes_binary	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack	Ph
0	0.0	1.0	1.0	1.0	40.0	1.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	25.0	1.0	0.0	0.0	
2	0.0	1.0	1.0	1.0	28.0	0.0	0.0	0.0	
3	0.0	1.0	0.0	1.0	27.0	0.0	0.0	0.0	
4	0.0	1.0	1.0	1.0	24.0	0.0	0.0	0.0	

5 rows × 22 columns

Preprocessing

Transform the data to integer

In [53]:
```
df["Diabetes_binary"] = df["Diabetes_binary"].astype(int)
df["HighBP"] = df["HighBP"].astype(int)
df["HighChol"] = df["HighChol"].astype(int)
df["CholCheck"] = df["CholCheck"].astype(int)
df["BMI"] = df["BMI"].astype(int)
df["Smoker"] = df["Smoker"].astype(int)
df["Stroke"] = df["Stroke"].astype(int)
df["HeartDiseaseorAttack"] = df["HeartDiseaseorAttack"].astype(int)
df["PhysActivity"] = df["PhysActivity"].astype(int)
df["Fruits"] = df["Fruits"].astype(int)
df["Veggies"] = df["Veggies"].astype(int)
df["HvyAlcoholConsump"] = df["HvyAlcoholConsump"].astype(int)
df["AnyHealthcare"] = df["AnyHealthcare"].astype(int)
df["NoDocbcCost"] = df["NoDocbcCost"].astype(int)
df["GenHlth"] = df["GenHlth"].astype(int)
df["MentHlth"] = df["MentHlth"].astype(int)
df["PhysHlth"] = df["PhysHlth"].astype(int)
df["DiffWalk"] = df["DiffWalk"].astype(int)
df["Sex"] = df["Sex"].astype(int)
df["Age"] = df["Age"].astype(int)
df["Education"] = df["Education"].astype(int)
df["Income"] =df["Income"].astype(int)
```

Check null values

In [54]:
```
df.isnull().sum()
```

Out[54]:
```
Diabetes_binary         0
HighBP                  0
HighChol                0
CholCheck               0
BMI                     0
Smoker                  0
Stroke                  0
HeartDiseaseorAttack    0
PhysActivity            0
Fruits                  0
Veggies                 0
HvyAlcoholConsump       0
AnyHealthcare           0
NoDocbcCost             0
GenHlth                 0
MentHlth                0
PhysHlth                0
DiffWalk                0
Sex                     0
Age                     0
Education               0
Income                  0
dtype: int64
```

checking unique values in different variables

In [55]:
```
uniq_vals = {}
for c in df.columns:
    uniq_vals[c] = df[c].value_counts().shape[0]

pd.DataFrame(uniq_vals, index=['uniq value count']).transpose()
```

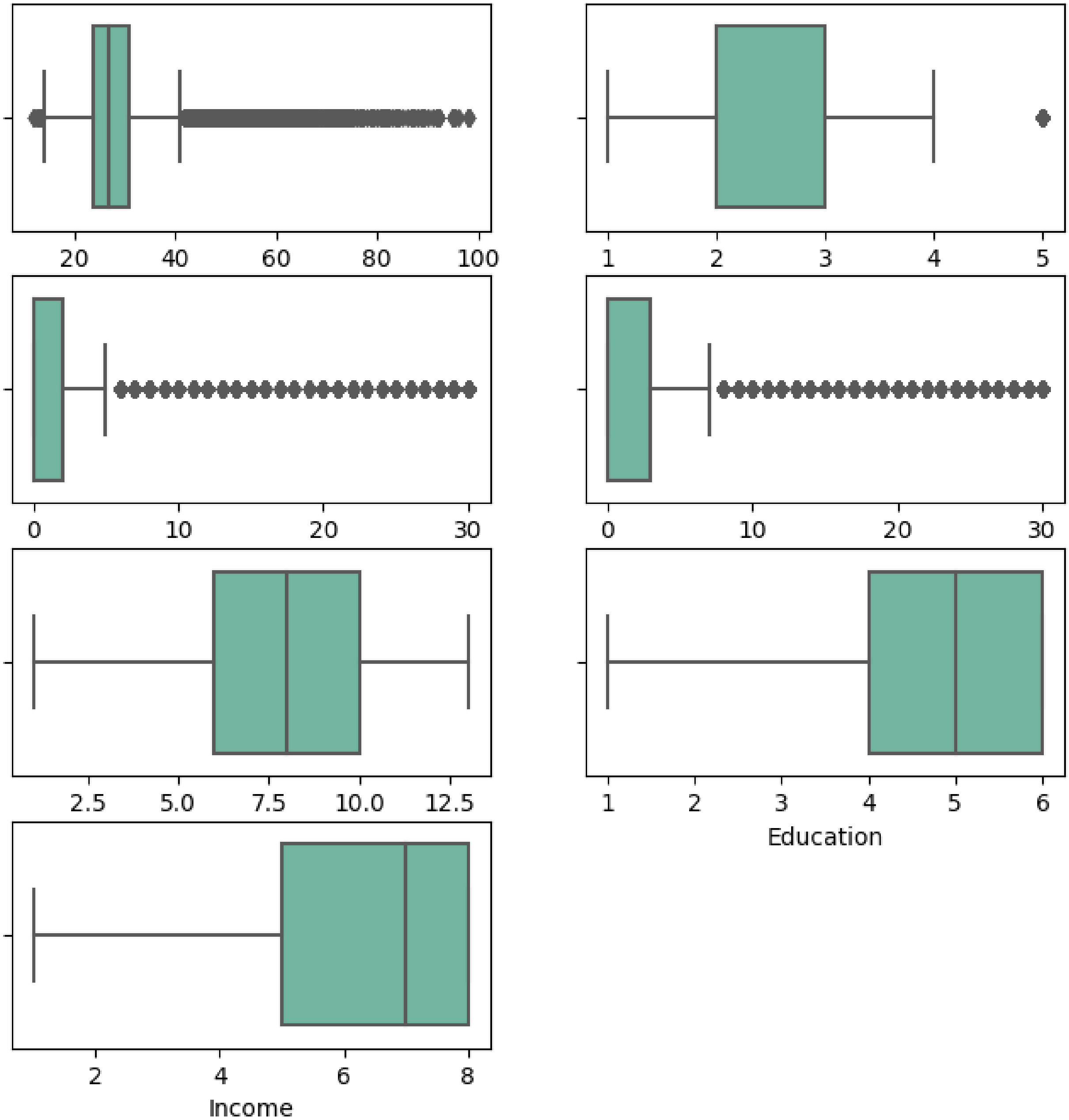
Out[55]:

	uniq value count
Diabetes_binary	2
HighBP	2
HighChol	2
CholCheck	2
BMI	84
Smoker	2
Stroke	2
HeartDiseaseorAttack	2
PhysActivity	2
Fruits	2
Veggies	2
HvyAlcoholConsump	2
AnyHealthcare	2
NoDocbcCost	2
GenHlth	5
MentHlth	31
PhysHlth	31
DiffWalk	2
Sex	2
Age	13
Education	6
Income	8

Check The Outliers

Most of the features are categorical and seven features are numerical, lets check the outliers for them in the following sections

In [56]:
```
plt.figure(figsize = (8, 8))
for i,col in enumerate(['BMI', 'GenHlth', 'MentHlth', 'PhysHlth', 'Age','Ed
    plt.subplot(4,2,i+1)
    sns.boxplot(x = col, data=df ,palette='Set2')
plt.show()
```



In [57]:
```
low = .05
high = .95
quant_df = df.quantile([low, high])
df = df[(df["BMI"] > quant_df.loc[low, "BMI"]) & (df["BMI"] < quant_df.loc[
df = df[(df["MentHlth"] > quant_df.loc[low, "MentHlth"]) & (df["MentHlth"]
df = df[(df["PhysHlth"] > quant_df.loc[low, "PhysHlth"]) & (df["PhysHlth"]
```

Check and drop dublicated data

In [58]:
```
df.duplicated().sum()
```

Out[58]: 67

In [59]:
```
df.drop_duplicates(inplace = True)
```

In [60]:
```
df.duplicated().sum()
```

Out[60]: 0

In [61]:
```
df.shape
```

Out[61]: (24936, 22)

Some codes that help us in our EDA

Replacing 0 into Non-Diabetic and 1 into Diabetic

adding new column Diabetes_binary_str

In [62]:
```
df["Diabetes_binary_str"] = df["Diabetes_binary"].replace({0:"Non-Diabetic"
```

help us to show the categorical variable

In [63]:
```
df2 = df.copy()
```

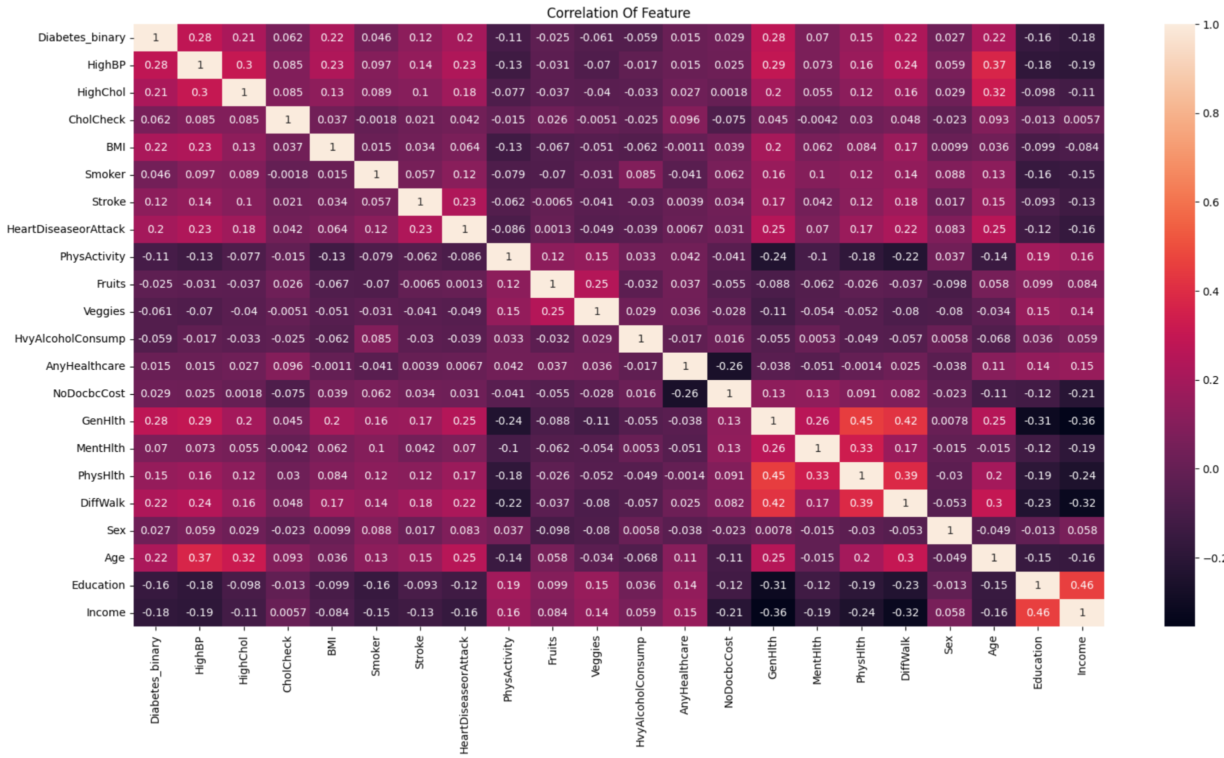
In [64]:
```
# That help us to show the relation between features clearly

df2.Age[df2['Age'] == 1] = '18 to 24'
df2.Age[df2['Age'] == 2] = '25 to 29'
df2.Age[df2['Age'] == 3] = '30 to 34'
df2.Age[df2['Age'] == 4] = '35 to 39'
df2.Age[df2['Age'] == 5] = '40 to 44'
df2.Age[df2['Age'] == 6] = '45 to 49'
df2.Age[df2['Age'] == 7] = '50 to 54'
df2.Age[df2['Age'] == 8] = '55 to 59'
df2.Age[df2['Age'] == 9] = '60 to 64'
df2.Age[df2['Age'] == 10] = '65 to 69'
df2.Age[df2['Age'] == 11] = '70 to 74'
df2.Age[df2['Age'] == 12] = '75 to 79'
df2.Age[df2['Age'] == 13] = '80 or older'

df2.Diabetes_binary[df2['Diabetes_binary'] == 0] = 'No Diabetes'
df2.Diabetes_binary[df2['Diabetes_binary'] == 1] = 'Diabetes'

df2.HighBP[df2['HighBP'] == 0] = 'No High'
df2.HighBP[df2['HighBP'] == 1] = 'High BP'

df2.HighChol[df2['HighChol'] == 0] = 'No High Cholesterol'
df2.HighChol[df2['HighChol'] == 1] = 'High Cholesterol'

df2.CholCheck[df2['CholCheck'] == 0] = 'No Cholesterol Check in 5 Years'
df2.CholCheck[df2['CholCheck'] == 1] = 'Cholesterol Check in 5 Years'

df2.Smoker[df2['Smoker'] == 0] = 'No'
df2.Smoker[df2['Smoker'] == 1] = 'Yes'

df2.Stroke[df2['Stroke'] == 0] = 'No'
df2.Stroke[df2['Stroke'] == 1] = 'Yes'

df2.HeartDiseaseorAttack[df2['HeartDiseaseorAttack'] == 0] = 'No'
df2.HeartDiseaseorAttack[df2['HeartDiseaseorAttack'] == 1] = 'Yes'

df2.PhysActivity[df2['PhysActivity'] == 0] = 'No'
df2.PhysActivity[df2['PhysActivity'] == 1] = 'Yes'

df2.Fruits[df2['Fruits'] == 0] = 'No'
df2.Fruits[df2['Fruits'] == 1] = 'Yes'

df2.Veggies[df2['Veggies'] == 0] = 'No'
df2.Veggies[df2['Veggies'] == 1] = 'Yes'

df2.HvyAlcoholConsump[df2['HvyAlcoholConsump'] == 0] = 'No'
df2.HvyAlcoholConsump[df2['HvyAlcoholConsump'] == 1] = 'Yes'

df2.AnyHealthcare[df2['AnyHealthcare'] == 0] = 'No'
df2.AnyHealthcare[df2['AnyHealthcare'] == 1] = 'Yes'

df2.NoDocbcCost[df2['NoDocbcCost'] == 0] = 'No'
df2.NoDocbcCost[df2['NoDocbcCost'] == 1] = 'Yes'

df2.GenHlth[df2['GenHlth'] == 5] = 'Excellent'
```

```
df2.GenHlth[df2['GenHlth'] == 4] = 'Very Good'
df2.GenHlth[df2['GenHlth'] == 3] = 'Good'
df2.GenHlth[df2['GenHlth'] == 2] = 'Fair'
df2.GenHlth[df2['GenHlth'] == 1] = 'Poor'

df2.DiffWalk[df2['DiffWalk'] == 0] = 'No'
df2.DiffWalk[df2['DiffWalk'] == 1] = 'Yes'

df2.Sex[df2['Sex'] == 0] = 'Female'
df2.Sex[df2['Sex'] == 1] = 'Male'

df2.Education[df2['Education'] == 1] = 'Never Attended School'
df2.Education[df2['Education'] == 2] = 'Elementary'
df2.Education[df2['Education'] == 3] = 'Junior High School'
df2.Education[df2['Education'] == 4] = 'Senior High School'
df2.Education[df2['Education'] == 5] = 'Undergraduate Degree'
df2.Education[df2['Education'] == 6] = 'Magister'

df2.Income[df2['Income'] == 1] = 'Less Than $10,000'
df2.Income[df2['Income'] == 2] = 'Less Than $10,000'
df2.Income[df2['Income'] == 3] = 'Less Than $10,000'
df2.Income[df2['Income'] == 4] = 'Less Than $10,000'
df2.Income[df2['Income'] == 5] = 'Less Than $35,000'
df2.Income[df2['Income'] == 6] = 'Less Than $35,000'
df2.Income[df2['Income'] == 7] = 'Less Than $35,000'
df2.Income[df2['Income'] == 8] = '$75,000 or More'
```

EDA

In [65]:
```
plt.figure(figsize = (20,10))
sns.heatmap(df.corr(),annot=True)
plt.title("Correlation Of Feature")
```

Out[65]:
```
Text(0.5, 1.0, 'Correlation Of Feature')
```

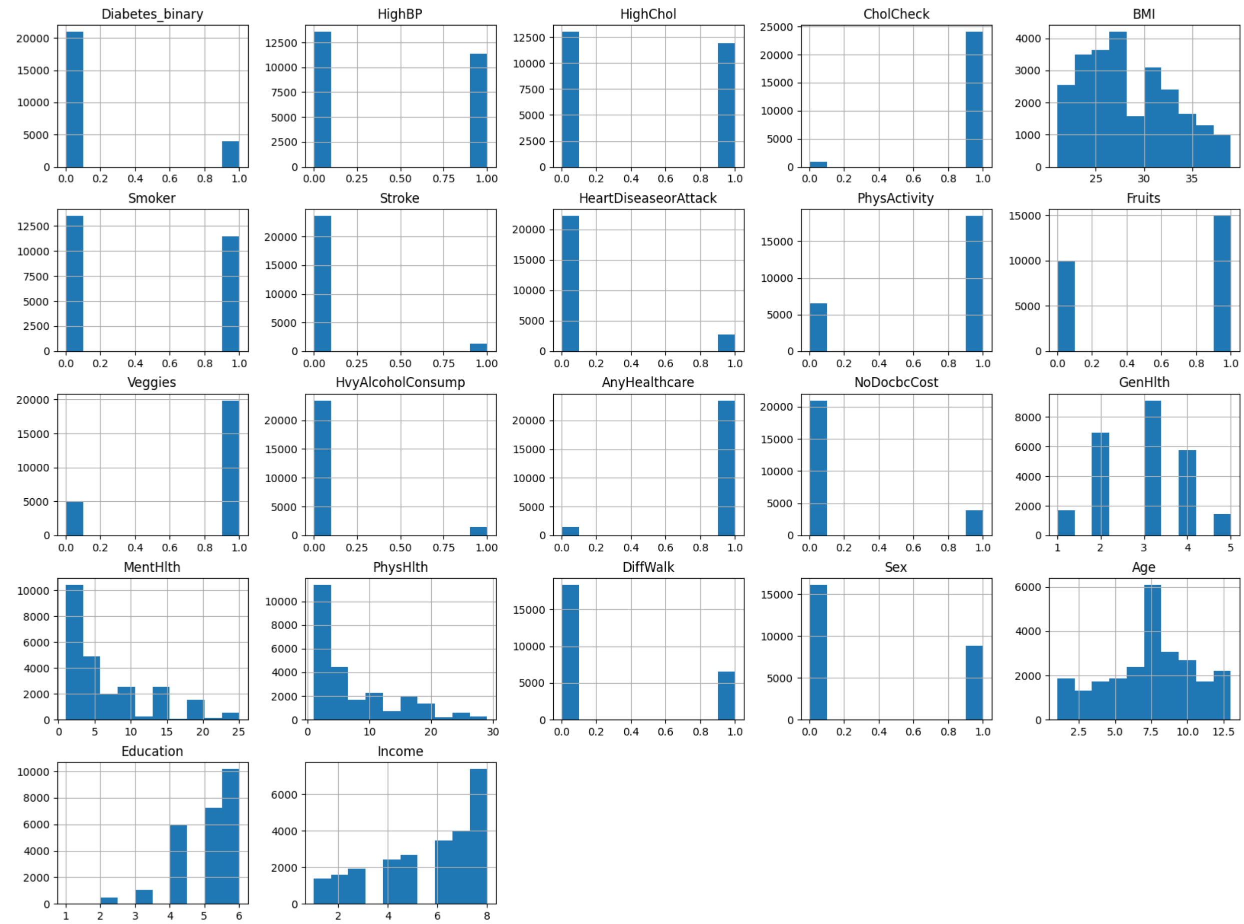


Correlation heatmap show relation between columns:

(GenHlth ,PhysHlth),(PhysHlth , DiffWalk),(GenHlth ,DiffWalk)are highly correleted with each other => **Positively Correlated**

(GenHlth ,Income) , (DiffWalk , Income) are highly correleted with each other => **Nagatively Correlated**

In [66]:
```
df.hist(figsize=(20,15));
```



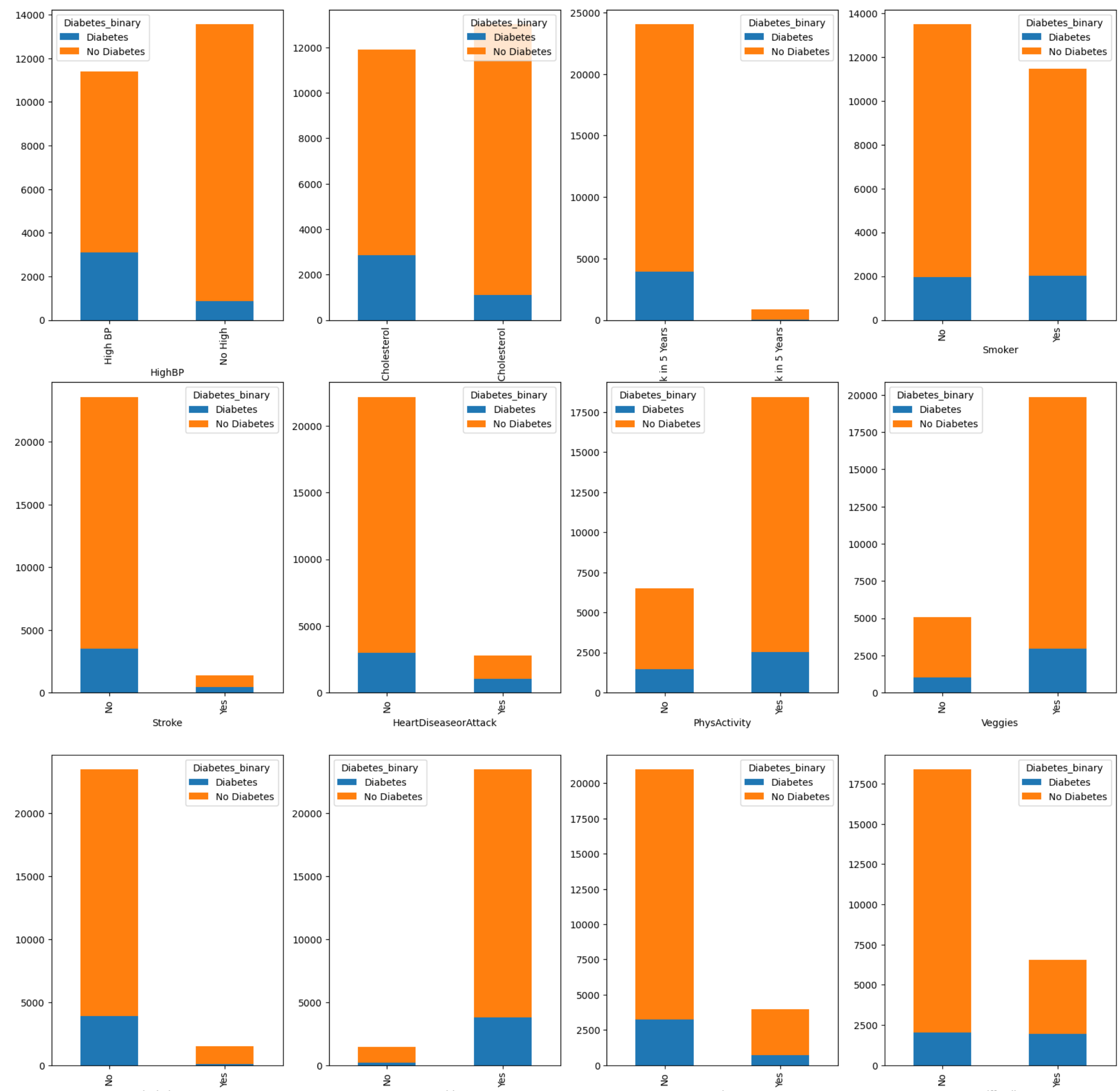
From the plots, we can observe that the Diabetes_binary and Sex are having imbalances in the data

Visualization Of [Yes - NO] Columns and their relation with the target

In [67]:
```
cols = ['HighBP', 'HighChol', 'CholCheck','Smoker',
        'Stroke', 'HeartDiseaseorAttack', 'PhysActivity', 'Veggies',
        'HvyAlcoholConsump', 'AnyHealthcare', 'NoDocbcCost', 'DiffWalk']
```

In [68]:
```
def create_plot_pivot(df2, x_column):
    df_plot = df2.groupby([x_column, 'Diabetes_binary']).size().reset_index(
    return df_plot
```

In [69]:
```
fig, ax = plt.subplots(3, 4, figsize=(20,20))
axe = ax.ravel()

c = len(cols)

for i in range(c):
    create_plot_pivot(df2, cols[i]).plot(kind='bar', stacked=True, ax=axe[i
    axe[i].set_xlabel(cols[i])

fig.show()
```

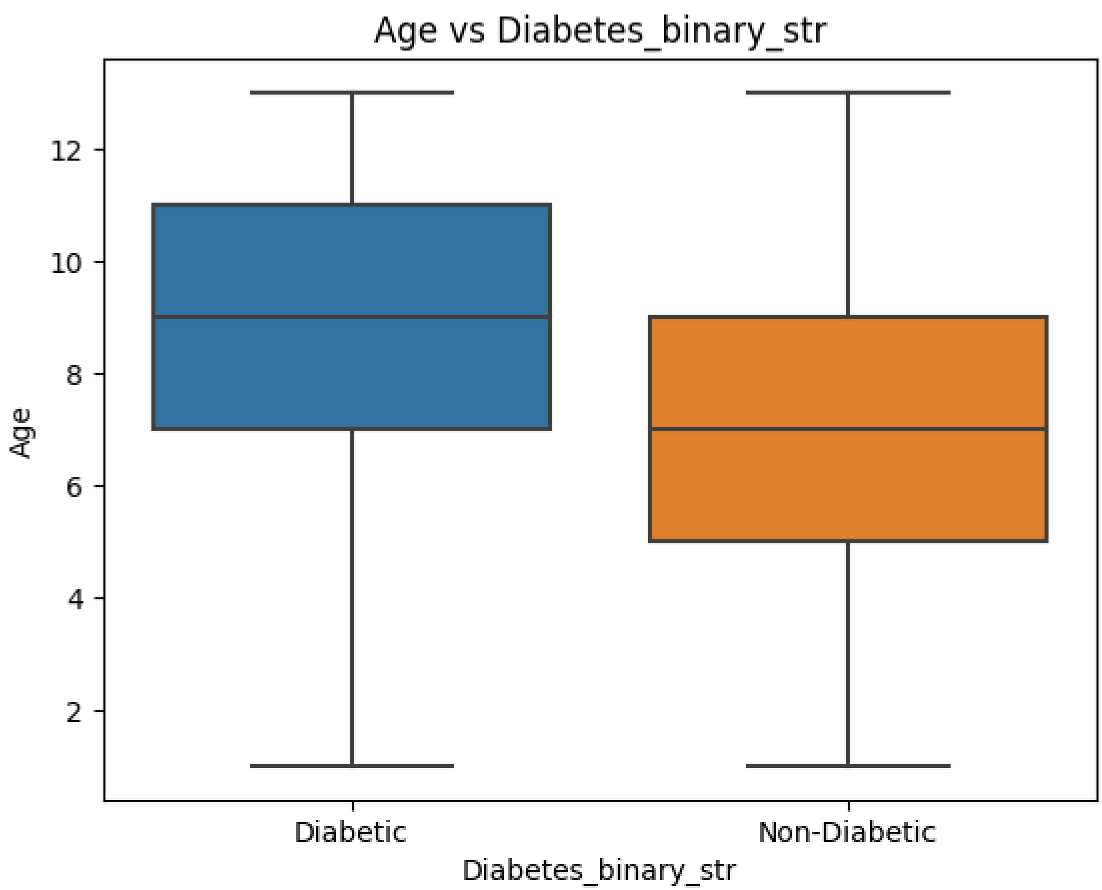


Observations

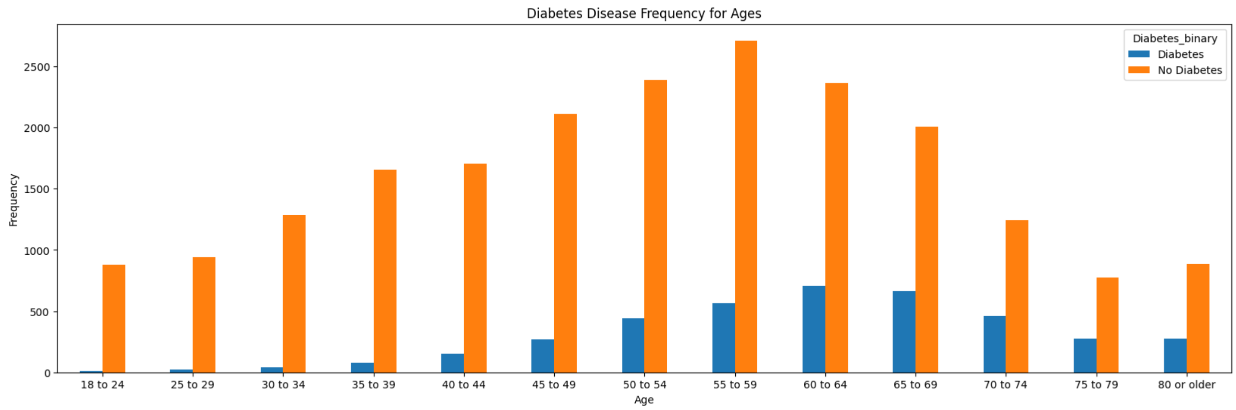
1. High BP and Chelostrol shows a postive sign of getting diabetes
2. Presence of Diabeties results in heart disease and stroke.
3. Eating vegitables doesn't show any impact on getting the diabeties, this might not be exactly true in the real time scenario, there could be a problem with the survey

The feature "Age" and it's relation with the target

In [70]:
```
sns.boxplot(x='Diabetes_binary_str', y='Age', data=df)
plt.title('Age vs Diabetes_binary_str')
plt.show()
```



In [71]:
```
pd.crosstab(df2.Age, df2.Diabetes_binary).plot(kind="bar",figsize=(20,6))
plt.title('Diabetes Disease Frequency for Ages')
plt.xlabel('Age')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```

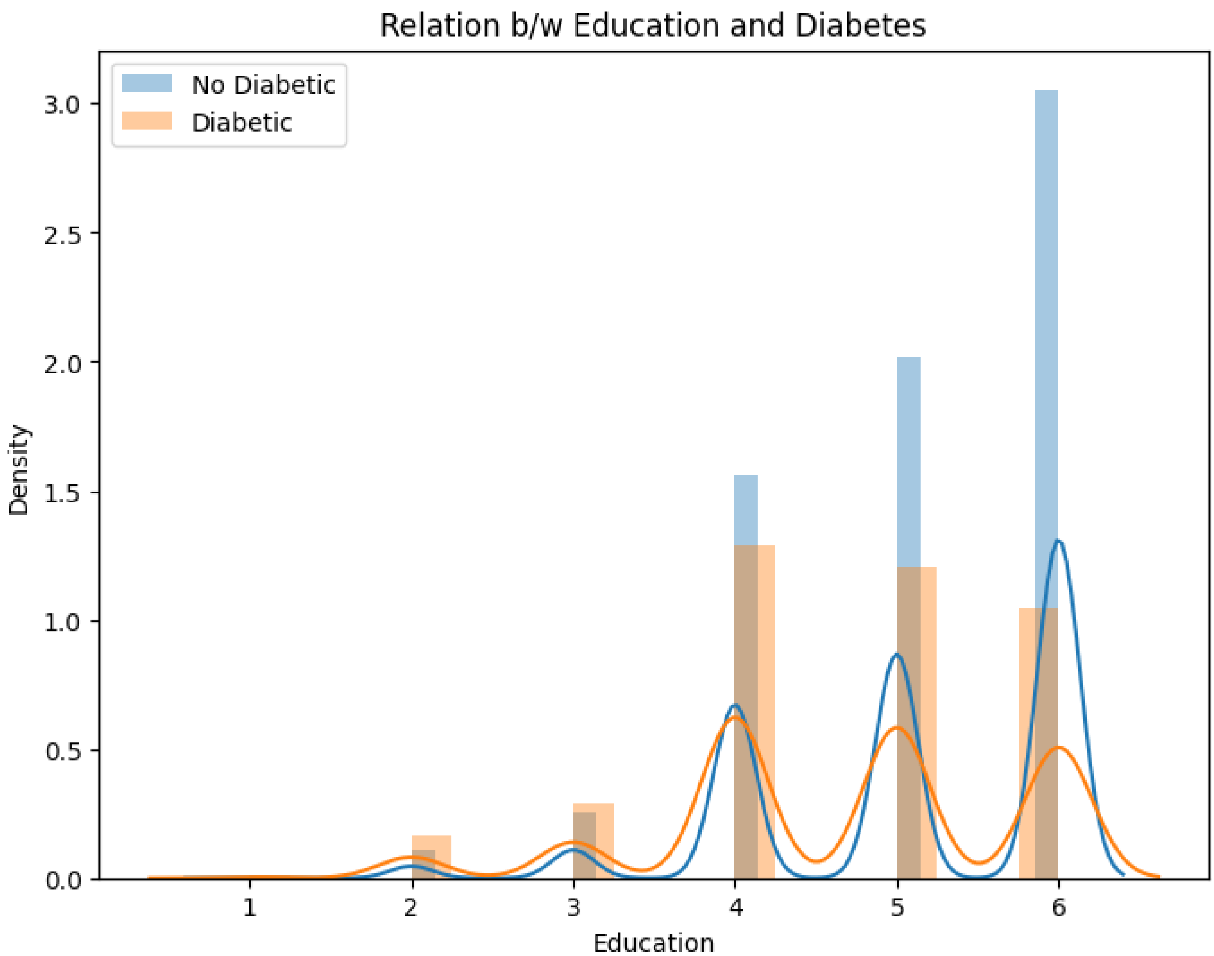


We know that as the age increases, the chances of diabetes also commonly increases. From above we can say, the median of the age of diabetic people is greater than that of non-diabetic people.

The feature "Education" and it's relation with the target

In [72]:
```
plt.figure(figsize=(8,6))

sns.distplot(df.Education[df.Diabetes_binary == 0], label="No Diabetic" )
sns.distplot(df.Education[df.Diabetes_binary == 1], label="Diabetic" )
plt.title("Relation b/w Education and Diabetes")

plt.legend()
```

Out[72]:
```
<matplotlib.legend.Legend at 0x7fe53be1bc70>
```



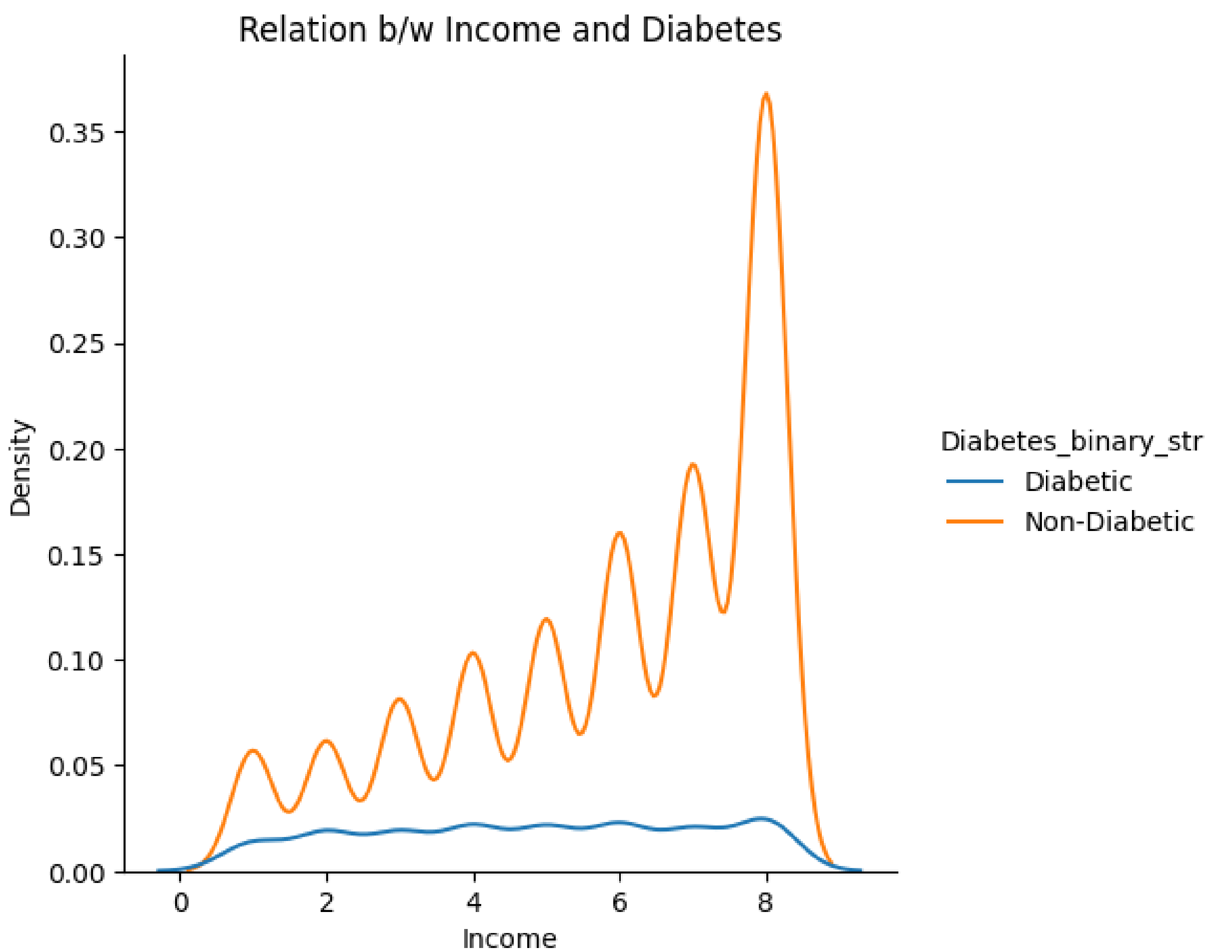
As the education increases, the count of presence of diabetes has been decreased, but it not much significant.

The feature "income" and it's relation with the target

In [73]:
```
plt.figure(figsize=(20,10))

sns.displot(data=df, x="Income", hue="Diabetes_binary_str", kind="kde")
plt.title("Relation b/w Income and Diabetes")
```

Out[73]:
```
Text(0.5, 1.0, 'Relation b/w Income and Diabetes')
```

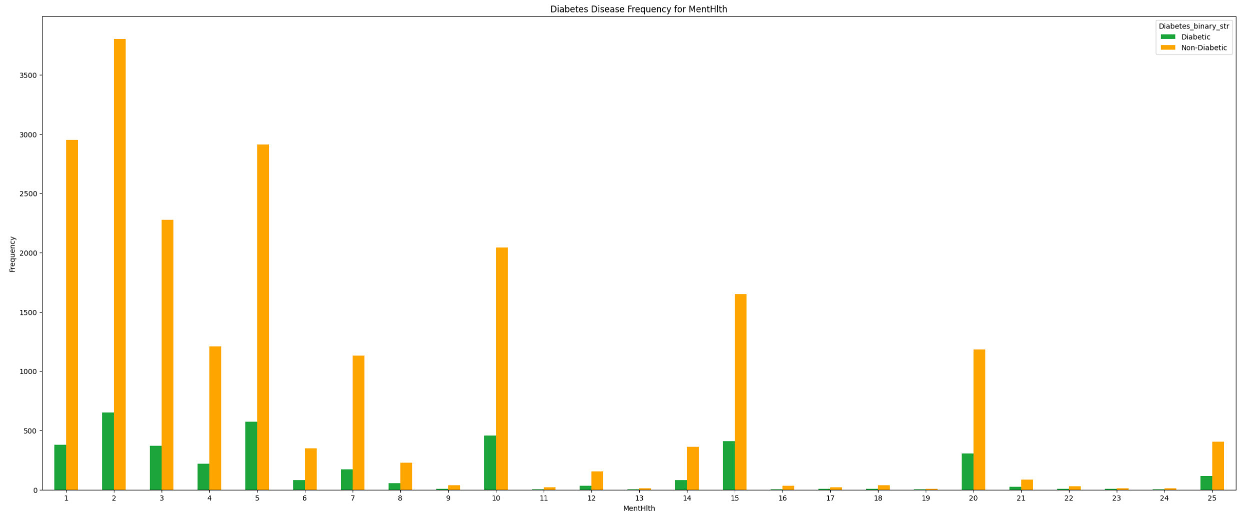
```
<Figure size 2000x1000 with 0 Axes>
```



The non diabetic count increased as the income increases. Where as the diabetic count is a contant across all the income groups.

The feature "MentHlth" and it's relation with the target

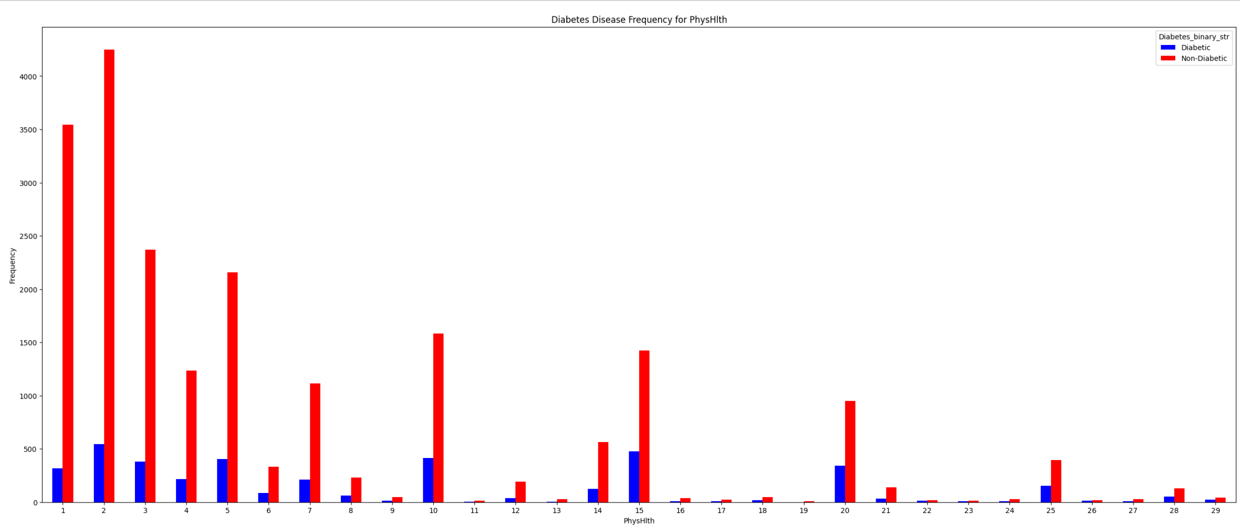
In [74]:
```
pd.crosstab(df.MentHlth, df.Diabetes_binary_str).plot(kind="bar", figsize=(
plt.title('Diabetes Disease Frequency for MentHlth')
plt.xlabel('MentHlth')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```



From figure we can say that Menthlth Group 0-5 have impact on Diabetic

The feature "PhysHlth" and it's relation with the target

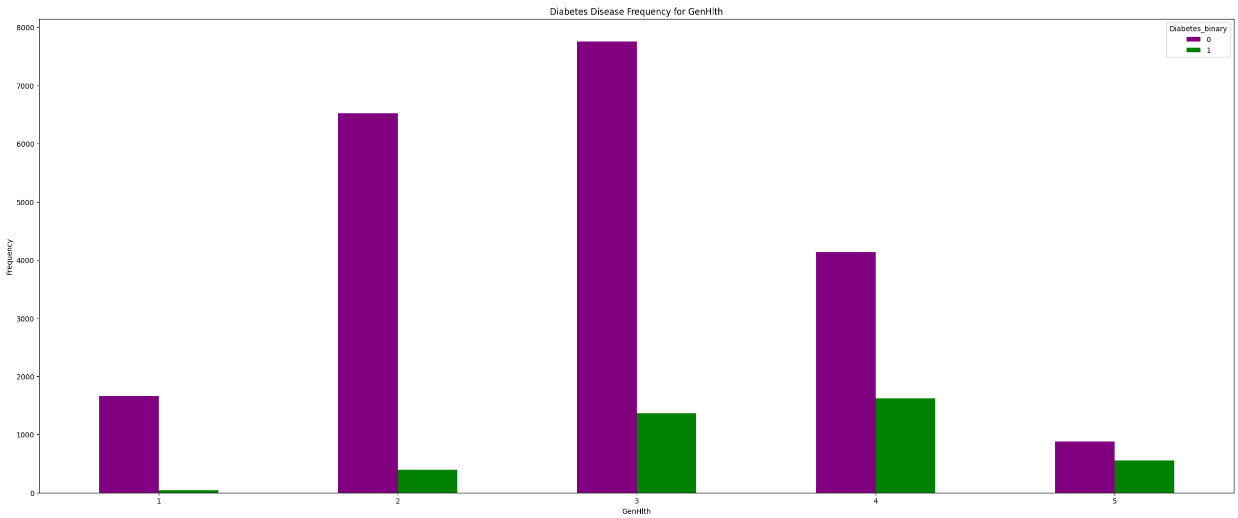
In [75]:
```
pd.crosstab(df.PhysHlth, df.Diabetes_binary_str).plot(kind="bar",figsize=(3
plt.title('Diabetes Disease Frequency for PhysHlth')
plt.xlabel('PhysHlth')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```



From figure we can say that PhysHlth Group 0-5 have impact on Diabetic

The feature "GenHlth" and it's relation with the target

In [76]:
```
pd.crosstab(df.GenHlth, df.Diabetes_binary).plot(kind="bar",figsize=(30,12)
plt.title('Diabetes Disease Frequency for GenHlth')
plt.xlabel('GenHlth')
plt.xticks(rotation=0)
plt.ylabel('Frequency')
plt.show()
```

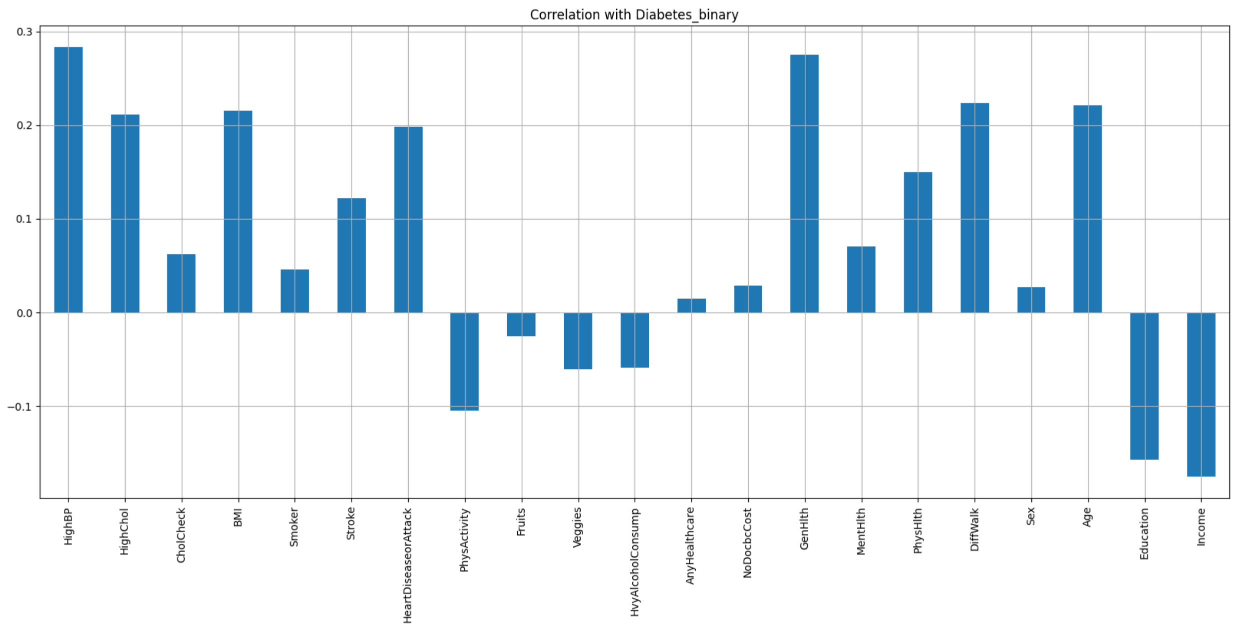


not many peolpe have "5" and "4" of GenHlth ,but they have diabetes !!!

Feature Selections

With correlation

In [77]:
```
df.drop('Diabetes_binary', axis=1).corrwith(df.Diabetes_binary).plot(kind='
, title="Correlation with Diabetes_binary");
```



Diabetes_binary's relation with other columns Through bar Graph Result:

1. Fruits , AnyHealthcare , NoDocbccost and sex are least correlated with Diabetes_binary.
2. HighBP , HighChol , BMI , smoker , stroke , HeartDiseaseorAttack , PhysActivity , Veggies , MentHlth , HvyAlcoholconsump , GenHlth , PhysHlth , Age , Education , Income and DiffWalk have a significant correlation with Diabetes_binary.

VIF Multi Collinearity Test

In [78]:
```
def calc_VIF(x):
    vif= pd.DataFrame()
    vif['variables']=x.columns
    vif["VIF"]=[variance_inflation_factor(x.values,i) for i in range(x.shap

    return(vif)


X = add_constant(Orginal_data)
ds=pd.Series([variance_inflation_factor(X.values, i) for i in range(X.shape
print(ds)
```

```
const                   116.856706
Diabetes_binary           1.193120
HighBP                    1.344502
HighChol                  1.180932
CholCheck                 1.033501
BMI                       1.160280
Smoker                    1.091872
Stroke                    1.081612
HeartDiseaseorAttack      1.175776
PhysActivity              1.157396
Fruits                    1.112540
Veggies                   1.112397
HvyAlcoholConsump         1.025418
AnyHealthcare             1.113209
NoDocbcCost               1.144200
GenHlth                   1.821914
MentHlth                  1.239497
PhysHlth                  1.623288
DiffWalk                  1.536636
Sex                       1.075748
Age                       1.354954
Education                 1.326495
Income                    1.505649
dtype: float64
```

In [79]:
```
X = Orginal_data.iloc[:,1:]
Y = Orginal_data.iloc[:,0]
```

Chi Square

In [80]:
```
BestFeatures = SelectKBest(score_func=chi2, k=10)
fit = BestFeatures.fit(X,Y)

df_scores = pd.DataFrame(fit.scores_)
df_columns = pd.DataFrame(X.columns)

f_Scores = pd.concat([df_columns, df_scores], axis=1)
f_Scores.columns = ['Feature', 'Score']

f_Scores
```

Out[80]:

	Feature	Score
0	HighBP	10029.013935
1	HighChol	5859.710582
2	CholCheck	39.716825
3	BMI	18355.166400
4	Smoker	521.978858
5	Stroke	2725.225194
6	HeartDiseaseorAttack	7221.975378
7	PhysActivity	861.887532
8	Fruits	154.291404
9	Veggies	153.169215
10	HvyAlcoholConsump	779.424807
11	AnyHealthcare	3.280938
12	NoDocbcCost	229.542412
13	GenHlth	9938.507776
14	MentHlth	21029.632228
15	PhysHlth	133424.406534
16	DiffWalk	10059.506391
17	Sex	140.248274
18	Age	9276.141199
19	Education	756.035496
20	Income	4829.816361

In [81]:
```
print(f_Scores.nlargest(16,'Score'))
```

```
                 Feature          Score
15              PhysHlth  133424.406534
14              MentHlth   21029.632228
3                    BMI   18355.166400
16              DiffWalk   10059.506391
0                 HighBP   10029.013935
13               GenHlth    9938.507776
18                   Age    9276.141199
6   HeartDiseaseorAttack    7221.975378
1               HighChol    5859.710582
20                Income    4829.816361
5                 Stroke    2725.225194
7           PhysActivity     861.887532
10     HvyAlcoholConsump     779.424807
19             Education     756.035496
4                 Smoker     521.978858
12           NoDocbcCost     229.542412
```

There are the features which we will use in our model

We will use those features in our model

"Fruits" , "Veggies" , "Sex" , "CholCheck" , " AnyHealthcare" will not be with us

In [82]:
```
colomns = ["Fruits" , "Veggies" , "Sex" , "CholCheck" , "AnyHealthcare" , "
df.drop(colomns, axis=1, inplace=True)
```

Data Splitting

In [83]:
```
X = df.drop("Diabetes_binary",axis=1)
Y = df["Diabetes_binary"]
```

In [84]:
```
X_train , X_test , Y_train , Y_test = train_test_split(X, Y, test_size=0.3
```

Data Scalling

In [85]:
```
from sklearn.preprocessing import StandardScaler

# create a scaler object
std_scaler = StandardScaler()
std_scaler
# fit and transform the data
X_train = pd.DataFrame(std_scaler.fit_transform(X_train), columns=X_train.c
```

In [86]:
```
from sklearn.preprocessing import StandardScaler

# create a scaler object
std_scaler = StandardScaler()
std_scaler
# fit and transform the data
X_test = pd.DataFrame(std_scaler.fit_transform(X_test), columns=X_test.colu
```

Modeling

Rondom Forest

In [87]:
```
rf = RandomForestClassifier(max_depth=12 ,n_estimators =10, random_state=42

# fitting the model on the train data
rf.fit(X_train, Y_train)
```

Out[87]:
```
▾ RandomForestClassifier
RandomForestClassifier(max_depth=12, n_estimators=10, random_state=42)
```

In [88]:
```
# make predictions on test set
y_pred=rf.predict(X_test)

print('Training set score: {:.4f}'.format(rf.score(X_train, Y_train)))

print('Test set score: {:.4f}'.format(rf.score(X_test, Y_test)))
```

```
Training set score: 0.9040
Test set score: 0.8392
```

In [89]:
```
#check MSE & RMSE
mse =mean_squared_error(Y_test, y_pred)
print('Mean Squared Error : '+ str(mse))
rmse = math.sqrt(mean_squared_error(Y_test, y_pred))
print('Root Mean Squared Error : '+ str(rmse))
```

```
Mean Squared Error : 0.16080737869268813
Root Mean Squared Error : 0.40100795340328116
```

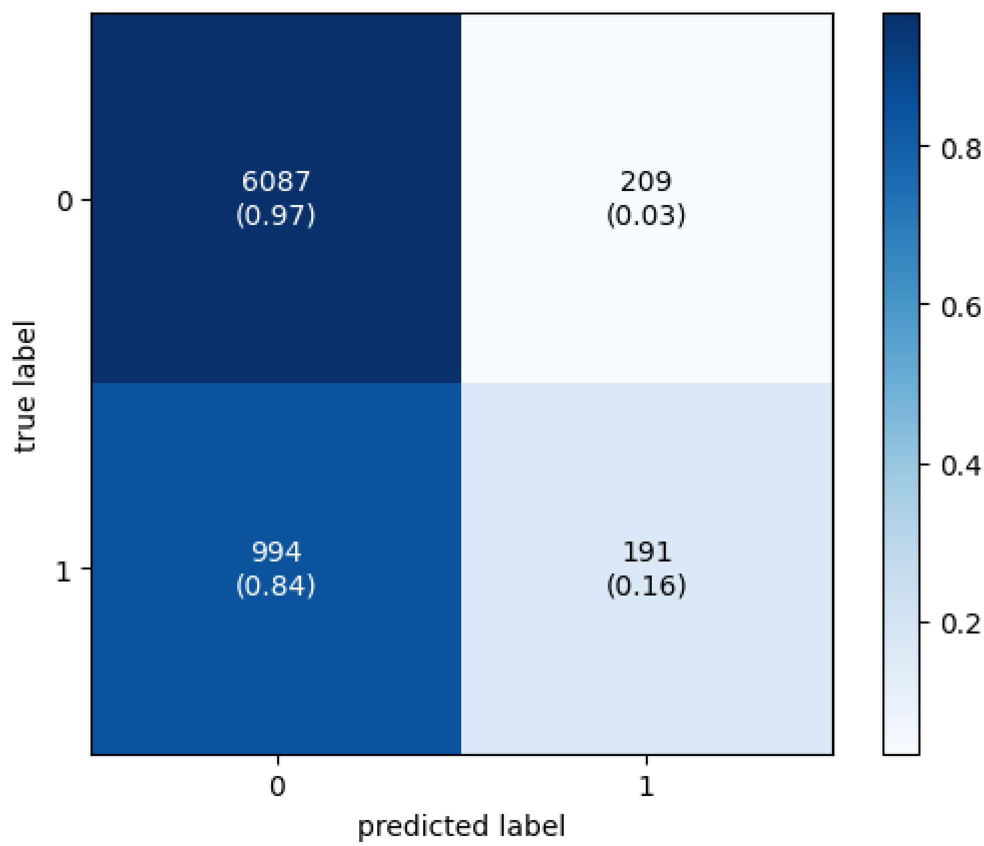
In [90]:
```
matrix = classification_report(Y_test,y_pred )
print(matrix)
```

```
              precision    recall  f1-score   support

           0       0.86      0.97      0.91      6296
           1       0.48      0.16      0.24      1185

    accuracy                           0.84      7481
   macro avg       0.67      0.56      0.58      7481
weighted avg       0.80      0.84      0.80      7481
```

Calculating and plotting the confusion matrix

Confusion Matrix

In [91]:
```
cm1 = confusion_matrix(Y_test,y_pred)
plot_confusion_matrix(conf_mat=cm1,show_absolute=True,
                                show_normed=True,
                                colorbar=True)
plt.show()
```



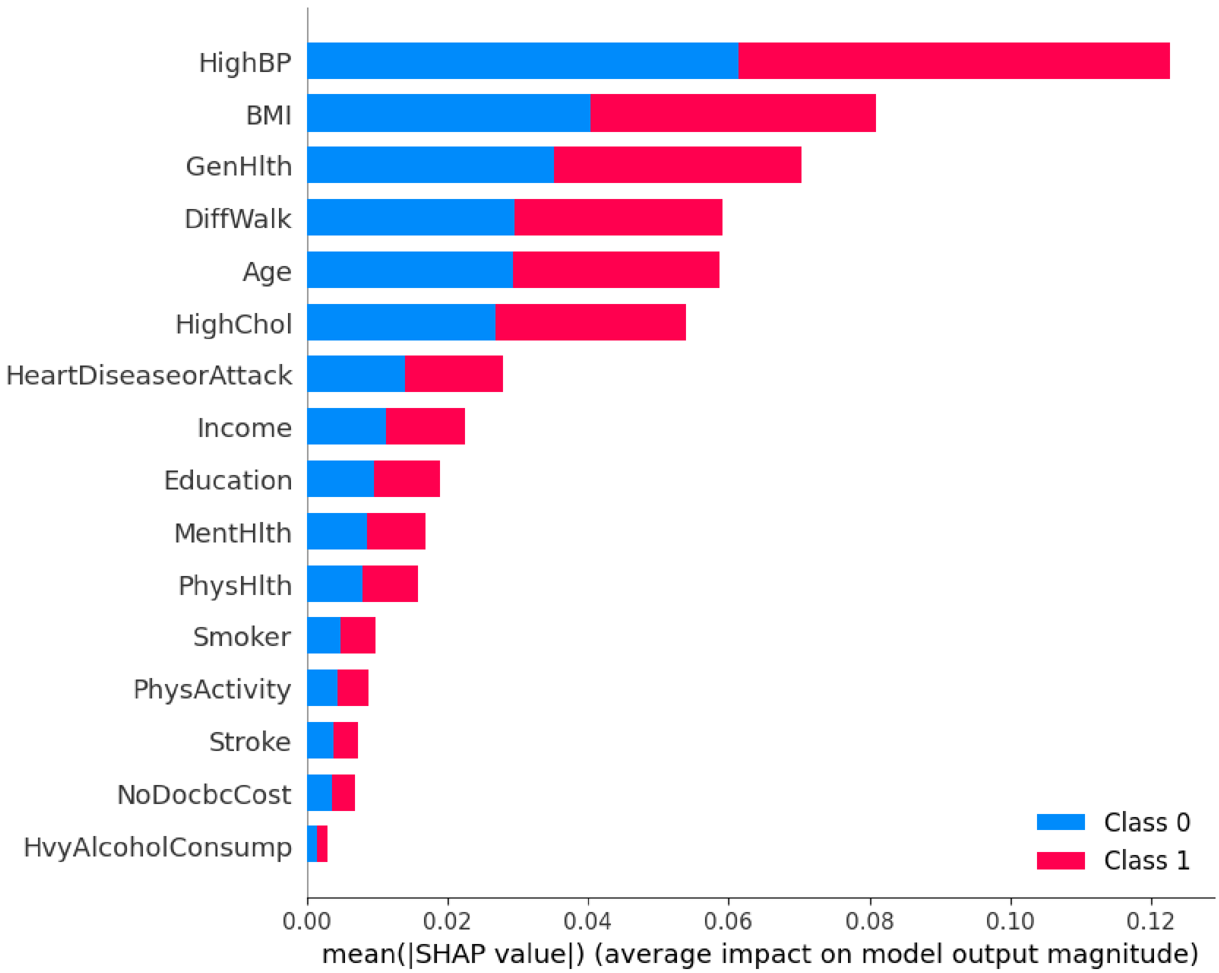
Model interpretability

In [92]:
```
import shap
```

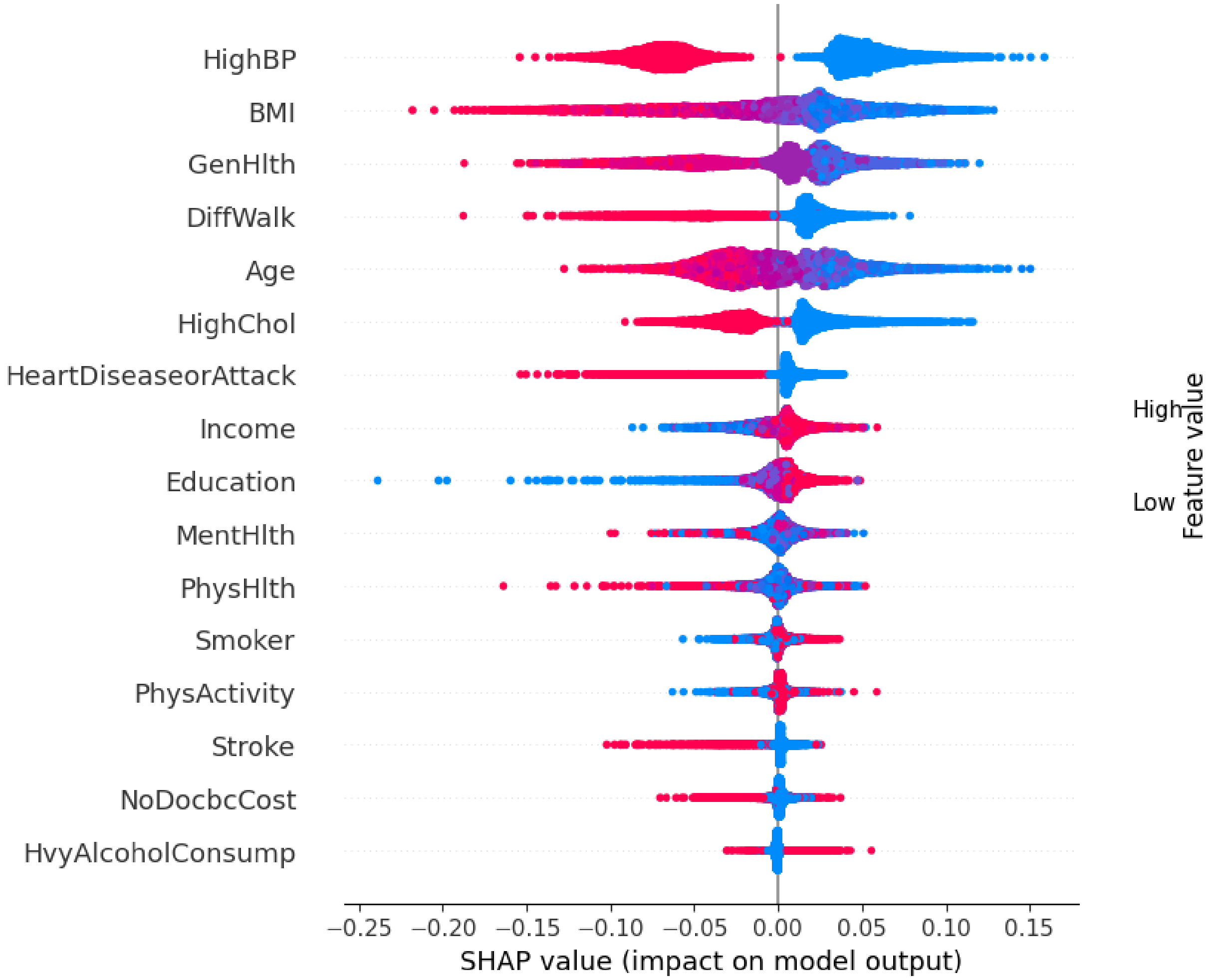
In [93]:
```
shap.initjs()
```

In [94]:
```
row = X_test.iloc[[5]]
tree_shap_explainer = shap.TreeExplainer(rf)
tree_shap_values_row = tree_shap_explainer.shap_values(row)
tree_shap_values = tree_shap_explainer.shap_values(X_test)
```

In [95]:
```
shap.summary_plot(tree_shap_values, X_test)
```



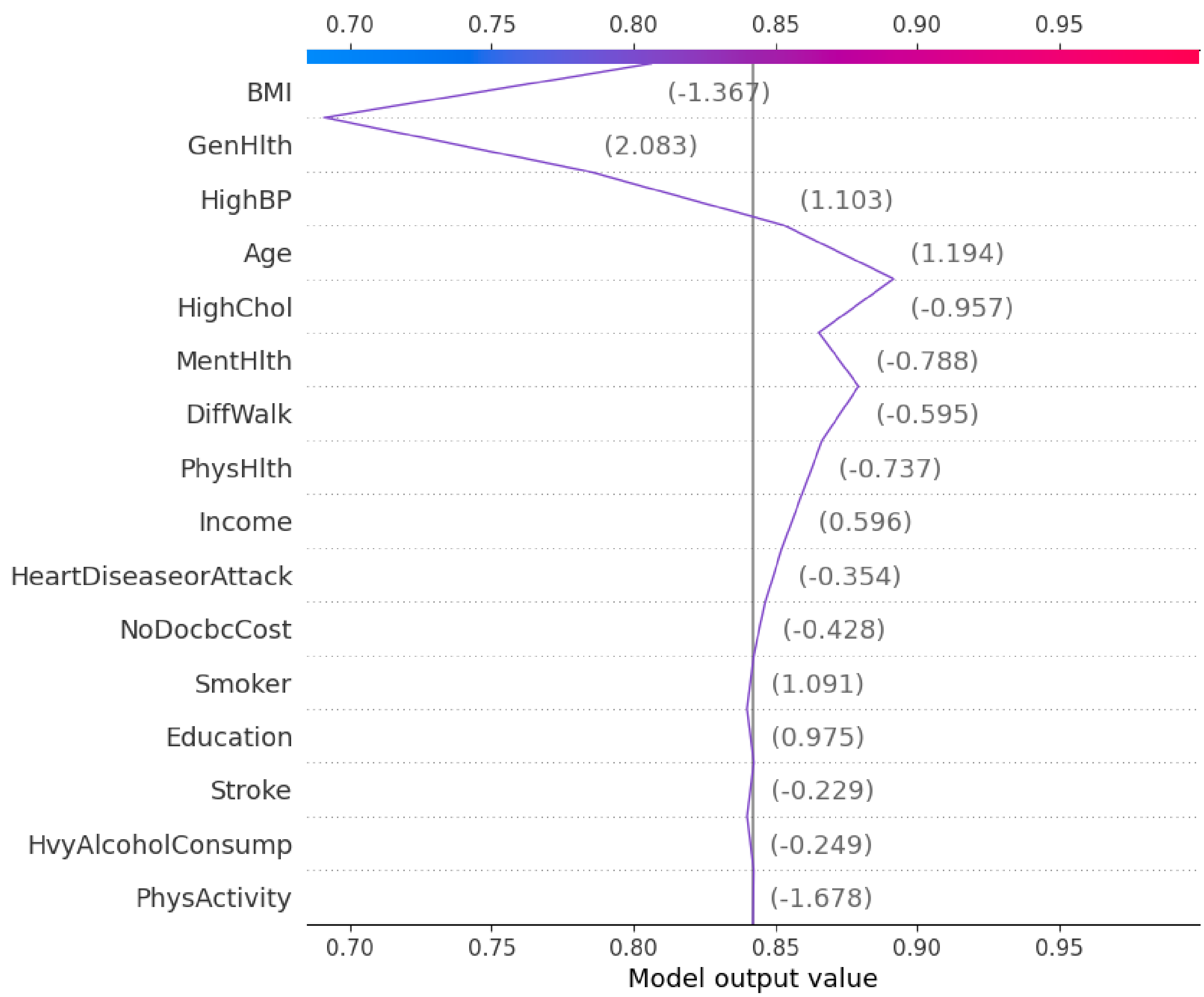
In [96]:
```
shap.initjs()
shap.summary_plot(tree_shap_values[0], X_test, feature_names=X_test.columns
```



High BMI resulted in Diabetes

Acohol consumption doesn't have much significance

In [98]:
```
shap.decision_plot(tree_shap_explainer.expected_value[0],
                        tree_shap_values[0][3,:], X_test.iloc[3,:])
```



Conclusion

This illness, which was formerly known as the "disease of the rich" and "slow killer," now affects people of all ages and socioeconomic backgrounds. This could be explained by increased consumption of foods that cause diabetes and easier access to cheap junk food.

Families' eating habits and patterns may alter as socioeconomic conditions improve. Less physical activity and exercise, as well as the outsourcing of tasks around the house that would normally have been done by the individual, can occasionally be a result of higher wealth. Increased rates of obesity, stress-related smoking, and increased adherence to unhealthy lifestyles could all have a cascading influence on the prevalence of diabetes.

By harming the blood arteries, diabetes also raises the risk of high blood pressure. Many times, people with high blood pressure do not yet have a diabetes diagnosis. With this in mind, it seems logical that **high blood pressure and BMI are the two best indicators of diabetes risk**, while other risk factors include income, education, and physical activity.

References

Refered the following links to understand the functions or the processes that are going to be required during the problem analysis.

1. `Scikit-learn Documentation`

2. `Pandas Official Documentation`

3. `Analytics Vidya`

4. `medium: towardsdatascience`

5. `Seaborn: statistical data visualization`

All the visualization code was referred form the **seaborn** and **scikit-learn** official documentations. **Data frame** functions and usage was referred from the **Pandas** official documentation. All the concepts and doubts in the machine learning cleared with the help of **medium(towardsdatascience)** and **analytics vidya** articles. Rest of the code is written individually.