```
In [1]:
         import pandas as pd
         import numpy as np
         import sklearn as sk
In [2]: dataset=pd.read_csv(r'C:\Users\HP\Downloads\Brain Stroke.csv')
In [3]:
         dataset
Out[3]:
                gender
                         age
                              hypertension heart_disease ever_married work_type
                                                                                  Residence_type avg_gli
              0
                                         0
                   Male
                        67.0
                                                       1
                                                                   Yes
                                                                           Private
                                                                                           Urban
              1
                   Male
                        80.0
                                         0
                                                       1
                                                                   Yes
                                                                           Private
                                                                                            Rural
                Female
                        49.0
                                         0
                                                       0
                                                                   Yes
                                                                           Private
                                                                                            Urban
                                                                             Self-
                Female 79.0
                                                       0
                                                                                            Rural
              3
                                         1
                                                                   Yes
                                                                         employed
              4
                   Male
                        81.0
                                         0
                                                       0
                                                                   Yes
                                                                           Private
                                                                                            Urban
             ...
                     ...
                                                      ...
                                                                    ...
           4976
                   Male
                        41.0
                                         0
                                                       0
                                                                   No
                                                                           Private
                                                                                            Rural
           4977
                   Male
                        40.0
                                         0
                                                       0
                                                                   Yes
                                                                           Private
                                                                                            Urban
           4978 Female
                        45.0
                                                       0
                                                                   Yes
                                                                         Govt_job
                                                                                            Rural
           4979
                   Male
                        40.0
                                         0
                                                       0
                                                                   Yes
                                                                           Private
                                                                                            Rural
                                                       0
           4980 Female 80.0
                                                                   Yes
                                                                           Private
                                                                                            Urban
         4981 rows × 11 columns
         dataset.isnull().sum()
In [4]:
Out[4]: gender
                                  0
                                  0
         age
         hypertension
                                  0
         heart_disease
                                  0
         ever married
                                  0
         work_type
                                  0
         Residence_type
                                  0
         avg_glucose_level
                                  0
         bmi
                                  0
         smoking_status
                                  0
                                  0
         stroke
```

dtype: int64

```
In [5]: dataset.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4981 entries, 0 to 4980
Data columns (total 11 columns):

#	Column	Non-Null Count	Dtype		
0	gender	4981 non-null	object		
1	age	4981 non-null	float64		
2	hypertension	4981 non-null	int64		
3	heart_disease	4981 non-null	int64		
4	ever_married	4981 non-null	object		
5	work_type	4981 non-null	object		
6	Residence_type	4981 non-null	object		
7	<pre>avg_glucose_level</pre>	4981 non-null	float64		
8	bmi	4981 non-null	float64		
9	<pre>smoking_status</pre>	4981 non-null	object		
10	stroke	4981 non-null	int64		
dtypes, £1eet(4/2) int(4/2) object(5)					

dtypes: float64(3), int64(3), object(5)

memory usage: 428.2+ KB

```
In [6]: from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
dataset["gender"]=le.fit_transform(dataset["gender"])
dataset["ever_married"]=le.fit_transform(dataset["ever_married"])
dataset["work_type"]=le.fit_transform(dataset["work_type"])
dataset["Residence_type"]=le.fit_transform(dataset["Residence_type"])
dataset["smoking_status"]=le.fit_transform(dataset["smoking_status"])
```

In [7]: dataset

Out[7]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glı
	0 1	67.0	0	1	1	1	1	
	1 1	80.0	0	1	1	1	0	
	2 0	49.0	0	0	1	1	1	
	3 0	79.0	1	0	1	2	0	
	4 1	81.0	0	0	1	1	1	
	··							
497	6 1	41.0	0	0	0	1	0	
497	7 1	40.0	0	0	1	1	1	
497	8 0	45.0	1	0	1	0	0	
497	9 1	40.0	0	0	1	1	0	
498	o 0	80.0	1	0	1	1	1	

4981 rows × 11 columns

```
In [8]: x=dataset.iloc[:,:-1].values #slicing independent and depedent variables.
         y=dataset.iloc[:,-1].values
         х,у
 Out[8]: (array([[
                           67. ,
                                    0., ..., 228.69, 36.6,
                                                                     ٦,
                    1.
                           80.
                                    0.,..., 105.92, 32.5,
                                                                 2.
                                                                     ],
                 0.
                           49.
                                       , ..., 171.23, 34.4,
                                                                     ٦,
                                    0.
                 . . . ,
                    0.
                           45.
                                    1. , ...,
                                                95.02, 31.8,
                                                                 3.
                                                                     ],
                                                83.94, 30. ,
                           40.,
                    1.
                                    0. , ...,
                                                                    ٦,
                           80.
                                    1.
                                                83.75,
                                                        29.1 ,
                                                                 2.
                                                                     ]]),
          array([1, 1, 1, ..., 0, 0, 0], dtype=int64))
 In [9]: dataset["stroke"].value_counts() #Checking Balancing data or not of the depender
 Out[9]: 0
              4733
               248
         Name: stroke, dtype: int64
In [10]:
         #balanceing the data
         from imblearn.over sampling import RandomOverSampler
         ab=RandomOverSampler()
         x data, y data =ab.fit resample(x,y)
In [11]: !pip install -U imbalanced-learn
         Requirement already up-to-date: imbalanced-learn in c:\users\hp\anaconda3\lib\s
         ite-packages (0.9.1)
         Requirement already satisfied, skipping upgrade: numpy>=1.17.3 in c:\users\hp\a
         naconda3\lib\site-packages (from imbalanced-learn) (1.23.5)
         Requirement already satisfied, skipping upgrade: joblib>=1.0.0 in c:\users\hp\a
         naconda3\lib\site-packages (from imbalanced-learn) (1.2.0)
         Requirement already satisfied, skipping upgrade: threadpoolctl>=2.0.0 in c:\use
         rs\hp\anaconda3\lib\site-packages (from imbalanced-learn) (2.1.0)
         Requirement already satisfied, skipping upgrade: scikit-learn>=1.1.0 in c:\user
         s\hp\anaconda3\lib\site-packages (from imbalanced-learn) (1.1.3)
         Requirement already satisfied, skipping upgrade: scipy>=1.3.2 in c:\users\hp\an
         aconda3\lib\site-packages (from imbalanced-learn) (1.5.2)
In [12]: from collections import Counter
```

```
localhost:8888/notebooks/brain stroke.ipynb
```

print(Counter(y_data))

Counter({1: 4733, 0: 4733})

```
In [13]: dataset.corr()
```

Out[13]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Res
gender	1.000000	-0.026538	0.021485	0.086476	-0.028971	0.065784	
age	-0.026538	1.000000	0.278120	0.264852	0.677137	-0.415935	
hypertension	0.021485	0.278120	1.000000	0.111974	0.164534	-0.061618	
heart_disease	0.086476	0.264852	0.111974	1.000000	0.114765	-0.036943	
ever_married	- 0.028971	0.677137	0.164534	0.114765	1.000000	-0.406439	
work_type	0.065784	-0.415935	-0.061618	-0.036943	-0.406439	1.000000	
Residence_type	- 0.004301	0.017155	-0.004755	0.002125	0.008191	-0.003524	
avg_glucose_level	0.055796	0.236763	0.170028	0.166847	0.150724	-0.059658	
bmi	-0.012093	0.373703	0.158762	0.060926	0.371690	-0.382418	
smoking_status	- 0.062666	0.265623	0.110045	0.048093	0.262384	-0.356738	
stroke	0.008870	0.246478	0.131965	0.134610	0.108398	-0.041835	

```
In [14]:
         # Normalization
         from sklearn.preprocessing import MinMaxScaler
         scaler=MinMaxScaler()
         x data1=scaler.fit transform(x data)
         x_data1
Out[14]: array([[1.
                            , 0.81689453, 0.
                                                     , ..., 0.80126489, 0.64756447,
                  0.33333333],
                 [1.
                            , 0.97558594, 0.
                                                     , ..., 0.23451205, 0.53008596,
                  0.66666667],
                            , 0.59716797, 0.
                 [0.
                                                     , ..., 0.53600776, 0.58452722,
                 1.
                            ],
                 . . . ,
                            , 0.82910156, 0.
                 [0.
                                                     , ..., 0.1245499 , 0.37535817,
                 0.
                            , 0.93896484, 0.
                 [0.
                                                     , ..., 0.8145139 , 0.65616046,
                 0.66666667],
                                                     , ..., 0.06190564, 0.29226361,
                 [1.
                            , 0.97558594, 0.
                  1.
                            ]])
In [15]: x_data1.max() # Max value after normalization
Out[15]: 1.0
In [16]: x_data1.min()
                          # Min value after normalization
Out[16]: 0.0
```

```
In [17]:
         #Standardization
         from sklearn.preprocessing import StandardScaler
         ss=StandardScaler()
         x data1=ss.fit transform(x)
         x data1
Out[17]: array([[ 1.18390850e+00,  1.04058433e+00, -3.26185770e-01, ...,
                  2.72341090e+00, 1.19323816e+00, -3.53933192e-01],
                [ 1.18390850e+00, 1.61427033e+00, -3.26185770e-01, ...,
                 -5.22766599e-04, 5.89389611e-01, 5.78839946e-01],
                [-8.44659868e-01, 2.46249882e-01, -3.26185770e-01, ...,
                  1.44852918e+00, 8.69221866e-01, 1.51161308e+00],
                [-8.44659868e-01, 6.97311148e-02, 3.06573766e+00, ...,
                 -2.42364234e-01, 4.86293516e-01, 1.51161308e+00],
                [ 1.18390850e+00, -1.50917344e-01, -3.26185770e-01, ...,
                 -4.88199415e-01, 2.21189274e-01, 1.51161308e+00],
                [-8.44659868e-01, 1.61427033e+00, 3.06573766e+00, ...,
                 -4.92415000e-01, 8.86371531e-02, 5.78839946e-01]])
In [18]: x_data1.max()
                          # Max value after Standardization
Out[18]: 4.136753228405977
In [19]: x data1.min() # Min value after Standardization
Out[19]: -2.1352928787181042
In [20]: # Spliting data into training testing
         from sklearn.model_selection import train_test_split
         x_train, x_test, y_train, y_test = train_test_split(x_data,y_data,test_size=0.30)
In [21]: print(Counter(y train))
         Counter({1: 3332, 0: 3294})
In [22]: print(Counter(y test))
         Counter({0: 1439, 1: 1401})
```

```
In [23]: #model fitting algorithum
         # 1. Logistic Regression
         from sklearn.linear_model import LogisticRegression
         11=LogisticRegression()
         lr=l1.fit(x_train,y_train)
         lr
         C:\Users\HP\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:444:
         ConvergenceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
         learn.org/stable/modules/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear model.html#logistic-regressi
         on (https://scikit-learn.org/stable/modules/linear model.html#logistic-regressi
         on)
           n_iter_i = _check_optimize_result(
Out[23]:
          ▼ LogisticRegression
          LogisticRegression()
In [24]: y_pred=l1.predict(x_test)
         y pred
Out[24]: array([0, 1, 1, ..., 0, 1, 0], dtype=int64)
In [25]: from sklearn.metrics import confusion matrix
         print(confusion_matrix(y_pred,y_test))
         [[1061 262]
          [ 378 1139]]
In [26]: from sklearn.metrics import accuracy score
In [27]: |print(accuracy_score(y_pred,y_test)*100)
         77.46478873239437
In [28]: # 2. support vector machine
         from sklearn.svm import SVC
         s1=SVC(kernel='linear', random_state=5)
         an=s1.fit(x_train,y_train)
Out[28]:
                           dvc
          SVC(kernel='linear', random_state=5)
```

```
In [29]: y_pred1=s1.predict(x_test)
         y_pred1
Out[29]: array([0, 1, 1, ..., 0, 1, 0], dtype=int64)
In [30]: | an1=accuracy_score(y_test,y_pred)*100
Out[30]: 77.46478873239437
In [31]: | an2=confusion_matrix(y_test,y_pred1)
Out[31]: array([[1030, 409],
                [ 240, 1161]], dtype=int64)
In [32]: #3. K-nearrest neighbors
         from sklearn.neighbors import KNeighborsClassifier
         k1=KNeighborsClassifier(n_neighbors=5,metric="euclidean",p=1)
         ks=k1.fit(x_train,y_train)
         ks
Out[32]:
                       KNeighborsClassifier
         KNeighborsClassifier(metric='euclidean', p=1)
In [33]: y pred2=k1.predict(x test)
         y pred2
Out[33]: array([1, 1, 1, ..., 0, 0, 1], dtype=int64)
In [34]:
         ks1=accuracy_score(y_test,y_pred)*100
Out[34]: 77.46478873239437
In [35]: ks2=confusion_matrix(y_test,y_pred1)
         ks2
Out[35]: array([[1030, 409],
                [ 240, 1161]], dtype=int64)
```

```
In [36]: #4.Random forest
         from sklearn.ensemble import RandomForestClassifier
         r1=RandomForestClassifier(n_estimators=5,criterion="entropy",max_depth=3,random_<
         rs=r1.fit(x_train,y_train)
         rs
Out[36]:
                                    RandomForestClassifier
          RandomForestClassifier(criterion='en|tropy', max_depth=3, n_estimators=5,
                                 random_state=10)
In [37]: y_pred3=r1.predict(x_test)
         y_pred3
Out[37]: array([1, 1, 1, ..., 0, 1, 0], dtype=int64)
In [38]: rs1=accuracy_score(y_test,y_pred)*100
         rs1
Out[38]: 77.46478873239437
In [39]: | rs2=confusion_matrix(y_test,y_pred1)
Out[39]: array([[1030, 409],
                [ 240, 1161]], dtype=int64)
In [40]: #5.Navie baysien
         from sklearn.naive_bayes import GaussianNB
         n1=GaussianNB()
         nb=n1.fit(x_train,y_train)
         nb
Out[40]:
          ▼ Gaus$ianNB
          GaussianNB()
In [41]: y_pred4=n1.predict(x_test)
         y_pred4
Out[41]: array([0, 1, 1, ..., 0, 1, 0], dtype=int64)
In [42]: |nb1=accuracy_score(y_test,y_pred)*100
         nb1
Out[42]: 77.46478873239437
In [43]: | nb2=confusion_matrix(y_test,y_pred1)
         nb2
Out[43]: array([[1030, 409],
                [ 240, 1161]], dtype=int64)
```

```
In [44]: #6. Decision tree
         from sklearn.tree import DecisionTreeClassifier
         d1=DecisionTreeClassifier(random_state=5,max_depth=3)
         dt=d1.fit(x train,y train)
         dt
Out[44]:
                         DecisionTreeClassifier
         DecisionTreeClassifier(max depth=3, random state=5)
In [45]: y_pred5=d1.predict(x_test)
         y_pred5
Out[45]: array([1, 1, 1, ..., 0, 1, 0], dtype=int64)
In [46]: dt1=accuracy_score(y_test,y_pred)*100
Out[46]: 77.46478873239437
In [47]: | dt2=confusion_matrix(y_test,y_pred1)
Out[47]: array([[1030, 409],
                [ 240, 1161]], dtype=int64)
In [48]: #
              Cross Validation Technique
         # 1) Leave one out cross validation technique
         # 2) K Fold Cross Validation
         # 3) Stratified K Fold Cross Validation
In [49]: #2) K Fold Cross validation
         from sklearn.model_selection import KFold
         from sklearn.model selection import cross val score
         from sklearn.model_selection import cross_val_predict
         kf= KFold(n_splits=5, random_state=13, shuffle=True)
         kf.get n splits(x data1,y data)
         print(kf)
         KFold(n_splits=5, random_state=13, shuffle=True)
```

```
In [50]: for train data, test data in kf.split(x data):
              x_train,x_test=x_data[train_data],x_data[test_data]
              y_train,y_test=y_data[train_data],y_data[test data]
              print("check y_test balance", Counter(y_test))
              scores=cross_val_score(dt,x_train,y_train,cv=kf)
              y_pred6=cross_val_predict(dt,x_test,y_test)
              print(y_pred6)
              print(scores)
              k1=accuracy_score(y_test,y_pred6)*100
              print(k1, "Accuracy score on testing set")
          check y_test balance Counter({1: 970, 0: 924})
          [1 \ 1 \ 1 \ \dots \ 0 \ 1 \ 1]
          [0.78679868 0.78547855 0.78467635 0.75825627 0.77344782]
          77.61351636747624 Accuracy score on testing set
          check y_test balance Counter({0: 998, 1: 895})
          [1 \ 1 \ 1 \ \dots \ 1 \ 1 \ 0]
```

```
[1 1 1 ... 0 1 1]
[0.78679868 0.78547855 0.78467635 0.75825627 0.77344782]
77.61351636747624 Accuracy score on testing set check y_test balance Counter({0: 998, 1: 895})
[1 1 1 ... 1 1 0]
[0.79207921 0.77227723 0.78283828 0.79260238 0.7681638 ]
77.33755942947703 Accuracy score on testing set check y_test balance Counter({0: 951, 1: 942})
[1 1 1 ... 1 1 0]
[0.76435644 0.76633663 0.79207921 0.7661823 0.77410832]
77.54886423666139 Accuracy score on testing set check y_test balance Counter({1: 974, 0: 919})
[1 1 1 ... 1 1 1]
[0.77953795 0.79207921 0.78481848 0.77741083 0.74900925]
79.55625990491284 Accuracy score on testing set check y_test balance Counter({1: 952, 0: 941})
[1 1 1 ... 1 1 1]
[0.75709571 0.77689769 0.77425743 0.78071334 0.75759577]
77.17908082408876 Accuracy score on testing set
```

```
In [51]: #3). stratified k-fold
```

```
In [52]: from sklearn.model_selection import StratifiedKFold
    skf=StratifiedKFold(n_splits=5, shuffle=True, random_state=10)
    skf.get_n_splits(x_data,y_data)
    print(skf)
```

StratifiedKFold(n_splits=5, random_state=10, shuffle=True)

```
In [53]: | for train_data,test_data in kf.split(x_data,y_data):
              x_train1,x_test1=x_data[train_data],x_data[test_data]
              y_train1,y_test1=y_data[train_data],y_data[test data]
              print("check y_test balance", Counter(y_test1))
              scores1=cross_val_score(dt,x_train1,y_train1,cv=kf)*100
              y_pred7=cross_val_predict(dt,x_test1,y_test1)
              print(y_pred7)
              print(scores1)
              print(np.mean(scores1))
              cb=accuracy_score(y_test,y_pred6)*100
              print(cb, "Accuracy score on testing set")
          check y_test balance Counter({1: 970, 0: 924})
          [1 \ 1 \ 1 \ \dots \ 0 \ 1 \ 1]
          [78.67986799 78.54785479 78.4676354 75.82562748 77.34478203]
          77.7731535372824
          77.17908082408876 Accuracy score on testing set
          check y_test balance Counter({0: 998, 1: 895})
          [1 \ 1 \ 1 \ \dots \ 1 \ 1 \ 0]
          [79.20792079 77.22772277 78.28382838 79.26023778 76.81638045]
          78.15921803540989
          77.17908082408876 Accuracy score on testing set
          check y test balance Counter({0: 951, 1: 942})
          [1 \ 1 \ 1 \ \dots \ 1 \ 1 \ 0]
          [76.43564356 76.63366337 79.20792079 76.61822985 77.41083223]
          77.26125796199172
          77.17908082408876 Accuracy score on testing set
          check y_test balance Counter({1: 974, 0: 919})
          [1 \ 1 \ 1 \ \dots \ 1 \ 1 \ 1]
          [77.95379538 79.20792079 78.48184818 77.74108322 74.9009247 ]
          77.65711445649188
          77.17908082408876 Accuracy score on testing set
          check y_test balance Counter({1: 952, 0: 941})
          [1 \ 1 \ 1 \ \dots \ 1 \ 1 \ 1]
          [75.70957096 77.68976898 77.42574257 78.07133421 75.75957728]
          76.93119880019707
          77.17908082408876 Accuracy score on testing set
 In [ ]:
 In [ ]:
 In [ ]:
```