STROKE PREDICTION

IMPORT CRUCIAL LIBRARIES

In [1]:
```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings("ignore")
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
```

IMPORTING CSV AS DATAFRAME.

In [2]:
```
df=pd.read_csv(r"C:\Users\icon\OneDrive\Desktop\DATASETS ML\healthcare-dataset
```

Attribute Information

1) id: unique identifier

2) gender: "Male", "Female" or "Other"

3) age: age of the patient

4) hypertension: 0 if the patient doesn't have hypertension, 1 if the patient has hypertension

5) heart_disease: 0 if the patient doesn't have any heart diseases, 1 if the patient has a heart disease

6) ever_married: "No" or "Yes"

7) work_type: "children", "Govt_jov", "Never_worked", "Private" or "Self-employed"

8) Residence_type: "Rural" or "Urban"

9) avg_glucose_level: average glucose level in blood

10) bmi: body mass index

11) smoking_status: "formerly smoked", "never smoked", "smokes" or "Unknown"

12) stroke: 1 if the patient had a stroke or 0 if not

This dataset is used to predict whether a patient is likely to get stroke based on the input parameters like gender, age, various diseases, and smoking status. Each row in the data provides relavant information about the patient.

DATA EXPLORATION

In [3]:
```
# Display first 20 records

df.head(20)
```

Out[3]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type
0	9046	Male	67.0	0	1	Yes	Private	Urban
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural
2	31112	Male	80.0	0	1	Yes	Private	Rural
3	60182	Female	49.0	0	0	Yes	Private	Urban
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural
5	56669	Male	81.0	0	0	Yes	Private	Urban
6	53882	Male	74.0	1	1	Yes	Private	Rural
7	10434	Female	69.0	0	0	No	Private	Urban
8	27419	Female	59.0	0	0	Yes	Private	Rural
9	60491	Female	78.0	0	0	Yes	Private	Urban
10	12109	Female	81.0	1	0	Yes	Private	Rural
11	12095	Female	61.0	0	1	Yes	Govt_job	Rural
12	12175	Female	54.0	0	0	Yes	Private	Urban
13	8213	Male	78.0	0	1	Yes	Private	Urban
14	5317	Female	79.0	0	1	Yes	Private	Urban
15	58202	Female	50.0	1	0	Yes	Self-employed	Rural
16	56112	Male	64.0	0	1	Yes	Private	Urban
17	34120	Male	75.0	1	0	Yes	Private	Urban
18	27458	Female	60.0	0	0	No	Private	Urban
19	25226	Male	57.0	0	1	No	Govt_job	Urban

In [4]:
```
# Display last 20 records

df.tail(20)
```

Out[4]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_ty
5090	4211	Male	26.00	0	0	No	Govt_job	Ru
5091	6369	Male	59.00	1	0	Yes	Private	Ru
5092	56799	Male	76.00	0	0	Yes	Govt_job	Urb
5093	32235	Female	45.00	1	0	Yes	Govt_job	Ru
5094	28048	Male	13.00	0	0	No	children	Urb
5095	68598	Male	1.08	0	0	No	children	Ru
5096	41512	Male	57.00	0	0	Yes	Govt_job	Ru
5097	64520	Male	68.00	0	0	Yes	Self-employed	Urb
5098	579	Male	9.00	0	0	No	children	Urb
5099	7293	Male	40.00	0	0	Yes	Private	Ru
5100	68398	Male	82.00	1	0	Yes	Self-employed	Ru
5101	36901	Female	45.00	0	0	Yes	Private	Urb
5102	45010	Female	57.00	0	0	Yes	Private	Ru
5103	22127	Female	18.00	0	0	No	Private	Urb
5104	14180	Female	13.00	0	0	No	children	Ru
5105	18234	Female	80.00	1	0	Yes	Private	Urb
5106	44873	Female	81.00	0	0	Yes	Self-employed	Urb
5107	19723	Female	35.00	0	0	Yes	Self-employed	Ru
5108	37544	Male	51.00	0	0	Yes	Private	Ru
5109	44679	Female	44.00	0	0	Yes	Govt_job	Urb

In [5]:
```
# Display statistical summary
# (age,hypertension,avg_glucose_level, mean>median so r.s. skewed)

df.describe()
```

Out[5]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	4909.000000
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7.854067
min	67.000000	0.080000	0.000000	0.000000	55.120000	10.300000
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23.500000
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.100000
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	33.100000
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97.600000

In [6]:
```
# Display Datatyes, No. of columns

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 5110 non-null   int64  
 1   gender             5110 non-null   object 
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   int64  
 4   heart_disease      5110 non-null   int64  
 5   ever_married       5110 non-null   object 
 6   work_type          5110 non-null   object 
 7   Residence_type     5110 non-null   object 
 8   avg_glucose_level  5110 non-null   float64
 9   bmi                4909 non-null   float64
 10  smoking_status     5110 non-null   object 
 11  stroke             5110 non-null   int64  
dtypes: float64(3), int64(4), object(5)
memory usage: 479.2+ KB
```

In [7]:
```
# Display the null values
# bmi has 201 null values

df.isnull().sum()
```

Out[7]:
```
id                    0
gender                0
age                   0
hypertension          0
heart_disease         0
ever_married          0
work_type             0
Residence_type        0
avg_glucose_level     0
bmi                 201
smoking_status        0
stroke                0
dtype: int64
```

In [8]:
```
# Display duplicate values
# There are no duplicate values

df.duplicated().sum()
```

Out[8]:
```
0
```

In [9]:
```
# Display unique values

df.nunique()
```

Out[9]:
```
id                   5110
gender                  3
age                   104
hypertension            2
heart_disease           2
ever_married            2
work_type               5
Residence_type          2
avg_glucose_level    3979
bmi                   418
smoking_status          4
stroke                  2
dtype: int64
```

EXPLORATORY DATA ANALYSIS

In [10]:
```
# Drop "id" column as it does not contribute the data

df.drop(["id"],axis=1,inplace=True)
```

In [11]:
```
# Display the number of value counts in gender
# Gender is classified into three groups ie (Female,Male and Other)
# As Other has only one value replace it with Female

df["gender"].value_counts()
```

Out[11]:
```
Female    2994
Male      2115
Other        1
Name: gender, dtype: int64
```

In [12]:
```
# Segregating the three groups using get dummies

pd.get_dummies(df["gender"])
```

Out[12]:

	Female	Male	Other
0	0	1	0
1	1	0	0
2	0	1	0
3	1	0	0
4	1	0	0
...	...	...	...
5105	1	0	0
5106	1	0	0
5107	1	0	0
5108	0	1	0
5109	1	0	0

5110 rows × 3 columns

In [13]:
```
# Replacing "other" with female as female has more counts

df["gender"].replace("Other","Male",inplace=True)
```

In [14]:
```
# Display the number of value counts in gender

df["gender"].value_counts()
```

Out[14]:
```
Female    2994
Male      2116
Name: gender, dtype: int64
```

In [15]:
```
# Deal with the 201 null values in bmi using SimpleImputer
# Null-values are more than

from sklearn.impute import SimpleImputer

si=SimpleImputer(missing_values=np.nan,strategy="mean")

df[["bmi"]]=si.fit_transform(df[["bmi"]])
```

In [16]:
```
# Null values in bmi are eliminated

df["bmi"].isnull().sum()
```

Out[16]:
```
0
```

In [17]:
```
# Segregating Numerical and Categorical data

Numcol=df.select_dtypes(["int64","float64"]).columns

Catcol=df.select_dtypes(["object"]).columns
```

In [18]:
```
Numcol
```

Out[18]:
```
Index(['age', 'hypertension', 'heart_disease', 'avg_glucose_level', 'bmi',
       'stroke'],
      dtype='object')
```

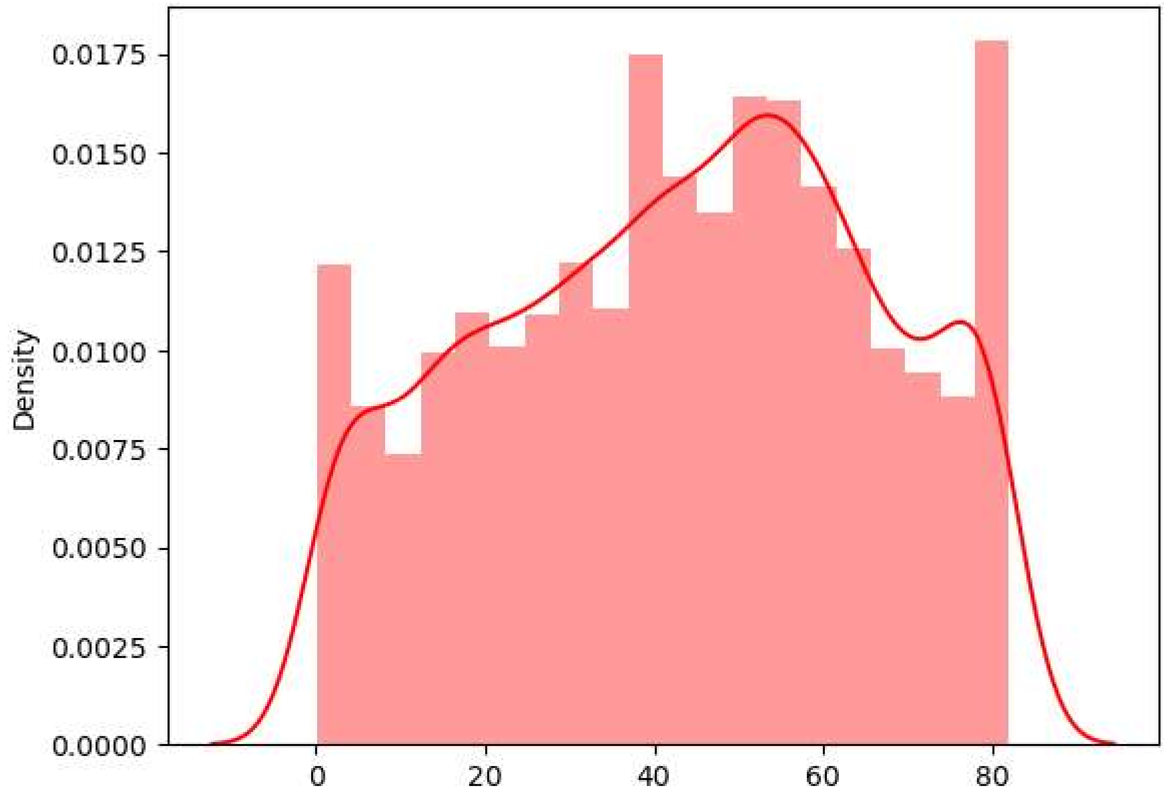
In [19]:
```
Catcol
```

Out[19]:
```
Index(['gender', 'ever_married', 'work_type', 'Residence_type',
       'smoking_status'],
      dtype='object')
```

VISUALIZATION (UNIVARIATE, BIVARIATE AND MULTIVARIATE)

In [20]:
```
sns.distplot(x = df['age'], color="red")
```

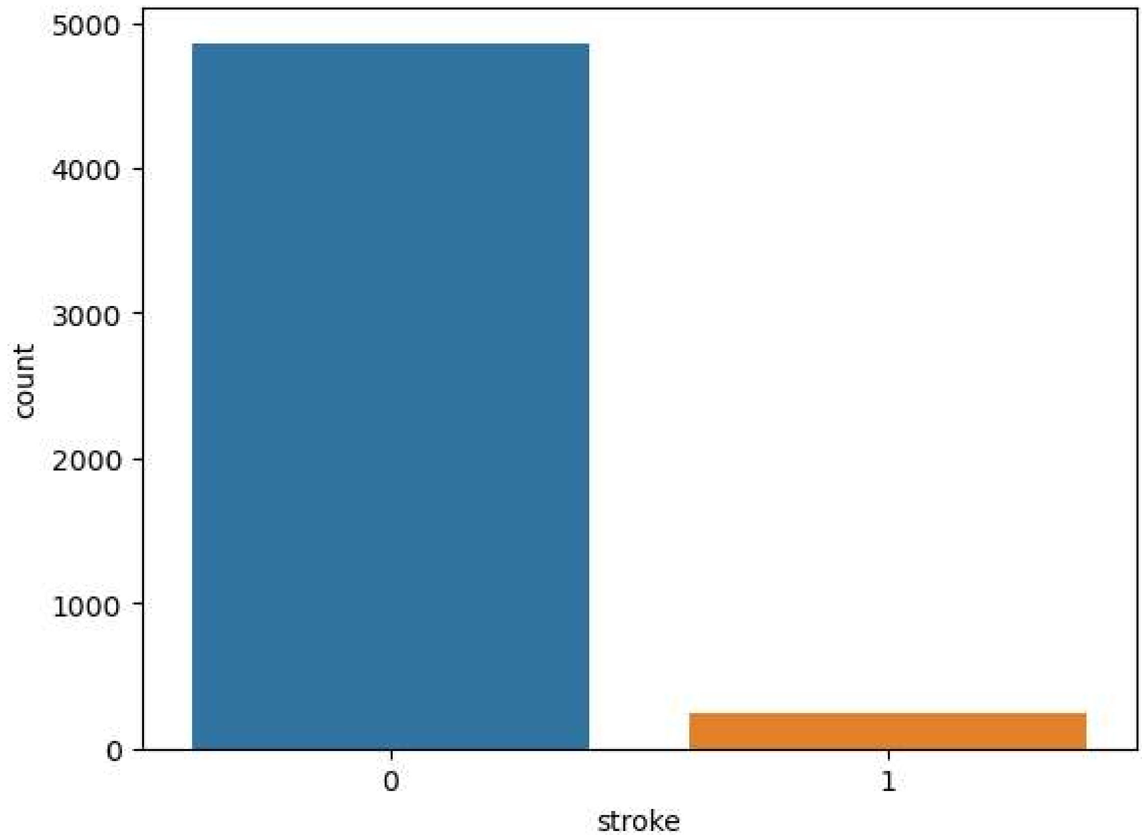
Out[20]: <AxesSubplot:ylabel='Density'>



Accordingly, the displot illustrate that the people suffering from stroke problems fall under a age catagory of 40 to 60 and old age people above 80

In [21]:
```
sns.countplot(df['stroke'])
```

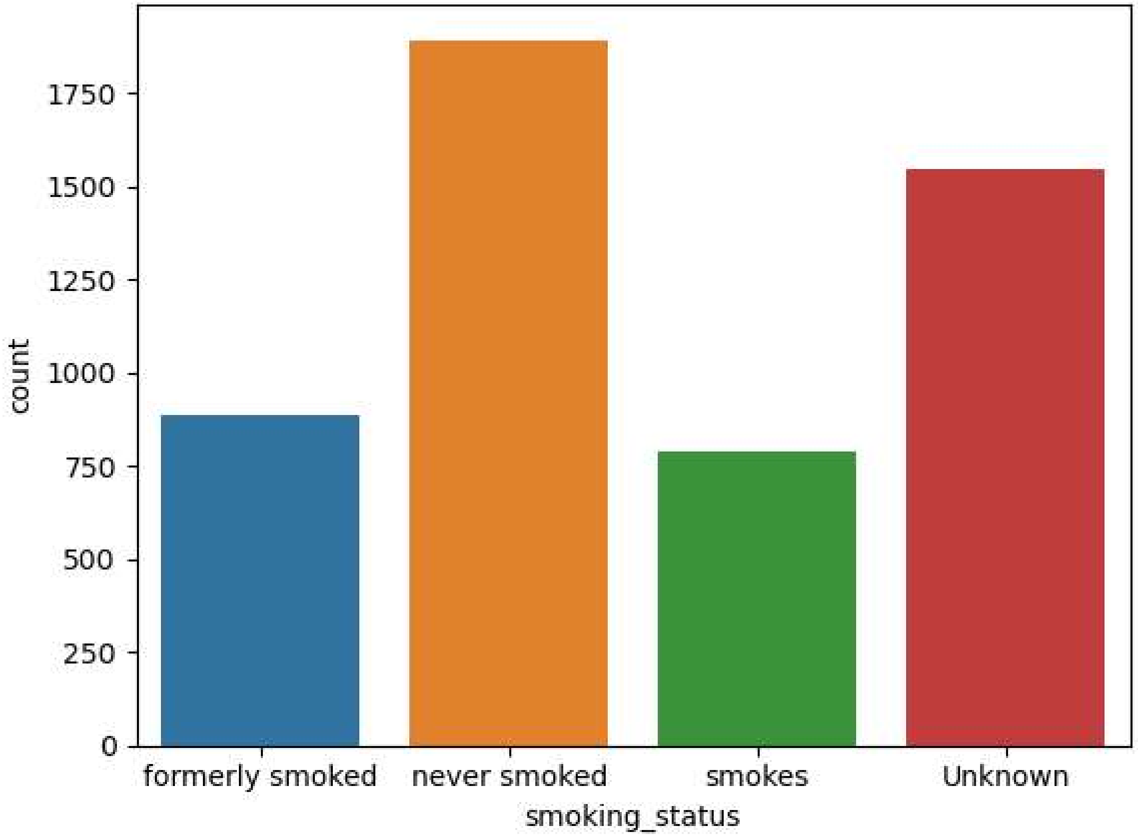
Out[21]: <AxesSubplot:xlabel='stroke', ylabel='count'>



The countplot shows that the possiblity of strokes occuring is substantially more when compared to not having stroke.

In [22]:
```
sns.countplot(df['smoking_status'])
```

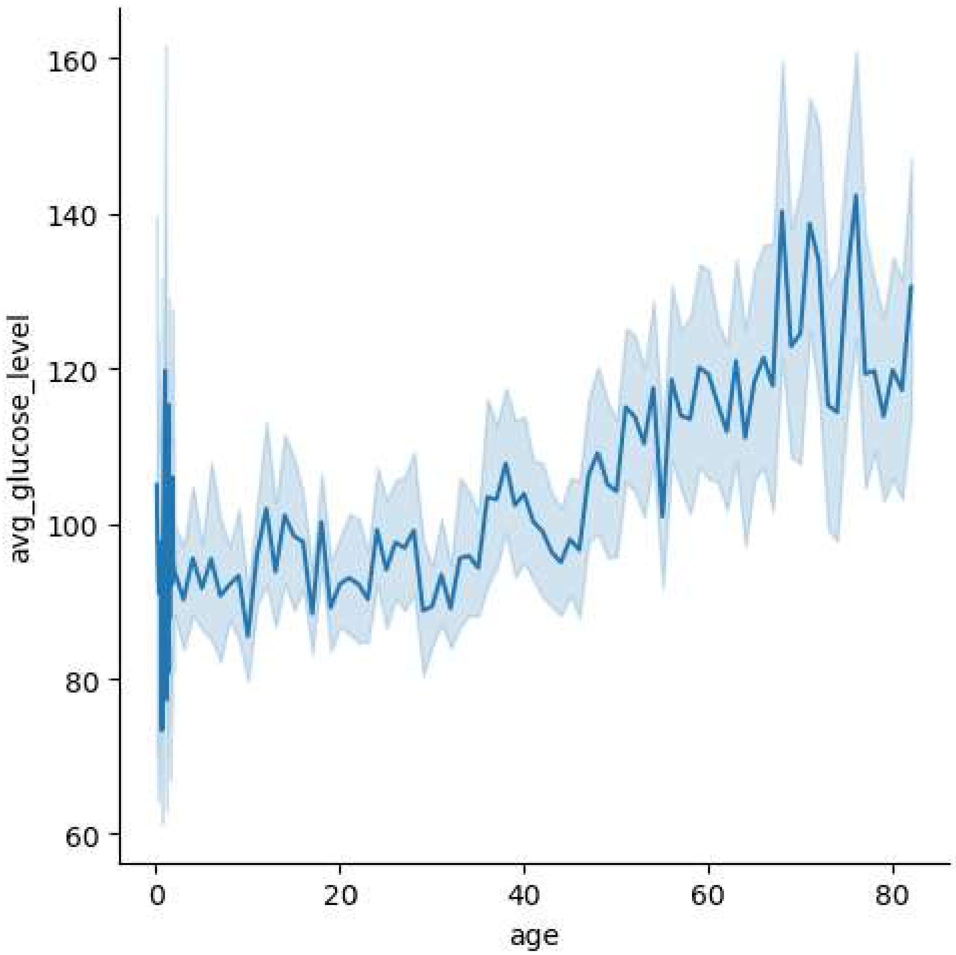
Out[22]:
```
<AxesSubplot:xlabel='smoking_status', ylabel='count'>
```



The barplot shows that around 800-900 people quit smoking while 750 are still smokers. On the other hand significant amount of people never smokes and rest were unknown.

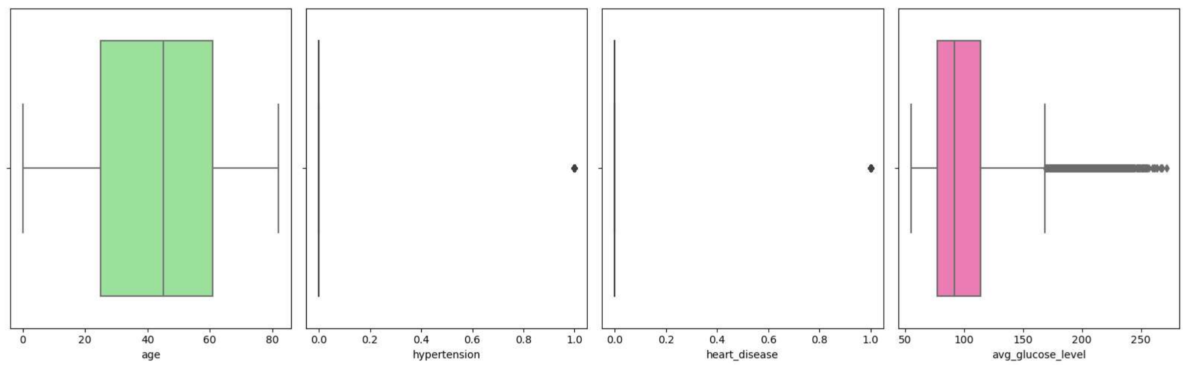
In [23]:
```
sns.relplot(data=df, x="age", y="avg_glucose_level", kind="line")
```

Out[23]: <seaborn.axisgrid.FacetGrid at 0x232a33b4910>



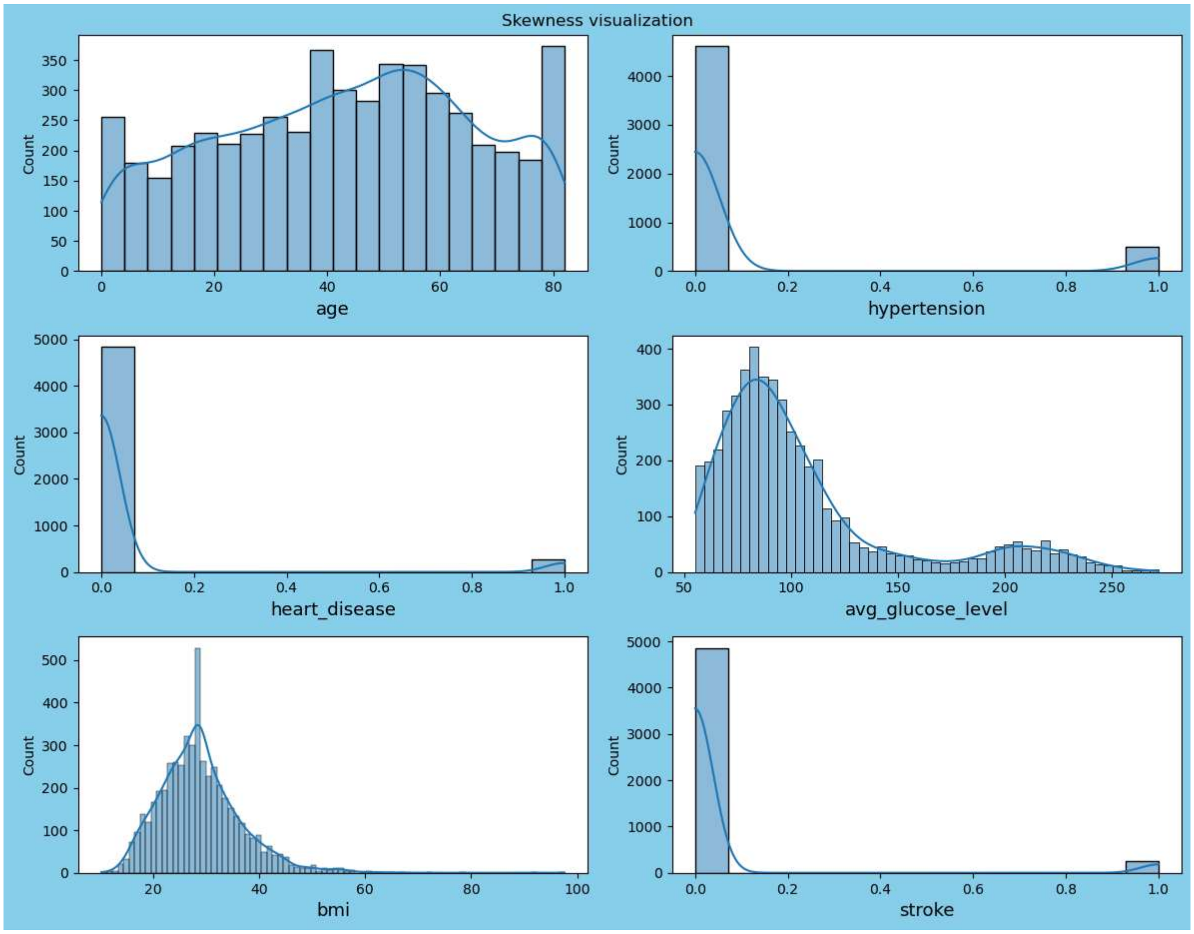
As can be seen, age and avg glucose level are directly proportional.

In [24]:
```
plt.subplots(1,4,figsize=(16,5))
plt.subplot(141)
sns.boxplot(df['age'],color='lightgreen')
plt.subplot(142)
sns.boxplot(df['hypertension'])
plt.subplot(143)
sns.boxplot(df['heart_disease'])
plt.subplot(144)
sns.boxplot(df['avg_glucose_level'],color='hotpink')
plt.tight_layout()
plt.show()
```



from the above boxplot outliers are clearly visible

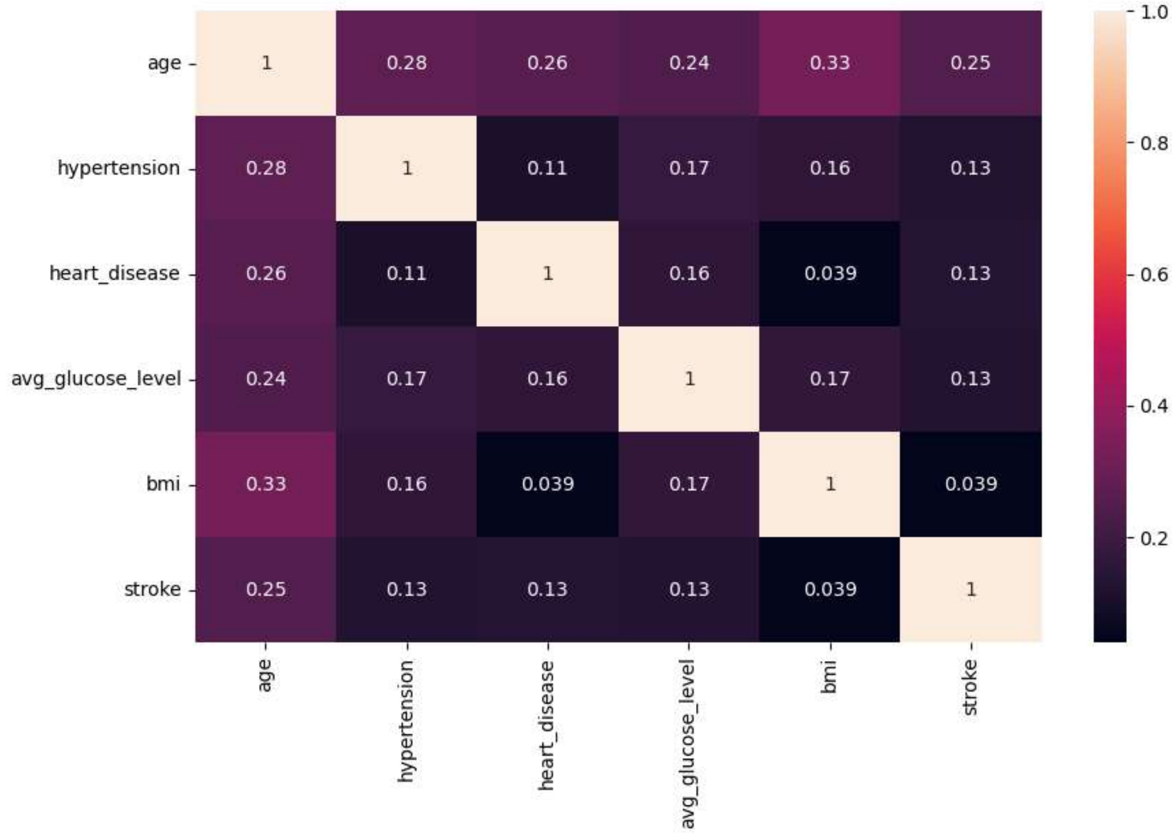
In [25]:
```
plt.figure(figsize=(12,12),facecolor="skyblue")
plt.suptitle("Skewness visualization")
pltn=1
for i in Numcol:
    if pltn<=10:
        ax=plt.subplot(4,2,pltn)

        sns.histplot(df[i],kde=True)
        plt.xlabel(i,fontsize=13)
    pltn=pltn+1
plt.tight_layout()
```



From the above graph it is clear that the data is not normally distributed as its right side skewed and contain outliers

In [26]:
```
# Display coorelation with target

plt.figure(figsize=(10,6))
sns.heatmap(df.corr(),annot=True)
```

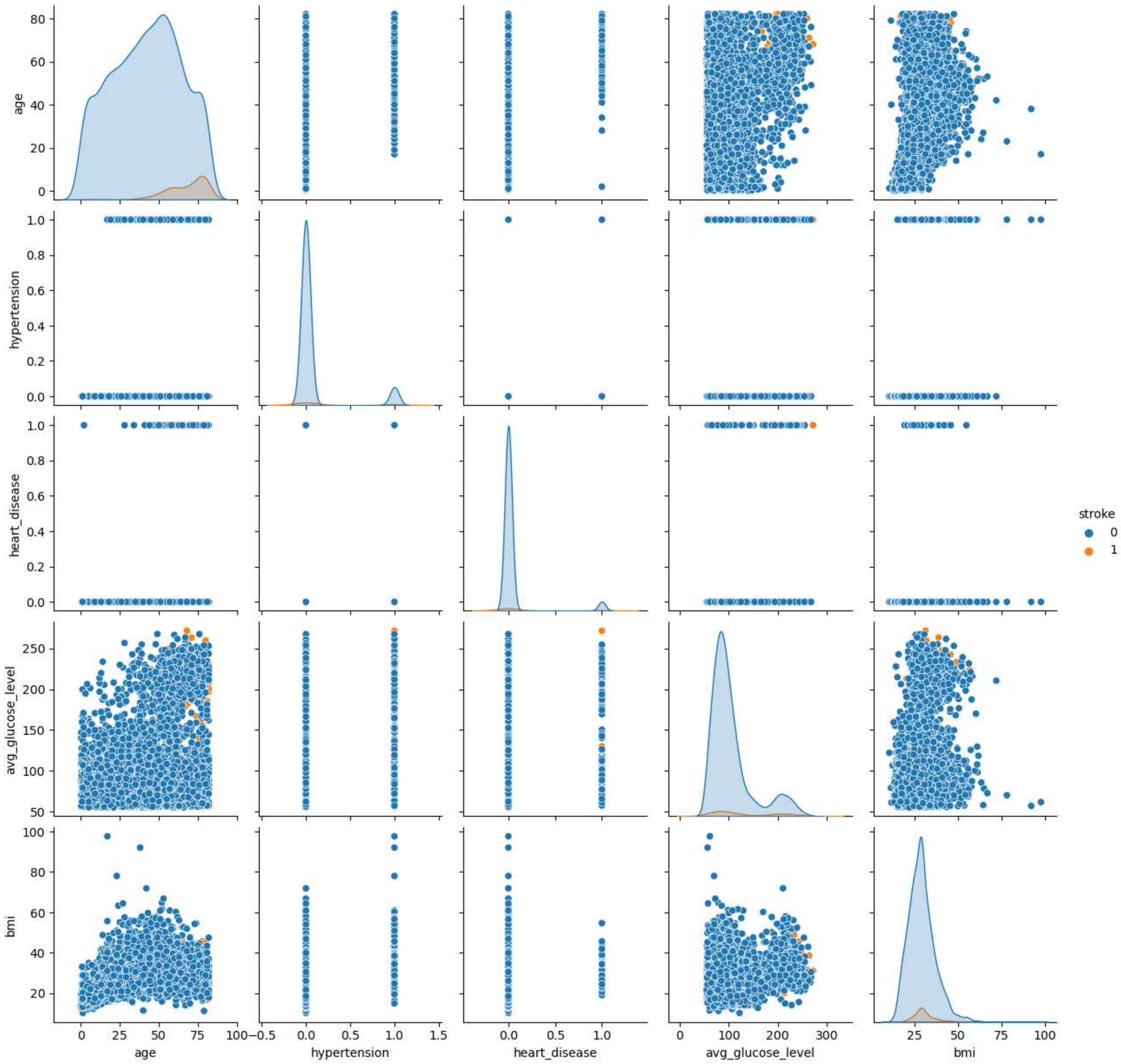
Out[26]: <AxesSubplot:>



As can be seen there is no strong corelation due to data being not normally distributed

In [27]:
```
# Multivariate visualization

sns.pairplot(df,hue="stroke")
```

Out[27]:
```
<seaborn.axisgrid.PairGrid at 0x232a4930ca0>
```



In [28]:
```
# Display skewness
#

df.skew()
```

Out[28]:
```
age                 -0.137059
hypertension         2.715392
heart_disease        3.947244
avg_glucose_level    1.572284
bmi                  1.076716
stroke               4.193284
dtype: float64
```

In [29]:
```
# Coverting categorical data to numerical using OrdinalEncoder

from sklearn.preprocessing import OrdinalEncoder
oe=OrdinalEncoder()
df[['gender', 'ever_married', 'work_type', 'Residence_type',
       'smoking_status']]=oe.fit_transform(df[['gender', 'ever_married', 'work
       'smoking_status']])
```

In [30]:
```
# Seperating dependent and independent variables features(x)/target(y)

x=df.drop("stroke",axis=1)

y=df["stroke"]
```

In [31]:
```
x
```

Out[31]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_
0	1.0	67.0	0	1	1.0	2.0	1.0	
1	0.0	61.0	0	0	1.0	3.0	0.0	
2	1.0	80.0	0	1	1.0	2.0	0.0	
3	0.0	49.0	0	0	1.0	2.0	1.0	
4	0.0	79.0	1	0	1.0	3.0	0.0	
...	...	...	...	...	...	...	...	
5105	0.0	80.0	1	0	1.0	2.0	1.0	
5106	0.0	81.0	0	0	1.0	3.0	1.0	
5107	0.0	35.0	0	0	1.0	3.0	0.0	
5108	1.0	51.0	0	0	1.0	2.0	0.0	
5109	0.0	44.0	0	0	1.0	0.0	1.0	

5110 rows × 10 columns

In [32]:
```
y
```

Out[32]:
```
0       1
1       1
2       1
3       1
4       1
       ..
5105    0
5106    0
5107    0
5108    0
5109    0
Name: stroke, Length: 5110, dtype: int64
```

In [33]:
```
# Train Test split to split the dataset   estimate the performance

from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.3,random_state=1)
```

IMPLEMENTING LOGISTIC REGRESSION

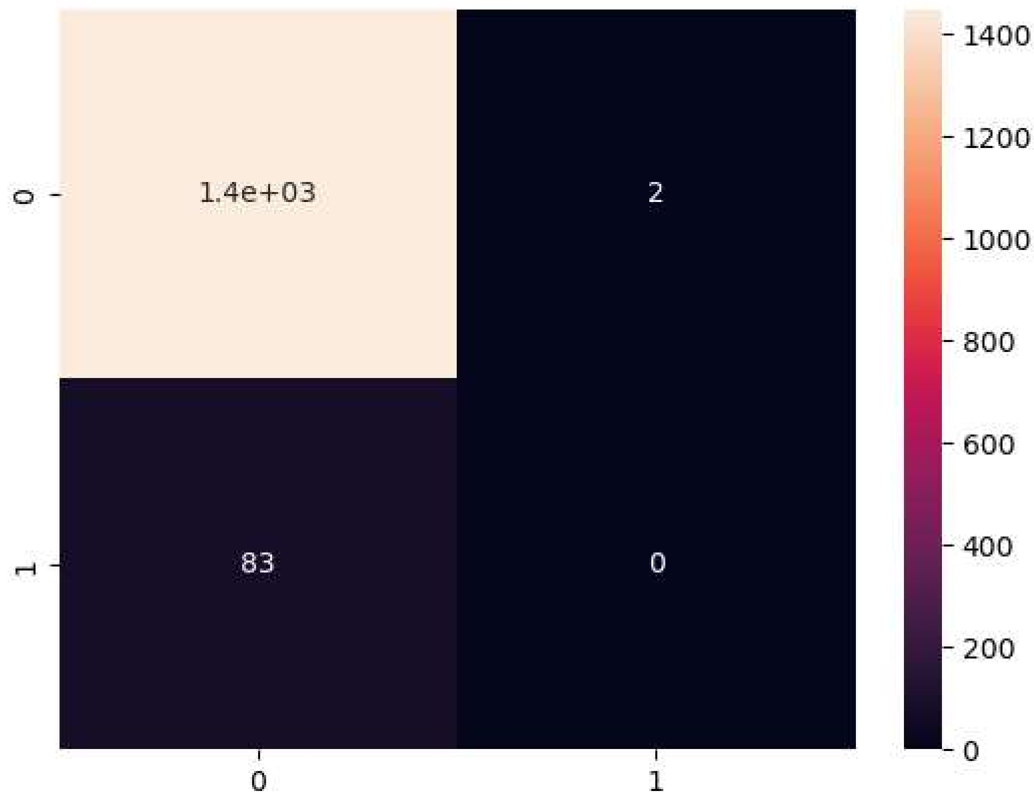
In [34]:
```
# As target is classification

from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()
lr.fit(xtrain,ytrain)
ypred=lr.predict(xtest)
```

In [35]:
```
# probability estimating

from sklearn.metrics import confusion_matrix, classification_report,accuracy_s
ac=accuracy_score(ytest,ypred)
cm=confusion_matrix(ytest,ypred)
cr=classification_report(ytest,ypred)
print(f"Accuracy: {ac*100}\n {cm}\n{cr}")
```

```
Accuracy: 94.45531637312459
 [[1448    2]
 [  83    0]]
              precision    recall  f1-score   support

           0       0.95      1.00      0.97      1450
           1       0.00      0.00      0.00        83

    accuracy                           0.94      1533
   macro avg       0.47      0.50      0.49      1533
weighted avg       0.89      0.94      0.92      1533
```

In [36]:
```
sns.heatmap(confusion_matrix(ytest,ypred),annot=True)
```

Out[36]: <AxesSubplot:>



In [37]:
```
# Display traing and testing accuracy

train=lr.score(xtrain,ytrain)
test=lr.score(xtest,ytest)
print(f"Training score: {train*100}\nTesting score: {test*100}")
```

```
Training score: 95.35923958624547
Testing score: 94.45531637312459
```

IMPLEMENTING NAIVE BAYES GAUSSION AS TARGET IS IN BINARY FORM

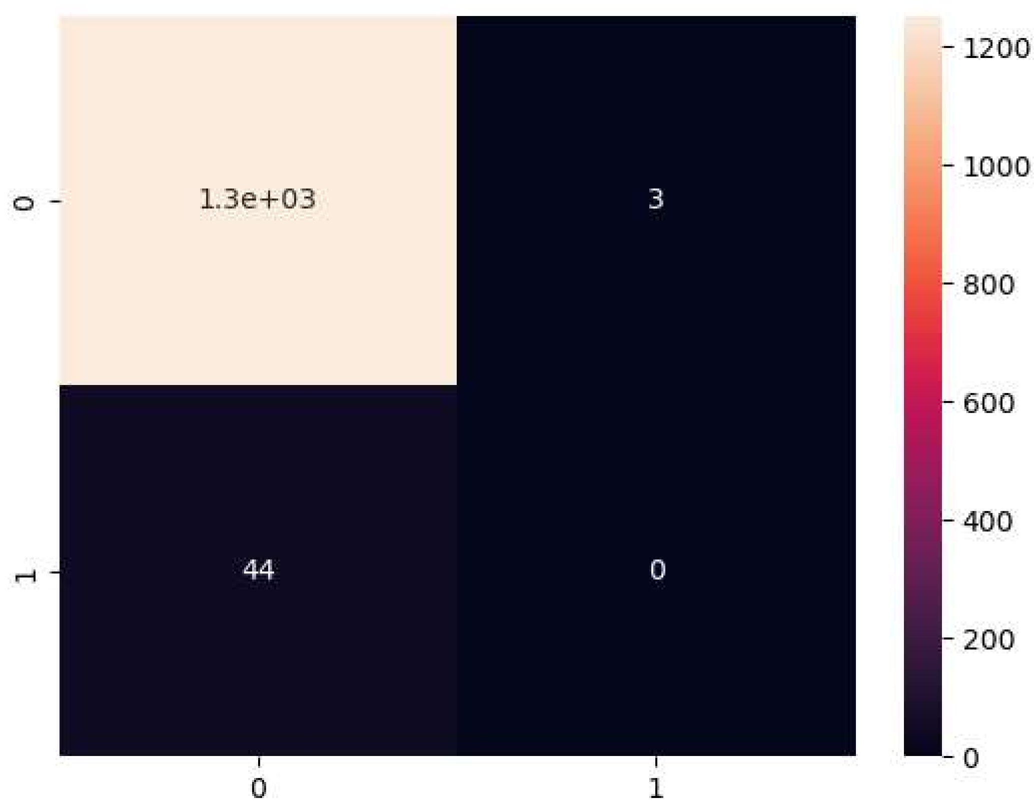
In [38]:
```
# As the target is in binary using gaussian nb

from sklearn.naive_bayes import GaussianNB
gb=GaussianNB()
gb.fit(xtrain,ytrain)
ypred=gb.predict(xtest)
```

In [39]:
```
# # probability estimating

from sklearn.metrics import confusion_matrix, classification_report,accuracy_s
ac=accuracy_score(ytest,ypred)
cm=confusion_matrix(ytest,ypred)
cr=classification_report(ytest,ypred)
print(f"Accuracy: {ac*100}\n {cm}\n{cr}")
```

```
Accuracy: 87.01891715590345
 [[1298  152]
 [  47   36]]
              precision    recall  f1-score   support

           0       0.97      0.90      0.93      1450
           1       0.19      0.43      0.27        83

    accuracy                           0.87      1533
   macro avg       0.58      0.66      0.60      1533
weighted avg       0.92      0.87      0.89      1533
```

In [63]:
```
# Confusion matrix through heatmap

sns.heatmap(confusion_matrix(ytest,ypred),annot=True)
```

Out[63]: <AxesSubplot:>



In [40]:
```
# # Display traing and testing accuracy

train=gb.score(xtrain,ytrain)
test=gb.score(xtest,ytest)
print(f"Training score: {train*100}\nTesting score: {test*100}")
```

```
Training score: 87.50349454850434
Testing score: 87.01891715590345
```

IMPLEMENTING KNN CLASSIFIER

In [41]:
```
# Classification Accuracy

from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=5)
knn.fit(xtrain,ytrain)
ypred=knn.predict(xtest)
```

In [42]:
```
# probability estimating

from sklearn.metrics import confusion_matrix, classification_report,accuracy_s
ac=accuracy_score(ytest,ypred)
cm=confusion_matrix(ytest,ypred)
cr=classification_report(ytest,ypred)
print(f"Accuracy: {ac*100}\n {cm}\n{cr}")
```

```
Accuracy: 93.9334637964775
 [[1440   10]
 [  83    0]]
              precision    recall  f1-score   support

           0       0.95      0.99      0.97      1450
           1       0.00      0.00      0.00        83

    accuracy                           0.94      1533
   macro avg       0.47      0.50      0.48      1533
weighted avg       0.89      0.94      0.92      1533
```

In [43]:
```
# Display traing and testing accuracy

train=knn.score(xtrain,ytrain)
test=knn.score(xtest,ytest)
print(f"Training score: {train*100}\nTesting score: {test*100}")
```

```
Training score: 95.44310875034945
Testing score: 93.9334637964775
```

REMOVING OUTLIERS

In [44]:
```
# Importing zscore

from scipy.stats import zscore

features=df[["hypertension","heart_disease","avg_glucose_level","bmi"]]
z=np.abs(zscore(features))
z.head()
```

Out[44]:

	hypertension	heart_disease	avg_glucose_level	bmi
0	0.328602	4.185032	2.706375	1.001234e+00
1	0.328602	0.238947	2.121559	4.615554e-16
2	0.328602	4.185032	0.005028	4.685773e-01
3	0.328602	0.238947	1.437358	7.154182e-01
4	3.043196	0.238947	1.501184	6.357112e-01

In [45]:
```
# Removing outliers using z-score

newdf=df[(z<=3).all(axis=1)]
newdf
```

Out[45]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_
1	0.0	61.0	0	0	1.0	3.0	0.0	
3	0.0	49.0	0	0	1.0	2.0	1.0	
5	1.0	81.0	0	0	1.0	2.0	1.0	
7	0.0	69.0	0	0	0.0	2.0	1.0	
8	0.0	59.0	0	0	1.0	2.0	0.0	
...	...	...	...	...	...	...	...	
5104	0.0	13.0	0	0	0.0	4.0	0.0	
5106	0.0	81.0	0	0	1.0	3.0	1.0	
5107	0.0	35.0	0	0	1.0	3.0	0.0	
5108	1.0	51.0	0	0	1.0	2.0	0.0	
5109	0.0	44.0	0	0	1.0	0.0	1.0	

4326 rows × 11 columns

In [46]:
```
df.shape
```

Out[46]: (5110, 11)

In [47]:
```
newdf.shape
```

Out[47]: (4326, 11)

In [48]:
```
# Data lost calculation

dtloss=((5110-4326)/5110)*100
dtloss
```

Out[48]: 15.342465753424658

In [49]:
```
# Display skewness

newdf.skew()
```

Out[49]:
```
gender               0.395042
age                  0.015629
hypertension         0.000000
heart_disease        0.000000
ever_married        -0.468334
work_type           -0.254953
Residence_type      -0.029602
avg_glucose_level    1.749650
bmi                  0.526752
smoking_status       0.022828
stroke               5.165614
dtype: float64
```

In [50]:
```
# # Seperating dependent and independent variables features(x)/target(y)

x=newdf.drop("stroke",axis=1)
y=newdf["stroke"]
```

In [51]:
```
x
```

Out[51]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_
1	0.0	61.0	0	0	1.0	3.0	0.0	
3	0.0	49.0	0	0	1.0	2.0	1.0	
5	1.0	81.0	0	0	1.0	2.0	1.0	
7	0.0	69.0	0	0	0.0	2.0	1.0	
8	0.0	59.0	0	0	1.0	2.0	0.0	
...	...	...	...	...	...	...	...	
5104	0.0	13.0	0	0	0.0	4.0	0.0	
5106	0.0	81.0	0	0	1.0	3.0	1.0	
5107	0.0	35.0	0	0	1.0	3.0	0.0	
5108	1.0	51.0	0	0	1.0	2.0	0.0	
5109	0.0	44.0	0	0	1.0	0.0	1.0	

4326 rows × 10 columns

In [52]:
```
y
```

Out[52]:
```
1       1
3       1
5       1
7       1
8       1
       ..
5104    0
5106    0
5107    0
5108    0
5109    0
Name: stroke, Length: 4326, dtype: int64
```

AFTER OUTLIERS REMOVAL APPLYING LOGISTIC REGRESSION

In [53]:
```
# To divide our dataset in training and tersting dataset

from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.3,random_state=1)
```

In [54]:
```
# Model implementation and object creation

from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()
lr.fit(xtrain,ytrain)
ypred=lr.predict(xtest)
```

In [55]:
```
# probability estimating

from sklearn.metrics import confusion_matrix, classification_report,accuracy_s
ac=accuracy_score(ytest,ypred)
cm=confusion_matrix(ytest,ypred)
cr=classification_report(ytest,ypred)
print(f"Accuracy: {ac*100}\n {cm}\n{cr}")
```

```
Accuracy: 96.61016949152543
 [[1254    0]
 [  44    0]]
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1254
           1       0.00      0.00      0.00        44

    accuracy                           0.97      1298
   macro avg       0.48      0.50      0.49      1298
weighted avg       0.93      0.97      0.95      1298
```

In [56]:
```
# Calculating traing and testing data

train=lr.score(xtrain,ytrain)
test=lr.score(xtest,ytest)
print(f"Training score: {train*100}\nTesting score: {test*100}")
```

```
Training score: 96.63143989431968
Testing score: 96.61016949152543
```

NAIVE BAYES

In [57]:
```
# As target is binary so gaussian algorithm

from sklearn.naive_bayes import GaussianNB
gb=GaussianNB()
gb.fit(xtrain,ytrain)
ypred=gb.predict(xtest)
```

In [58]:
```
# probability estimating

from sklearn.metrics import confusion_matrix, classification_report,accuracy_s
ac=accuracy_score(ytest,ypred)
cm=confusion_matrix(ytest,ypred)
cr=classification_report(ytest,ypred)
print(f"Accuracy: {ac*100}\n {cm}\n{cr}")
```

```
Accuracy: 93.37442218798151
 [[1206   48]
 [  38    6]]
              precision    recall  f1-score   support

           0       0.97      0.96      0.97      1254
           1       0.11      0.14      0.12        44

    accuracy                           0.93      1298
   macro avg       0.54      0.55      0.54      1298
weighted avg       0.94      0.93      0.94      1298
```

In [59]:
```
# Display Training and testing Accuracy

train=gb.score(xtrain,ytrain)
test=gb.score(xtest,ytest)
print(f"Training score: {train*100}\nTesting score: {test*100}")
```

```
Training score: 93.75825627476883
Testing score: 93.37442218798151
```

KNN

In [60]:
```
# Claasification Algorithm

from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=5)
knn.fit(xtrain,ytrain)
ypred=knn.predict(xtest)
```

In [61]:
```
# probability estimating

from sklearn.metrics import confusion_matrix, classification_report,accuracy_s
ac=accuracy_score(ytest,ypred)
cm=confusion_matrix(ytest,ypred)
cr=classification_report(ytest,ypred)
print(f"Accuracy: {ac*100}\n {cm}\n{cr}")
```

```
Accuracy: 96.37904468412944
 [[1251    3]
 [  44    0]]
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1254
           1       0.00      0.00      0.00        44

    accuracy                           0.96      1298
   macro avg       0.48      0.50      0.49      1298
weighted avg       0.93      0.96      0.95      1298
```

In [62]:
```
# Display traing and testing accuracy

train=knn.score(xtrain,ytrain)
test=knn.score(xtest,ytest)
print(f"Training score: {train*100}\nTesting score: {test*100}")
```

```
Training score: 96.79656538969617
Testing score: 96.37904468412944
```

Logistic Regression is the best algorithm for this dataset with accuracy of Training:- 96.63 Testing:- 96.61

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: