In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
df=pd.read_csv("healthcare-dataset-stroke-data.csv")
```

In [3]:

```
df
```

Out[3]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1
...	...	...	...	...	...	...	...	...	...	...	...	...
5105	18234	Female	80.0	1	0	Yes	Private	Urban	83.75	NaN	never smoked	0
5106	44873	Female	81.0	0	0	Yes	Self-employed	Urban	125.20	40.0	never smoked	0
5107	19723	Female	35.0	0	0	Yes	Self-employed	Rural	82.99	30.6	never smoked	0
5108	37544	Male	51.0	0	0	Yes	Private	Rural	166.29	25.6	formerly smoked	0
5109	44679	Female	44.0	0	0	Yes	Govt_job	Urban	85.28	26.2	Unknown	0

5110 rows × 12 columns

In [4]:

```
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 [5]:

```
df.describe()
```

Out[5]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	4909.000000	5110.000000
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237	0.048728
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7.854067	0.215320
min	67.000000	0.080000	0.000000	0.000000	55.120000	10.300000	0.000000
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23.500000	0.000000
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.100000	0.000000
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	33.100000	0.000000
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97.600000	1.000000

Step 1:Handling Missing Values

the three rules :

1.if mv<3 then use dropna

2.if mv is between 3-30% then fillna

3.if mv>30% drop column

In [6]:

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

Out[6]:

```
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 [7]:

```
percent=df[df.columns].isnull().sum()/df.shape[0]*100
percent
for i in df.columns:
    print(i)
    print(percent[i])
```

```
id
0.0
gender
0.0
age
0.0
hypertension
0.0
heart_disease
0.0
ever_married
0.0
work_type
0.0
Residence_type
0.0
avg_glucose_level
0.0
bmi
3.9334637964774952
smoking_status
0.0
stroke
0.0
```

In [8]:

```
from sklearn.impute import SimpleImputer

for i in df.columns:
    print(i)
    if percent[i]<3:
        print(f"Percentange of null value is {percent[i]}")
        df.dropna(subset=[i],inplace=True)
    elif percent[i]>=3 and percent[i]<30:
        print(f"Percentange of null value is {percent[i]}")
        col=df.select_dtypes([int,float]).columns
        ki=SimpleImputer(missing_values=np.nan,strategy="mean")
        df[col]=ki.fit_transform(df[col])
    elif percent[i]>=30:
        print(f"Percentange of null value is {percent[i]}")
        df.drop(i,axis="columns",inplace=True)
```

```
id
Percentange of null value is 0.0
gender
Percentange of null value is 0.0
age
Percentange of null value is 0.0
hypertension
Percentange of null value is 0.0
heart_disease
Percentange of null value is 0.0
ever_married
Percentange of null value is 0.0
work_type
Percentange of null value is 0.0
Residence_type
Percentange of null value is 0.0
avg_glucose_level
Percentange of null value is 0.0
bmi
Percentange of null value is 3.9334637964774952
smoking_status
Percentange of null value is 0.0
stroke
Percentange of null value is 0.0
```

In [9]:

```
df
```

Out[9]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046.0	Male	67.0	0.0	1.0	Yes	Private	Urban	228.69	36.600000	formerly smoked	1.0
1	51676.0	Female	61.0	0.0	0.0	Yes	Self-employed	Rural	202.21	28.893237	never smoked	1.0
2	31112.0	Male	80.0	0.0	1.0	Yes	Private	Rural	105.92	32.500000	never smoked	1.0
3	60182.0	Female	49.0	0.0	0.0	Yes	Private	Urban	171.23	34.400000	smokes	1.0
4	1665.0	Female	79.0	1.0	0.0	Yes	Self-employed	Rural	174.12	24.000000	never smoked	1.0
...	...	...	...	...	...	...	...	...	...	...	...	...
5105	18234.0	Female	80.0	1.0	0.0	Yes	Private	Urban	83.75	28.893237	never smoked	0.0
5106	44873.0	Female	81.0	0.0	0.0	Yes	Self-employed	Urban	125.20	40.000000	never smoked	0.0
5107	19723.0	Female	35.0	0.0	0.0	Yes	Self-employed	Rural	82.99	30.600000	never smoked	0.0
5108	37544.0	Male	51.0	0.0	0.0	Yes	Private	Rural	166.29	25.600000	formerly smoked	0.0
5109	44679.0	Female	44.0	0.0	0.0	Yes	Govt_job	Urban	85.28	26.200000	Unknown	0.0

5110 rows × 12 columns

In [10]:

```
df.head(20)
```

Out[10]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046.0	Male	67.0	0.0	1.0	Yes	Private	Urban	228.69	36.600000	formerly smoked	1.0
1	51676.0	Female	61.0	0.0	0.0	Yes	Self-employed	Rural	202.21	28.893237	never smoked	1.0
2	31112.0	Male	80.0	0.0	1.0	Yes	Private	Rural	105.92	32.500000	never smoked	1.0
3	60182.0	Female	49.0	0.0	0.0	Yes	Private	Urban	171.23	34.400000	smokes	1.0
4	1665.0	Female	79.0	1.0	0.0	Yes	Self-employed	Rural	174.12	24.000000	never smoked	1.0
5	56669.0	Male	81.0	0.0	0.0	Yes	Private	Urban	186.21	29.000000	formerly smoked	1.0
6	53882.0	Male	74.0	1.0	1.0	Yes	Private	Rural	70.09	27.400000	never smoked	1.0
7	10434.0	Female	69.0	0.0	0.0	No	Private	Urban	94.39	22.800000	never smoked	1.0
8	27419.0	Female	59.0	0.0	0.0	Yes	Private	Rural	76.15	28.893237	Unknown	1.0
9	60491.0	Female	78.0	0.0	0.0	Yes	Private	Urban	58.57	24.200000	Unknown	1.0
10	12109.0	Female	81.0	1.0	0.0	Yes	Private	Rural	80.43	29.700000	never smoked	1.0
11	12095.0	Female	61.0	0.0	1.0	Yes	Govt_job	Rural	120.46	36.800000	smokes	1.0
12	12175.0	Female	54.0	0.0	0.0	Yes	Private	Urban	104.51	27.300000	smokes	1.0
13	8213.0	Male	78.0	0.0	1.0	Yes	Private	Urban	219.84	28.893237	Unknown	1.0
14	5317.0	Female	79.0	0.0	1.0	Yes	Private	Urban	214.09	28.200000	never smoked	1.0
15	58202.0	Female	50.0	1.0	0.0	Yes	Self-employed	Rural	167.41	30.900000	never smoked	1.0
16	56112.0	Male	64.0	0.0	1.0	Yes	Private	Urban	191.61	37.500000	smokes	1.0
17	34120.0	Male	75.0	1.0	0.0	Yes	Private	Urban	221.29	25.800000	smokes	1.0
18	27458.0	Female	60.0	0.0	0.0	No	Private	Urban	89.22	37.800000	never smoked	1.0
19	25226.0	Male	57.0	0.0	1.0	No	Govt_job	Urban	217.08	28.893237	Unknown	1.0

In [11]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 5110 non-null   float64
 1   gender             5110 non-null   object 
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   float64
 4   heart_disease      5110 non-null   float64
 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                5110 non-null   float64
 10  smoking_status     5110 non-null   object 
 11  stroke             5110 non-null   float64
dtypes: float64(7), object(5)
memory usage: 519.0+ KB
```

Step 2:Handling Outliers

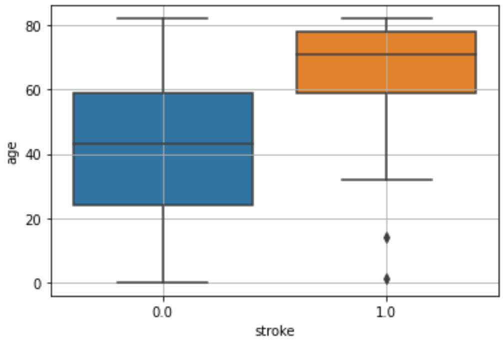
1.Feature & Response should be saperated from dataset

2.Feature and Response should be numeric in nature

3.Feature and Response should be in a proper shape & dimension

In [12]:

```
sns.boxplot(data=df,x='stroke',y='age')
plt.grid()
plt.show()
```



In [13]:

```
def getquan(colum):
    q1=df[colum].quantile(0.25)
    q3=df[colum].quantile(0.75)
    iqr=q3-q1
    uplim=q3+(1.5*iqr)
    lowlim=q1-(1.5*iqr)
    return uplim,lowlim
```

In [14]:

```
getquan("age")
```

Out[14]:

```
(115.0, -29.0)
```

In [15]:

```
out=df[((df.age>115.0)|(df.age<-29.0)&(df.stroke==0.0))]
out
```

Out[15]:

id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke

Here we can observe that there are not that much outliers and there is no need to remove the outliers also after applying the

the methods we came to this conclusion.

Step 3:Handling Skewness

In [16]:

```
from scipy.stats import skew
```

In [17]:

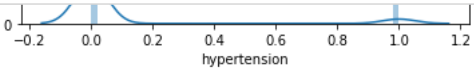
```
numdata=df.select_dtypes([int,float]).columns
numdata
```

Out[17]:

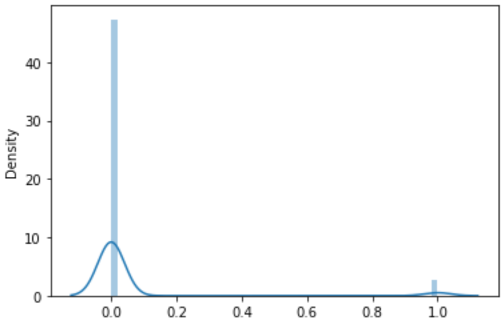
```
Index(['id', 'age', 'hypertension', 'heart_disease', 'avg_glucose_level',
       'bmi', 'stroke'],
      dtype='object')
```

In [18]:

```
for i in numdata:
    print(f"Skewness of {i} is {df[i].skew()}")
    plt.figure()
    sns.distplot(df[i])
    plt.show()
```




```
Skewness of heart_disease is 3.947243966661894
```



In [19]:

```
df.corr()["stroke"].sort_values()
```

Out[19]:

```
id                   0.006388
bmi                  0.038947
hypertension         0.127904
avg_glucose_level    0.131945
heart_disease        0.134914
age                  0.245257
stroke               1.000000
Name: stroke, dtype: float64
```

In [20]:

```
df.corr()["stroke"].sort_values()
```

Out[20]:

```
id                   0.006388
bmi                  0.038947
hypertension         0.127904
avg_glucose_level    0.131945
heart_disease        0.134914
age                  0.245257
stroke               1.000000
Name: stroke, dtype: float64
```

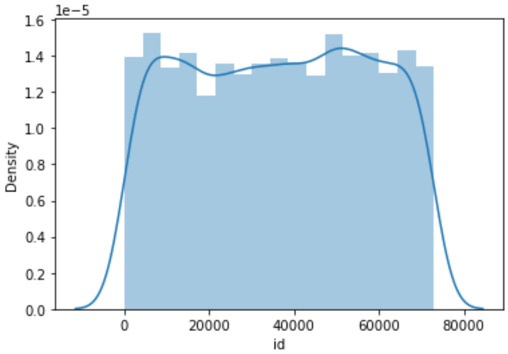
In [21]:

```
df["stroke"]=np.sqrt(df["stroke"])
df["bmi"]=np.log(df["bmi"])
df["avg_glucose_level"]=np.log(df["avg_glucose_level"])
df["heart_disease"]=np.sqrt(df["heart_disease"])
df["hypertension"]=np.sqrt(df["hypertension"])
```

In [22]:

```
for i in numdata:
    print(f"Skewness of {i} is {df[i].skew()}")
    plt.figure()
    sns.distplot(df[i])
    plt.show()
```

```
Skewness of id is -0.019912979190701046
```



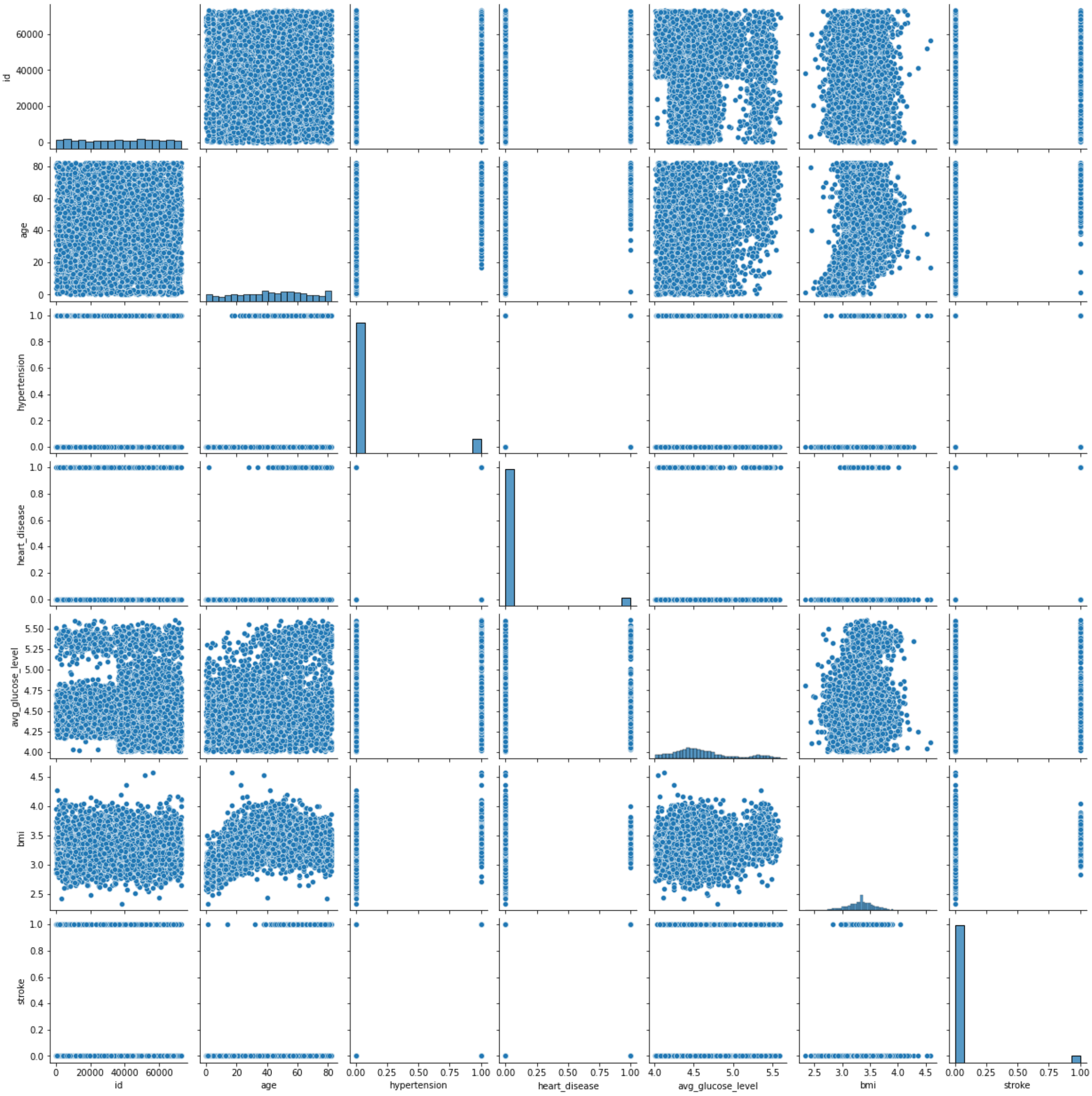

```
Skewness of age is -0.13705932259846944
```

There is not that much improvement after dealing with the skewness

Visualisation

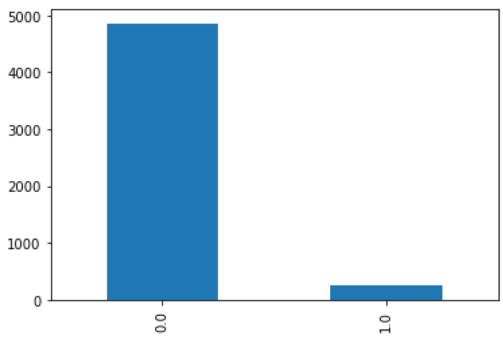
In [64]:

```
sns.pairplot(df)
plt.show()
```



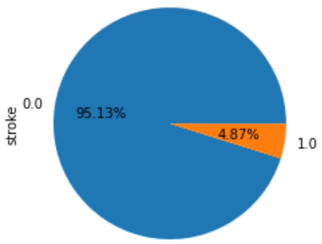
In [65]:

```
df["stroke"].value_counts().plot(kind="bar")
plt.show()
```



In [67]:

```
df["stroke"].value_counts().plot(kind="pie",autopct="%.2f%%")
plt.show()
```

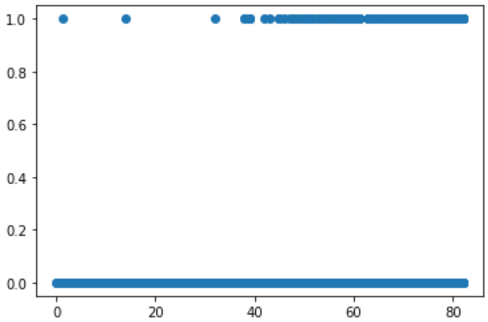


In [26]:

```
plt.scatter(df["age"],df["stroke"])
```

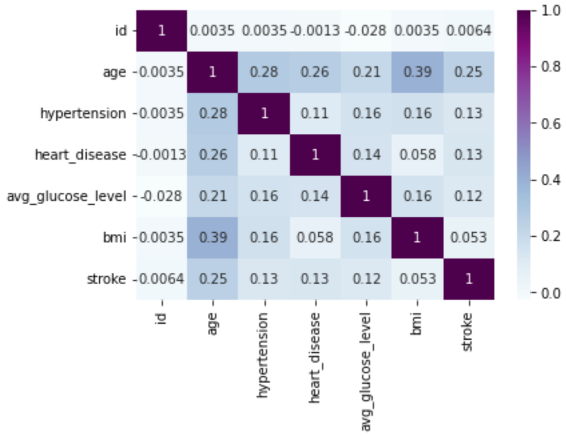
Out[26]:

```
<matplotlib.collections.PathCollection at 0x27e60a834f0>
```



In [27]:

```
sns.heatmap(df.corr(),annot=True,cmap="BuPu")
plt.show()
```



Seperating Features and Target

x-> Features

y->Target

In [28]:

```
x=df.iloc[:,:-1]
y=df.iloc[:,-1]
```

In [29]:

```
x
```

Out[29]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status
0	9046.0	Male	67.0	0.0	1.0	Yes	Private	Urban	5.432367	3.600048	formerly smoked
1	51676.0	Female	61.0	0.0	0.0	Yes	Self-employed	Rural	5.309307	3.363608	never smoked
2	31112.0	Male	80.0	0.0	1.0	Yes	Private	Rural	4.662684	3.481240	never smoked
3	60182.0	Female	49.0	0.0	0.0	Yes	Private	Urban	5.143008	3.538057	smokes
4	1665.0	Female	79.0	1.0	0.0	Yes	Self-employed	Rural	5.159745	3.178054	never smoked
...	...	...	...	...	...	...	...	...	...	...	...
5105	18234.0	Female	80.0	1.0	0.0	Yes	Private	Urban	4.427836	3.363608	never smoked
5106	44873.0	Female	81.0	0.0	0.0	Yes	Self-employed	Urban	4.829912	3.688879	never smoked
5107	19723.0	Female	35.0	0.0	0.0	Yes	Self-employed	Rural	4.418720	3.421000	never smoked
5108	37544.0	Male	51.0	0.0	0.0	Yes	Private	Rural	5.113733	3.242592	formerly smoked
5109	44679.0	Female	44.0	0.0	0.0	Yes	Govt_job	Urban	4.445940	3.265759	Unknown

5110 rows × 11 columns

In [30]:

```
y
```

Out[30]:

```
0       1.0
1       1.0
2       1.0
3       1.0
4       1.0
       ...
5105    0.0
5106    0.0
5107    0.0
5108    0.0
5109    0.0
Name: stroke, Length: 5110, dtype: float64
```

Encoding

In [31]:

```
from sklearn.preprocessing import OrdinalEncoder
```

In [32]:

```
oe=OrdinalEncoder()
```

In [33]:

```
oe.fit_transform(x[["gender","ever_married","work_type","Residence_type","smoking_status"]])
```

Out[33]:

```
array([[1., 1., 2., 1., 1.],
       [0., 1., 3., 0., 2.],
       [1., 1., 2., 0., 2.],
       ...,
       [0., 1., 3., 0., 2.],
       [1., 1., 2., 0., 1.],
       [0., 1., 0., 1., 0.]])
```

In [34]:

```
catcol=x.select_dtypes(object).columns
```

In [35]:

```
catcol
```

Out[35]:

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

In [36]:

```
x[catcol]=oe.fit_transform(x[catcol])
```

In [37]:

```
x
```

Out[37]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status
0	9046.0	1.0	67.0	0.0	1.0	1.0	2.0	1.0	5.432367	3.600048	1.0
1	51676.0	0.0	61.0	0.0	0.0	1.0	3.0	0.0	5.309307	3.363608	2.0
2	31112.0	1.0	80.0	0.0	1.0	1.0	2.0	0.0	4.662684	3.481240	2.0
3	60182.0	0.0	49.0	0.0	0.0	1.0	2.0	1.0	5.143008	3.538057	3.0
4	1665.0	0.0	79.0	1.0	0.0	1.0	3.0	0.0	5.159745	3.178054	2.0
...	...	...	...	...	...	...	...	...	...	...	...
5105	18234.0	0.0	80.0	1.0	0.0	1.0	2.0	1.0	4.427836	3.363608	2.0
5106	44873.0	0.0	81.0	0.0	0.0	1.0	3.0	1.0	4.829912	3.688879	2.0
5107	19723.0	0.0	35.0	0.0	0.0	1.0	3.0	0.0	4.418720	3.421000	2.0
5108	37544.0	1.0	51.0	0.0	0.0	1.0	2.0	0.0	5.113733	3.242592	1.0
5109	44679.0	0.0	44.0	0.0	0.0	1.0	0.0	1.0	4.445940	3.265759	0.0

5110 rows × 11 columns

Training my Model

In [38]:

```
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 [39]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
```

In [40]:

```
from sklearn.metrics import classification_report,accuracy_score
```

In [41]:

```
def mymodel(model):

    #Model Creation
    model.fit(xtrain,ytrain)
    ypred = model.predict(xtest)

    #Checkeing Bais and Variance

    train = model.score(xtrain,ytrain)
    test = model.score(xtest,ytest)

    print(f"Training Acuuracy:- {train}\n Testing Accuracy:- {test}")

    #Model Evaluation

    print(classification_report(ytest,ypred))
    return model
```

In [42]:

```
lg=mymodel(LogisticRegression())
```

```
Training Acuuracy:- 0.9535923958624546
 Testing Accuracy:- 0.9458577951728636
              precision    recall  f1-score   support

         0.0       0.95      1.00      0.97      1450
         1.0       0.00      0.00      0.00        83

    accuracy                           0.95      1533
   macro avg       0.47      0.50      0.49      1533
weighted avg       0.89      0.95      0.92      1533
```

In [43]:

```
sv=mymodel(SVC())
```

```
Training Acuuracy:- 0.9535923958624546
 Testing Accuracy:- 0.9458577951728636
              precision    recall  f1-score   support

         0.0       0.95      1.00      0.97      1450
         1.0       0.00      0.00      0.00        83

    accuracy                           0.95      1533
   macro avg       0.47      0.50      0.49      1533
weighted avg       0.89      0.95      0.92      1533
```

In [44]:

```
knn=mymodel(KNeighborsClassifier())
```

```
Training Acuuracy:- 0.9541515236231479
 Testing Accuracy:- 0.9465101108936725
              precision    recall  f1-score   support

         0.0       0.95      1.00      0.97      1450
         1.0       1.00      0.01      0.02        83

    accuracy                           0.95      1533
   macro avg       0.97      0.51      0.50      1533
weighted avg       0.95      0.95      0.92      1533
```

In [49]:

```
dt=mymodel(DecisionTreeClassifier())
```

```
Training Acuuracy:- 1.0
 Testing Accuracy:- 0.9099804305283757
              precision    recall  f1-score   support

         0.0       0.95      0.95      0.95      1450
         1.0       0.16      0.16      0.16        83

    accuracy                           0.91      1533
   macro avg       0.56      0.55      0.56      1533
weighted avg       0.91      0.91      0.91      1533
```

Let us check what is the accuracy of the dataset after scaling it.

In [ ]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
xtrain = sc.fit_transform(xtrain)
xtest = sc.transform(xtest)
```

In [46]:

```
lg=mymodel(LogisticRegression())
```

```
Training Acuuracy:- 0.9535923958624546
 Testing Accuracy:- 0.9458577951728636
              precision    recall  f1-score   support

         0.0       0.95      1.00      0.97      1450
         1.0       0.00      0.00      0.00        83

    accuracy                           0.95      1533
   macro avg       0.47      0.50      0.49      1533
weighted avg       0.89      0.95      0.92      1533
```

In [47]:

```
sv=mymodel(SVC())
```

```
Training Acuuracy:- 0.9535923958624546
 Testing Accuracy:- 0.9458577951728636
              precision    recall  f1-score   support

         0.0       0.95      1.00      0.97      1450
         1.0       0.00      0.00      0.00        83

    accuracy                           0.95      1533
   macro avg       0.47      0.50      0.49      1533
weighted avg       0.89      0.95      0.92      1533
```

In [48]:

```
knn=mymodel(KNeighborsClassifier())
```

```
Training Acuuracy:- 0.9541515236231479
 Testing Accuracy:- 0.9465101108936725
              precision    recall  f1-score   support

         0.0       0.95      1.00      0.97      1450
         1.0       1.00      0.01      0.02        83

    accuracy                           0.95      1533
   macro avg       0.97      0.51      0.50      1533
weighted avg       0.95      0.95      0.92      1533
```

In [50]:

```
dt=mymodel(DecisionTreeClassifier())
```

```
Training Acuuracy:- 1.0
 Testing Accuracy:- 0.9119373776908023
              precision    recall  f1-score   support

         0.0       0.95      0.96      0.95      1450
         1.0       0.17      0.16      0.16        83

    accuracy                           0.91      1533
   macro avg       0.56      0.56      0.56      1533
weighted avg       0.91      0.91      0.91      1533
```

So here after applying Decision Tree we can observe that there is a little bit improvement in Decision Tree Classifier model and looking at other algorithms there is no change in the accuracy after and before scaling .

Hyperparameter Tuning:Grid Search Cv

In [51]:

```
list(range(1,100,5))
```

Out[51]:

```
[1, 6, 11, 16, 21, 26, 31, 36, 41, 46, 51, 56, 61, 66, 71, 76, 81, 86, 91, 96]
```

In [52]:

```
parameter = {

            "criterion":["gini","entropy"],
            "max_depth":list(range(1,50,5)),
            "min_samples_leaf":list(range(1,50,5))

}
```

In [53]:

```
from sklearn.model_selection import GridSearchCV

grid = GridSearchCV(DecisionTreeClassifier(),parameter,verbose=2)
grid.fit(xtrain,ytrain)
```

```
[CV] END ..criterion=gini, max_depth=46, min_samples_leaf=41; total time=   0.0s
[CV] END ..criterion=gini, max_depth=46, min_samples_leaf=41; total time=   0.0s
[CV] END ..criterion=gini, max_depth=46, min_samples_leaf=41; total time=   0.0s
[CV] END ..criterion=gini, max_depth=46, min_samples_leaf=41; total time=   0.0s
[CV] END ..criterion=gini, max_depth=46, min_samples_leaf=41; total time=   0.0s
[CV] END ..criterion=gini, max_depth=46, min_samples_leaf=46; total time=   0.0s
[CV] END ..criterion=gini, max_depth=46, min_samples_leaf=46; total time=   0.0s
[CV] END ..criterion=gini, max_depth=46, min_samples_leaf=46; total time=   0.0s
[CV] END ..criterion=gini, max_depth=46, min_samples_leaf=46; total time=   0.0s
[CV] END ..criterion=gini, max_depth=46, min_samples_leaf=46; total time=   0.0s
[CV] END .criterion=entropy, max_depth=1, min_samples_leaf=1; total time=   0.0s
[CV] END .criterion=entropy, max_depth=1, min_samples_leaf=1; total time=   0.0s
[CV] END .criterion=entropy, max_depth=1, min_samples_leaf=1; total time=   0.0s
[CV] END .criterion=entropy, max_depth=1, min_samples_leaf=1; total time=   0.0s
[CV] END .criterion=entropy, max_depth=1, min_samples_leaf=1; total time=   0.0s
[CV] END .criterion=entropy, max_depth=1, min_samples_leaf=6; total time=   0.0s
[CV] END .criterion=entropy, max_depth=1, min_samples_leaf=6; total time=   0.0s
[CV] END .criterion=entropy, max_depth=1, min_samples_leaf=6; total time=   0.0s
[CV] END .criterion=entropy, max_depth=1, min_samples_leaf=6; total time=   0.0s
```

In [60]:

```
grid.best_params_
```

Out[60]:

```
{'criterion': 'gini', 'max_depth': 1, 'min_samples_leaf': 1}
```

In [61]:

```
grid.best_score_
```

Out[61]:

```
0.9535926085088097
```

In [62]:

```
grid.best_estimator_
```

Out[62]:

```
DecisionTreeClassifier(max_depth=1)
```

In [63]:

```
dt= mymodel(grid.best_estimator_)
```

```
Training Acuuracy:- 0.9535923958624546
 Testing Accuracy:- 0.9458577951728636
              precision    recall  f1-score   support

         0.0       0.95      1.00      0.97      1450
         1.0       0.00      0.00      0.00        83

    accuracy                           0.95      1533
   macro avg       0.47      0.50      0.49      1533
weighted avg       0.89      0.95      0.92      1533
```

So here after applying Gridsearch CV we can see that our model is giving a good accuracy score and training ,testing score is also good.

Conclusion: We can observe that in the given dataset after applying all the models we can conclude that KNN is giving the best Result and after training the model we can say that it is giving pretty much accurate result and my model is working good.

In [ ]: