LOGISTIC REGRESSION

IMPORTING LIBRARIES

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
```

```
In [3]:
```

```
In [4]: df = pd.read_csv("1_ionosphere.csv")
```

Out[4]:

	1	0	0.99539	-0.05889	0.85243	0.02306	0.83398	-0.37708	1.1	0.03760	...	-0.51
0	1	0	1.00000	-0.18829	0.93035	-0.36156	-0.10868	-0.93597	1.00000	-0.04549	...	-0.26
1	1	0	1.00000	-0.03365	1.00000	0.00485	1.00000	-0.12062	0.88965	0.01198	...	-0.40
2	1	0	1.00000	-0.45161	1.00000	1.00000	0.71216	-1.00000	0.00000	0.00000	...	0.90
3	1	0	1.00000	-0.02401	0.94140	0.06531	0.92106	-0.23255	0.77152	-0.16399	...	-0.65
4	1	0	0.02337	-0.00592	-0.09924	-0.11949	-0.00763	-0.11824	0.14706	0.06637	...	-0.01
...	...	...	...	...	...	...	...	...	...	...	...	
345	1	0	0.83508	0.08298	0.73739	-0.14706	0.84349	-0.05567	0.90441	-0.04622	...	-0.04
346	1	0	0.95113	0.00419	0.95183	-0.02723	0.93438	-0.01920	0.94590	0.01606	...	0.01
347	1	0	0.94701	-0.00034	0.93207	-0.03227	0.95177	-0.03431	0.95584	0.02446	...	0.03
348	1	0	0.90608	-0.01657	0.98122	-0.01989	0.95691	-0.03646	0.85746	0.00110	...	-0.02
349	1	0	0.84710	0.13533	0.73638	-0.06151	0.87873	0.08260	0.88928	-0.09139	...	-0.15

350 rows × 35 columns

```
In [5]: f_m=df.iloc[:,0:34]
```

```
In [6]:
```

```
Out[6]: (350, 34)
```

```
In [7]:
```

```
Out[7]: (350,)
```

```
In [8]:
```

```
In [11]: fs=StandardScaler().fit_transform(f_m)
```

In [14]:
```
logr=LogisticRegression()
```

Out[14]:
```
LogisticRegression()
```

In [22]:

In [23]:
```
prediction=logr.predict(observation)
```

Out[23]:
```
array(['g'], dtype=object)
```

In [24]:

Out[24]:
```
array(['b', 'g'], dtype=object)
```

In [25]:

Out[25]:
```
0.037620171662807955
```

In [26]:

Out[26]:
```
0.962379828337192
```

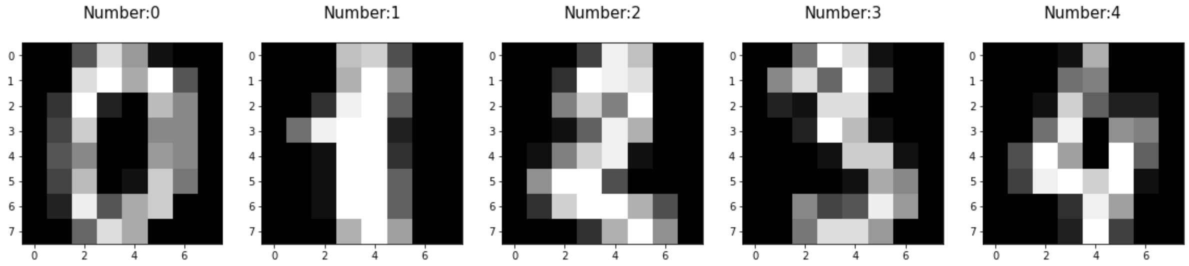
LOGISTICREGRESSION - II

In [32]:
```
import re
from sklearn.datasets import load_digits
from sklearn.linear_model import LogisticRegression
```

In [33]:
```
digits=load_digits()
```

Out[33]:
```
{'data': array([[ 0.,  0.,  5., ...,  0.,  0.,  0.],
        [ 0.,  0.,  0., ..., 10.,  0.,  0.],
        [ 0.,  0.,  0., ..., 16.,  9.,  0.],
        ...,
        [ 0.,  0.,  1., ...,  6.,  0.,  0.],
        [ 0.,  0.,  2., ..., 12.,  0.,  0.],
        [ 0.,  0., 10., ..., 12.,  1.,  0.]]),
 'target': array([0, 1, 2, ..., 8, 9, 8]),
 'frame': None,
 'feature_names': ['pixel_0_0',
  'pixel_0_1',
  'pixel_0_2',
  'pixel_0_3',
  'pixel_0_4',
  'pixel_0_5',
  'pixel_0_6',
  'pixel_0_7',
  'pixel_1_0',
  'pixel_1_1',
```

In [36]:
```
plt.figure(figsize=(20,4))
for index,(image,label) in enumerate(zip(digits.data[0:5],digits.target[0:5])):
    plt.subplot(1,5,index+1)
    plt.imshow(np.reshape(image,(8,8)),cmap=plt.cm.gray)
```



In [37]:

In [40]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
```

```
(1257, 64)
(540, 64)
(1257,)
(540,)
```

In [42]:
```
logre=LogisticRegression(max_iter=10000)
```

Out[42]:
```
LogisticRegression(max_iter=10000)
```

In [44]:
```
[illegible]
```

Out[44]:
```
array([8, 9, 4, 2, 6, 4, 8, 1, 3, 3, 9, 8, 0, 8, 5, 9, 3, 9, 8, 1, 0, 3,
       7, 7, 5, 6, 0, 6, 0, 7, 4, 4, 7, 4, 8, 5, 3, 5, 8, 2, 9, 4, 4, 1,
       4, 8, 2, 5, 8, 4, 2, 7, 1, 8, 7, 4, 2, 4, 7, 6, 5, 4, 4, 3, 9, 4,
       7, 5, 5, 5, 1, 0, 0, 7, 8, 8, 0, 9, 0, 3, 2, 5, 5, 0, 4, 3, 8, 0,
       0, 5, 5, 9, 6, 8, 4, 1, 3, 7, 6, 5, 0, 3, 6, 0, 8, 1, 6, 0, 0, 8,
       8, 2, 7, 3, 9, 2, 9, 2, 2, 2, 9, 5, 5, 2, 3, 9, 9, 4, 4, 6, 7, 5,
       2, 4, 3, 3, 4, 3, 4, 7, 0, 6, 0, 6, 2, 0, 7, 3, 1, 9, 0, 4, 3, 1,
       3, 1, 2, 4, 1, 2, 3, 2, 4, 7, 6, 2, 5, 4, 4, 9, 4, 7, 9, 2, 2, 9,
       4, 5, 6, 6, 3, 1, 9, 5, 7, 4, 6, 2, 7, 9, 3, 5, 4, 8, 7, 1, 3, 1,
       3, 3, 9, 6, 1, 6, 4, 4, 4, 6, 0, 4, 4, 5, 9, 5, 1, 1, 1, 3, 8, 9,
       2, 0, 0, 8, 5, 3, 8, 4, 5, 3, 5, 5, 0, 9, 3, 4, 2, 0, 0, 7, 9, 5,
       7, 5, 8, 7, 5, 1, 0, 8, 3, 5, 7, 4, 3, 2, 7, 7, 2, 6, 5, 8, 4, 1,
       4, 9, 2, 5, 1, 8, 6, 3, 7, 4, 0, 5, 1, 0, 1, 5, 0, 9, 9, 5, 1, 7,
       9, 5, 0, 4, 4, 6, 0, 2, 3, 5, 1, 9, 9, 4, 6, 8, 2, 0, 7, 1, 9, 6,
       2, 8, 1, 9, 7, 6, 3, 4, 4, 8, 8, 9, 4, 3, 5, 5, 1, 8, 6, 5, 8, 8,
       7, 1, 2, 9, 7, 5, 5, 9, 3, 2, 4, 7, 1, 0, 5, 1, 9, 6, 2, 8, 4, 5,
       6, 3, 1, 7, 2, 7, 6, 5, 3, 0, 1, 5, 6, 4, 2, 5, 5, 7, 2, 0, 3, 6,
       5, 0, 7, 4, 5, 0, 4, 9, 4, 5, 2, 5, 2, 2, 2, 8, 5, 1, 0, 8, 0, 0,
       5, 2, 0, 3, 9, 0, 7, 6, 1, 8, 6, 3, 2, 9, 1, 3, 4, 2, 9, 4, 6, 6,
       8, 1, 8, 6, 3, 1, 4, 2, 2, 5, 3, 9, 3, 3, 5, 6, 2, 9, 5, 6, 3, 2,
       8, 4, 6, 2, 4, 3, 9, 8, 1, 4, 5, 2, 3, 9, 5, 5, 5, 5, 8, 7, 8, 9,
       4, 2, 1, 7, 7, 2, 6, 9, 6, 7, 7, 6, 5, 6, 9, 9, 1, 2, 4, 1, 8, 5,
       9, 1, 9, 1, 1, 7, 5, 0, 0, 2, 8, 1, 1, 9, 1, 6, 5, 9, 0, 0, 8, 2,
       8, 3, 2, 6, 3, 1, 5, 3, 5, 5, 7, 8, 6, 1, 1, 8, 0, 8, 8, 2, 3, 7,
       6, 9, 7, 8, 9, 0, 8, 9, 1, 0, 6, 1])
```

In [43]:
```
[illegible]
```

Out[43]:
```
0.9648148148148148
```

RANDOM FOREST

In [6]:
```
[illegible]
```

Out[6]:
```
g    224
b    126
Name: g, dtype: int64
```

In [10]:
```
x=df.drop('g',axis=1)
y=df['g']
```

In [11]:
```
g1={"g":{'g':1,'b':2}}
df=df.replace(g1)
df
```

Out[11]:

	1	0	0.99539	-0.05889	0.85243	0.02306	0.83398	-0.37708	1.1	0.03760	...	-0.51
0	1	0	1.00000	-0.18829	0.93035	-0.36156	-0.10868	-0.93597	1.00000	-0.04549	...	-0.26
1	1	0	1.00000	-0.03365	1.00000	0.00485	1.00000	-0.12062	0.88965	0.01198	...	-0.40
2	1	0	1.00000	-0.45161	1.00000	1.00000	0.71216	-1.00000	0.00000	0.00000	...	0.90
3	1	0	1.00000	-0.02401	0.94140	0.06531	0.92106	-0.23255	0.77152	-0.16399	...	-0.65
4	1	0	0.02337	-0.00592	-0.09924	-0.11949	-0.00763	-0.11824	0.14706	0.06637	...	-0.01
...	...	...	...	...	...	...	...	...	...	...	...	
345	1	0	0.83508	0.08298	0.73739	-0.14706	0.84349	-0.05567	0.90441	-0.04622	...	-0.04
346	1	0	0.95113	0.00419	0.95183	-0.02723	0.93438	-0.01920	0.94590	0.01606	...	0.01
347	1	0	0.94701	-0.00034	0.93207	-0.03227	0.95177	-0.03431	0.95584	0.02446	...	0.03
348	1	0	0.90608	-0.01657	0.98122	-0.01989	0.95691	-0.03646	0.85746	0.00110	...	-0.02
349	1	0	0.84710	0.13533	0.73638	-0.06151	0.87873	0.08260	0.88928	-0.09139	...	-0.15

350 rows × 35 columns

In [21]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.70)
```

In [22]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [23]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[23]:
```
RandomForestClassifier()
```

In [30]:
```
parameters={'max_depth':[1,2,3,4,5],
            'min_samples_leaf':[5,10,15,20,25],
            'n_estimators':[10,20,30,40,50]}
```

In [41]:
```
from sklearn.model_selection import GridSearchCV
grid_search =GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="ac
grid_search.fit(x_train,y_train)
```

Out[41]:
```
GridSearchCV(cv=2, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [1, 2, 3, 4, 5],
                         'min_samples_leaf': [5, 10, 15, 20, 25],
                         'n_estimators': [10, 20, 30, 40, 50]},
             scoring='accuracy')
```

In [42]:
```
grid_search.best_score_
```

Out[42]:
```
0.9385245901639344
```

In [44]:
```
rfc_best=grid_search.best_estimator_
```

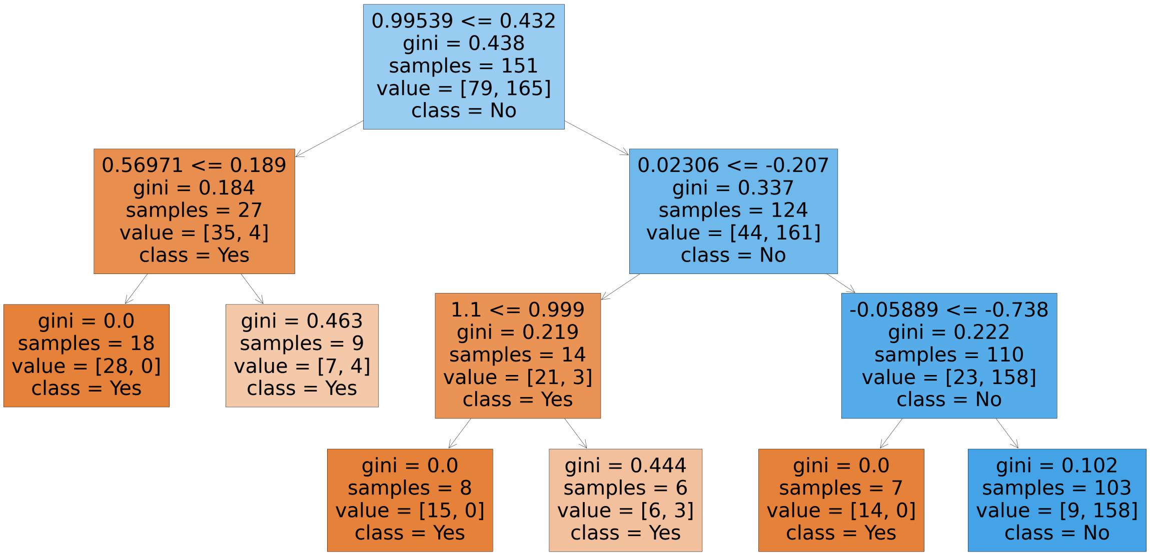
In [45]:

```
from sklearn.tree import plot_tree

plt.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['Yes','
```

Out[45]:

```
[Text(1826.1818181818182, 1902.6000000000001, '0.99539 <= 0.432\ngini = 0.43
8\nsamples = 151\nvalue = [79, 165]\nclass = No'),
 Text(811.6363636363636, 1359.0, '0.56971 <= 0.189\ngini = 0.184\nsamples = 2
7\nvalue = [35, 4]\nclass = Yes'),
 Text(405.8181818181818, 815.4000000000001, 'gini = 0.0\nsamples = 18\nvalue
= [28, 0]\nclass = Yes'),
 Text(1217.4545454545455, 815.4000000000001, 'gini = 0.463\nsamples = 9\nvalu
e = [7, 4]\nclass = Yes'),
 Text(2840.7272727272725, 1359.0, '0.02306 <= -0.207\ngini = 0.337\nsamples =
124\nvalue = [44, 161]\nclass = No'),
 Text(2029.090909090909, 815.4000000000001, '1.1 <= 0.999\ngini = 0.219\nsamp
les = 14\nvalue = [21, 3]\nclass = Yes'),
 Text(1623.2727272727273, 271.79999999999995, 'gini = 0.0\nsamples = 8\nvalue
= [15, 0]\nclass = Yes'),
 Text(2434.909090909091, 271.79999999999995, 'gini = 0.444\nsamples = 6\nvalu
e = [6, 3]\nclass = Yes'),
 Text(3652.3636363636365, 815.4000000000001, '-0.05889 <= -0.738\ngini = 0.22
2\nsamples = 110\nvalue = [23, 158]\nclass = No'),
 Text(3246.5454545454545, 271.79999999999995, 'gini = 0.0\nsamples = 7\nvalue
= [14, 0]\nclass = Yes'),
 Text(4058.181818181818, 271.79999999999995, 'gini = 0.102\nsamples = 103\nva
lue = [9, 158]\nclass = No')]
```


0.99539 <= 0.432
gini = 0.438
samples = 151
value = [79, 165]
class = No
0.56971 <= 0.189
gini = 0.184
samples = 27
value = [35, 4]
class = Yes
0.02306 <= -0.207
gini = 0.337
samples = 124
value = [44, 161]
class = No
gini = 0.0
samples = 18
value = [28, 0]
class = Yes
gini = 0.463
samples = 9
value = [7, 4]
class = Yes
1.1 <= 0.999
gini = 0.219
samples = 14
value = [21, 3]
class = Yes
-0.05889 <= -0.738
gini = 0.222
samples = 110
value = [23, 158]
class = No
gini = 0.0
samples = 8
value = [15, 0]
class = Yes
gini = 0.444
samples = 6
value = [6, 3]
class = Yes
gini = 0.0
samples = 7
value = [14, 0]
class = Yes
gini = 0.102
samples = 103
value = [9, 158]
class = No