```
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
```

Import all require module

In [1]:

```
#import all require module
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
#import csv file in dataframe
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_ty
0	9046	Male	67.0	0	1	Yes	Private	Urt
1	51676	Female	61.0	0	0	Yes	Self-employed	Ru
2	31112	Male	80.0	0	1	Yes	Private	Ru
3	60182	Female	49.0	0	0	Yes	Private	Urt
4	1665	Female	79.0	1	0	Yes	Self-employed	Ru
...	...	...	...	...	...	...	...	
5105	18234	Female	80.0	1	0	Yes	Private	Urt
5106	44873	Female	81.0	0	0	Yes	Self-employed	Urt
5107	19723	Female	35.0	0	0	Yes	Self-employed	Ru
5108	37544	Male	51.0	0	0	Yes	Private	Ru
5109	44679	Female	44.0	0	0	Yes	Govt_job	Urt

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

In [6]:

```
#set id in df
df.insert(0, 'ID', range(1, 1 + len(df)))
df.set_index("ID",inplace=True)
```

In [7]:

```
#measure the nan(null) values in df
df.isnull().sum()
```

Out[7]:

```
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]:

```
#percentage of nan(null) values in df
nullper=(df.isnull().sum()/len(df))*100
print(nullper)
```

```
gender               0.000000
age                  0.000000
hypertension         0.000000
heart_disease        0.000000
ever_married         0.000000
work_type            0.000000
Residence_type       0.000000
avg_glucose_level    0.000000
bmi                  3.933464
smoking_status       0.000000
stroke               0.000000
dtype: float64
```

In [9]:

```
# missing value treatment in bmi
df['bmi']=df['bmi'].fillna(df['bmi'].mean())
```

In [10]:

```
df
```

Out[10]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg
ID								
1	Male	67.0	0	1	Yes	Private	Urban	
2	Female	61.0	0	0	Yes	Self-employed	Rural	
3	Male	80.0	0	1	Yes	Private	Rural	
4	Female	49.0	0	0	Yes	Private	Urban	
5	Female	79.0	1	0	Yes	Self-employed	Rural	
...	...	...	...	...	...	...	...	
5106	Female	80.0	1	0	Yes	Private	Urban	
5107	Female	81.0	0	0	Yes	Self-employed	Urban	
5108	Female	35.0	0	0	Yes	Self-employed	Rural	
5109	Male	51.0	0	0	Yes	Private	Rural	
5110	Female	44.0	0	0	Yes	Govt_job	Urban	

5110 rows × 11 columns

In [11]:

```
# we need diff analysis to make analysis process faster during EDA process we will seperate
# our entier dataframe into two part 1) df_num 2) df_cat
# df_num = int,float
# df_cat = object
```

In [12]:

```
df_num=df.select_dtypes(['int64','float64'])
```

In [13]:

```
df_num.columns
```

Out[13]:

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

In [14]:

```
df_cat=df.select_dtypes(['object'])
```

In [15]:

```
df_cat.columns
```

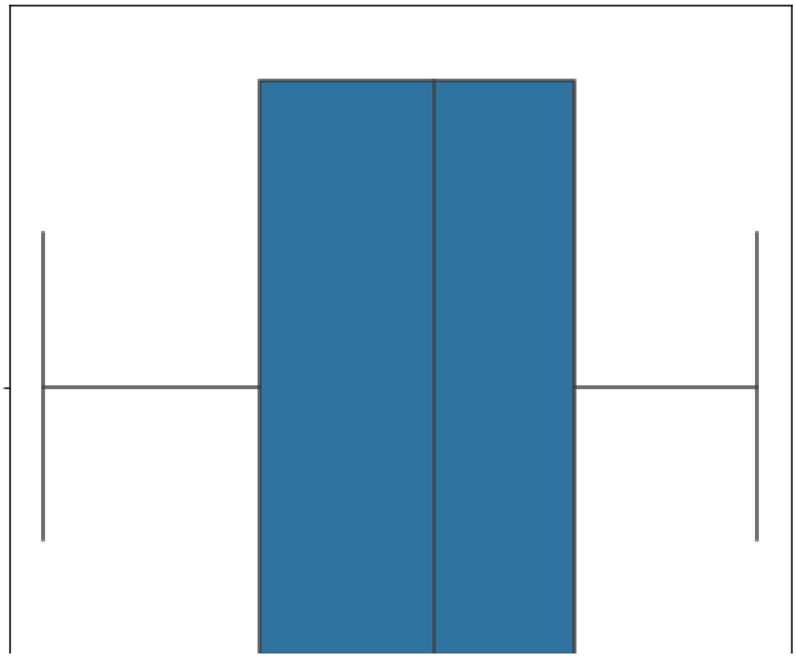
Out[15]:

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

Outlier Analysis on numeric values

In [16]:

```
for i in df_num:
    plt.figure(figsize=(7,7))
    sns.boxplot(data=df_num,x=i,whis=3)
    # upper whisker = q3+1.5*IQR
    # lower whisker = q1 - 1.5*IQR
    # boxplot will calculate upper whisker and lower whisker by it's own and the nit will p
    plt.show()
```



Outlier Treatments

In [17]:

```
df_num.shape
```

Out[17]:

```
(5110, 6)
```

In [18]:

```
# avg_glucose_level Column Outlier Treatment
q1=np.quantile(df_num["avg_glucose_level"],0.25)
q3=np.quantile(df_num["avg_glucose_level"],0.75)
iqr=q3-q1
print("Quantile1 for avg_glucose_level is => ",q1)
print("Quantile3 for avg_glucose_level is => ",q3)
print("IQR for avg_glucose_level column is => ",iqr)
#as we know we have higher extream values so no need to calculate lower whisker will only g
up_whs=q3+3*iqr
print("upper whisker with 3 penalty is => ",up_whs)
# accept all those records which come below given whisker values
df_num=df_num[df_num["avg_glucose_level"]<up_whs]
df_num.shape
```

```
Quantile1 for avg_glucose_level is =>  77.24499999999999
Quantile3 for avg_glucose_level is =>  114.09
IQR for avg_glucose_level column is =>  36.845000000000001
upper whisker with 3 penalty is =>  224.62500000000006
```

Out[18]:

```
(4944, 6)
```

In [19]:

```
# bmi Column Outlier Treatment
q1=np.quantile(df_num["bmi"],0.25)
q3=np.quantile(df_num["bmi"],0.75)
iqr=q3-q1
print("Quantile1 for bmi is => ",q1)
print("Quantile3 for bmi is => ",q3)
print("IQR for bmi column is => ",iqr)
#as we know we have higher extream values so no need to calculate lower whisker will only g
up_whs=q3+3*iqr
print("upper whisker with 3 penalty is => ",up_whs)
# accept all those records which come below given whisker values
df_num=df_num[df_num["bmi"]<up_whs]
df_num.shape
```

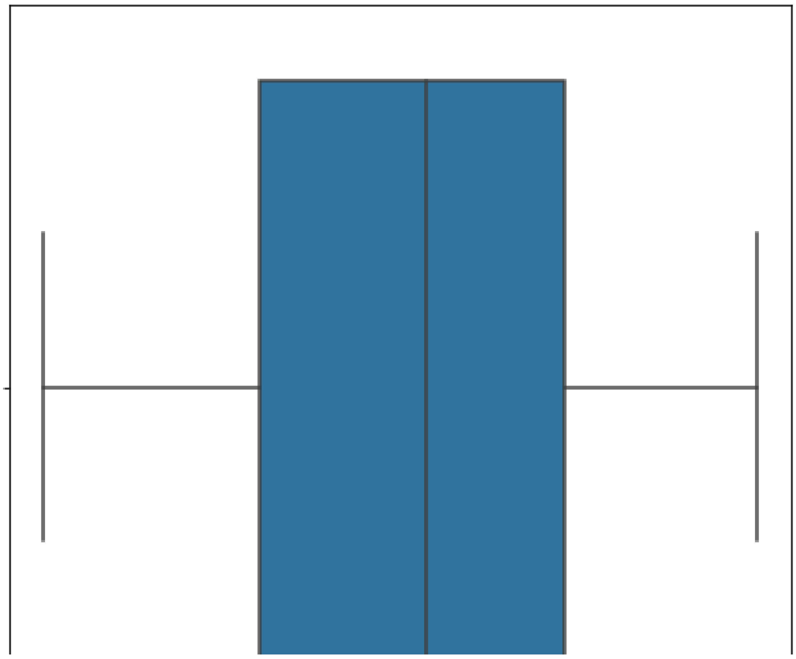
```
Quantile1 for bmi is =>  23.6
Quantile3 for bmi is =>  32.6
IQR for bmi column is =>  9.0
upper whisker with 3 penalty is =>  59.6
```

Out[19]:

```
(4930, 6)
```

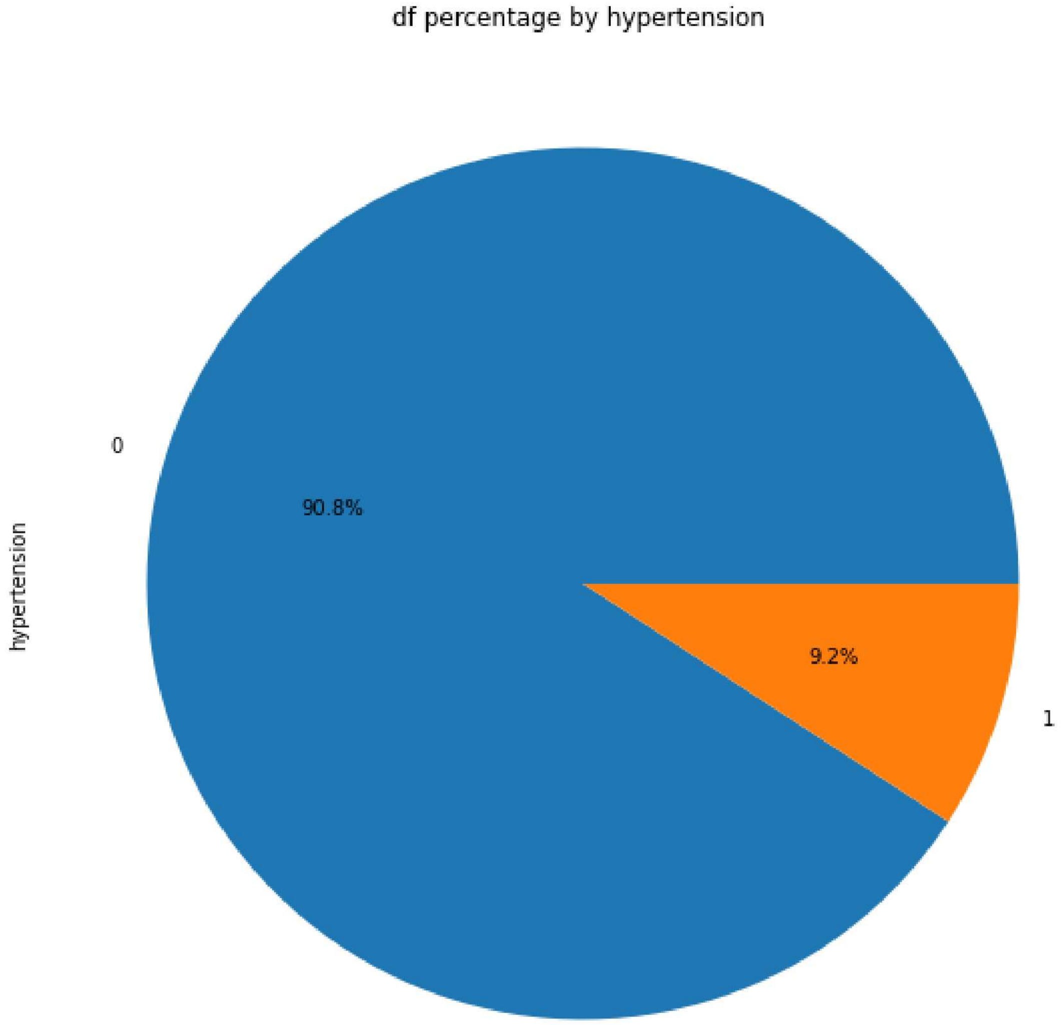
In [20]:

```
for i in df_num:
    plt.figure(figsize=(7,7))
    sns.boxplot(data=df_num,x=i,whis=3)
    # upper whisker = q3+1.5*IQR
    # lower whisker = q1 - 1.5*IQR
    # boxplot will calculate upper whisker and lower whisker by it's own and the nit will p
    plt.show()
```



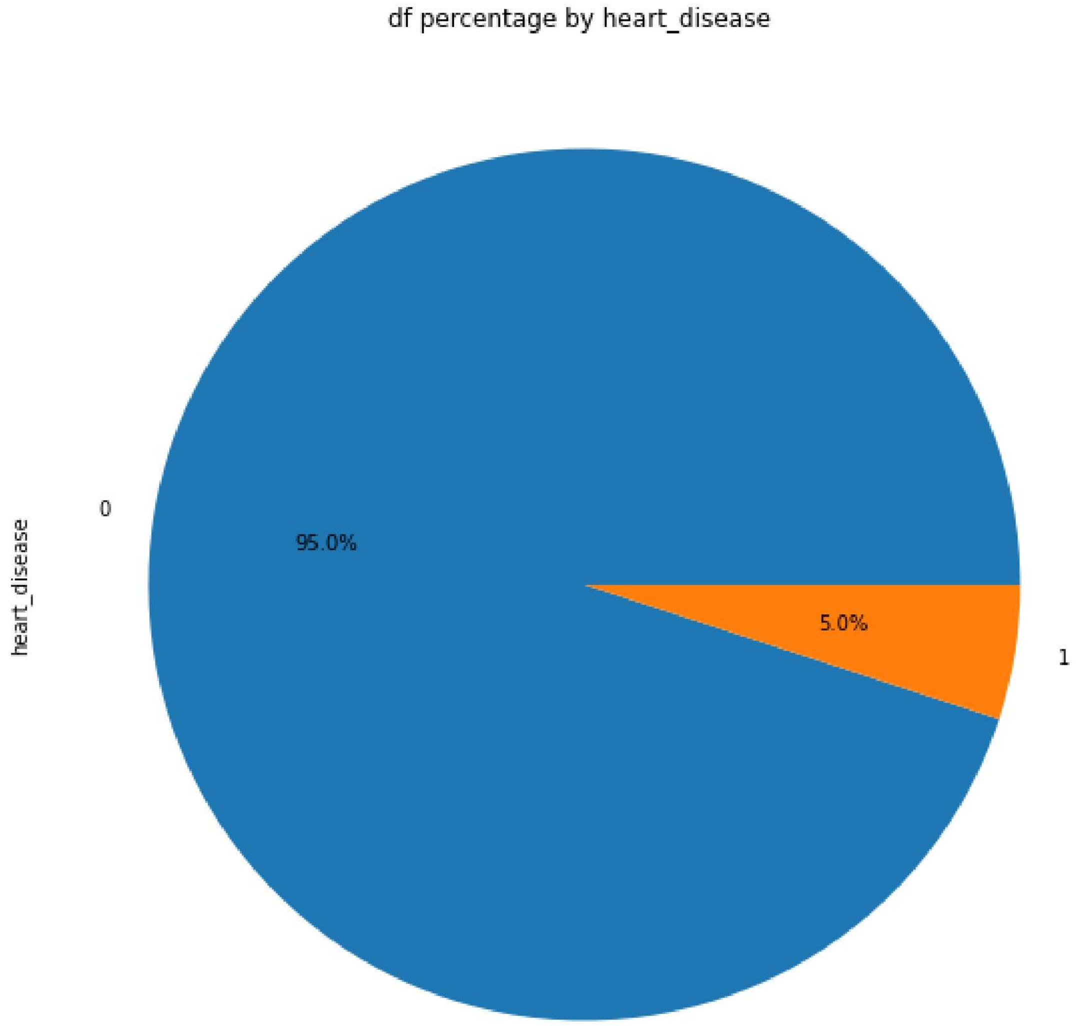
In [21]:

```
# graphical analysis on categorical column Method data share percentage
# using pie plot
plt.figure(figsize=(10,10))
df_num['hypertension'].value_counts().plot.pie(autopct="%1.1f%%")
plt.title("df percentage by hypertension ")
plt.show()
#hypertension: 0 if the patient doesn't have hypertension, 1 if the patient has hypertensio
```



In [22]:

```
# graphical analysis on categorical column Method data share percentage
# using pie plot
plt.figure(figsize=(10,10))
df_num['heart_disease'].value_counts().plot.pie(autopct="%1.1f%%")
plt.title("df percentage by heart_disease ")
plt.show()
#0 if the patient doesn't have any heart diseases, 1 if the patient has a heart disease
```



categorical data analysis

In [23]:

```
df_cat
```

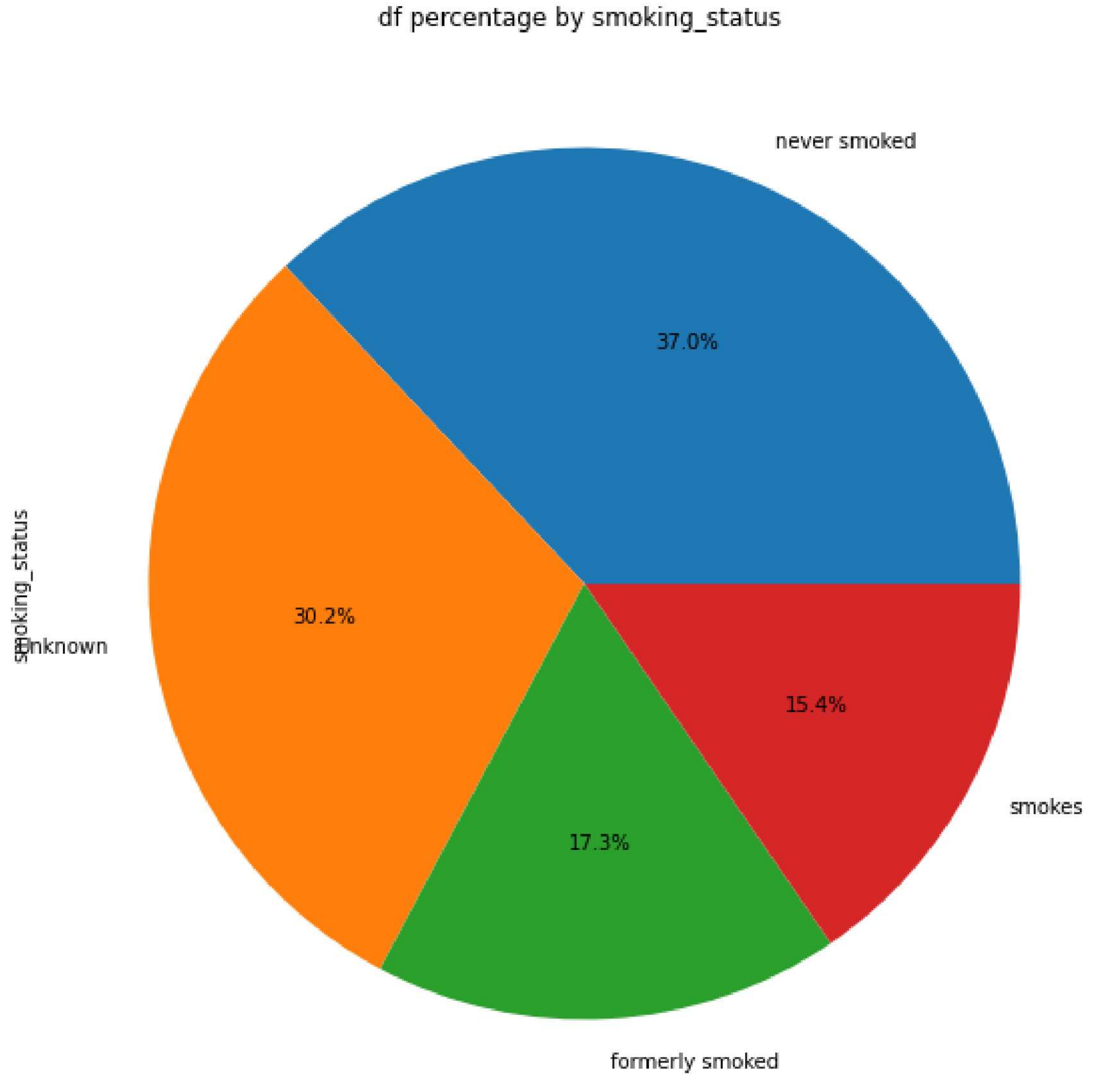
Out[23]:

	gender	ever_married	work_type	Residence_type	smoking_status
ID					
1	Male	Yes	Private	Urban	formerly smoked
2	Female	Yes	Self-employed	Rural	never smoked
3	Male	Yes	Private	Rural	never smoked
4	Female	Yes	Private	Urban	smokes
5	Female	Yes	Self-employed	Rural	never smoked
...	...	...	...	...	...
5106	Female	Yes	Private	Urban	never smoked
5107	Female	Yes	Self-employed	Urban	never smoked
5108	Female	Yes	Self-employed	Rural	never smoked
5109	Male	Yes	Private	Rural	formerly smoked
5110	Female	Yes	Govt_job	Urban	Unknown

5110 rows × 5 columns

In [24]:

```
# graphical analysis on categorical column Method data share percentage
# using pie plot
plt.figure(figsize=(10,10))
df_cat['smoking_status'].value_counts().plot.pie(autopct="%1.1f%%")
plt.title("df percentage by smoking_status ")
plt.show()
```



Label Encoding categorical data

In [25]:

```
from sklearn.preprocessing import LabelEncoder
```

In [26]:

```
le=LabelEncoder()
for col in df_cat:
    df_cat[col]=le.fit_transform(df_cat[col])
```

In [27]:

```
df_cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5110 entries, 1 to 5110
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   gender          5110 non-null   int32
 1   ever_married    5110 non-null   int32
 2   work_type       5110 non-null   int32
 3   Residence_type  5110 non-null   int32
 4   smoking_status  5110 non-null   int32
dtypes: int32(5)
memory usage: 139.7 KB
```

In [28]:

```
#merge the df_cat and df_num to all together
df_new=pd.merge(df_num,df_cat,on="ID")
```

In [29]:

```
df_new
```

Out[29]:

ID	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke	gender	ever_ma
2	61.0	0	0	202.21	28.893237	1	0	
3	80.0	0	1	105.92	32.500000	1	1	
4	49.0	0	0	171.23	34.400000	1	0	
5	79.0	1	0	174.12	24.000000	1	0	
6	81.0	0	0	186.21	29.000000	1	1	
...	...	...	...	...	...	...	...	
5106	80.0	1	0	83.75	28.893237	0	0	
5107	81.0	0	0	125.20	40.000000	0	0	
5108	35.0	0	0	82.99	30.600000	0	0	
5109	51.0	0	0	166.29	25.600000	0	1	
5110	44.0	0	0	85.28	26.200000	0	0	

4930 rows × 11 columns

In [30]:

```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4930 entries, 2 to 5110
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   age                4930 non-null   float64
 1   hypertension       4930 non-null   int64  
 2   heart_disease      4930 non-null   int64  
 3   avg_glucose_level  4930 non-null   float64
 4   bmi                4930 non-null   float64
 5   stroke             4930 non-null   int64  
 6   gender             4930 non-null   int32  
 7   ever_married       4930 non-null   int32  
 8   work_type          4930 non-null   int32  
 9   Residence_type     4930 non-null   int32  
 10  smoking_status     4930 non-null   int32  
dtypes: float64(3), int32(5), int64(3)
memory usage: 365.9 KB
```

In [31]:

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

In [32]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=1,test_size=0.3)
```

Random forest

In [33]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
```

In [34]:

```
rf=RandomForestClassifier(n_estimators=10,          #n_estimators, The number of trees in
                          max_features=5,           #The number of features to consider w
                          random_state=1)
rf.fit(x_train,y_train)
y_pred=rf.predict(x_test)
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      1.00      0.97      1407
           1       0.33      0.03      0.05        72

    accuracy                           0.95      1479
   macro avg       0.64      0.51      0.51      1479
weighted avg       0.92      0.95      0.93      1479
```

boosting techniques

adaboost

In [35]:

```
# algorithm based ensemple ML
from sklearn.ensemble import AdaBoostClassifier
```

In [36]:

```
from sklearn.metrics import classification_report
```

In [37]:

```
ada=AdaBoostClassifier()
ada.fit(x_train,y_train)
y_pred=ada.predict(x_test)
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      1.00      0.97      1407
           1       0.25      0.03      0.05        72

    accuracy                           0.95      1479
   macro avg       0.60      0.51      0.51      1479
weighted avg       0.92      0.95      0.93      1479
```

DL

In [38]:

```
import tensorflow as tf
from sklearn.metrics import roc_auc_score
from sklearn.preprocessing import StandardScaler
```

In [39]:

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

In [40]:

```
ss=StandardScaler()
x = ss.fit_transform(x)
```

In [41]:

```
x.shape[1]
```

Out[41]:

```
10
```

In [42]:

```
x_train,x_test, y_train, y_test = train_test_split(x, y, test_size=0.3)
```

In [43]:

```
model = tf.keras.Sequential([tf.keras.layers.Dense(2, activation="relu",input_shape=(x.shap
                            tf.keras.layers.Dense(3, activation="relu"),
                            tf.keras.layers.Dense(1, activation="sigmoid")]
                           )
```

In [44]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense (Dense)                (None, 2)                 22        
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 9         
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 4         
=================================================================
Total params: 35
Trainable params: 35
Non-trainable params: 0
_________________________________________________________________
```

In [45]:

```
model.compile(optimizer="sgd", loss="binary_crossentropy")
```

In [46]:

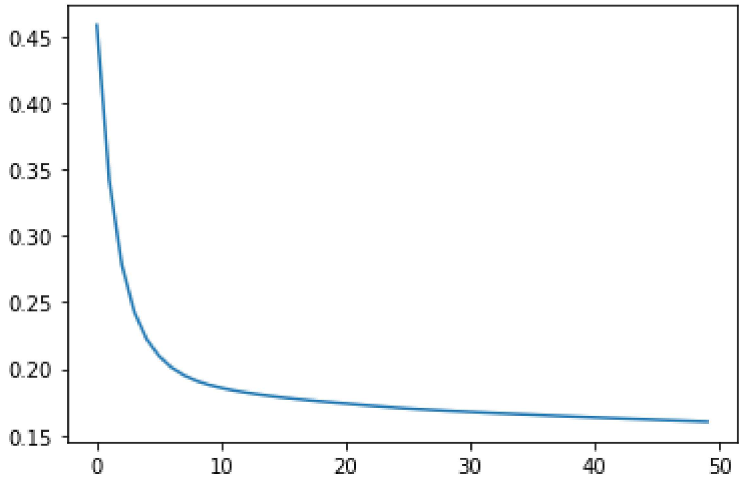
```
trained_model = model.fit(x_train, y_train, epochs=50, batch_size=50)
```

```
Epoch 1/50
70/70 [==============================] - 1s 1ms/step - loss: 0.4958
Epoch 2/50
70/70 [==============================] - 0s 1ms/step - loss: 0.3634
Epoch 3/50
70/70 [==============================] - 0s 1ms/step - loss: 0.2829
Epoch 4/50
70/70 [==============================] - 0s 984us/step - loss: 0.2332
Epoch 5/50
70/70 [==============================] - 0s 926us/step - loss: 0.2380
Epoch 6/50
70/70 [==============================] - 0s 984us/step - loss: 0.2119
Epoch 7/50
70/70 [==============================] - 0s 811us/step - loss: 0.2000
Epoch 8/50
70/70 [==============================] - 0s 868us/step - loss: 0.1913
Epoch 9/50
70/70 [==============================] - 0s 984us/step - loss: 0.2002
Epoch 10/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1956
Epoch 11/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1865
Epoch 12/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1947
Epoch 13/50
70/70 [==============================] - 0s 984us/step - loss: 0.1837
Epoch 14/50
70/70 [==============================] - 0s 926us/step - loss: 0.2082
Epoch 15/50
70/70 [==============================] - 0s 984us/step - loss: 0.1863
Epoch 16/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1839
Epoch 17/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1659
Epoch 18/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1680
Epoch 19/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1657
Epoch 20/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1777
Epoch 21/50
70/70 [==============================] - 0s 984us/step - loss: 0.1724
Epoch 22/50
70/70 [==============================] - 0s 868us/step - loss: 0.1586
Epoch 23/50
70/70 [==============================] - 0s 926us/step - loss: 0.1751
Epoch 24/50
70/70 [==============================] - 0s 926us/step - loss: 0.1665
Epoch 25/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1685
Epoch 26/50
70/70 [==============================] - 0s 926us/step - loss: 0.1672
Epoch 27/50
70/70 [==============================] - 0s 868us/step - loss: 0.1696
Epoch 28/50
70/70 [==============================] - 0s 984us/step - loss: 0.1734
```

```
Epoch 29/50
70/70 [==============================] - 0s 926us/step - loss: 0.1686
Epoch 30/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1682
Epoch 31/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1688
Epoch 32/50
70/70 [==============================] - 0s 926us/step - loss: 0.1687
Epoch 33/50
70/70 [==============================] - 0s 984us/step - loss: 0.1677
Epoch 34/50
70/70 [==============================] - 0s 868us/step - loss: 0.1607
Epoch 35/50
70/70 [==============================] - 0s 810us/step - loss: 0.1701
Epoch 36/50
70/70 [==============================] - 0s 926us/step - loss: 0.1606
Epoch 37/50
70/70 [==============================] - 0s 926us/step - loss: 0.1711
Epoch 38/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1618
Epoch 39/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1566
Epoch 40/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1537
Epoch 41/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1767
Epoch 42/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1623
Epoch 43/50
70/70 [==============================] - 0s 1ms/step - loss: 0.1577
Epoch 44/50
70/70 [==============================] - 0s 984us/step - loss: 0.1607
Epoch 45/50
70/70 [==============================] - 0s 926us/step - loss: 0.1683
Epoch 46/50
70/70 [==============================] - 0s 926us/step - loss: 0.1595
Epoch 47/50
70/70 [==============================] - 0s 926us/step - loss: 0.1624
Epoch 48/50
70/70 [==============================] - 0s 868us/step - loss: 0.1584
Epoch 49/50
70/70 [==============================] - 0s 926us/step - loss: 0.1501
Epoch 50/50
70/70 [==============================] - 0s 984us/step - loss: 0.1686
```

In [47]:

```
plt.plot(trained_model.history['loss'])
plt.show()
```



In [48]:

```
y_hat = model.predict(x_test)
```

In [49]:

```
y_hat
```

Out[49]:

```
array([[0.04863954],
       [0.10777244],
       [0.06539109],
       ...,
       [0.10777244],
       [0.10777244],
       [0.01348683]], dtype=float32)
```

In [50]:

```
y_hat1 = np.where(y_hat >= 0.5, 1, 0) #where value is o.5 than greater then shows 1 else 0
```

In [51]:

```
y_hat1.flatten()
```

Out[51]:

```
array([0, 0, 0, ..., 0, 0, 0])
```

In [52]:

```
from sklearn.metrics import classification_report
```

In [53]:

```
print(classification_report(y_test, y_hat1))
```

```
              precision    recall  f1-score   support

           0       0.95      1.00      0.98      1409
           1       0.00      0.00      0.00        70

    accuracy                           0.95      1479
   macro avg       0.48      0.50      0.49      1479
weighted avg       0.91      0.95      0.93      1479
```

In [54]:

```
roc_auc_score(y_test, y_hat1)
```

Out[54]:

```
0.5
```

In [ ]:

```

```