# Diabetes Predictions By using Machine Learning

IMPORT LIBRARIES AS WELL AS DATASET

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import os
%matplotlib inline
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv("Downloads/diabetes_prediction_.csv")
```

In [3]:
```
df
```

Out[3]:

| | gender | age | hypertension | heart_disease | smoking_history | bmi | HbA1c_level | blood |
|---|---|---|---|---|---|---|---|---|
| **0** | Female | 80.0 | 0 | 1 | never | 25.19 | 6.6 | |
| **1** | Female | 54.0 | 0 | 0 | No Info | 27.32 | 6.6 | |
| **2** | Male | 28.0 | 0 | 0 | never | 27.32 | 5.7 | |
| **3** | Female | 36.0 | 0 | 0 | current | 23.45 | 5.0 | |
| **4** | Male | 76.0 | 1 | 1 | current | 20.14 | 4.8 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **99995** | Female | 80.0 | 0 | 0 | No Info | 27.32 | 6.2 | |
| **99996** | Female | 2.0 | 0 | 0 | No Info | 17.37 | 6.5 | |
| **99997** | Male | 66.0 | 0 | 0 | former | 27.83 | 5.7 | |
| **99998** | Female | 24.0 | 0 | 0 | never | 35.42 | 4.0 | |
| **99999** | Female | 57.0 | 0 | 0 | current | 22.43 | 6.6 | |

100000 rows × 9 columns

We make two copy of the original dataset

In [4]:
```
df1 = df.copy(deep=True)
df2 = df.copy(deep=True)
```

# DATA PREPROCESSING

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
gender                 0
age                    0
hypertension           0
heart_disease          0
smoking_history        0
bmi                    0
HbA1c_level            0
blood_glucose_level    0
diabetes               0
dtype: int64
```

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 9 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   gender               100000 non-null  object 
 1   age                  100000 non-null  float64
 2   hypertension         100000 non-null  int64  
 3   heart_disease        100000 non-null  int64  
 4   smoking_history      100000 non-null  object 
 5   bmi                  100000 non-null  float64
 6   HbA1c_level          100000 non-null  float64
 7   blood_glucose_level  100000 non-null  int64  
 8   diabetes             100000 non-null  int64  
dtypes: float64(3), int64(4), object(2)
memory usage: 6.9+ MB
```

In [7]:
```
df.describe()
```

Out[7]:

| | age | hypertension | heart_disease | bmi | HbA1c_level | blood_gluc |
|---|---|---|---|---|---|---|
| **count** | 100000.000000 | 100000.00000 | 100000.000000 | 100000.000000 | 100000.000000 | 1000 |
| **mean** | 41.885856 | 0.07485 | 0.039420 | 27.320767 | 5.527507 | 1 |
| **std** | 22.516840 | 0.26315 | 0.194593 | 6.636783 | 1.070672 | |
| **min** | 0.080000 | 0.00000 | 0.000000 | 10.010000 | 3.500000 | |
| **25%** | 24.000000 | 0.00000 | 0.000000 | 23.630000 | 4.800000 | 1 |
| **50%** | 43.000000 | 0.00000 | 0.000000 | 27.320000 | 5.800000 | 1 |
| **75%** | 60.000000 | 0.00000 | 0.000000 | 29.580000 | 6.200000 | 1 |
| **max** | 80.000000 | 1.00000 | 1.000000 | 95.690000 | 9.000000 | 3 |

In [8]:
```
df.columns
```

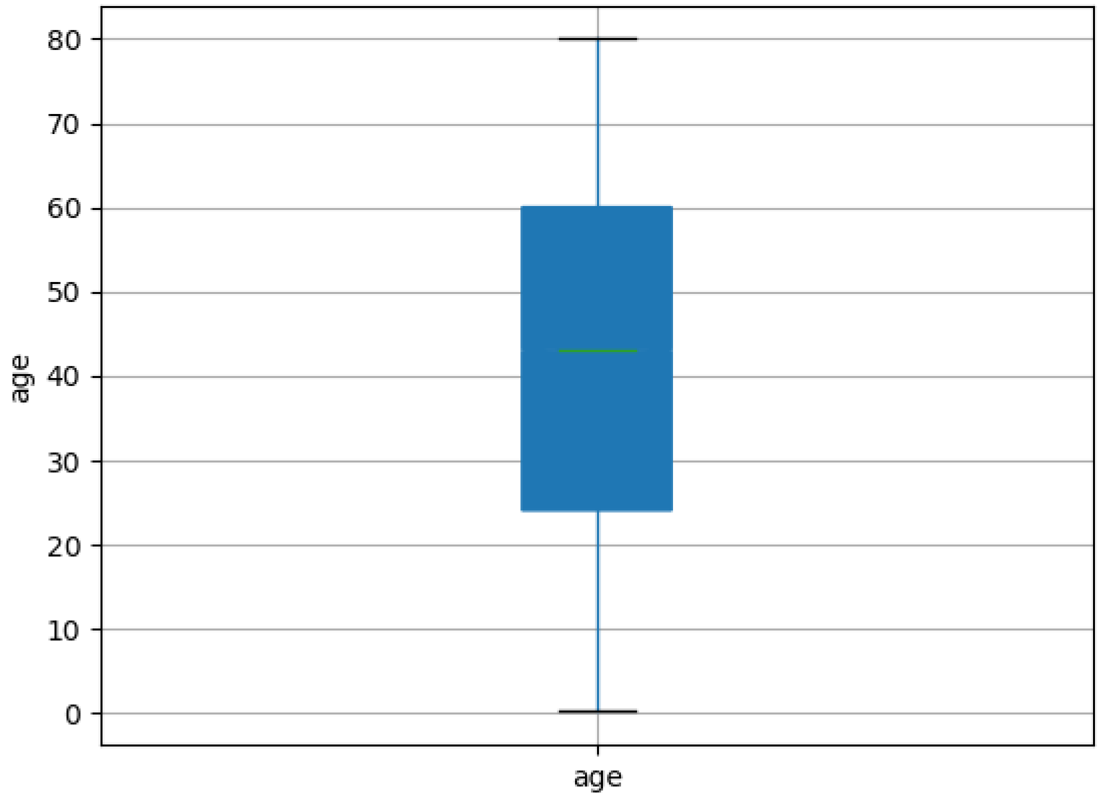
Out[8]:
```
Index(['gender', 'age', 'hypertension', 'heart_disease', 'smoking_histor
y',
       'bmi', 'HbA1c_level', 'blood_glucose_level', 'diabetes'],
      dtype='object')
```

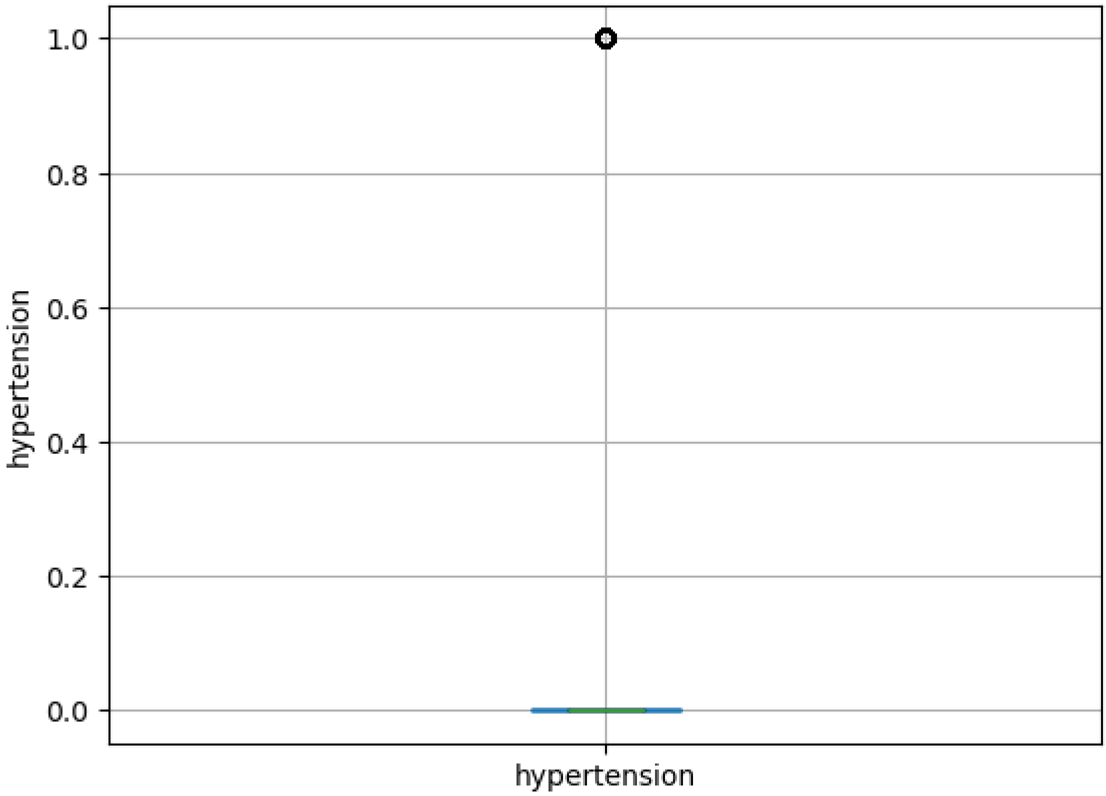
# EXPLORATORY DATA ANALYSIS

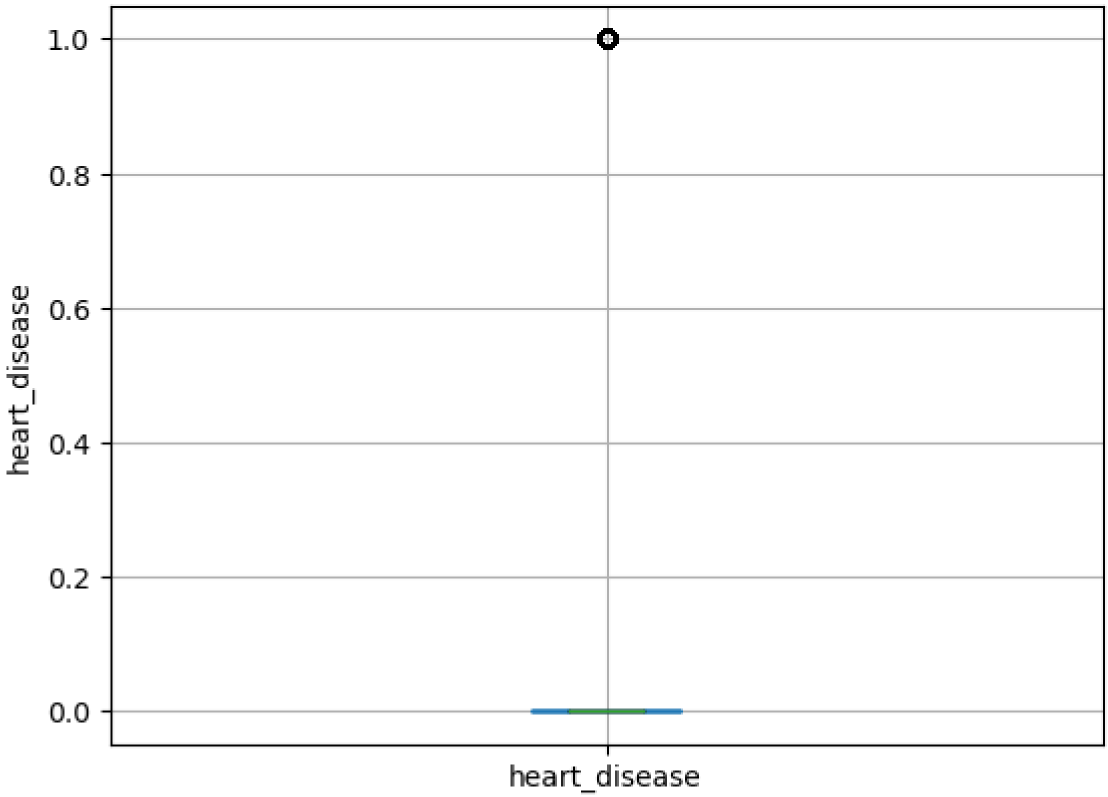
Here, in this dataset have Categorical features for that we seperate categorical and numerical features. So, now create EDA for numerical data.First, check the Outliers

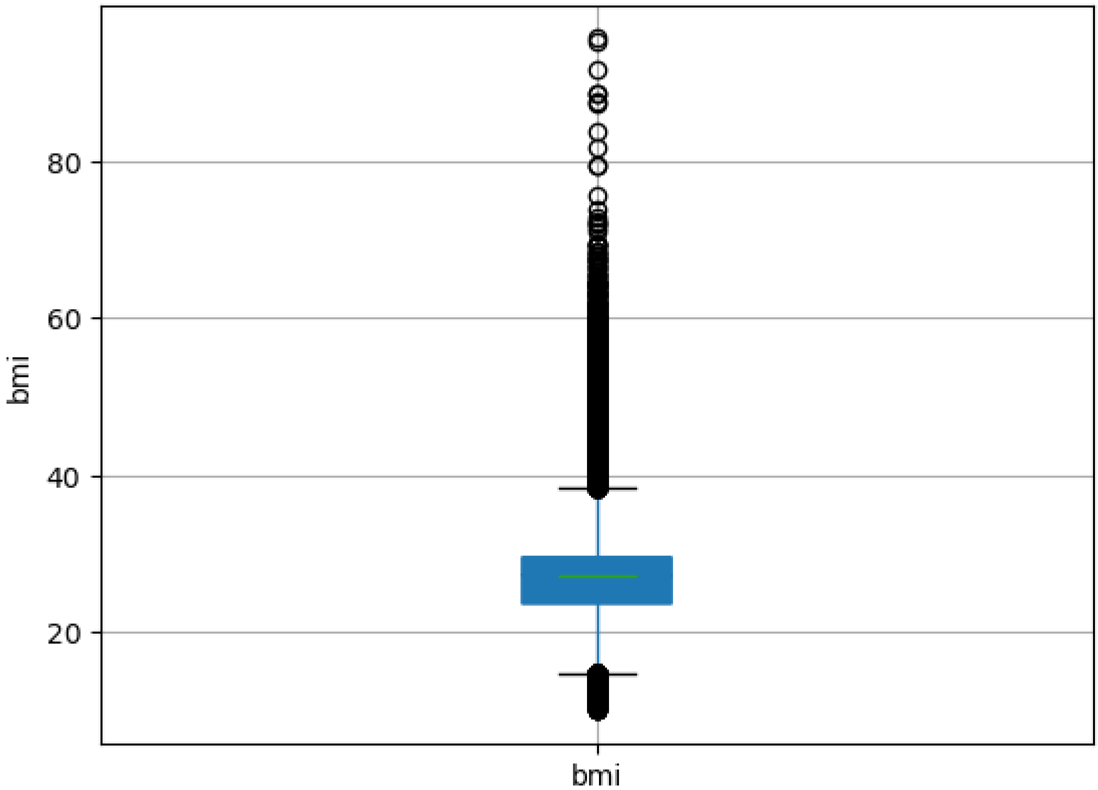
In [9]:
```
cat = df.select_dtypes(include="object")
num = df.select_dtypes(include="number")
```

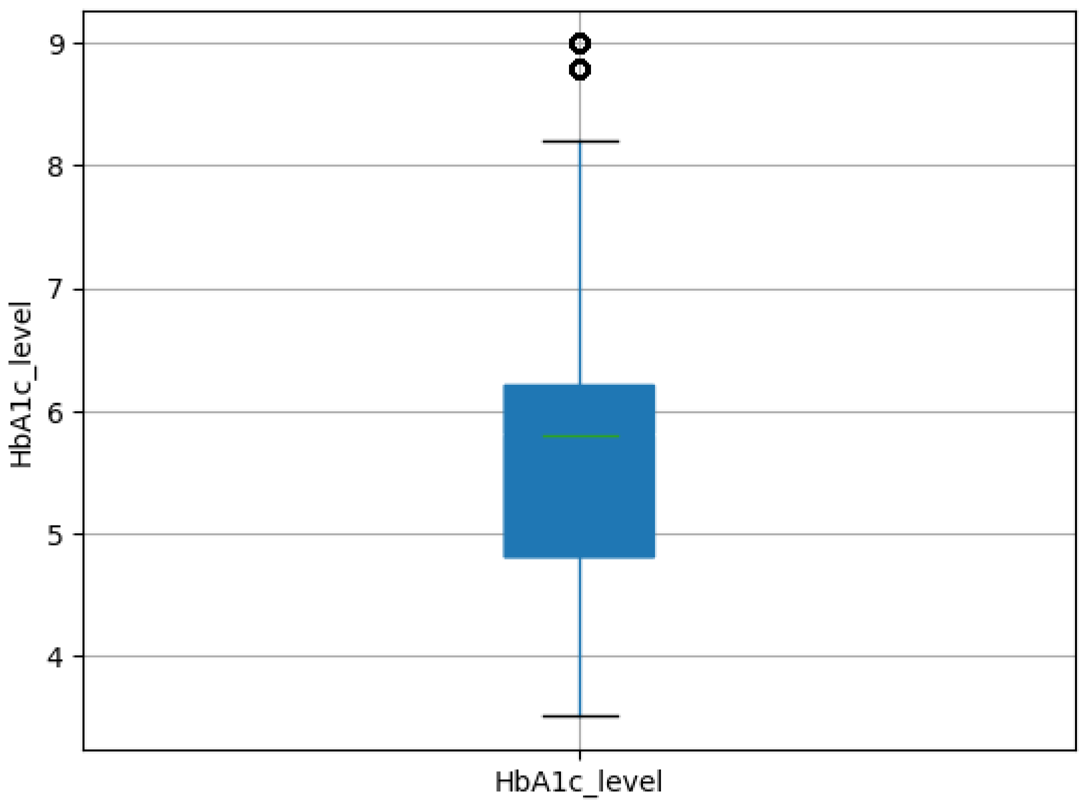
In [10]:
```
for i in num:
    num.boxplot(column=i, patch_artist = True, notch ='True')
    plt.ylabel(i)
    plt.show()
```

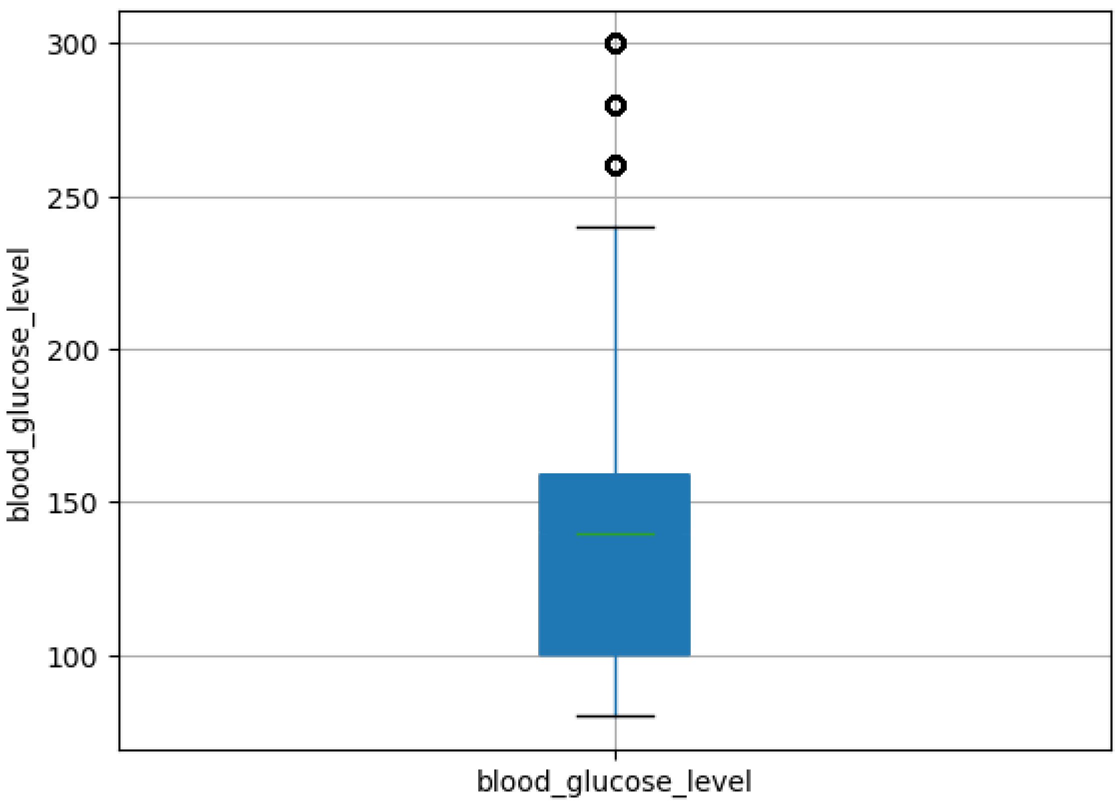

80
70
60
50
40
30
20
10
0
age
age

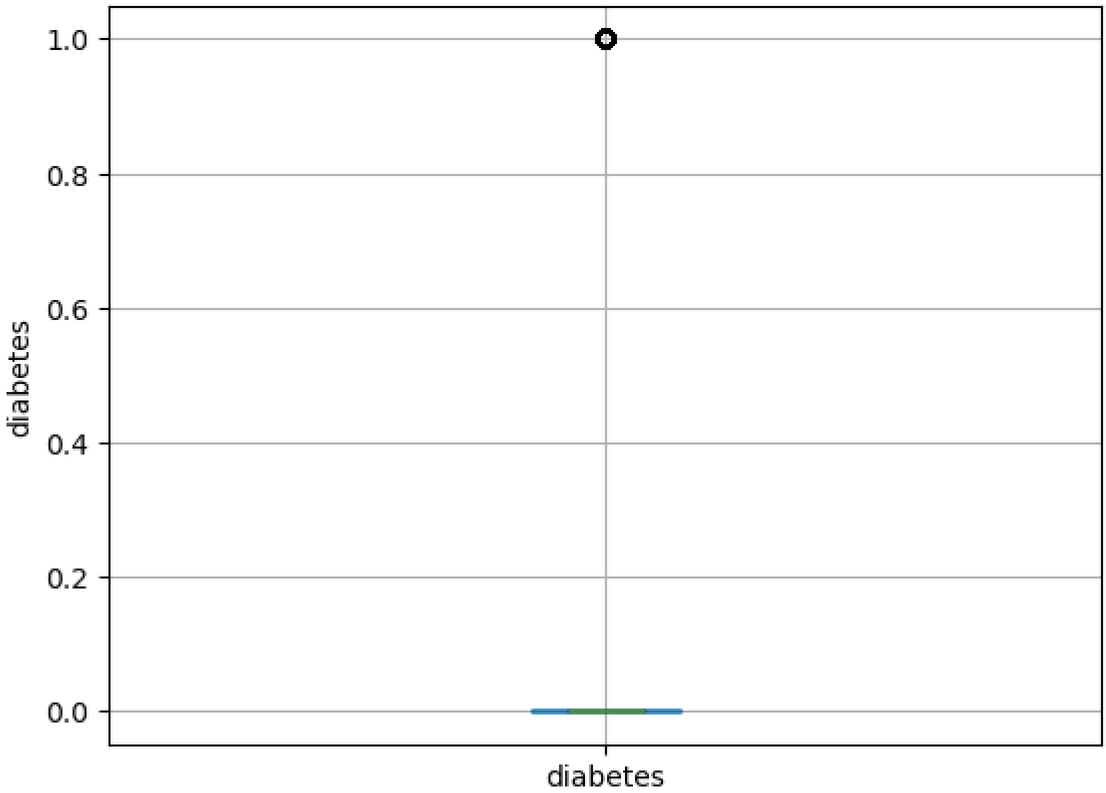

1.0
0.8
0.6
0.4
0.2
0.0
hypertension
hypertension


1.0
0.8
0.6
0.4
0.2
0.0
heart_disease
heart_disease

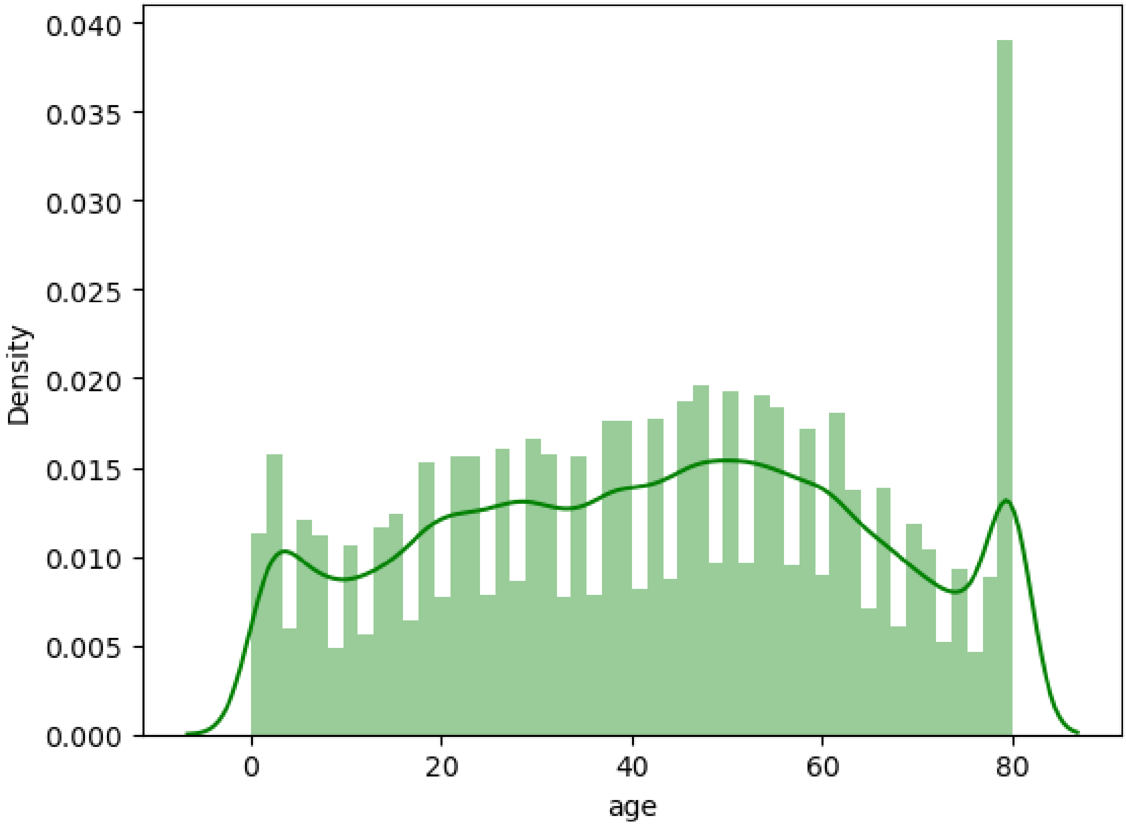

80
60
40
20
bmi
bmi

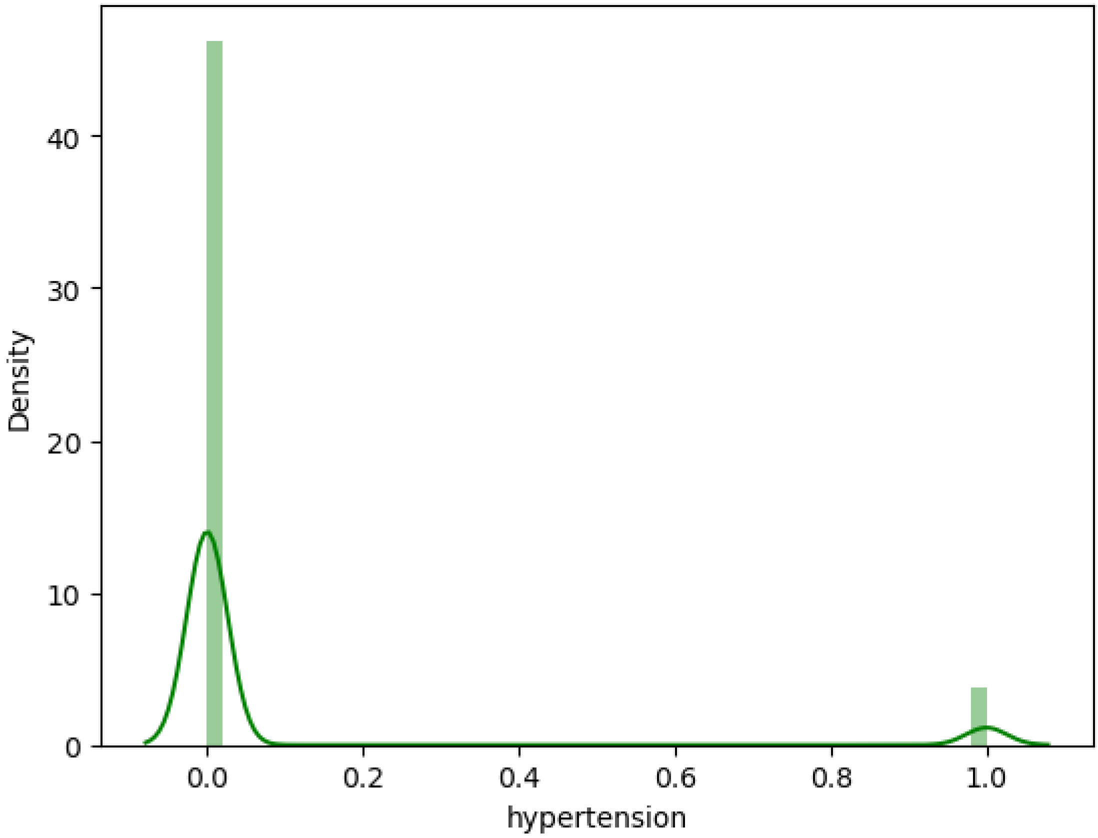

9
8
7
6
5
4
HbA1c_level
HbA1c_level

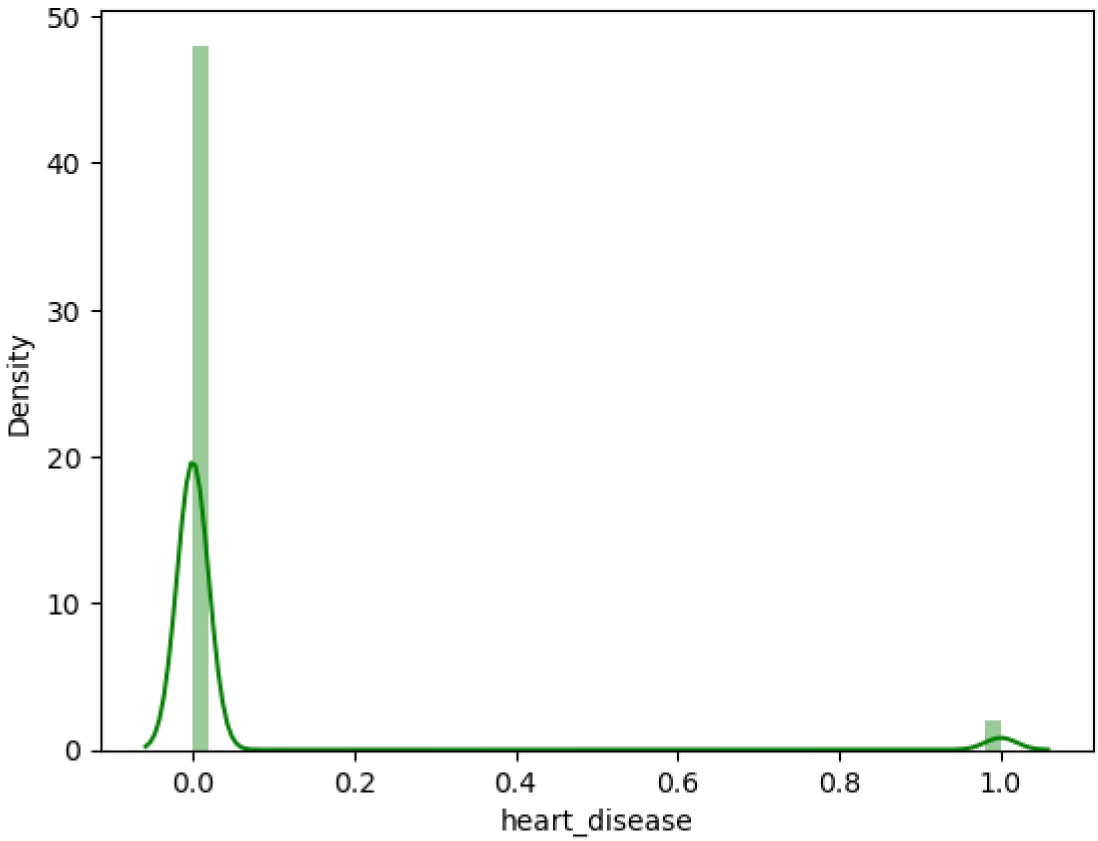

300
250
200
150
100
blood_glucose_level
blood_glucose_level

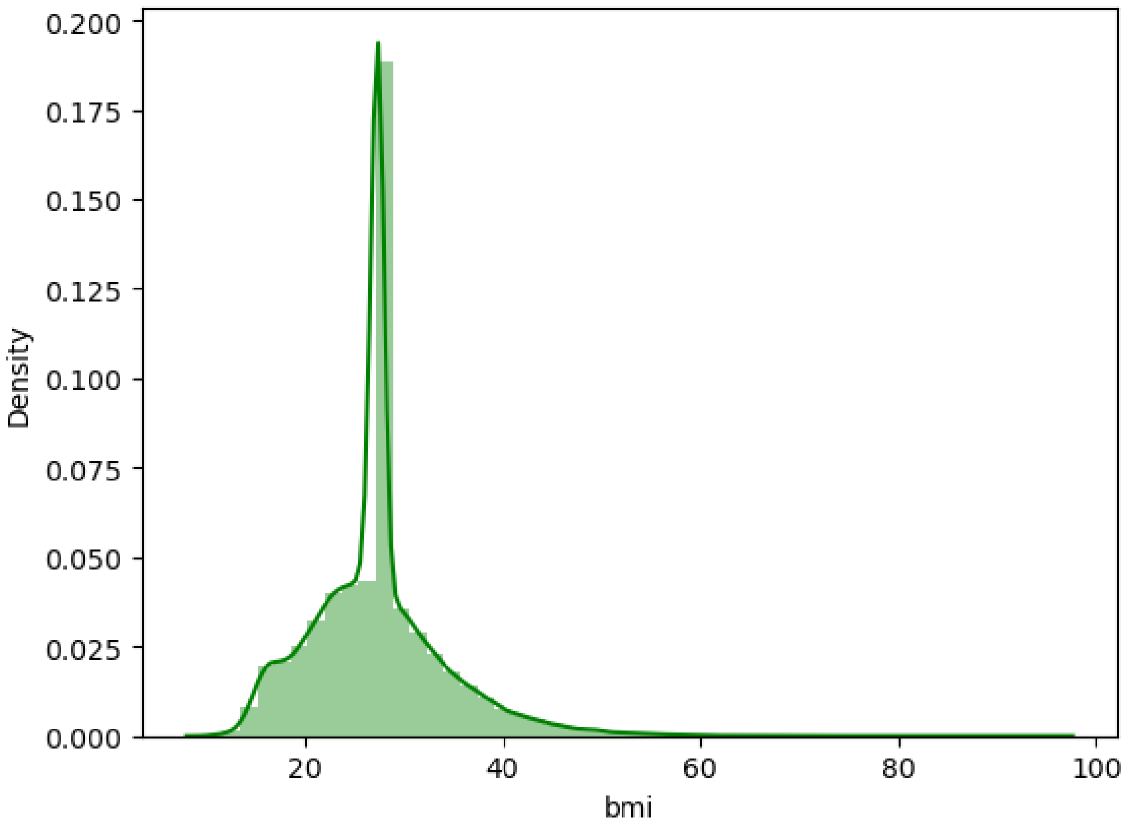

1.0
0.8
0.6
0.4
0.2
0.0
diabetes
diabetes

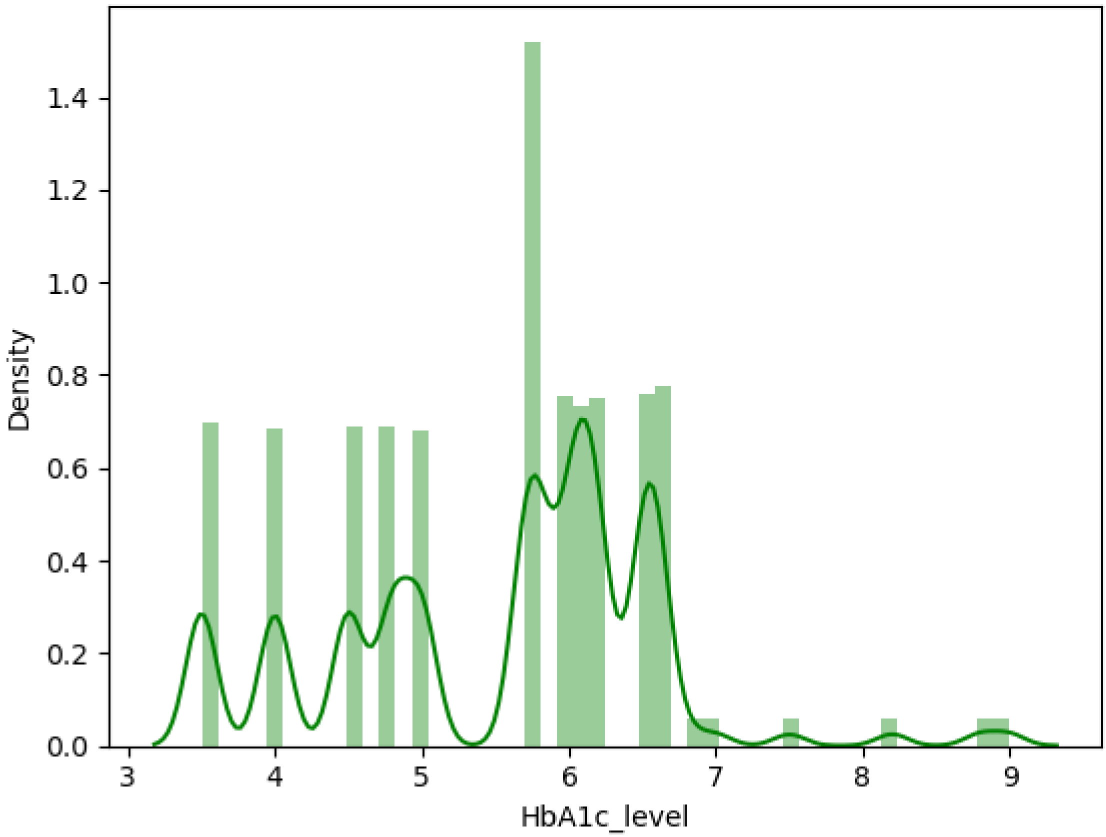
In [11]:
```
for i in num:
    sns.distplot(df[i], kde = True, color = 'green')
    plt.show()
```

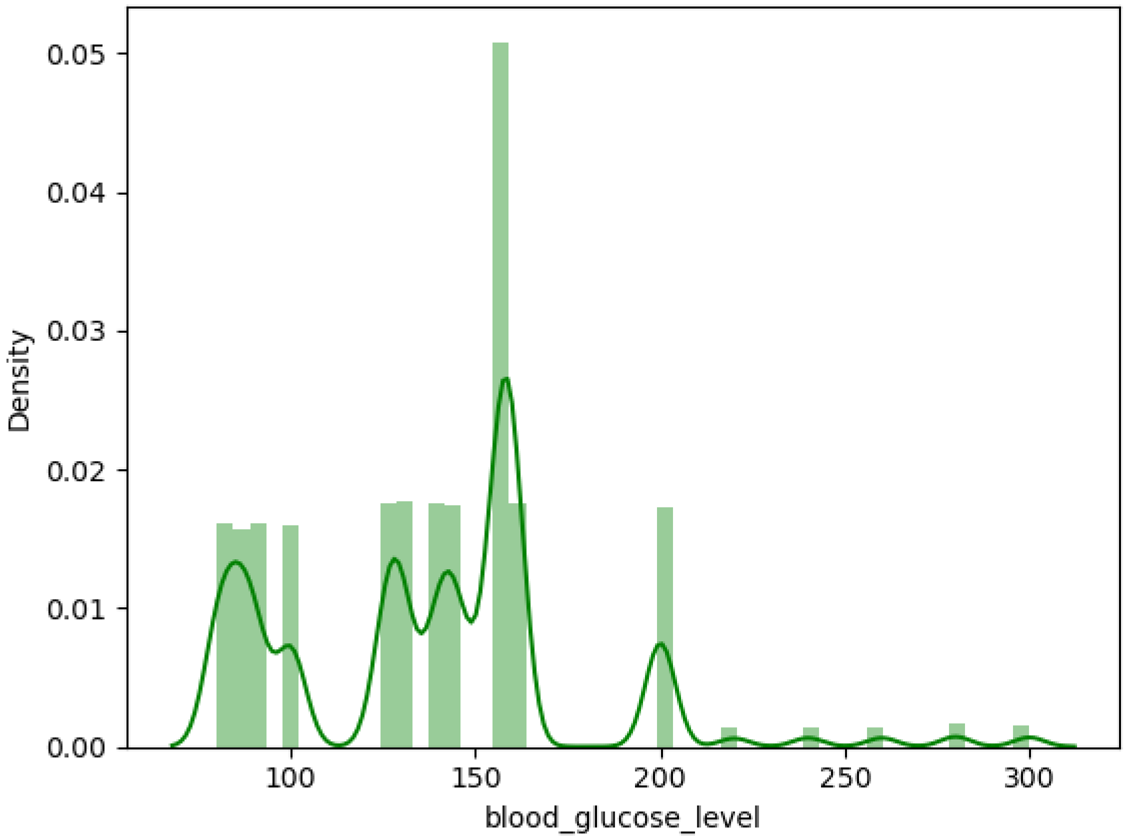

0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
Density
0
20
40
60
80
age

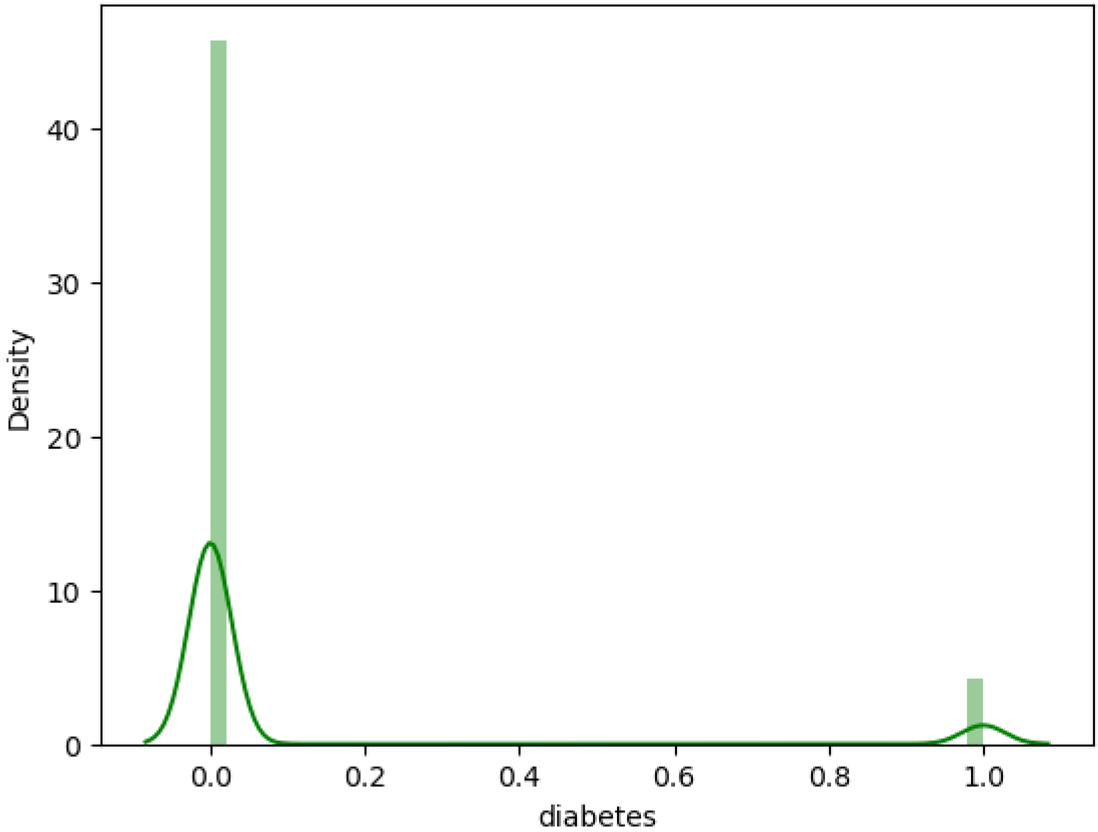

40
30
20
10
0
Density
0.0
0.2
0.4
0.6
0.8
1.0
hypertension


Density
heart_disease
50
40
30
20
10
0
0.0
0.2
0.4
0.6
0.8
1.0


Density
bmi
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
20
40
60
80
100

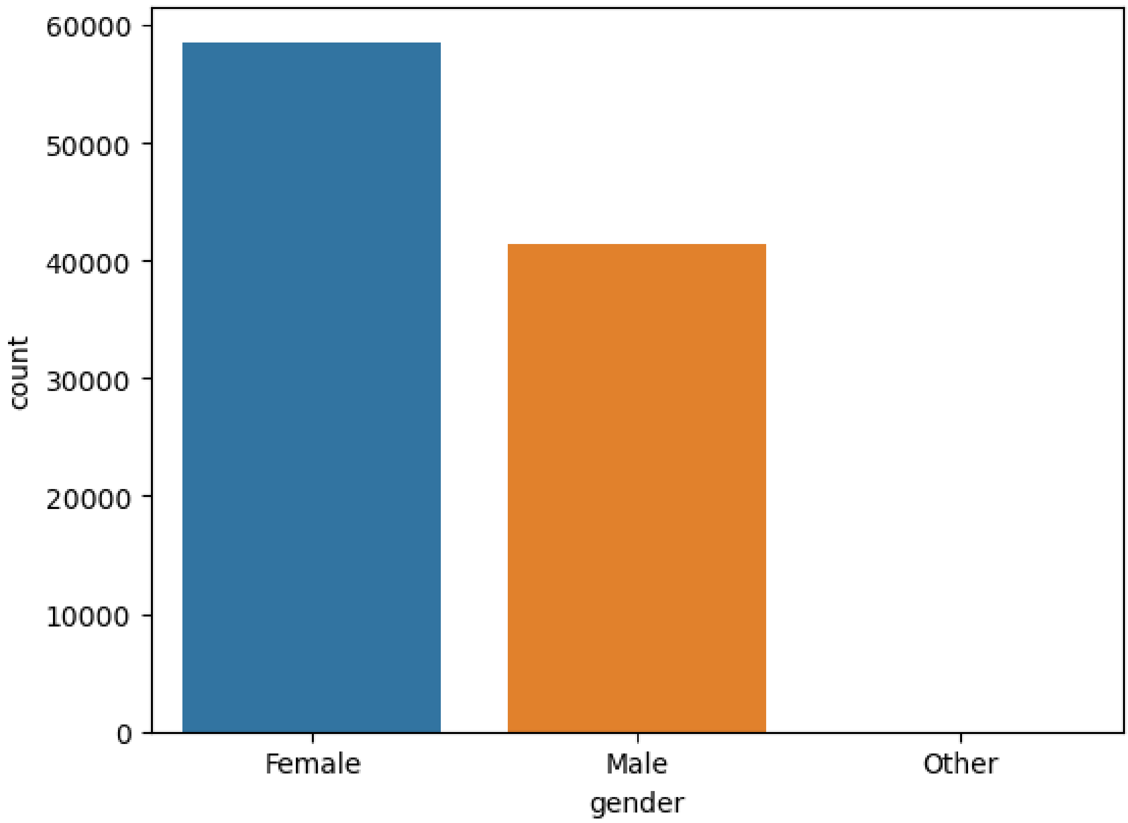

Density
HbA1c_level
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
3
4
5
6
7
8
9

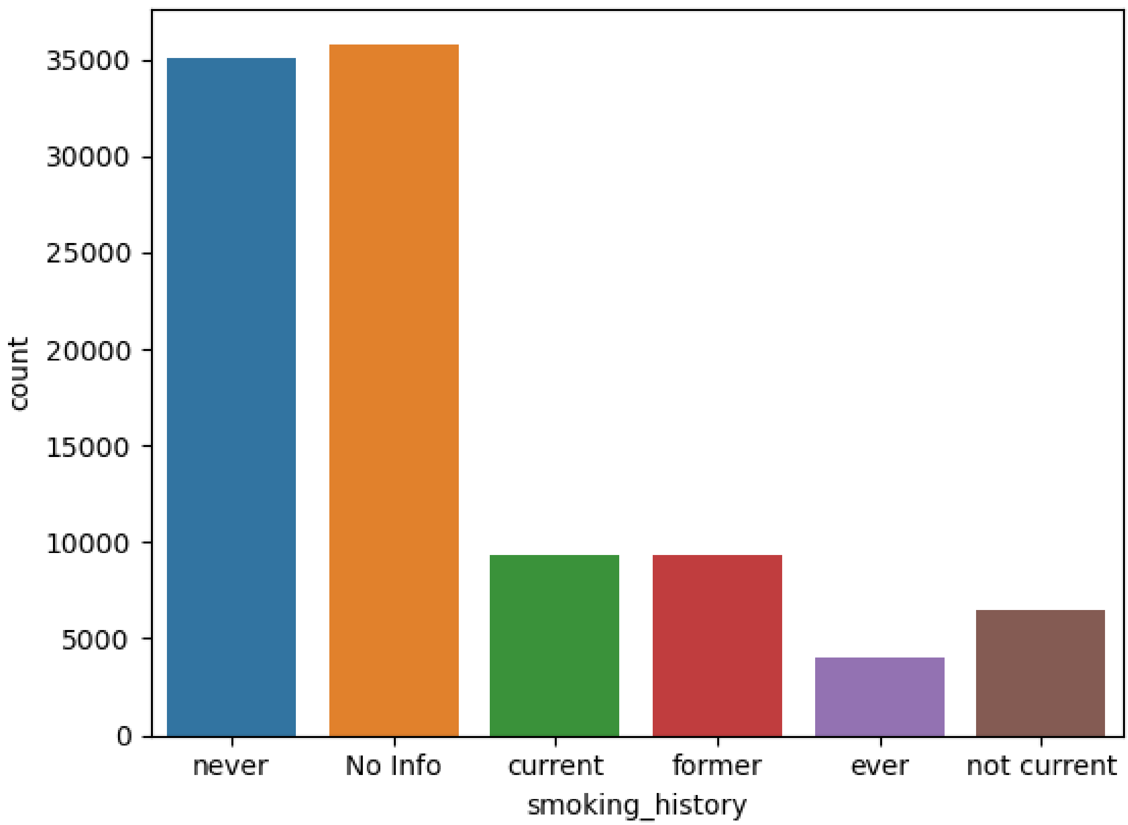

Density
blood_glucose_level
0.00
0.01
0.02
0.03
0.04
0.05
100
150
200
250
300




Now, we Check the categorical distrubition.

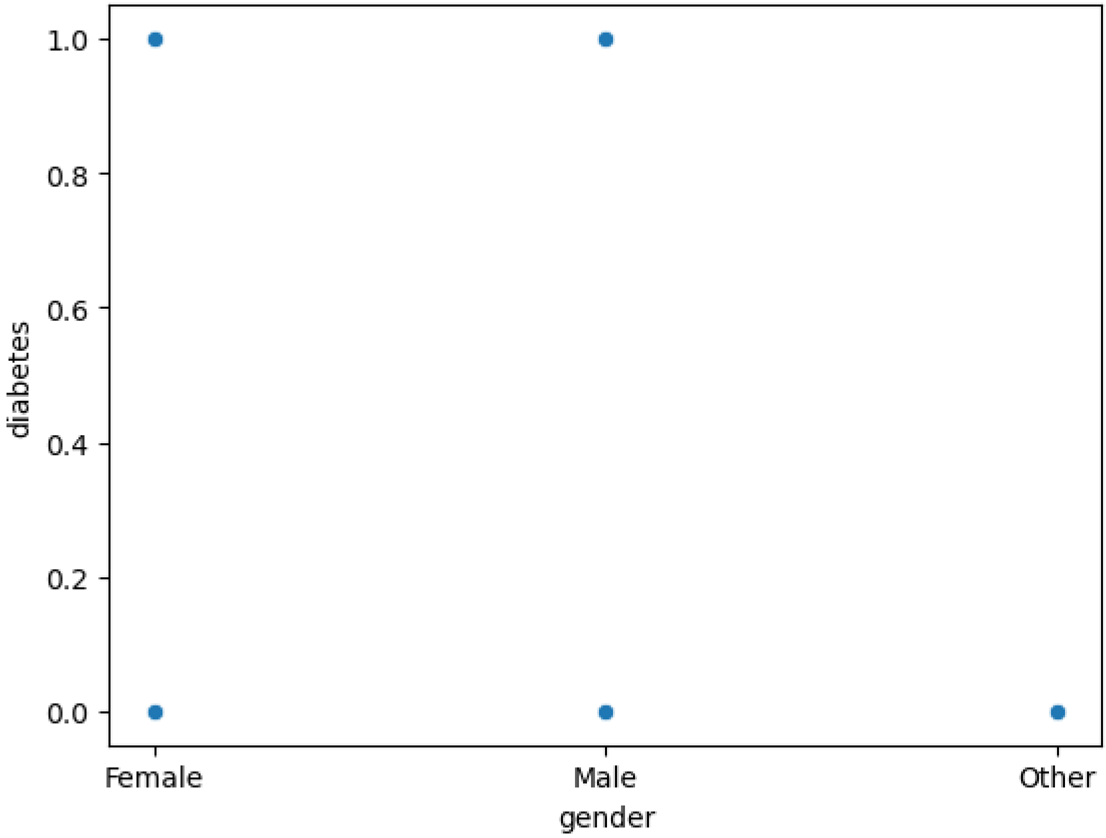
In [12]:
```
for i in cat:
    sns.countplot(df, x = df[i])
    plt.show()
```

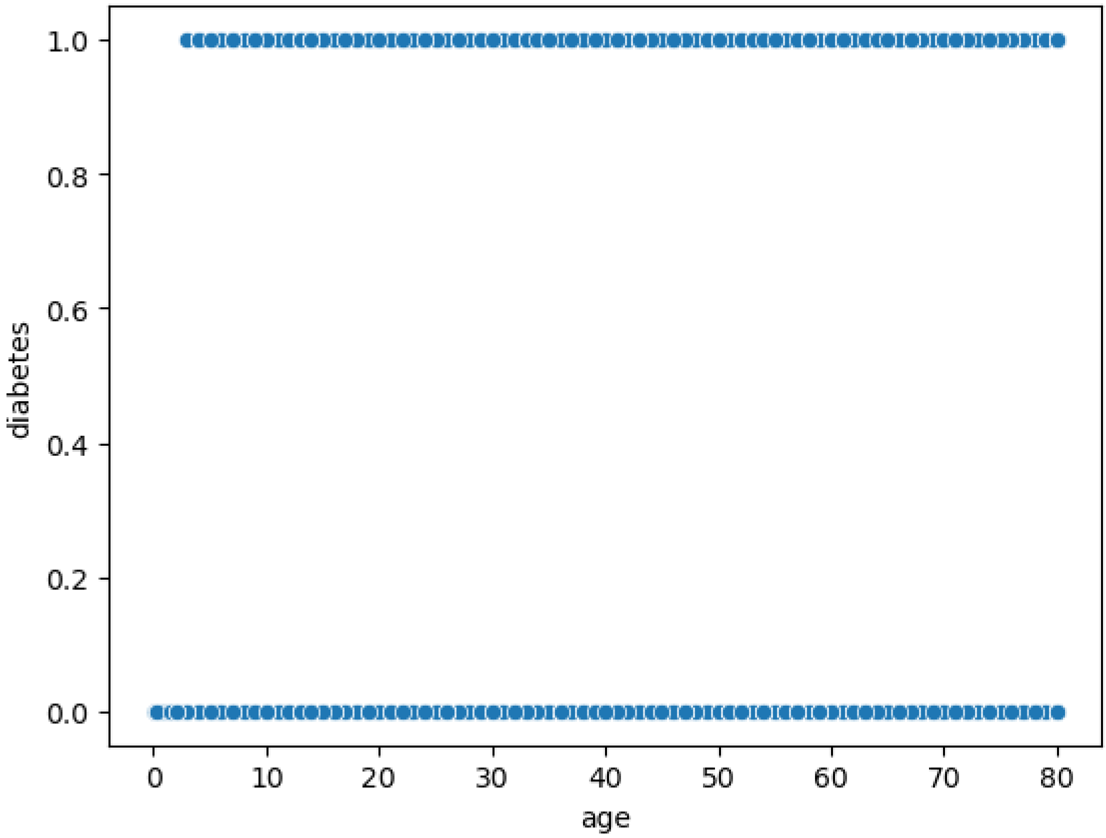


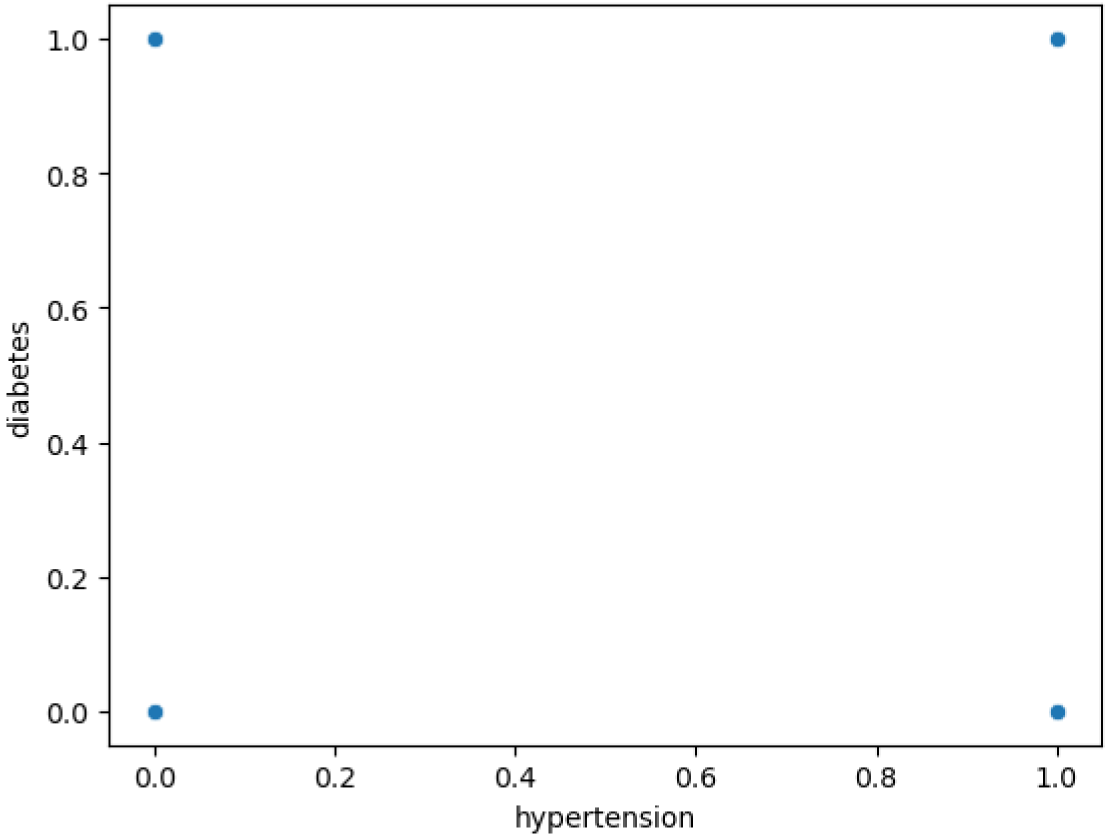



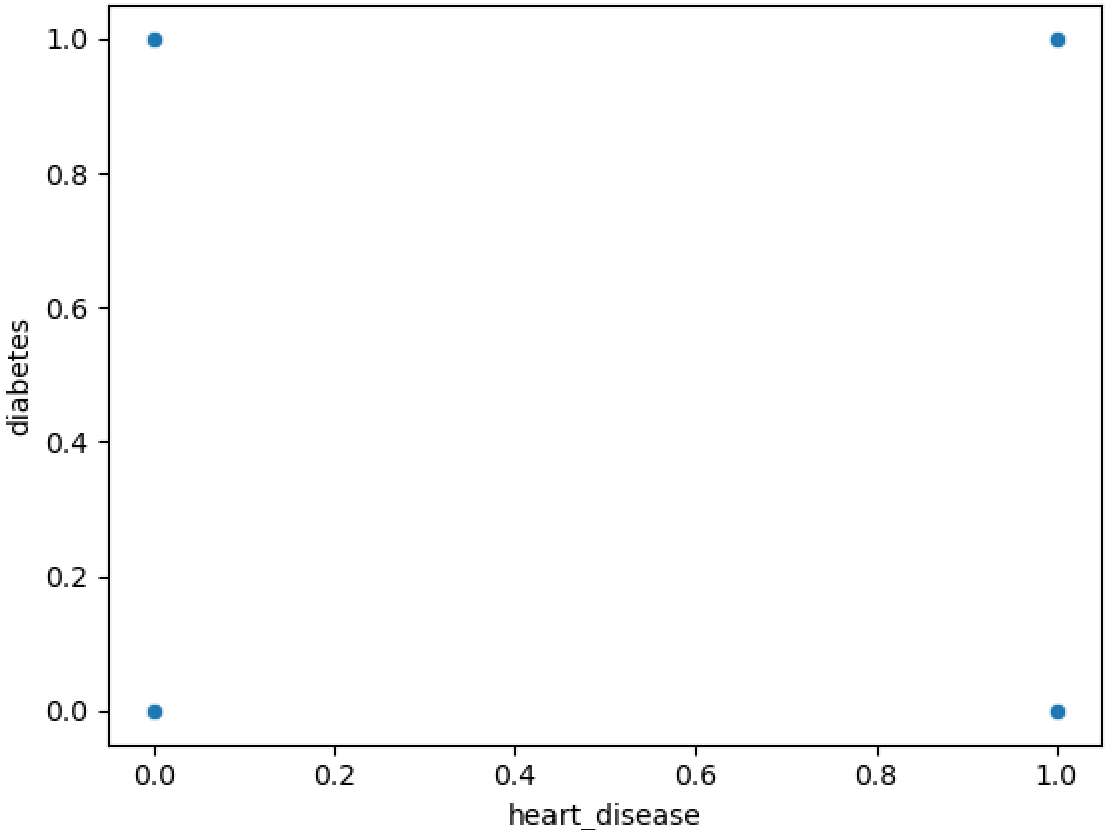

Now, lets check the correlation of the input and output Features.

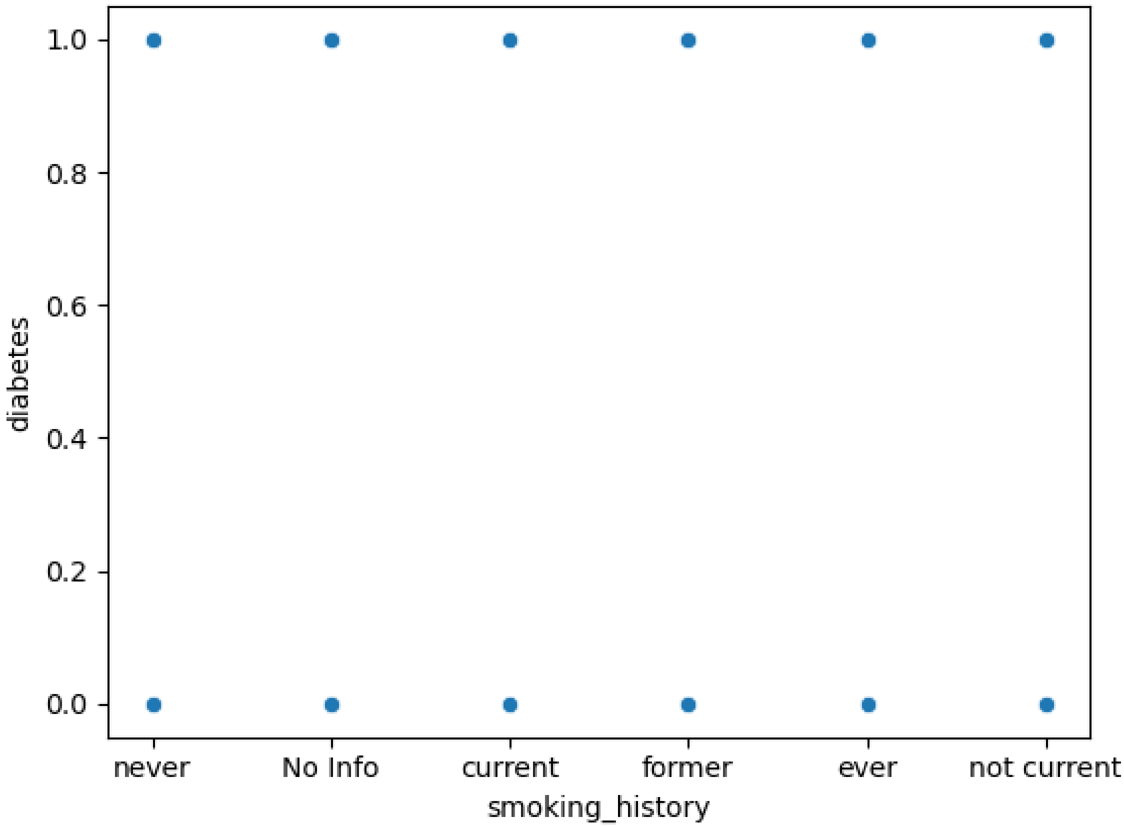
In [13]:
```
for i in df:
    sns.scatterplot(df, y=df["diabetes"], x=df[i])
    plt.show()
```

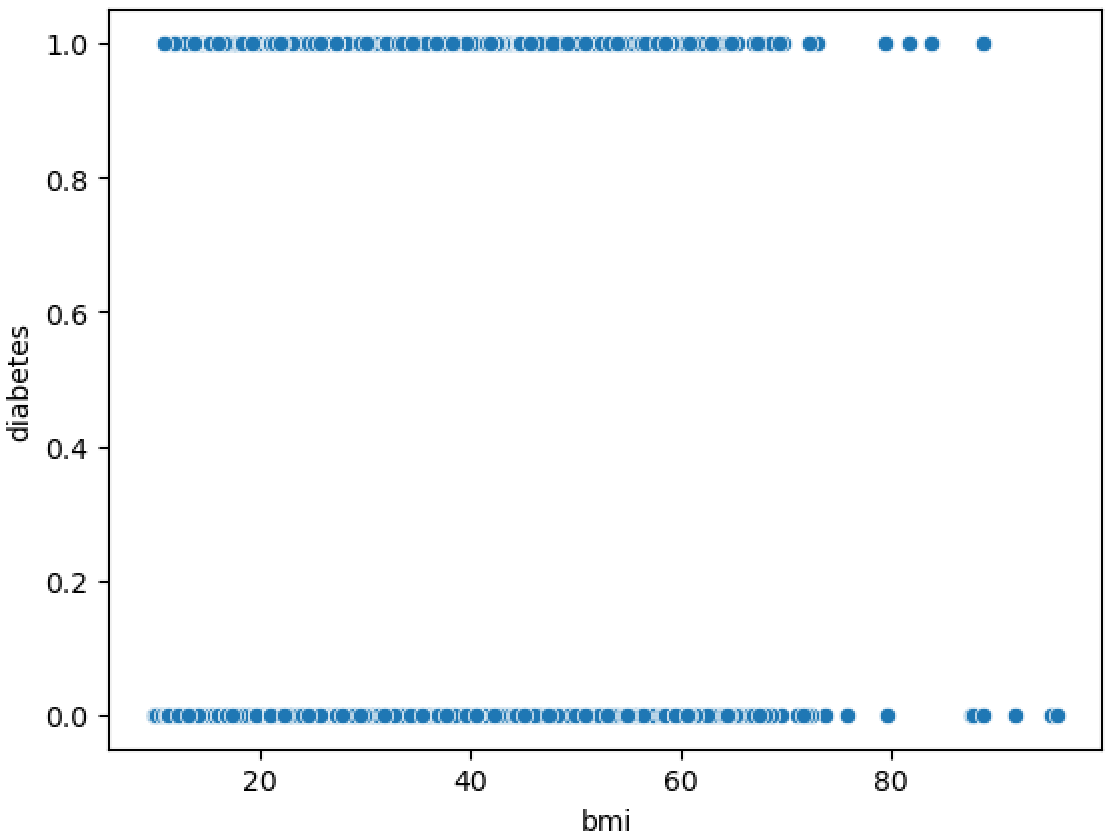

1.0
0.8
0.6
0.4
0.2
0.0
diabetes
Female
Male
Other
gender

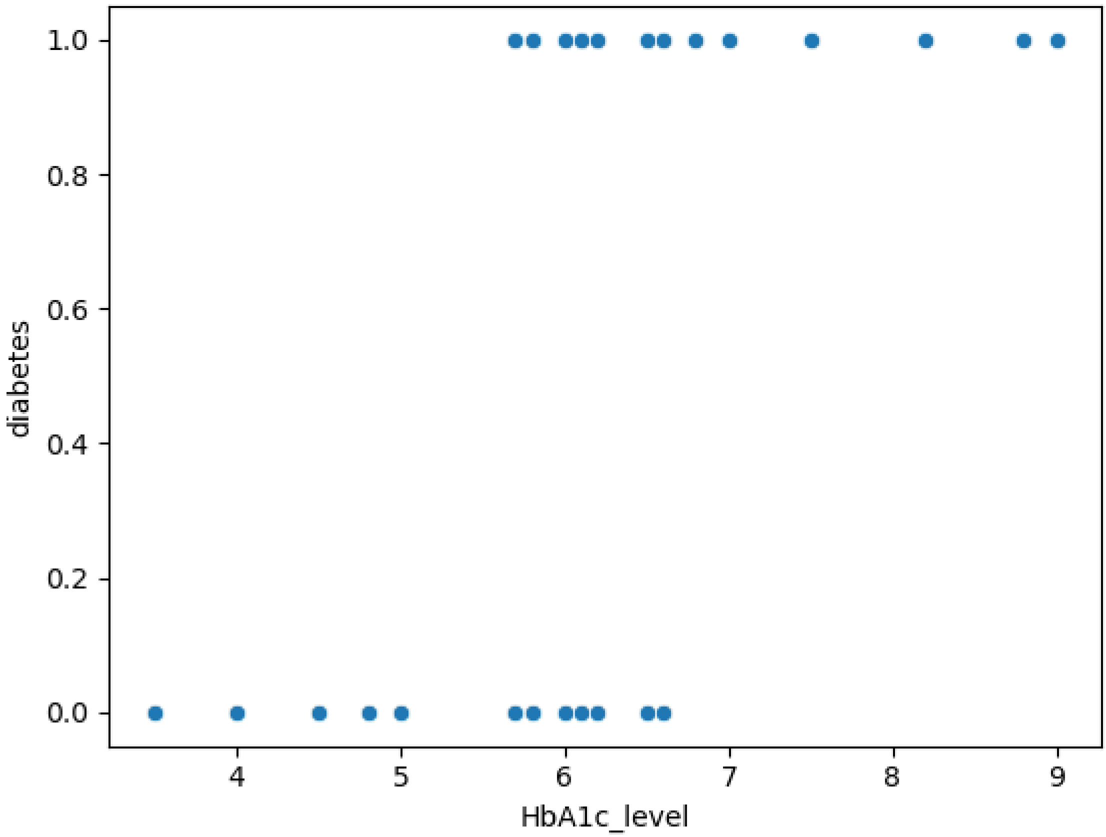

1.0
0.8
0.6
0.4
0.2
0.0
diabetes
0
10
20
30
40
50
60
70
80
age

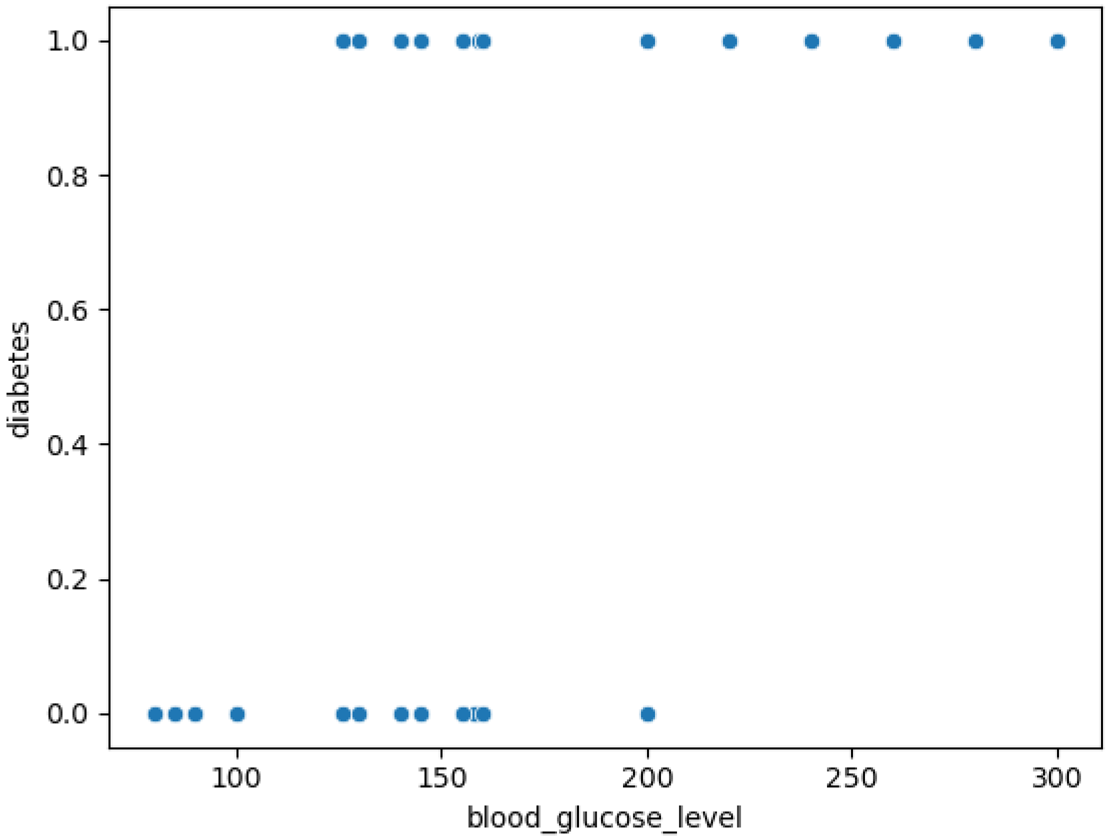

1.0
0.8
0.6
0.4
0.2
0.0
diabetes
0.0
0.2
0.4
0.6
0.8
1.0
hypertension

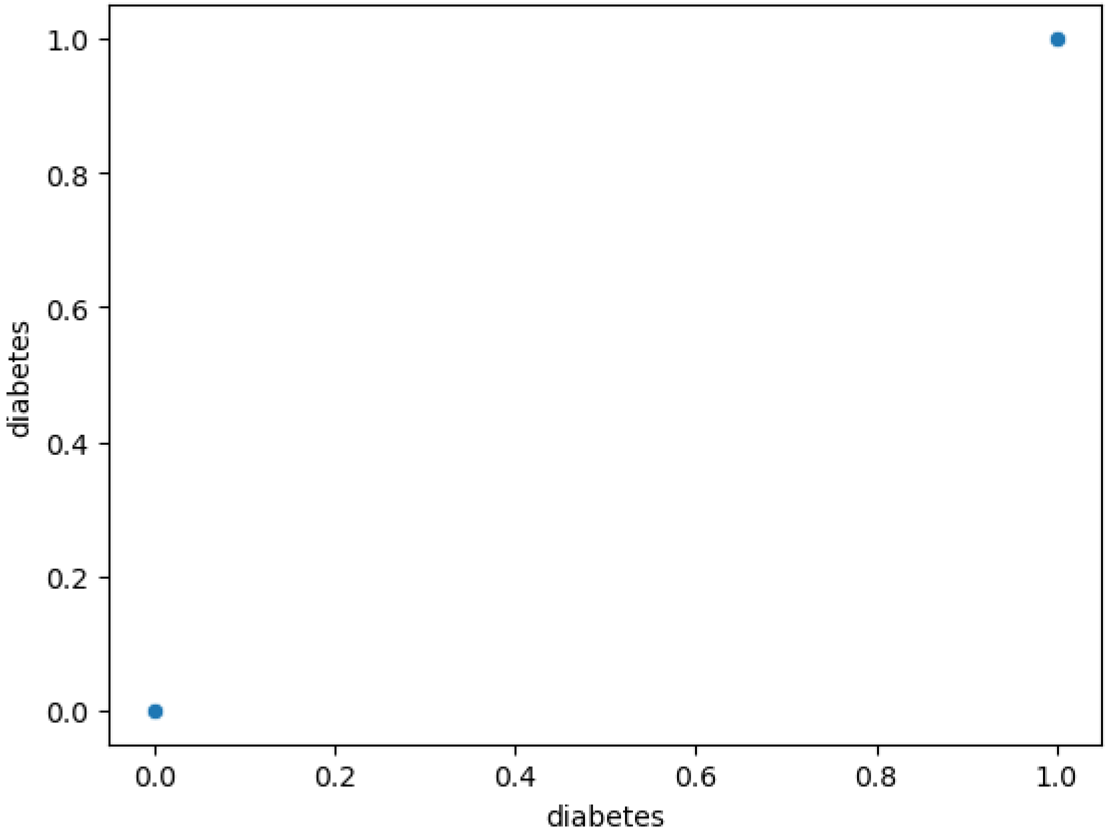

1.0
0.8
0.6
0.4
0.2
0.0
diabetes
0.0
0.2
0.4
0.6
0.8
1.0
heart_disease


1.0
0.8
0.6
0.4
0.2
0.0
diabetes
never
No Info
current
former
ever
not current
smoking_history


1.0
0.8
0.6
0.4
0.2
0.0
diabetes
20
40
60
80
bmi


1.0
0.8
0.6
0.4
0.2
0.0
diabetes
4
5
6
7
8
9
HbA1c_level


1.0
0.8
0.6
0.4
0.2
0.0
diabetes
100
150
200
250
300
blood_glucose_level




In [14]:
```
df.columns
```

Out[14]:
```
Index(['gender', 'age', 'hypertension', 'heart_disease', 'smoking_histor
y',
       'bmi', 'HbA1c_level', 'blood_glucose_level', 'diabetes'],
      dtype='object')
```

In [15]:
```
df["diabetes"].value_counts()
```

Out[15]:
```
0    91500
1     8500
Name: diabetes, dtype: int64
```

In [16]:
```
df[df.duplicated()]
```

Out[16]:

| | gender | age | hypertension | heart_disease | smoking_history | bmi | HbA1c_level | blood |
|---|---|---|---|---|---|---|---|---|
| **2756** | Male | 80.0 | 0 | 0 | No Info | 27.32 | 6.6 | |
| **3272** | Female | 80.0 | 0 | 0 | No Info | 27.32 | 3.5 | |
| **3418** | Female | 19.0 | 0 | 0 | No Info | 27.32 | 6.5 | |
| **3939** | Female | 78.0 | 1 | 0 | former | 27.32 | 3.5 | |
| **3960** | Male | 47.0 | 0 | 0 | No Info | 27.32 | 6.0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **99980** | Female | 52.0 | 0 | 0 | never | 27.32 | 6.1 | |
| **99985** | Male | 25.0 | 0 | 0 | No Info | 27.32 | 5.8 | |
| **99989** | Female | 26.0 | 0 | 0 | No Info | 27.32 | 5.0 | |
| **99990** | Male | 39.0 | 0 | 0 | No Info | 27.32 | 6.1 | |
| **99995** | Female | 80.0 | 0 | 0 | No Info | 27.32 | 6.2 | |

3854 rows × 9 columns

Here, we get the duplicate value but in this case we can't drop duplicate but all the details are important for ML.

# Seperate data in X and Y as well as Split data into trainand Test

I am using a df1 data which was copy of the original data set.

In [17]:
```
x = df1.drop(["diabetes"], axis=1)
y = df1["diabetes"]
```

In [18]:
```
x
```

Out[18]:

| | gender | age | hypertension | heart_disease | smoking_history | bmi | HbA1c_level | blood |
|---|---|---|---|---|---|---|---|---|
| **0** | Female | 80.0 | 0 | 1 | never | 25.19 | 6.6 | |
| **1** | Female | 54.0 | 0 | 0 | No Info | 27.32 | 6.6 | |
| **2** | Male | 28.0 | 0 | 0 | never | 27.32 | 5.7 | |
| **3** | Female | 36.0 | 0 | 0 | current | 23.45 | 5.0 | |
| **4** | Male | 76.0 | 1 | 1 | current | 20.14 | 4.8 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **99995** | Female | 80.0 | 0 | 0 | No Info | 27.32 | 6.2 | |
| **99996** | Female | 2.0 | 0 | 0 | No Info | 17.37 | 6.5 | |
| **99997** | Male | 66.0 | 0 | 0 | former | 27.83 | 5.7 | |
| **99998** | Female | 24.0 | 0 | 0 | never | 35.42 | 4.0 | |
| **99999** | Female | 57.0 | 0 | 0 | current | 22.43 | 6.6 | |

100000 rows × 8 columns

In [19]:
```
from sklearn.model_selection import train_test_split
train_x, test_x, train_y, test_y = train_test_split(x,y, random_state=50, t
est_size=0.25, stratify=y)
```

In [20]:
```
train_x
```

Out[20]:

| | gender | age | hypertension | heart_disease | smoking_history | bmi | HbA1c_level | blood |
|---|---|---|---|---|---|---|---|---|
| **28986** | Female | 32.0 | 0 | 0 | never | 30.47 | 6.2 | |
| **25188** | Male | 61.0 | 0 | 1 | current | 24.96 | 4.0 | |
| **37902** | Male | 30.0 | 0 | 0 | ever | 27.32 | 6.5 | |
| **55404** | Female | 61.0 | 0 | 0 | ever | 27.88 | 5.0 | |
| **69525** | Female | 15.0 | 0 | 0 | No Info | 27.32 | 6.1 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **51401** | Male | 31.0 | 0 | 0 | former | 31.21 | 4.5 | |
| **6802** | Male | 16.0 | 0 | 0 | No Info | 27.32 | 4.8 | |
| **72319** | Male | 38.0 | 0 | 0 | never | 23.10 | 4.8 | |
| **31823** | Female | 50.0 | 0 | 0 | current | 19.87 | 4.0 | |
| **96394** | Male | 65.0 | 0 | 0 | never | 33.30 | 6.1 | |

75000 rows × 8 columns

Reset index

In [21]:
```
train_x.reset_index(inplace=True, drop=True)
test_x.reset_index(inplace=True, drop=True)
train_y.reset_index(inplace=True, drop=True)
test_y.reset_index(inplace=True, drop=True)
```

In [22]:
```
test_x
```

Out[22]:

| | gender | age | hypertension | heart_disease | smoking_history | bmi | HbA1c_level | blood |
|---|---|---|---|---|---|---|---|---|
| **0** | Female | 53.0 | 0 | 0 | No Info | 27.32 | 6.0 | |
| **1** | Female | 16.0 | 0 | 0 | No Info | 27.32 | 6.6 | |
| **2** | Female | 31.0 | 0 | 0 | No Info | 27.32 | 5.7 | |
| **3** | Female | 38.0 | 0 | 0 | current | 39.01 | 4.0 | |
| **4** | Female | 59.0 | 0 | 0 | never | 27.32 | 6.5 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **24995** | Male | 80.0 | 0 | 1 | ever | 28.24 | 8.8 | |
| **24996** | Male | 57.0 | 0 | 0 | No Info | 20.63 | 6.1 | |
| **24997** | Male | 37.0 | 0 | 0 | never | 27.32 | 4.8 | |
| **24998** | Female | 22.0 | 0 | 0 | never | 24.50 | 3.5 | |
| **24999** | Female | 63.0 | 0 | 0 | No Info | 35.68 | 9.0 | |

25000 rows × 8 columns

We can seperate categorical and numerical features for encoding and scaling.

In [23]:
```
train_cat = train_x.select_dtypes(include="object")
train_num = train_x.select_dtypes(include="number")
test_cat = test_x.select_dtypes(include="object")
test_num = test_x.select_dtypes(include="number")
```

In [24]:
```
train_cat.head()
```

Out[24]:

| | gender | smoking_history |
|---|---|---|
| **0** | Female | never |
| **1** | Male | current |
| **2** | Male | ever |
| **3** | Female | ever |
| **4** | Female | No Info |

In [25]:
```
train_num.head()
```

Out[25]:

| | age | hypertension | heart_disease | bmi | HbA1c_level | blood_glucose_level |
|---|---|---|---|---|---|---|
| **0** | 32.0 | 0 | 0 | 30.47 | 6.2 | 126 |
| **1** | 61.0 | 0 | 1 | 24.96 | 4.0 | 130 |
| **2** | 30.0 | 0 | 0 | 27.32 | 6.5 | 158 |
| **3** | 61.0 | 0 | 0 | 27.88 | 5.0 | 130 |
| **4** | 15.0 | 0 | 0 | 27.32 | 6.1 | 100 |

In [26]:
```
test_cat.head()
```

Out[26]:

| | gender | smoking_history |
|---|---|---|
| **0** | Female | No Info |
| **1** | Female | No Info |
| **2** | Female | No Info |
| **3** | Female | current |
| **4** | Female | never |

In [27]:
```
test_num.head()
```

Out[27]:

| | age | hypertension | heart_disease | bmi | HbA1c_level | blood_glucose_level |
|---|---|---|---|---|---|---|
| **0** | 53.0 | 0 | 0 | 27.32 | 6.0 | 160 |
| **1** | 16.0 | 0 | 0 | 27.32 | 6.6 | 80 |
| **2** | 31.0 | 0 | 0 | 27.32 | 5.7 | 160 |
| **3** | 38.0 | 0 | 0 | 39.01 | 4.0 | 200 |
| **4** | 59.0 | 0 | 0 | 27.32 | 6.5 | 145 |

# Encoding By Using CatboostEncoder

Now for categorical encoding

In [28]:
```
import category_encoders as ce
```

In [29]:
```
encoder = ce.CatBoostEncoder()
encoder.fit(train_cat, train_y)
```

Out[29]:
```
▾                    CatBoostEncoder
CatBoostEncoder(cols=['gender', 'smoking_history'])
```

In [30]:
```
train_cat = encoder.transform(train_cat)
test_cat = encoder.transform(test_cat)
```

In [31]:
```
train_cat
```

Out[31]:

| | gender | smoking_history |
|---|---|---|
| 0 | 0.076283 | 0.095679 |
| 1 | 0.097311 | 0.099381 |
| 2 | 0.097311 | 0.119856 |
| 3 | 0.076283 | 0.119856 |
| 4 | 0.076283 | 0.040511 |
| ... | ... | ... |
| 74995 | 0.097311 | 0.169112 |
| 74996 | 0.097311 | 0.040511 |
| 74997 | 0.097311 | 0.095679 |
| 74998 | 0.076283 | 0.099381 |
| 74999 | 0.097311 | 0.095679 |

75000 rows × 2 columns

Now concate train_cat and train_num as well as test_cat and test_num

In [32]:
```
train_x = pd.concat([train_num, train_cat], axis=1)
test_x = pd.concat([test_num, test_cat], axis=1)
```

In [33]:
```
train_x.head()
```

Out[33]:

| | age | hypertension | heart_disease | bmi | HbA1c_level | blood_glucose_level | gender | smo |
|---|---|---|---|---|---|---|---|---|
| 0 | 32.0 | 0 | 0 | 30.47 | 6.2 | 126 | 0.076283 | |
| 1 | 61.0 | 0 | 1 | 24.96 | 4.0 | 130 | 0.097311 | |
| 2 | 30.0 | 0 | 0 | 27.32 | 6.5 | 158 | 0.097311 | |
| 3 | 61.0 | 0 | 0 | 27.88 | 5.0 | 130 | 0.076283 | |
| 4 | 15.0 | 0 | 0 | 27.32 | 6.1 | 100 | 0.076283 | |

Now we can scaling the input variables

# Sacling Features By Using MinMaxScaler

In [34]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler
```

In [35]:
```
scaler = MinMaxScaler()
scaler.fit(train_x)
```

Out[35]:
```
▾ MinMaxScaler
MinMaxScaler()
```

In [36]:
```
train_x = pd.DataFrame(scaler.transform(train_x), columns=train_x.columns)
test_x = pd.DataFrame(scaler.transform(test_x), columns=test_x.columns)
```

In [37]:
```
test_x.head()
```

Out[37]:

| | age | hypertension | heart_disease | bmi | HbA1c_level | blood_glucose_level | gend |
|---|---|---|---|---|---|---|---|
| **0** | 0.662162 | 0.0 | 0.0 | 0.202031 | 0.454545 | 0.363636 | 0.76527 |
| **1** | 0.199199 | 0.0 | 0.0 | 0.202031 | 0.563636 | 0.000000 | 0.76527 |
| **2** | 0.386887 | 0.0 | 0.0 | 0.202031 | 0.400000 | 0.363636 | 0.76527 |
| **3** | 0.474474 | 0.0 | 0.0 | 0.338469 | 0.090909 | 0.545455 | 0.76527 |
| **4** | 0.737237 | 0.0 | 0.0 | 0.202031 | 0.545455 | 0.295455 | 0.76527 |

# Basic Model Building And Evaluation

In [38]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
import xgboost as Xgb
from sklearn.naive_bayes import GaussianNB
```

In [39]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score,
classification_report, f1_score
```

In [40]:
```
model1 = LogisticRegression(random_state=50)
model1.fit(train_x, train_y)
pred1 = model1.predict(test_x)
print("Testing Score :",recall_score(test_y, pred1))
print(classification_report(test_y, pred1))
print("Training Score :",model1.score(train_x, train_y))
```

```
Testing Score : 0.611764705882353
              precision    recall  f1-score   support

           0       0.96      0.99      0.98     22875
           1       0.88      0.61      0.72      2125

    accuracy                           0.96     25000
   macro avg       0.92      0.80      0.85     25000
weighted avg       0.96      0.96      0.96     25000

Training Score : 0.9603866666666667
```

In [41]:
```
model2 = KNeighborsClassifier()
model2.fit(train_x, train_y)
pred2 = model2.predict(test_x)
print("Testing Score :",recall_score(test_y, pred2))
print(classification_report(test_y, pred2))
print("Training Score :", model2.score(train_x, train_y))
```

```
Testing Score : 0.6202352941176471
              precision    recall  f1-score   support

           0       0.97      0.99      0.98     22875
           1       0.91      0.62      0.74      2125

    accuracy                           0.96     25000
   macro avg       0.94      0.81      0.86     25000
weighted avg       0.96      0.96      0.96     25000

Training Score : 0.97064
```

In [42]:
```
model3 = RandomForestClassifier(random_state=50)
model3.fit(train_x, train_y)
pred3 = model3.predict(test_x)
print("Testing Score :",recall_score(test_y, pred3))
print(classification_report(test_y, pred3))
print("Training Score :",model3.score(train_x, train_y))
```

```
Testing Score : 0.6781176470588235
              precision    recall  f1-score   support

           0       0.97      1.00      0.98     22875
           1       0.95      0.68      0.79      2125

    accuracy                           0.97     25000
   macro avg       0.96      0.84      0.89     25000
weighted avg       0.97      0.97      0.97     25000

Training Score : 0.9991866666666667
```

In [43]:
```
model4 = DecisionTreeClassifier()
model4.fit(train_x, train_y)
pred4 = model4.predict(test_x)
print("Testing Score :",recall_score(test_y, pred4))
print(classification_report(test_y, pred4))
print("Training Score :",model4.score(train_x, train_y))
```

```
Testing Score : 0.7369411764705882
              precision    recall  f1-score   support

           0       0.98      0.97      0.97     22875
           1       0.70      0.74      0.72      2125

    accuracy                           0.95     25000
   macro avg       0.84      0.85      0.85     25000
weighted avg       0.95      0.95      0.95     25000

Training Score : 0.9992266666666667
```

In [44]:
```
model5 = SVC(random_state=50)
model5.fit(train_x, train_y)
pred5 = model5.predict(test_x)
print("Testing Score :",recall_score(test_y, pred5))
print(classification_report(test_y, pred5))
print("Training Score :",model5.score(train_x, train_y))
```

```
Testing Score : 0.5609411764705883
              precision    recall  f1-score   support

           0       0.96      1.00      0.98     22875
           1       0.98      0.56      0.71      2125

    accuracy                           0.96     25000
   macro avg       0.97      0.78      0.85     25000
weighted avg       0.96      0.96      0.96     25000

Training Score : 0.963
```

In [45]:
```
model6 = Xgb.XGBClassifier()
model6.fit(train_x, train_y)
pred6 = model6.predict(test_x)
print("Testing Score :",recall_score(test_y, pred6))
print(classification_report(test_y, pred6))
print("Training Score :", model6.score(train_x, train_y))
```

```
Testing Score : 0.6856470588235294
              precision    recall  f1-score   support

           0       0.97      1.00      0.98     22875
           1       0.95      0.69      0.80      2125

    accuracy                           0.97     25000
   macro avg       0.96      0.84      0.89     25000
weighted avg       0.97      0.97      0.97     25000

Training Score : 0.97644
```

In [46]:
```
model7 = AdaBoostClassifier(random_state=50)
model7.fit(train_x, train_y)
pred7 = model7.predict(test_x)
print("Testing Score :",recall_score(test_y, pred7))
print(classification_report(test_y, pred7))
print("Training Score :", model7.score(train_x, train_y))
```

```
Testing Score : 0.6795294117647059
              precision    recall  f1-score   support

           0       0.97      1.00      0.98     22875
           1       0.97      0.68      0.80      2125

    accuracy                           0.97     25000
   macro avg       0.97      0.84      0.89     25000
weighted avg       0.97      0.97      0.97     25000

Training Score : 0.9723866666666666
```

In [47]:
```
model8 = GaussianNB()
model8.fit(train_x, train_y)
pred8 = model8.predict(test_x)
print("Testing Score :",recall_score(test_y, pred8))
print(classification_report(test_y, pred8))
print("Training Score :", model8.score(train_x, train_y))
```

```
Testing Score : 0.6357647058823529
              precision    recall  f1-score   support

           0       0.96      0.93      0.95     22875
           1       0.45      0.64      0.53      2125

    accuracy                           0.90     25000
   macro avg       0.71      0.78      0.74     25000
weighted avg       0.92      0.90      0.91     25000

Training Score : 0.9034533333333333
```

Here, Decision Tree, Random forest and Xgboost model are overfiting of train and test dataset. So, we do a Hyper parameter tuning and Features selections.

# HYPERPARAMETER TUNING

In [48]:
```
#HYPERPERAMETER TUNING OF LOGISTIC REGRESSOR
from sklearn.model_selection import GridSearchCV
log = LogisticRegression()
params = { "tol" : [0.1,0.5,0.8,0.9], "C" :[1,2,8,6,9],
 "solver": ['lbfgs', "liblinear", "newton-cg", "newton-cholesky", "sag", "s
aga"]}
clf1 = GridSearchCV(log, params, cv=5, scoring="recall")
clf1.fit(train_x, train_y)
print(clf1.best_params_)
print(clf1.best_score_)
```

```
{'C': 8, 'solver': 'sag', 'tol': 0.9}
0.7007058823529412
```

In [49]:
```
#HYPERPERAMETER TUNING OF NB
nb = GaussianNB()
params_nb = {'var_smoothing' : [0.96,0.25,0.30,0.40, 0.50]}
clf3 = GridSearchCV(nb, params_nb, cv=5, scoring="recall")
clf3.fit(train_x, train_y)
print(clf3.best_params_)
print(clf3.best_score_)
```

```
{'var_smoothing': 0.25}
0.5069803921568627
```

In [50]:
```
#HYPERPERAMETER TUNING OF DECISION TREE
dt = DecisionTreeClassifier()
params_dt = {'criterion':['gini', 'entropy', 'log_loss'], 'max_depth' :[1,2
5,14,13,45,75,26],'splitter':['best', 'random']}
clf5 = GridSearchCV(dt, params_dt, cv=5, scoring="recall")
clf5.fit(train_x, train_y)
print(clf5.best_params_)
print(clf5.best_score_)
```

```
{'criterion': 'gini', 'max_depth': 75, 'splitter': 'random'}
0.7408627450980392
```

In [51]:
```
#HYPERPERAMETER TUNING OF RANDOMFOREST
rfc = RandomForestClassifier()
params_rfc = {"n_estimators" : [10,15,125,10,8,85],"max_depth" : [10,25,48,
85,42,3]}
clf6 = GridSearchCV(rfc, params_rfc, cv=5, scoring="recall")
clf6.fit(train_x, train_y)
print(clf6.best_params_)
print(clf6.best_score_)
```

```
{'max_depth': 85, 'n_estimators': 15}
0.6967843137254902
```

In [52]:
```
#HYPERPERAMETER TUNING OF XGBOOST
xgb = Xgb.XGBClassifier()
params_xgb = {'eta': [0.1, 0.2, 0.3,0.4,0.5], 'n_estimators' : [10, 50, 10
0,12,15], 'max_depth': [3, 6, 9,14]}
clf7 = GridSearchCV(xgb, params_xgb, cv=5, scoring="recall")
clf7.fit(train_x, train_y)
print(clf7.best_params_)
print(clf7.best_score_)
```

```
{'eta': 0.5, 'max_depth': 14, 'n_estimators': 100}
0.7162352941176471
```

In [53]:
```
#HYPERPERAMETER TUNING OF ADABOOST
adb = AdaBoostClassifier()
params_adb = {'n_estimators' : [10, 50, 100,12,15]}
clf8 = GridSearchCV(xgb, params_adb, cv=5, scoring="recall")
clf8.fit(train_x, train_y)
print(clf8.best_params_)
print(clf8.best_score_)
```

```
{'n_estimators': 100}
0.6986666666666667
```

In [54]:
```
#best perameter for model
print("LogisticRegression score is :", clf1.best_params_)
print("GaussianNB score is :", clf3.best_params_)
print("DecisionTreeClassifier score is :", clf5.best_params_)
print("RandomForestClassifier score is :", clf6.best_params_)
print("XGBOOST score is :", clf7.best_params_)
print("AdaBoostClassifier score is :", clf8.best_params_)
```

```
LogisticRegression score is : {'C': 8, 'solver': 'sag', 'tol': 0.9}
GaussianNB score is : {'var_smoothing': 0.25}
DecisionTreeClassifier score is : {'criterion': 'gini', 'max_depth': 75,
'splitter': 'random'}
RandomForestClassifier score is : {'max_depth': 85, 'n_estimators': 15}
XGBOOST score is : {'eta': 0.5, 'max_depth': 14, 'n_estimators': 100}
AdaBoostClassifier score is : {'n_estimators': 100}
```

In [55]:
```
#Score for all model
print("LogisticRegression score is :", clf1.best_score_)
print("GaussianNB score is :", clf3.best_score_)
print("DecisionTreeClassifier score is :", clf5.best_score_)
print("RandomForestClassifier score is :", clf6.best_score_)
print("XGBOOST score is :", clf7.best_score_)
print("AdaBoostClassifier score is :", clf8.best_score_)
```

```
LogisticRegression score is : 0.7007058823529412
GaussianNB score is : 0.5069803921568627
DecisionTreeClassifier score is : 0.7408627450980392
RandomForestClassifier score is : 0.6967843137254902
XGBOOST score is : 0.7162352941176471
AdaBoostClassifier score is : 0.6986666666666667
```

# Feature Selection

In [56]:
```
#Correlation
corr = train_x.corr()
corr.style.background_gradient(cmap='coolwarm')
```

Out[56]:

| | age | hypertension | heart_disease | bmi | HbA1c_level | blood_gl |
|---|---|---|---|---|---|---|
| **age** | 1.000000 | 0.251624 | 0.234324 | 0.336925 | 0.099437 | |
| **hypertension** | 0.251624 | 1.000000 | 0.115795 | 0.146456 | 0.082221 | |
| **heart_disease** | 0.234324 | 0.115795 | 1.000000 | 0.058238 | 0.067776 | |
| **bmi** | 0.336925 | 0.146456 | 0.058238 | 1.000000 | 0.083463 | |
| **HbA1c_level** | 0.099437 | 0.082221 | 0.067776 | 0.083463 | 1.000000 | |
| **blood_glucose_level** | 0.110175 | 0.082860 | 0.067703 | 0.089174 | 0.164899 | |
| **gender** | -0.028546 | 0.014241 | 0.080006 | -0.022681 | 0.018533 | |
| **smoking_history** | 0.322796 | 0.128296 | 0.094244 | 0.220150 | 0.053638 | |

In [57]:
```
def correlation(dataset, threshold):
    col_corr = set()
    corr_matrix = dataset.corr()
    for i in range (len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i,j]) > threshold:
                colname = corr_matrix.columns[i]
                col_corr.add(colname)
    return col_corr
```

In [58]:
```
corr_features = correlation(train_x, 0.7)
len(set(corr_features))
```

Out[58]: 0

In [59]:
```
corr_features
```

Out[59]: set()

In [60]:
```
#Apply SelectKbest class to extract top Features
from sklearn.feature_selection import SelectKBest, chi2
bestfeatures = SelectKBest(score_func=chi2, k=7)
fit = bestfeatures.fit(train_x, train_y)
```

In [61]:
```
dfscores = pd.DataFrame(fit.scores_)
```

In [62]:
```
dfcolumns = pd.DataFrame(x.columns)
```

In [63]:
```
features = pd.concat([dfcolumns, dfscores], axis=1)
features.columns = ["specs", "score"]
```

In [64]:
```
features
```

Out[64]:

| | specs | score |
|---|---|---|
| 0 | gender | 766.343405 |
| 1 | age | 2699.337830 |
| 2 | hypertension | 2057.257217 |
| 3 | heart_disease | 102.219875 |
| 4 | smoking_history | 1243.196875 |
| 5 | bmi | 1696.135881 |
| 6 | HbA1c_level | 1.631301 |
| 7 | blood_glucose_level | 388.198706 |

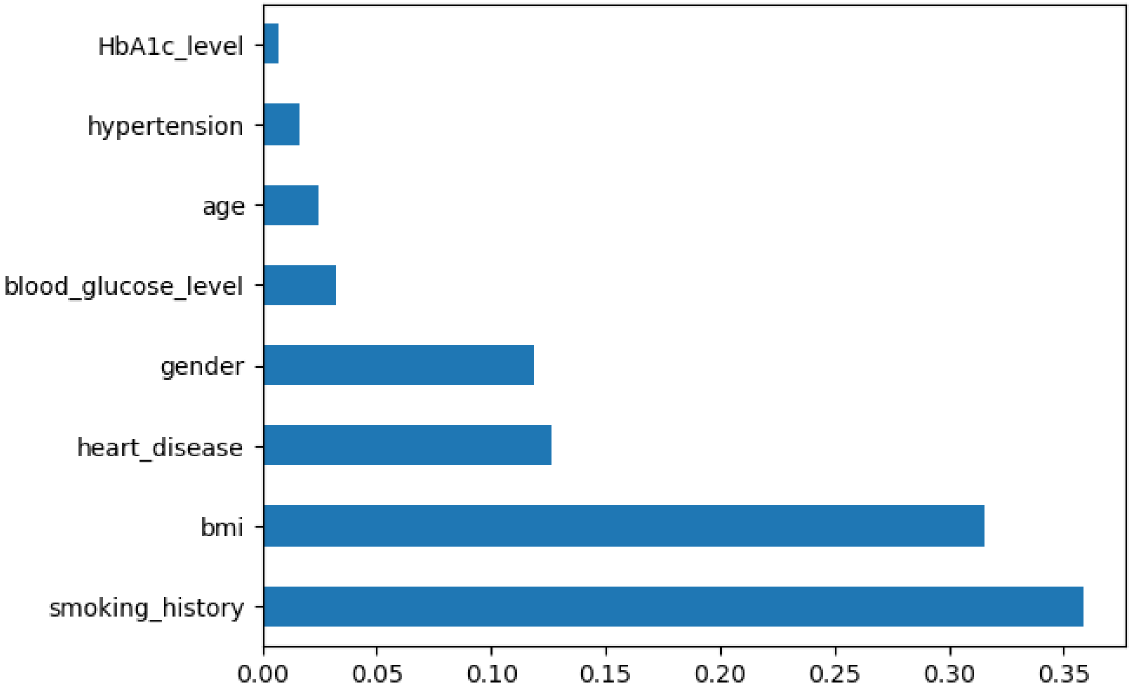
In [65]:
```
from sklearn.ensemble import ExtraTreesClassifier
model = ExtraTreesClassifier()
model.fit(train_x, train_y)
```

Out[65]:
```
▾ ExtraTreesClassifier
ExtraTreesClassifier()
```

In [66]:
```
print(model.feature_importances_)
```

```
[0.11904528 0.02451056 0.01631071 0.12639277 0.35885373 0.31576748
 0.00724419 0.03187528]
```

In [67]:
```
feat_importance = pd.Series(model.feature_importances_, index=x.columns)
feat_importance.nlargest(9).plot(kind="barh")
plt.show()
```




In [68]:
```
fe_model = RandomForestClassifier(random_state=50)
fe_model.fit(train_x, train_y)
```

Out[68]:
```
RandomForestClassifier
RandomForestClassifier(random_state=50)
```

In [69]:
```
feature_scores = pd.Series(fe_model.feature_importances_, index=train_x.col
umns).sort_values(ascending=False)
```

In [70]:
```
feature_scores
```

Out[70]:
```
HbA1c_level            0.388938
blood_glucose_level    0.327517
bmi                    0.122289
age                    0.100137
smoking_history        0.026238
hypertension           0.016730
heart_disease          0.010683
gender                 0.007469
dtype: float64
```

After the all Feature Selection method use then we decide to drop a gender, heart_disease column for best accuracy. So, start with second time generate Model

# Start Whole Process of Model training in second time

In [71]:
```
X = df1.drop(["gender", "heart_disease", "diabetes"], axis=1)
Y = df1["diabetes"]
```

In [72]:
```
X
```

Out[72]:

| | age | hypertension | smoking_history | bmi | HbA1c_level | blood_glucose_level |
|---|---|---|---|---|---|---|
| **0** | 80.0 | 0 | never | 25.19 | 6.6 | 140 |
| **1** | 54.0 | 0 | No Info | 27.32 | 6.6 | 80 |
| **2** | 28.0 | 0 | never | 27.32 | 5.7 | 158 |
| **3** | 36.0 | 0 | current | 23.45 | 5.0 | 155 |
| **4** | 76.0 | 1 | current | 20.14 | 4.8 | 155 |
| **...** | ... | ... | ... | ... | ... | ... |
| **99995** | 80.0 | 0 | No Info | 27.32 | 6.2 | 90 |
| **99996** | 2.0 | 0 | No Info | 17.37 | 6.5 | 100 |
| **99997** | 66.0 | 0 | former | 27.83 | 5.7 | 155 |
| **99998** | 24.0 | 0 | never | 35.42 | 4.0 | 100 |
| **99999** | 57.0 | 0 | current | 22.43 | 6.6 | 90 |

100000 rows × 6 columns

In [73]:
```
train_x1, test_x1, train_y1, test_y1 = train_test_split(X,Y, random_state=5
0,test_size=0.25, stratify=y)
```

In [74]:
```
train_x1
```

Out[74]:

| | age | hypertension | smoking_history | bmi | HbA1c_level | blood_glucose_level |
|---|---|---|---|---|---|---|
| **28986** | 32.0 | 0 | never | 30.47 | 6.2 | 126 |
| **25188** | 61.0 | 0 | current | 24.96 | 4.0 | 130 |
| **37902** | 30.0 | 0 | ever | 27.32 | 6.5 | 158 |
| **55404** | 61.0 | 0 | ever | 27.88 | 5.0 | 130 |
| **69525** | 15.0 | 0 | No Info | 27.32 | 6.1 | 100 |
| **...** | ... | ... | ... | ... | ... | ... |
| **51401** | 31.0 | 0 | former | 31.21 | 4.5 | 160 |
| **6802** | 16.0 | 0 | No Info | 27.32 | 4.8 | 126 |
| **72319** | 38.0 | 0 | never | 23.10 | 4.8 | 100 |
| **31823** | 50.0 | 0 | current | 19.87 | 4.0 | 90 |
| **96394** | 65.0 | 0 | never | 33.30 | 6.1 | 130 |

75000 rows × 6 columns

In [75]:
```
train_x1.reset_index(inplace=True, drop=True)
test_x1.reset_index(inplace=True, drop=True)
train_y1.reset_index(inplace=True, drop=True)
test_y1.reset_index(inplace=True, drop=True)
```

In [76]:
```
train_cat = train_x1.select_dtypes(include="object")
train_num = train_x1.select_dtypes(include="number")
test_cat = test_x1.select_dtypes(include="object")
test_num = test_x1.select_dtypes(include="number")
```

In [77]:
```
train_cat.head()
```

Out[77]:

| | smoking_history |
|---|---|
| **0** | never |
| **1** | current |
| **2** | ever |
| **3** | ever |
| **4** | No Info |

In [78]:
```
encoder.fit(train_cat, train_y)
```

Out[78]:
```
▾ CatBoostEncoder
CatBoostEncoder(cols=['smoking_history'])
```

In [79]:
```
train_cat = encoder.transform(train_cat)
test_cat = encoder.transform(test_cat)
```

In [80]:
```
test_cat.head()
```

Out[80]:

| | smoking_history |
|---|---|
| 0 | 0.040511 |
| 1 | 0.040511 |
| 2 | 0.040511 |
| 3 | 0.099381 |
| 4 | 0.095679 |

In [81]:
```
train_x1 = pd.concat([train_num, train_cat], axis=1)
test_x1 = pd.concat([test_num, test_cat], axis=1)
```

In [82]:
```
train_x1.head()
```

Out[82]:

| | age | hypertension | bmi | HbA1c_level | blood_glucose_level | smoking_history |
|---|---|---|---|---|---|---|
| 0 | 32.0 | 0 | 30.47 | 6.2 | 126 | 0.095679 |
| 1 | 61.0 | 0 | 24.96 | 4.0 | 130 | 0.099381 |
| 2 | 30.0 | 0 | 27.32 | 6.5 | 158 | 0.119856 |
| 3 | 61.0 | 0 | 27.88 | 5.0 | 130 | 0.119856 |
| 4 | 15.0 | 0 | 27.32 | 6.1 | 100 | 0.040511 |

In [83]:
```
scaler.fit(train_x1)
```

Out[83]:

```
▾ MinMaxScaler
MinMaxScaler()
```

In [84]:
```
train_x1 = pd.DataFrame(scaler.transform(train_x1), columns=train_x1.column
s)
test_x1 = pd.DataFrame(scaler.transform(test_x1), columns=test_x1.columns)
```

In [85]:
```
train_x1.head()
```

Out[85]:

| | age | hypertension | bmi | HbA1c_level | blood_glucose_level | smoking_history |
|---|---|---|---|---|---|---|
| 0 | 0.399399 | 0.0 | 0.238796 | 0.490909 | 0.209091 | 0.428981 |
| 1 | 0.762262 | 0.0 | 0.174486 | 0.090909 | 0.227273 | 0.457773 |
| 2 | 0.374374 | 0.0 | 0.202031 | 0.545455 | 0.354545 | 0.616985 |
| 3 | 0.762262 | 0.0 | 0.208567 | 0.272727 | 0.227273 | 0.616985 |
| 4 | 0.186687 | 0.0 | 0.202031 | 0.472727 | 0.090909 | 0.000000 |

In [86]:
```
#LogisticRegression
log = LogisticRegression(C=1, solver="sag", tol=0.8)
log.fit(train_x1, train_y1)
pred1 = log.predict(test_x1)
print(classification_report(test_y1,pred1))
print(recall_score(test_y1, pred1))
```

```
              precision    recall  f1-score   support

           0       0.97      0.98      0.98     22875
           1       0.80      0.66      0.72      2125

    accuracy                           0.96     25000
   macro avg       0.88      0.82      0.85     25000
weighted avg       0.95      0.96      0.95     25000

0.6574117647058824
```

In [87]:
```
#GaussianNB
nb = GaussianNB(var_smoothing=0.25)
nb.fit(train_x1, train_y1)
pred3 = nb.predict(test_x1)
print(classification_report(test_y1,pred3))
print(recall_score(test_y1, pred3))
```

```
              precision    recall  f1-score   support

           0       0.95      0.96      0.96     22875
           1       0.52      0.49      0.51      2125

    accuracy                           0.92     25000
   macro avg       0.74      0.73      0.73     25000
weighted avg       0.92      0.92      0.92     25000

0.49270588235294116
```

In [88]:
```
#DecisionTreeClassifier
dt = DecisionTreeClassifier(criterion="entropy", max_depth=75, splitter="ra
ndom")
dt.fit(train_x1, train_y1)
pred5 = dt.predict(test_x1)
print(classification_report(test_y1,pred5))
print(recall_score(test_y1, pred5))
```

```
              precision    recall  f1-score   support

           0       0.97      0.97      0.97     22875
           1       0.72      0.73      0.72      2125

    accuracy                           0.95     25000
   macro avg       0.85      0.85      0.85     25000
weighted avg       0.95      0.95      0.95     25000

0.7312941176470589
```

In [89]:
```
#RandomForestClassifier
rfc = RandomForestClassifier(max_depth=85 ,n_estimators= 15)
rfc.fit(train_x1, train_y1)
pred6 = rfc.predict(test_x1)
print(classification_report(test_y1,pred6))
print(recall_score(test_y1, pred6))
```

```
              precision    recall  f1-score   support

           0       0.97      0.99      0.98     22875
           1       0.89      0.69      0.77      2125

    accuracy                           0.97     25000
   macro avg       0.93      0.84      0.88     25000
weighted avg       0.96      0.97      0.96     25000

0.6856470588235294
```

In [90]:
```
#XGBClassifier
xgb = Xgb.XGBClassifier(eta=0.5 ,max_depth=14 ,n_estimators= 100)
xgb.fit(train_x1, train_y1)
pred7 = xgb.predict(test_x1)
print(classification_report(test_y1,pred7))
print(recall_score(test_y1, pred7))
```

```
              precision    recall  f1-score   support

           0       0.97      0.99      0.98     22875
           1       0.85      0.70      0.77      2125

    accuracy                           0.96     25000
   macro avg       0.91      0.85      0.87     25000
weighted avg       0.96      0.96      0.96     25000

0.7021176470588235
```

In [91]:
```
#AdaBoostClassifier
adb = AdaBoostClassifier(n_estimators= 100)
adb.fit(train_x1, train_y1)
pred8 = adb.predict(test_x1)
print(classification_report(test_y1,pred8))
print(recall_score(test_y1, pred8))
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.98     22875
           1       0.98      0.68      0.80      2125

    accuracy                           0.97     25000
   macro avg       0.98      0.84      0.89     25000
weighted avg       0.97      0.97      0.97     25000

0.676235294117647
```

In [92]:
```
print('LogisticRegression score is ', recall_score(test_y1, pred1))
print('GaussianNB score is', recall_score(test_y1, pred3))
print('DecisionTreeClassifier score is', recall_score(test_y1, pred5))
print('RandomForestClassifier score is', recall_score(test_y1, pred6))
print('XGBClassifier score is', recall_score(test_y1, pred7))
print('AdaBoostClassifier score is', recall_score(test_y1, pred8))
```

```
LogisticRegression score is  0.6574117647058824
GaussianNB score is 0.49270588235294116
DecisionTreeClassifier score is 0.7312941176470589
RandomForestClassifier score is 0.6856470588235294
XGBClassifier score is 0.7021176470588235
AdaBoostClassifier score is 0.676235294117647
```

CONCLUSION :- IN ABOVE GENERATED MODEL IN RANDOM FOREST AND XGBOOST CLASSIFIER AND DECISIONTREE CLASSIFIER GIVE RECALL SCORE WAS LOW. ALSO MODEL PERFORMING OVERFITING. SO THAT WE DO A OVERSAMPLING BECAUSE THE DATASET HAVE INBALANCED SO WE DO IT AND CHECK THE ACCURACY OF M0DEL.

# OVER SAMPLING

In [93]:
```
xx = df2.drop(["gender", "heart_disease", "diabetes"], axis=1)
yy = df2["diabetes"]
```

In [94]:
```
xx_cat = xx.select_dtypes(include="object")
xx_num = xx.select_dtypes(include="number")
```

In [95]:
```
encoder.fit(xx_cat, yy)
xx_cat = encoder.transform(xx_cat)
```

In [96]:
```
xx = pd.concat([xx_num,xx_cat], axis=1)
```

In [97]:
```
from imblearn.over_sampling import SMOTE
os = SMOTE(random_state=50)
xos, yos = os.fit_resample(xx, yy)
```

In [98]:
```
train_x11, test_x11, train_y11, test_y11 = train_test_split(xos,yos, random
_state=50, test_size=0.2)
```

In [99]:
```
train_x11.reset_index(inplace=True, drop=True)
train_y11.reset_index(inplace=True, drop=True)
test_x11.reset_index(inplace=True, drop=True)
test_y11.reset_index(inplace=True, drop=True)
```

In [100]:
```
train_x11.count()
```

Out[100]:
```
age                    146400
hypertension           146400
bmi                    146400
HbA1c_level            146400
blood_glucose_level    146400
smoking_history        146400
dtype: int64
```

In [101]:
```
test_x11.count()
```

Out[101]:
```
age                    36600
hypertension           36600
bmi                    36600
HbA1c_level            36600
blood_glucose_level    36600
smoking_history        36600
dtype: int64
```

In [102]:
```
scaler.fit(train_x11)
```

Out[102]:
```
▾ MinMaxScaler
MinMaxScaler()
```

In [103]:
```
train_x11 = pd.DataFrame(scaler.transform(train_x11), columns=train_x11.col
umns)
test_x11 = pd.DataFrame(scaler.transform(test_x11), columns=test_x11.column
s)
```

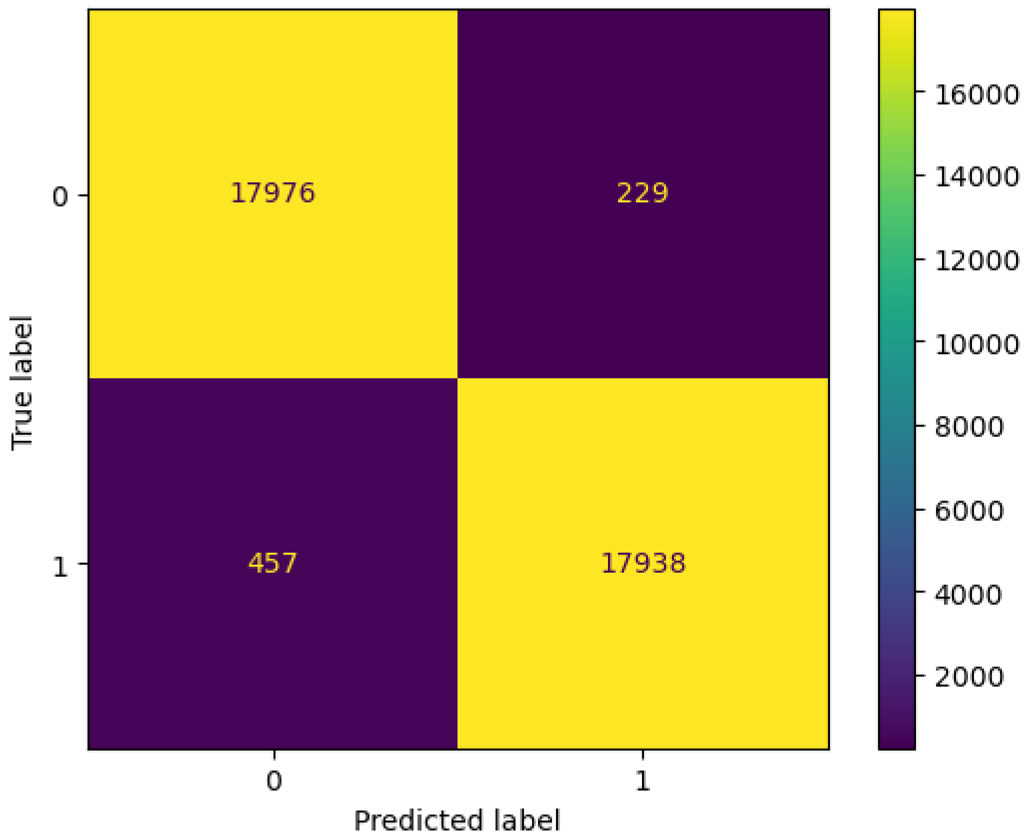
In [104]:
```
#XGBClassifier
xgb.fit(train_x11, train_y11)
pred_1x = xgb.predict(test_x11)
print(classification_report(test_y11,pred_1x))
print("Testing Score :", recall_score(test_y11, pred_1x))
print("Training Score :", xgb.score(train_x11, train_y11))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.98     18205
           1       0.99      0.98      0.98     18395

    accuracy                           0.98     36600
   macro avg       0.98      0.98      0.98     36600
weighted avg       0.98      0.98      0.98     36600

Testing Score : 0.9751562924707801
Training Score : 0.9985314207650273
```

In [105]:
```
from sklearn.metrics import ConfusionMatrixDisplay
```

In [106]:
```
print('XGBClassifier of confusion_matrix is:')
print(ConfusionMatrixDisplay.from_predictions(test_y11, pred_1x))
```

```
XGBClassifier of confusion_matrix is:
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at 0
x000001CA52307970>
```

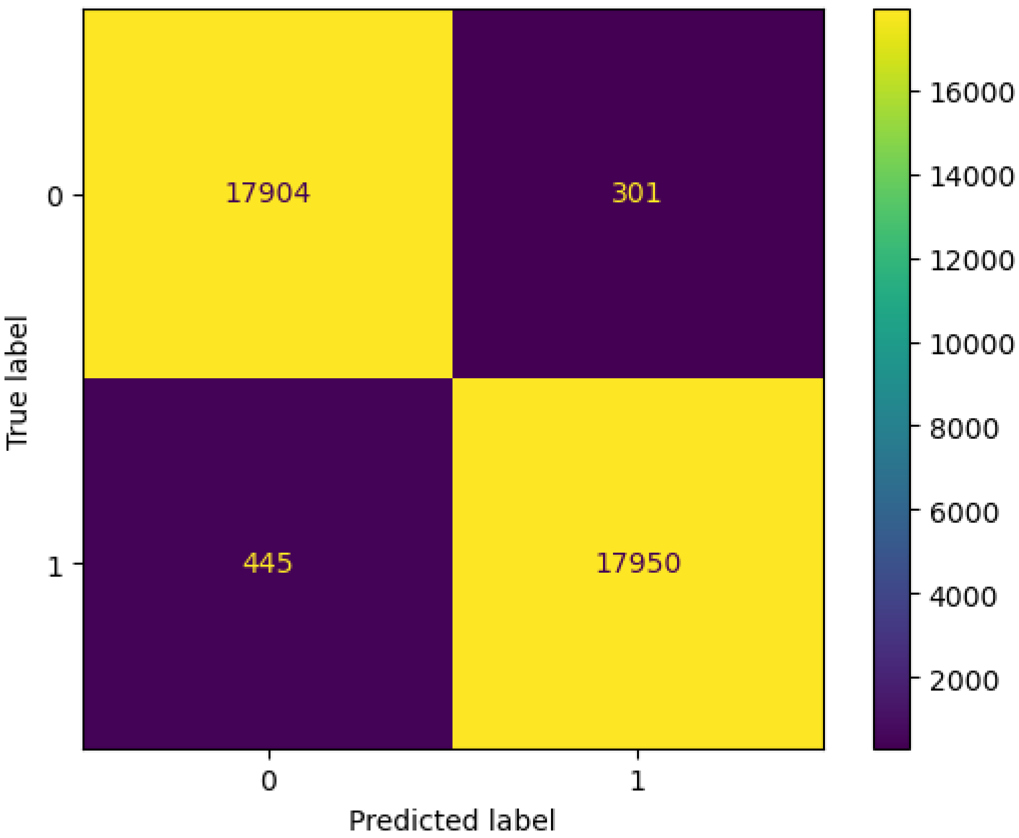



In [107]:
```
#RandomForestClassifier
rfc.fit(train_x11, train_y11)
pred_2r = rfc.predict(test_x11)
print(classification_report(test_y11,pred_2r))
print("Testing Score :", recall_score(test_y11, pred_2r))
print("Training Score :", rfc.score(train_x11, train_y11))
```

```
              precision    recall  f1-score   support

           0       0.98      0.98      0.98     18205
           1       0.98      0.98      0.98     18395

    accuracy                           0.98     36600
   macro avg       0.98      0.98      0.98     36600
weighted avg       0.98      0.98      0.98     36600

Testing Score : 0.9758086436531667
Training Score : 0.9985792349726776
```

In [108]:
```
print('RandomForestClassifier of confusion_matrix is:')
print(ConfusionMatrixDisplay.from_predictions(test_y11, pred_2r))
```

```
RandomForestClassifier of confusion_matrix is:
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at 0
x000001CA55304700>
```

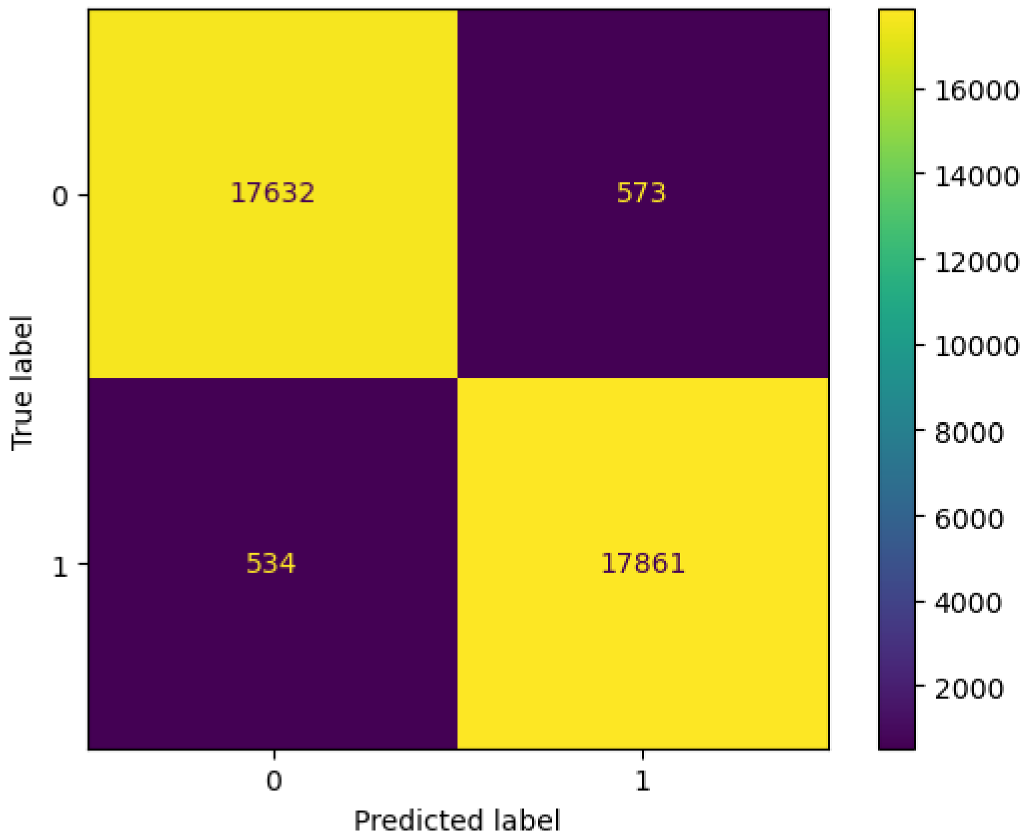



In [109]:
```
#DecisionTreeClassifier
dt.fit(train_x11, train_y11)
pred_2d = dt.predict(test_x11)
print(classification_report(test_y11,pred_2d))
print("Testing Score :",recall_score(test_y11, pred_2d))
print("Training Score :",rfc.score(train_x11, train_y11))
```

```
              precision    recall  f1-score   support

           0       0.97      0.97      0.97     18205
           1       0.97      0.97      0.97     18395

    accuracy                           0.97     36600
   macro avg       0.97      0.97      0.97     36600
weighted avg       0.97      0.97      0.97     36600

Testing Score : 0.9709703723837999
Training Score : 0.9985792349726776
```

In [110]:
```
print('RandomForestClassifier of confusion_matrix is:')
print(ConfusionMatrixDisplay.from_predictions(test_y11, pred_2d))
```

```
RandomForestClassifier of confusion_matrix is:
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at 0
x000001CA553C24A0>
```




# Testing the new data for checking

In [111]:
```
df["smoking_history"].unique()
```

Out[111]:
```
array(['never', 'No Info', 'current', 'former', 'ever', 'not current'],
      dtype=object)
```

In [112]:
```
xx.head()
```

Out[112]:

| | age | hypertension | bmi | HbA1c_level | blood_glucose_level | smoking_history |
|---|---|---|---|---|---|---|
| **0** | 80.0 | 0 | 25.19 | 6.6 | 140 | 0.095341 |
| **1** | 54.0 | 0 | 27.32 | 6.6 | 80 | 0.040598 |
| **2** | 28.0 | 0 | 27.32 | 5.7 | 158 | 0.095341 |
| **3** | 36.0 | 0 | 23.45 | 5.0 | 155 | 0.102087 |
| **4** | 76.0 | 1 | 20.14 | 4.8 | 155 | 0.102087 |

In [113]:
```
new_df = {'age': 42, 'hypertension': 0, 'bmi': 25.36, 'HbA1c_level': 6.2,'b
lood_glucose_level': 156,'smoking_history':'current'}
```

In [114]:
```
index = [0]
```

In [115]:
```
new_df = pd.DataFrame(new_df,index=index)
```

In [116]:
```
new_df
```

Out[116]:

| | age | hypertension | bmi | HbA1c_level | blood_glucose_level | smoking_history |
|---|---|---|---|---|---|---|
| **0** | 42 | 0 | 25.36 | 6.2 | 156 | current |

In [117]:
```
cat = new_df.select_dtypes(include="object")
num = new_df.select_dtypes(include="number")
```

In [118]:
```
cat = encoder.transform(cat)
```

In [119]:
```
cat
```

Out[119]:

| | smoking_history |
|---|---|
| **0** | 0.102087 |

In [120]:
```
new_df = pd.concat([num,cat], axis=1)
```

In [121]:
```
new_df
```

Out[121]:

| | age | hypertension | bmi | HbA1c_level | blood_glucose_level | smoking_history |
|---|---|---|---|---|---|---|
| **0** | 42 | 0 | 25.36 | 6.2 | 156 | 0.102087 |

In [122]:
```
new_df = pd.DataFrame(scaler.transform(new_df), columns=new_df.columns)
```

In [123]:
```
new_df
```

Out[123]:

| | age | hypertension | bmi | HbA1c_level | blood_glucose_level | smoking_history |
|---|---|---|---|---|---|---|
| **0** | 0.524525 | 0.0 | 0.179155 | 0.490909 | 0.345455 | 0.475153 |

In [124]:
```
prediction = xgb.predict(new_df)
prediction
```

Out[124]:
```
array([0])
```

In [125]:
```
predic1 = rfc.predict(new_df)
predic1
```

Out[125]:
```
array([0], dtype=int64)
```

In [126]:
```
predic2 = dt.predict(new_df)
predic2
```

Out[126]:
```
array([0], dtype=int64)
```

In [127]:
```
new_df1= {'age': 86, 'hypertension': 1, 'bmi': 29.50, 'HbA1c_level':7.6 ,'b
lood_glucose_level': 17.,'smoking_history':'never'}
```

In [128]:
```
index = [0]
```

In [129]:
```
new_df1 = pd.DataFrame(new_df1, index = index)
```

In [130]:
```
new_df1
```

Out[130]:

| | age | hypertension | bmi | HbA1c_level | blood_glucose_level | smoking_history |
|---|---|---|---|---|---|---|
| **0** | 86 | 1 | 29.5 | 7.6 | 17.0 | never |

In [131]:
```
cat = new_df1.select_dtypes(include="object")
num = new_df1.select_dtypes(include="number")
```

In [132]:
```
cat = encoder.transform(cat)
```

In [133]:
```
cat
```

Out[133]:

| | smoking_history |
|---|---|
| **0** | 0.095341 |

In [134]:
```
new_df1 = pd.concat([num,cat], axis=1)
```

In [135]:
```
new_df1
```

Out[135]:

| | age | hypertension | bmi | HbA1c_level | blood_glucose_level | smoking_history |
|---|---|---|---|---|---|---|
| **0** | 86 | 1 | 29.5 | 7.6 | 17.0 | 0.095341 |

In [136]:
```
new_df1 = pd.DataFrame(scaler.transform(new_df1), columns=new_df1.columns)
```

In [137]:
```
new_df1
```

Out[137]:

| | age | hypertension | bmi | HbA1c_level | blood_glucose_level | smoking_history |
|---|---|---|---|---|---|---|
| **0** | 1.075075 | 1.0 | 0.227474 | 0.745455 | -0.286364 | 0.423021 |

In [138]:
```
predic1 = xgb.predict(new_df1)
predic1
```

Out[138]:
```
array([1])
```

In [139]:
```
predic2 = rfc.predict(new_df1)
predic2
```

Out[139]:
```
array([1], dtype=int64)
```

In [140]:
```
predic3 = dt.predict(new_df1)
predic3
```

Out[140]:
```
array([0], dtype=int64)
```

CONCLUSION : The journey of developing machine learning models to solve our problem has been an iterative and comprehensive one, involving several crucial stages, including data processing, exploratory data analysis (EDA), basic model evaluation, hyperparameter tuning, and feature selection. Throughout this process, we employed nine different models to predict our target variable.

Upon evaluating these models, we observed the following performance scores:

Decision Tree Classifier: Testing Score: 0.9719, Training Score: 0.9986 Random Forest Classifier: Testing Score: 0.9748, Training Score: 0.9985 XGBoost Classifier: Testing Score: 0.9752, Training Score: 0.9985 Initially, our models did not meet our expectations in terms of testing scores, indicating a need for further improvement. In response, we decided to employ data sampling techniques to enhance model performance.

Among the three models, the XGBoost Classifier demonstrated the best performance, achieving the highest testing score of 0.9752. This result suggests that XGBoost was able to capture complex relationships within the data and make more accurate predictions compared to the other models.

In summary, our extensive efforts in data processing, EDA, model evaluation, hyperparameter tuning, and feature selection, combined with the use of advanced techniques like data sampling, culminated in the selection of the XGBoost Classifier as the most effective model for our task. This outcome underscores the importance of a systematic and iterative approach to machine learning model development, as it ultimately led to a model that meets or exceeds our desired level of performance.