Brain Tumor Classification

In [3]:
```
pwd
```
Out[3]: 'E:\\DataScience\\MachineLearning\\Brain_Tumor_Data'

In [4]:
```
path='E:\\DataScience\\MachineLearning\\Brain_Tumor_Data'
```

In [5]:
```
import os
os.listdir(path)
```
Out[5]:
```
['.ipynb_checkpoints',
 'archive.zip',
 'Brain-Tumor-Classification.ipynb',
 'data.csv']
```

In [6]:
```
#importing lib
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('darkgrid')
import plotly.express as px
from wordcloud import WordCloud
from scipy import signal

#to supress warning
import warnings
warnings.filterwarnings('ignore')


# setting up the chart size and background
plt.rcParams['figure.figsize'] = (16, 8)
plt.style.use('fivethirtyeight')
```

In [7]:
```
df = pd.read_csv(path+"\\data.csv")
```

In [8]:
```
df.head(10)
```
Out[8]:

	Unnamed: 0	X53416	M83670	X90908	M97496	X90908.1	U37019	R48602	T96548	X64559	...	H87456	R64130	H11125.1	U22055
0	0	70	-81	25	10	22	113	36	163	9	...	75	5	68	138
1	1	108	-30	-7	60	0	24	8	113	-3	...	186	6	60	93
2	2	75	-1	5	48	6	34	27	35	-1	...	186	225	94	62
3	3	871	4	14	78	-6	85	65	227	19	...	77	6	78	30
4	4	-92	-34	14	19	11	-6	27	-8	9	...	87	303	204	81
5	5	21	-13	5	11	-18	78	4	143	14	...	51	3	131	38
6	6	225	118	-5	175	-40	108	54	272	32	...	64	-3	142	55
7	7	-346	-35	37	42	39	18	14	28	34	...	84	-5	13	102
8	8	-378	31	-29	105	-54	19	-4	11	16	...	87	-4	110	25
9	9	475	-79	20	41	10	65	-13	225	17	...	115	-4	95	47

10 rows × 7466 columns

In [9]:
```
df.shape
```
Out[9]: (36, 7466)

In [10]:
```
df.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36 entries, 0 to 35
Columns: 7466 entries, Unnamed: 0 to y
dtypes: int64(7465), object(1)
memory usage: 2.1+ MB
```

In [11]:
```
df.columns
```
Out[11]:
```
Index(['Unnamed: 0', 'X53416', 'M83670', 'X90908', 'M97496', 'X90908.1',
       'U37019', 'R48602', 'T96548', 'X64559',
       ...
       'H87456', 'R64130', 'H11125.1', 'U22055', 'L22524', 'M13699.1',
       'X54489', 'T55008', 'M10065.2', 'y'],
      dtype='object', length=7466)
```

In [12]:
```
df.describe()
```
Out[12]:

	Unnamed: 0	X53416	M83670	X90908	M97496	X90908.1	U37019	R48602	T96548	X64559	...	D
count	36.000000	36.000000	36.000000	36.000000	36.000000	36.000000	36.000000	36.000000	36.000000	36.000000	...	36.0
mean	17.500000	378.750000	177.305556	128.027778	568.305556	93.555556	366.833333	140.166667	644.194444	73.444444	...	31.7
std	10.535654	648.716067	243.494655	787.935802	637.451928	557.527370	427.166645	171.443202	685.514231	88.504219	...	50.0
min	0.000000	-694.000000	-117.000000	-50.000000	8.000000	-54.000000	-6.000000	-18.000000	-8.000000	-8.000000	...	-21.0
25%	8.750000	-95.750000	-31.000000	-13.250000	47.250000	-7.000000	27.250000	17.750000	33.250000	8.250000	...	1.5
50%	17.500000	194.500000	117.000000	-4.500000	293.500000	3.000000	110.500000	37.500000	333.500000	37.500000	...	10.0
75%	26.250000	721.750000	330.500000	14.000000	1079.250000	10.250000	675.000000	268.500000	1185.250000	107.750000	...	48.0
max	35.000000	1815.000000	718.000000	4723.000000	2261.000000	3344.000000	1354.000000	718.000000	2203.000000	357.000000	...	156.0

8 rows × 7465 columns

In [13]:
```
df['y'].value_counts()
```
Out[13]:
```
Normal    18
tumor     18
Name: y, dtype: int64
```

In [14]:
```
df.tail(5)
```
Out[14]:

	Unnamed: 0	X53416	M83670	X90908	M97496	X90908.1	U37019	R48602	T96548	X64559	...	H87456	R64130	H11125.1	U22055
31	31	488	564	-29	1303	-9	1236	265	2203	41	...	16	0	109	21
32	32	164	330	-13	721	12	504	154	1381	78	...	-18	1	-1484	-4
33	33	1282	116	-4	542	0	1070	344	1903	42	...	5	3	128	25
34	34	68	718	-50	1816	-28	251	38	598	73	...	47	-2	190	3
35	35	928	332	4	412	0	681	267	1132	357	...	9	1	67	19

5 rows × 7466 columns

In [15]:
```
df.drop('Unnamed: 0', axis=1,inplace=True)
```

In [16]:
```
df.head()
```
Out[16]:

	X53416	M83670	X90908	M97496	X90908.1	U37019	R48602	T96548	X64559	T55741	...	H87456	R64130	H11125.1	U22055
0	70	-81	25	10	22	113	36	163	9	25	...	75	5	68	138
1	108	-30	-7	60	0	24	8	113	-3	9	...	186	6	60	93
2	75	-1	5	48	6	34	27	35	-1	4	...	186	225	94	62
3	871	4	14	78	-6	85	65	227	19	22	...	77	6	78	30
4	-92	-34	14	19	11	-6	27	-8	9	-5	...	87	303	204	81

5 rows × 7465 columns

Binaries Target Column

In [17]:
```
target =pd.get_dummies(df['y'],dummy_na=True)
```

In [18]:
```
target
```
Out[18]:

	Normal	tumor	NaN
0	0	1	0
1	0	1	0
2	0	1	0
3	0	1	0
4	0	1	0
5	0	1	0
6	0	1	0
7	0	1	0
8	0	1	0
9	0	1	0
10	0	1	0
11	0	1	0
12	0	1	0
13	0	1	0
14	0	1	0
15	0	1	0
16	0	1	0
17	0	1	0
18	1	0	0
19	1	0	0
20	1	0	0
21	1	0	0
22	1	0	0
23	1	0	0
24	1	0	0
25	1	0	0
26	1	0	0
27	1	0	0
28	1	0	0
29	1	0	0
30	1	0	0
31	1	0	0
32	1	0	0
33	1	0	0
34	1	0	0
35	1	0	0

In [19]:
```
target = target.iloc[:,1]
```

In [20]:
```
target
```
Out[20]:
```
0     1
1     1
2     1
3     1
4     1
5     1
6     1
7     1
8     1
9     1
10    1
11    1
12    1
13    1
14    1
15    1
16    1
17    1
18    0
19    0
20    0
21    0
22    0
23    0
24    0
25    0
26    0
27    0
28    0
29    0
30    0
31    0
32    0
33    0
34    0
35    0
Name: tumor, dtype: uint8
```

In [21]:
```
df = pd.concat([df,target],axis=1)
```

In [22]:
```
df.head()
```
Out[22]:

	X53416	M83670	X90908	M97496	X90908.1	U37019	R48602	T96548	X64559	T55741	...	R64130	H11125.1	U22055	L22524
0	70	-81	25	10	22	113	36	163	9	25	...	5	68	138	53
1	108	-30	-7	60	0	24	8	113	-3	9	...	6	60	93	140
2	75	-1	5	48	6	34	27	35	-1	4	...	225	94	62	39
3	871	4	14	78	-6	85	65	227	19	22	...	6	78	30	87
4	-92	-34	14	19	11	-6	27	-8	9	-5	...	303	204	81	105

5 rows × 7466 columns

In [23]:
```
df.drop('y',axis=1,inplace=True)
```

In [24]:
```
df.head(3)
```
Out[24]:

	X53416	M83670	X90908	M97496	X90908.1	U37019	R48602	T96548	X64559	T55741	...	H87456	R64130	H11125.1	U22055
0	70	-81	25	10	22	113	36	163	9	25	...	75	5	68	138
1	108	-30	-7	60	0	24	8	113	-3	9	...	186	6	60	93
2	75	-1	5	48	6	34	27	35	-1	4	...	186	225	94	62

3 rows × 7465 columns

Feature_Engineering

In [25]:
```
#importing feauture_selection from sklearn
# stastistical fuction --- chi
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2 ,f_classif
```

In [26]:
```
# X - independent variable , y - dependent varibale
X = df.iloc[:,:-1]
y = df.iloc[:,-1]
```

In [27]:
```
X.shape
```
Out[27]: (36, 7464)

In [28]:
```
X.head()
```
Out[28]:

	X53416	M83670	X90908	M97496	X90908.1	U37019	R48602	T96548	X64559	T55741	...	D14657	H87456	R64130	H11125.1
0	70	-81	25	10	22	113	36	163	9	25	...	44	75	5	68
1	108	-30	-7	60	0	24	8	113	-3	9	...	110	186	6	60
2	75	-1	5	48	6	34	27	35	-1	4	...	98	186	225	94
3	871	4	14	78	-6	85	65	227	19	22	...	54	77	6	78
4	-92	-34	14	19	11	-6	27	-8	9	-5	...	142	87	303	204

5 rows × 7464 columns

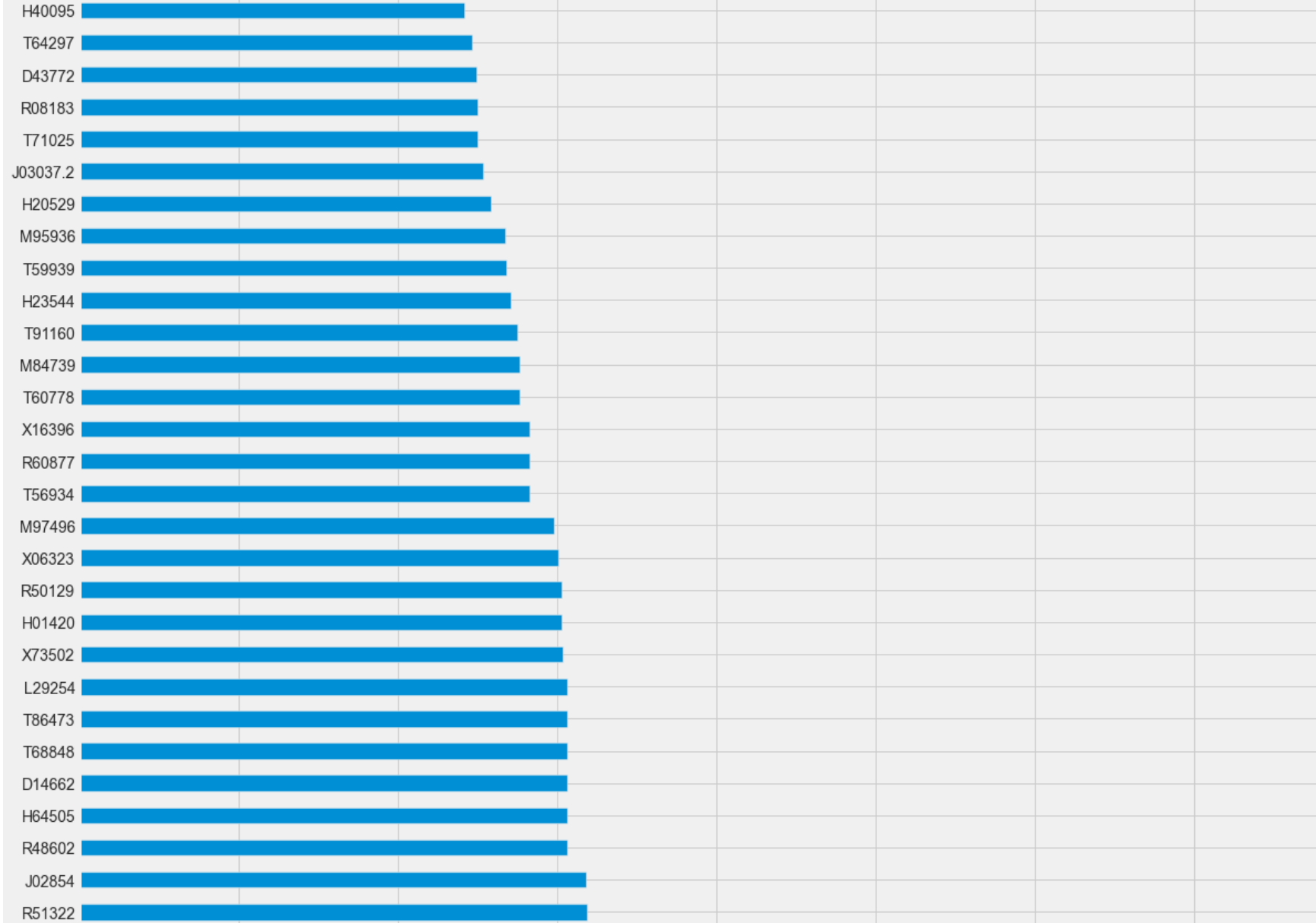
In [29]:
```
# k=50 : selecting top=50 rows values  which are highly co-related to taget
# using f_classif function
fs_f =SelectKBest(f_classif ,k=50)
X_f_classif = fs_f.fit_transform(X,y)
```

In [30]:
```
#X_f_classif Selected
dfscores = pd.DataFrame(fs_f.scores_)
dfcolumns =pd.DataFrame(X.columns)
featureScores = pd.concat([dfcolumns,dfscores],axis=1)
#naming the dataframe columns
featureScores.columns = ['Specs','Score']
print(featureScores.nlargest(50,'Score'))
```
```
          Specs      Score
7450     M77836  84.507552
1        M83670  81.238841
7        T96548  73.278478
67       U17077  72.741454
102      H06524  71.839985
35       J02854  69.898215
3        M97496  69.160545
106      T64297  66.327772
141      U14631  64.502637
110      M36634  64.430439
86       M12272  63.058184
137    Z49269.1  60.598889
7416     T51961  60.146450
7398     R61502  59.253926
7298     M26697  58.832810
71       X73502  58.037545
105      T67077  55.845284
14       H57136  55.372992
62       H43887  55.196710
7415     R88575  54.416065
117      T60155  54.099347
33       M95787  54.000241
167    Z49269.2  53.875574
7444     R08183  52.900725
7325     X12671  52.034783
7397     M22382  51.593770
5        U37019  51.455706
7360     R71676  51.057209
111      X12496  50.182784
2572     M80244  50.044666
85       T71025  49.420960
12       M95936  49.298914
7359     T52362  48.958963
7382     H40095  48.861731
7263     X70326  48.600413
39       M84526  48.554626
206      Z31695  48.452208
30       M63391  48.396879
123      Z49269  47.938445
40       T76971  47.741425
43       R99208  47.623957
31       M63603  47.571114
7417     L03840  47.112439
57     M76378.1  45.669761
74       T51913  45.604381
60     M76378.2  45.400463
7219     D63874  45.088360
7421     H65842  44.336720
7391     H09351  43.574908
182      R46753  43.449759
```

In [31]:
```
from sklearn.ensemble import ExtraTreesClassifier
import matplotlib.pyplot as plt
model = ExtraTreesClassifier()

#calling fit function
model.fit(X,y)
print(model.feature_importances_) #use inbuilt class feature_importances of tree based classifiers
```
```
[0.         0.00098765 0.         ... 0.0044     0.         0.        ]
```

In [32]:
```
#plot graph of feature importances for better visualization
plt.figure(figsize=(18,25))
feat_importances = pd.Series(model.feature_importances_, index=X.columns)
feat_importances.nlargest(50).plot(kind='barh')
plt.show()
```



In [33]:
```
lst =df.columns
lst
```
Out[33]:
```
Index(['X53416', 'M83670', 'X90908', 'M97496', 'X90908.1', 'U37019', 'R48602',
       'T96548', 'X64559', 'T55741',
       ...
       'H87456', 'R64130', 'H11125.1', 'U22055', 'L22524', 'M13699.1',
       'X54489', 'T55008', 'M10065.2', 'tumor'],
      dtype='object', length=7465)
```

In [34]:
```
lst_f =featureScores.nlargest(50,'Score')
lst_f=lst_f['Specs']
lst_f = list(lst_f)
lst_f
```
Out[34]:
```
['M77836',
 'M83670',
 'T96548',
 'U17077',
 'H06524',
 'J02854',
 'M97496',
 'T64297',
 'U14631',
 'M36634',
 'M12272',
 'Z49269.1',
 'T51961',
 'R61502',
 'M26697',
 'X73502',
 'T67077',
 'H57136',
 'H43887',
 'R88575',
 'T60155',
 'M95787',
 'Z49269.2',
 'R08183',
 'X12671',
 'M22382',
 'U37019',
 'R71676',
 'X12496',
 'M80244',
 'T71025',
 'M95936',
 'T52362',
 'H40095',
 'X70326',
 'M84526',
 'Z31695',
 'M63391',
 'Z49269',
 'T76971',
 'R99208',
 'M63603',
 'L03840',
 'M76378.1',
 'T51913',
 'M76378.2',
 'D63874',
 'H65842',
 'H09351',
 'R46753']
```

In [38]:
```
df_new = df[['M77836',
 'M83670','T96548','U17077','H06524','J02854','M97496',
 'T64297','U14631','M36634','M12272','Z49269.1','T51961','R61502','M26697','X73502','T67077',
 'H57136','H43887','R88575','T60155','M95787','Z49269.2','R08183','X12671','M22382','U37019','R71676','X12496',
 'T71025','M95936','T52362','H40095','X70326','M84526','Z31695','M63391','Z49269','T76971','R99208','M63603','I
 'M76378.1','T51913','M76378.2','D63874','H65842','H09351','R46753','tumor']]
```

In [39]:
```
df_new
```
Out[39]:

	M77836	M83670	T96548	U17077	H06524	J02854	M97496	T64297	U14631	M36634	...	M63603	L03840	M76378.1	T51913
0	108	-81	163	16	107	67	10	249	71	18	...	23	106	145	7
1	106	-30	113	40	115	70	60	131	111	18	...	16	100	118	7
2	123	-1	35	35	34	30	48	228	109	29	...	16	49	90	0
3	51	4	227	29	33	84	78	661	164	26	...	28	111	119	6
4	122	-34	-8	47	19	22	19	125	206	17	...	5	102	81	-4
5	54	-13	143	49	57	133	11	628	74	49	...	45	47	202	33
6	67	118	272	41	60	116	175	139	163	24	...	33	96	226	5
7	67	-35	28	13	78	67	42	128	40	16	...	16	71	112	27
8	74	31	11	50	55	83	105	541	95	12	...	19	40	121	9
9	63	-79	225	36	53	40	41	711	163	19	...	21	43	172	5
10	85	45	175	22	75	43	72	212	53	22	...	12	43	127	16
11	67	-41	8	42	12	29	67	365	188	26	...	23	104	69	-18
12	147	-104	14	3	102	74	18	-5	32	26	...	15	62	40	6
13	99	-45	97	8	19	40	66	291	77	11	...	18	109	160	-16
14	93	6	4	50	22	35	68	495	72	38	...	27	110	119	-1
15	155	-38	17	15	35	27	45	137	115	45	...	9	86	76	-2
16	85	-23	-6	83	17	22	33	255	17	8	...	3	77	42	0
17	150	-117	22	4	43	44	8	14	33	43	...	11	47	94	-6
18	9	320	1249	190	195	595	1231	1003	371	82	...	229	54	935	79
19	10	172	1327	106	243	618	700	753	302	86	...	252	14	220	103
20	23	275	622	156	191	299	446	808	278	85	...	84	53	395	46
21	40	379	684	125	132	222	1128	1183	485	90	...	92	28	402	28
22	3	549	793	121	278	332	1070	1152	372	157	...	125	26	165	28
23	47	127	460	73	93	110	491	1810	248	45	...	24	17	334	19
24	8	463	1536	162	219	461	1296	801	268	71	...	125	0	984	32
25	12	641	395	189	155	138	2261	1675	378	156	...	41	-2	234	30
26	31	185	2100	225	87	303	1107	956	83	31	...	64	36	754	58
27	18	288	1033	102	186	378	731	835	365	75	...	131	16	658	34
28	24	416	1164	80	255	313	1559	973	350	88	...	161	8	384	40
29	8	625	1599	169	223	481	1762	1264	226	85	...	152	15	810	26
30	27	320	1472	106	191	358	917	807	429	92	...	131	15	732	53
31	1	564	2203	261	295	426	1303	748	195	66	...	91	-6	991	41
32	22	330	1381	139	282	437	721	917	269	105	...	219	14	936	30
33	9	116	1903	140	197	629	542	1103	313	79	...	153	63	950	33
34	2	718	598	221	91	162	1816	1646	284	94	...	38	46	409	38
35	27	332	1132	92	219	380	412	773	264	80	...	159	-5	399	65

36 rows × 51 columns

In [40]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.decomposition import PCA
```

In [41]:
```
## independent and dependent varible
X = df_new.iloc[:,:-1]
y = df_new.iloc[:,-1]
```

In [42]:
```
# train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=.2,random_state=0)
```

In [43]:
```
##
pipe_LR=Pipeline([('scaler1',StandardScaler()),
                  ('LR',LogisticRegression())])
pipe_SVM =Pipeline([('scaler2',StandardScaler()),
                    ('SVR',SVC())])
pipe_DT=Pipeline([('scaler3',StandardScaler()),
                   ('DTR',DecisionTreeClassifier())])
pipe_RF=Pipeline([('scaler4',StandardScaler()),
                   ('RFR',RandomForestClassifier())])
pipe_Knn=Pipeline([('scaler4',StandardScaler()),
                    ('Knn',KNeighborsClassifier())])
```

In [44]:
```
pipeline1=[pipe_LR,pipe_SVM,pipe_DT,pipe_RF,pipe_Knn]
```

In [45]:
```
pipe_dict={0:'Logistic_Regression',1:'SVC',2:'Decesion_Tree_Classifier',3:'Random_Tree_classifier',4:'KNN_class
```

In [46]:
```
for pipe in pipeline1:
  pipe.fit(X_train,y_train)
```

In [47]:
```
from sklearn.metrics import accuracy_score
```

In [48]:
```
for i,model in enumerate(pipeline1):
  print("{}_Accuracy: {}".format(pipe_dict[i],model.score(X_test,y_test)))
```
```
Logistic_Regression_Accuracy: 1.0
SVC_Accuracy: 1.0
Decesion_Tree_Classifier_Accuracy: 1.0
Random_Tree_classifier_Accuracy: 1.0
KNN_classifier_Accuracy: 1.0
```

In [ ]: