```
In [1]:
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.linear model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train test split
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross val score
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
sonar=pd.read_csv('sonar.csv')
```

In [3]:

```
sonar.info()
```

RangeIndex: 208 entries, 0 to 207 Data columns (total 61 columns): # Column Non-Null Count Dtype V1208 non-null float64 float64 208 non-null 7/2 1 V3 208 non-null float64 3 V4 208 non-null float64 208 non-null float64 4 V5 V6 208 non-null 5 float64 77 208 non-null 6 float64 7 V8 208 non-null float64 8 V9 208 non-null float64 V10 208 non-null float64 9 10 V11 208 non-null float64 11 V12 208 non-null float64 12 V13 208 non-null float64 13 V14 208 non-null float64 14 V15 208 non-null float64 15 V16 float64 208 non-null V17 208 non-null 16 float.64 17 V18 208 non-null float.64 18 V19 208 non-null float64 19 V20 208 non-null float64 float64 20 V21 208 non-null 21 V22 208 non-null float64 22 V23 208 non-null float64 23 V24 208 non-null float64 24 V25 208 non-null float64 float64 25 V26 208 non-null 208 non-null 26 V27 float64 V28 208 non-null 2.7 float64 28 V29 208 non-null float64 29 V30 208 non-null float.64 30 V31 208 non-null float64 31 V32 208 non-null float64 32 V33 208 non-null float64 33 V34 208 non-null float64 34 V35 208 non-null float.64 35 V36 208 non-null float64 36 V37 208 non-null float64 float64 37 V38 208 non-null 7720 20 200 202 211

<class 'pandas.core.frame.DataFrame'>

```
20
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              ∠∪o non-nu⊥⊥
                                LLUal04
     V40
              208 non-null
 39
                                float64
     V41
              208 non-null
 40
                                float64
 41
    V42
              208 non-null
                                float64
 42 V43
              208 non-null
                              float64
 43 V44
                              float.64
              208 non-null
 44
     V45
              208 non-null
                                float64
 45
     V46
              208 non-null
                                float64
              208 non-null
    V47
 46
                                float64
 47
    V48
              208 non-null
                               float.64
 48
    V/49
              208 non-null
                               float64
 49
     V50
              208 non-null
                                float64
 50
     V51
              208 non-null
                                float.64
    V52
              208 non-null
 51
                                float64
 52 V53
              208 non-null
                               float64
 53 V54
              208 non-null
                              float64
 54 V55
              208 non-null
                              float64
 55
     V56
              208 non-null
                                float64
 56
    V57
              208 non-null
                                float64
 57 V58
              208 non-null
                                float.64
 58 V59
              208 non-null
                               float64
                             float64
 59 V60
              208 non-null
 60 Class 208 non-null
                              int.64
dtypes: float64(60), int64(1)
memory usage: 99.2 KB
In [4]:
sonar
Out[4]:
                                                                  V10 ... V52
                                                                                               V55
                                                                                                            V57
        V1
              V2
                     V3
                           V4
                                 V5
                                        V6
                                               V7
                                                     V8
                                                            V9
                                                                                  V53
                                                                                        V54
                                                                                                     V56
  0 0.0200 0.0371 0.0428 0.0207 0.0954 0.0986 0.1539 0.1601 0.3109 0.2111 ... 0.0027 0.0065 0.0159 0.0072 0.0167 0.0180
  1 0.0453 0.0523 0.0843 0.0689 0.1183 0.2583 0.2156 0.3481 0.3337 0.2872 ... 0.0084 0.0089 0.0048 0.0094 0.0191 0.0140
  2 0.0262 0.0582 0.1099 0.1083 0.0974 0.2280 0.2431 0.3771 0.5598 0.6194 ... 0.0232 0.0166 0.0095 0.0180 0.0244 0.0316
  4 0.0762 0.0666 0.0481 0.0394 0.0590 0.0649 0.1209 0.2467 0.3564 0.4459 ... 0.0031 0.0054 0.0105 0.0110 0.0015 0.0072
                                                                   ... ...
 203 0.0187 0.0346 0.0168 0.0177 0.0393 0.1630 0.2028 0.1694 0.2328 0.2684 ... 0.0116 0.0098 0.0199 0.0033 0.0101 0.0065
 204 0.0323 0.0101 0.0298 0.0564 0.0760 0.0958 0.0990 0.1018 0.1030 0.2154 ... 0.0061 0.0093 0.0135 0.0063 0.0063 0.0063
 205 0.0522 0.0437 0.0180 0.0292 0.0351 0.1171 0.1257 0.1178 0.1258 0.2529 ... 0.0160 0.0029 0.0051 0.0062 0.0089 0.0140
 206 0.0303 0.0353 0.0490 0.0608 0.0167 0.1354 0.1465 0.1123 0.1945 0.2354 ... 0.0086 0.0046 0.0126 0.0036 0.0035 0.0034
 207 0.0260 0.0363 0.0136 0.0272 0.0214 0.0338 0.0655 0.1400 0.1843 0.2354 ... 0.0146 0.0129 0.0047 0.0039 0.0061 0.0040
208 rows × 61 columns
4
In [5]:
sonar.columns
Out[5]:
Index(['V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10', 'V11',
        'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20', 'V21',
        'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'V29', 'V30', 'V31', 'V32', 'V33', 'V34', 'V35', 'V36', 'V37', 'V38', 'V39', 'V40', 'V41', 'V42', 'V43', 'V44', 'V45', 'V46', 'V47', 'V48', 'V49', 'V50', 'V51',
        'V52', 'V53', 'V54', 'V55', 'V56', 'V57', 'V58', 'V59', 'V60', 'Class'],
      dtype='object')
```

In [6]:

Out[6]:

sonar.dtypes

```
V1
                     float64
V2
                     float64
                     float64
V3
V4
                     float64
V5
                     float64
V57
                     float64
V58
                     float64
V59
                     float64
V60
                     float64
                         int64
Class
Length: 61, dtype: object
In [7]:
sonar.describe()
Out[7]:
                            V1
                                                 V2
                                                                      V3
                                                                                           V4
                                                                                                                V5
                                                                                                                                     V6
                                                                                                                                                          V7
                                                                                                                                                                               V8
                                                                                                                                                                                                    V9
                                                                                                                                                                                                                        V10 ...

        count
        208.000000
        208.000000
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        208.0000000
        208.0000000
        208.00000
                                                                                                                                                                                                           208.000000 ...
                                                                                                                                                                                          0.178003
                                                                                                                                                                                                               0.208259 ...
                  0.029164
                                       0.038437
                                                            0.043832
                                                                                 0.053892
                                                                                                      0.075202
                                                                                                                           0.104570
                                                                                                                                                0.121747
                                                                                                                                                                     0.134799
  mean
                 0.022991
                                       0.032960
                                                            0.038428
                                                                                 0.046528
                                                                                                      0.055552
                                                                                                                           0.059105
                                                                                                                                                0.061788
                                                                                                                                                                     0.085152
                                                                                                                                                                                          0.118387
                                                                                                                                                                                                                0.134416 ...
     std
                                                                                 0.005800
                                                                                                                                                                                                               0.011300 ...
                  0.001500
                                       0.000600
                                                            0.001500
                                                                                                      0.006700
                                                                                                                           0.010200
                                                                                                                                                0.003300
                                                                                                                                                                     0.005500
                                                                                                                                                                                          0.007500
     min
    25%
                 0.013350
                                       0.016450
                                                            0.018950
                                                                                 0.024375
                                                                                                      0.038050
                                                                                                                           0.067025
                                                                                                                                                0.080900
                                                                                                                                                                     0.080425
                                                                                                                                                                                          0.097025
                                                                                                                                                                                                                0.111275 ...
    50%
                  0.022800
                                       0.030800
                                                            0.034300
                                                                                 0.044050
                                                                                                      0.062500
                                                                                                                           0.092150
                                                                                                                                                0.106950
                                                                                                                                                                     0.112100
                                                                                                                                                                                          0.152250
                                                                                                                                                                                                                0.182400
    75%
                  0.035550
                                       0.047950
                                                            0.057950
                                                                                 0.064500
                                                                                                      0.100275
                                                                                                                           0.134125
                                                                                                                                                0.154000
                                                                                                                                                                     0.169600
                                                                                                                                                                                          0.233425
                                                                                                                                                                                                                0.268700 ...
    max
                  0.137100
                                       0.233900
                                                            0.305900
                                                                                 0.426400
                                                                                                      0.401000
                                                                                                                           0.382300
                                                                                                                                                0.372900
                                                                                                                                                                     0.459000
                                                                                                                                                                                          0.682800
                                                                                                                                                                                                                0.710600 ...
8 rows × 61 columns
In [8]:
sonar.skew()
Out[8]:
V1
                     2.131088
V2
                     2.155644
                     2.652518
V3
V4
                     3.401697
V5
                     2.018141
                          . . .
V57
                     1.653090
V58
                     2.098330
V59
                     1.737506
V60
                     2.775754
                    0.135903
Class
Length: 61, dtype: float64
In [9]:
for col in sonar.columns:
          if sonar.skew().loc[col]>0.55:
                   sonar[col]=np.log1p(sonar[col])
In [10]:
 #reduced skewness
 sonar.skew()
Out[10]:
V1
                     2.036001
                     1.969917
V2
```

V3

77/

2.344713

2 212320

```
Z.UIUJZU
νĦ
V5
          1.698684
V57
          1.629182
V58
          2.058207
V59
          1.713349
V60
          2.711412
Class
          0.135903
Length: 61, dtype: float64
In [11]:
#to understand it has two or more unique variables and is it regression or classification
sonar.Class.unique()
Out[11]:
array([1, 0], dtype=int64)
In [12]:
# identifing null values
sonar.isnull().sum()
Out[12]:
          0
V1
V2
          0
V3
          0
          0
V4
V5
          0
V57
          0
V58
V59
          0
V60
          0
Class
          0
Length: 61, dtype: int64
In [13]:
sns.heatmap(sonar.isnull())
Out[13]:
<matplotlib.axes._subplots.AxesSubplot at 0x19777cd6688>
                                               -0.100
 0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
                                               - 0.075
                                              - 0.050
                                              - 0.025
                                               - 0.000
                                               -0.025
                                                -0.050
```

In [14]:

```
#Removing outliers
from scipy.stats import zscore
z_score=abs(zscore(sonar))
print(sonar.shape)
sonar_df=sonar.loc[(z_score<3).all(axis=1)]
print(sonar_df.shape)</pre>
```

-0.075 -0.100

```
(208, 61)
(173, 61)
In [15]:
sonar df
Out[15]:
         V1
                V2
                        V3
                                V4
                                       V5
                                               V6
                                                      V7
                                                              V8
                                                                     V9
                                                                            V10 ...
                                                                                      V52
                                                                                              V53
  1 0.044304 0.050978 0.080935 0.066630 0.111810 0.229762 0.195238 0.298696 0.287957 0.252469 ... 0.008365 0.008861 0.004
  4 0.073436 0.064476 0.046979 0.038644 0.057325 0.062881 0.114132 0.220500 0.304834 0.368732 ... 0.003095 0.005385 0.010
  5 0.028199 0.044304 0.027323 0.017250 0.037681 0.094401 0.113418 0.168307 0.191033 0.265360 ... 0.004490 0.001399 0.003
 203 0.018527 0.034015 0.016660 0.017545 0.038547 0.151003 0.184652 0.156491 0.209288 0.237756 ... 0.011533 0.009752 0.019
 204 0.031789 0.010049 0.029365 0.054867 0.073250 0.091485 0.094401 0.096945 0.098034 0.195073 ... 0.006081 0.009257 0.013
 205 0.050883 0.042772 0.017840 0.028782 0.034498 0.110736 0.118405 0.111362 0.118494 0.225461 ... 0.015873 0.002896 0.005
 206 0.029850 0.034691 0.047837 0.059023 0.016562 0.126985 0.136714 0.106430 0.177728 0.211395 ... 0.008563 0.004589 0.012
 207 0.025668 0.035657 0.013508 0.026837 0.021174 0.033241 0.063444 0.131028 0.169152 0.211395 ... 0.014494 0.012818 0.004
173 rows × 61 columns
4
                                                                                                    Þ.
In [16]:
sonar df=pd.DataFrame(data=sonar df)
sonar_df
Out[16]:
         V1
                V2
                        V3
                               V4
                                       V5
                                               V6
                                                      V7
                                                              V8
                                                                     V9
                                                                            V10 ...
                                                                                       V52
  1 0.044304 0.050978 0.080935 0.066630 0.111810 0.229762 0.195238 0.298696 0.287957 0.252469 ... 0.008365 0.008861 0.004
  4 0.073436 0.064476 0.046979 0.038644 0.057325 0.062881 0.114132 0.220500 0.304834 0.368732 ... 0.003095 0.005385 0.010
   5 \quad 0.028199 \quad 0.044304 \quad 0.027323 \quad 0.017250 \quad 0.037681 \quad 0.094401 \quad 0.113418 \quad 0.168307 \quad 0.191033 \quad 0.265360 \quad \dots \quad 0.004490 \quad 0.001399 
 203 0.018527 0.034015 0.016660 0.017545 0.038547 0.151003 0.184652 0.156491 0.209288 0.237756 ... 0.011533 0.009752 0.019
 204 0.031789 0.010049 0.029365 0.054867 0.073250 0.091485 0.094401 0.096945 0.098034 0.195073 ... 0.006081 0.009257 0.013
 205 0.050883 0.042772 0.017840 0.028782 0.034498 0.110736 0.118405 0.111362 0.118494 0.225461 ... 0.015873 0.002896 0.005
 206 0.029850 0.034691 0.047837 0.059023 0.016562 0.126985 0.136714 0.106430 0.177728 0.211395 ... 0.008563 0.004589 0.012
 207 0.025668 0.035657 0.013508 0.026837 0.021174 0.033241 0.063444 0.131028 0.169152 0.211395 ... 0.014494 0.012818 0.004
173 rows × 61 columns
4
In [17]:
#x and y values allocation for training and testing
x=sonar df.iloc[:,0:-1]
In [18]:
```

Out[18]:

```
V10 ...
        V1
              V2
                     V3
                            V4
                                   V5
                                          V6
                                                 V7
                                                       V8
                                                              V9
                                                                             V51
                                                                                    V52
  1 0.044304 0.050978 0.080935 0.066630 0.111810 0.229762 0.195238 0.298696 0.287957 0.252469 ... 0.012423 0.008365 0.008
  4 0.073436 0.064476 0.046979 0.038644 0.057325 0.062881 0.114132 0.220500 0.304834 0.368732 ... 0.015480 0.003095 0.005
  203 0.018527 0.034015 0.016660 0.017545 0.038547 0.151003 0.184652 0.156491 0.209288 0.237756 ... 0.020097 0.011533 0.009
204 0.031789 0.010049 0.029365 0.054867 0.073250 0.091485 0.094401 0.096945 0.098034 0.195073 ... 0.005087 0.006081 0.009
205 0.050883 0.042772 0.017840 0.028782 0.034498 0.110736 0.118405 0.111362 0.118494 0.225461 ... 0.015381 0.015873 0.002
206 0.029850 0.034691 0.047837 0.059023 0.016562 0.126985 0.136714 0.106430 0.177728 0.211395 ... 0.004191 0.008563 0.004
207 0.025668 0.035657 0.013508 0.026837 0.021174 0.033241 0.063444 0.131028 0.169152 0.211395 ... 0.017938 0.014494 0.012
173 rows × 60 columns
4
                                                                                          Þ
In [19]:
x.shape
Out[19]:
(173, 60)
In [20]:
\#x columns are more in number ,so using PCA reducing and them to 10
pca=PCA(n components=10)
x=pca.fit transform(x)
In [21]:
x.shape
Out[21]:
(173, 10)
In [22]:
y=sonar_df.iloc[:,-1]
In [23]:
Out[23]:
1
      1
3
      1
5
      1
203
     0
204
      0
205
206
      0
207
      Ω
Name: Class, Length: 173, dtype: int64
In [24]:
y.shape
```

```
Out[24]:
 (173,)
In [25]:
sonar.corr()
Out [25]:
                          V1
                                             V2
                                                                 V3
                                                                                     V4
                                                                                                       V5
                                                                                                                           V6
                                                                                                                                                V7
                                                                                                                                                                V8
                                                                                                                                                                                      V9
                                                                                                                                                                                                         V10 ...
                                                                                                                                                                                                                                    V52
                                                                                                                                                                                                                                                        V53
       V1 1.000000 0.735222 0.570685 0.485743 0.336469 0.244380 0.260978 0.351766 0.348769 0.312130 ... 0.353387 0.312563 0.3
        \textbf{V3} \quad 0.570685 \quad 0.773040 \quad 1.000000 \quad 0.765006 \quad 0.524464 \quad 0.351185 \quad 0.192678 \quad 0.246778 \quad 0.263476 \quad 0.226283 \quad \dots \quad 0.396473 \quad 0.335055 \quad 0.33505
       V4 0.485743 0.590833 0.765006 1.000000 0.708444 0.362016 0.252227 0.260257 0.252504 0.242135 ... 0.379065 0.370981 0.3
       V5 0.336469 0.404392 0.524464 0.708444 1.000000 0.605497 0.340052 0.212995 0.188492 0.194106 ... 0.267553 0.315872 0.2
     V57 0.316519 0.286026 0.388956 0.351808 0.216137 0.164213 0.183444 0.259359 0.179931 0.128099 ... 0.190659 0.306836 0.3
     V58 0.371517 0.358558 0.342265 0.357230 0.236755 0.208964 0.241244 0.283423 0.223121 0.203778 ... 0.309571 0.369978 0.4
     V59 0.358920 0.354793 0.431001 0.430703 0.288460 0.224321 0.179633 0.186581 0.082903 0.052438 ... 0.297710 0.346919 0.4
     V60 0.348455 0.358427 0.375295 0.400941 0.247061 0.183374 0.220841 0.142316 0.082875 0.093219 ... 0.196169 0.282185 0.2
  Class 0.272710 0.232735 0.194547 0.257889 0.227755 0.141348 0.120424 0.196120 0.337322 0.354554 ... 0.289856 0.141687 0.1
61 rows × 61 columns
                                                                                                                                                                                                                                                                    Þ
In [26]:
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.22,random_state=39)
In [27]:
 #we are using follwing models for prediction
 #LogisticRegression
 #KNeighborsClassifier
 #GaussianNB
 #SVC
 #DecisionTreeClassifier
 #RandomForestClassifier
 #AdaBoostClassifier
In [28]:
lr=LogisticRegression()
lr.fit(x_train,y_train)
lr.score(x_train,y_train)
pred=lr.predict(x_test)
 print(accuracy_score(y_test,pred))
print(confusion_matrix(y_test,pred))
print(classification report(y test,pred))
0.717948717948718
[[11 10]
   [ 1 17]]
                                    precision recall f1-score support
                                             0.92
                                                                        0.52 0.67
                                                                                                                                       21
```

```
0.63
                        0.94
                                  0.76
          1
                                              18
                                   0.72
                                               39
   accuracy
                 0.77
                          0.73
                                   0.71
  macro avg
                                               39
weighted avg
                 0.78
                                   0.71
                                              39
                          0.72
```

In [29]:

```
lrscores=cross_val_score(lr,x,y,cv=5)
print(lrscores.mean(),lrscores.std())
```

[0.51428571 0.85714286 0.48571429 0.94117647 0.44117647] 0.6478991596638656 0.2081755328275781

In [30]:

```
knn=KNeighborsClassifier()
knn.fit(x_train,y_train)
knn.score(x_train,y_train)
predknn=knn.predict(x_test)
print(accuracy_score(y_test,predknn))
print(confusion_matrix(y_test,predknn))
print(classification_report(y_test,predknn))

0.7435897435897436
[[15 6]
```

[4 14]] recall f1-score support precision 0 0.79 0.71 0.75 21 0.70 0.78 0.74 18 0.74 39 accuracy 0.74 macro avg 0.75 0.74 39 0.74 0.75 39 weighted avg 0.74

In [31]:

```
knnscores=cross_val_score(knn,x,y,cv=5)
print(knnscores.mean(),knnscores.std())
```

[0.57142857 0.68571429 0.48571429 0.73529412 0.41176471] 0.577983193277311 0.12044734544692169

In [32]:

```
gnb=GaussianNB()
gnb.fit(x_train,y_train)
gnb.score(x_train,y_train)
predgnb=gnb.predict(x_test)
print(accuracy_score(y_test,predgnb))
print(confusion_matrix(y_test,predgnb))
print(classification_report(y_test,predgnb))
```

0.7692307692307693

[[13 8] [1 17]]

[1 17]]					
		precision	recall	f1-score	support
	0	0.93	0.62	0.74	21
	1	0.68	0.94	0.79	18
accuracy				0.77	39
macro a	avg	0.80	0.78	0.77	39
weighted a	avg	0.81	0.77	0.76	39

```
In [33]:
```

0.5971428571428572 0.15120596589148816

In [34]:

```
svc=SVC(kernel='rbf')
svc.fit(x_train,y_train)
svc.score(x_train,y_train)
predsvc=svc.predict(x_test)
print(accuracy_score(y_test,predsvc))
print(confusion_matrix(y_test,predsvc))
print(classification_report(y_test,predsvc))
```

0.8461538461538461

[[16 5] [1 17]]

[+ +/]]	precision	recall	f1-score	support
0	0.94	0.76	0.84	21
1	0.77	0.94	0.85	18
accuracy			0.85	39
macro avg	0.86	0.85	0.85	39
weighted avg	0.86	0.85	0.85	39

In [35]:

```
svcscores=cross_val_score(svc,x,y,cv=5)
print(svcscores)
print(svcscores.mean(),svcscores.std())
```

[0.62857143 0.68571429 0.4 0.88235294 0.55882353] 0.63109243697479 0.1579545834992282

In [36]:

```
dtc=DecisionTreeClassifier()
dtc.fit(x_train,y_train)
dtc.score(x_train,y_train)
preddtc=dtc.predict(x_test)
print(accuracy_score(y_test,preddtc))
print(confusion_matrix(y_test,preddtc))
print(classification_report(y_test,preddtc))
```

0.666666666666666

[[13 8]

[2 13]]	precision	recall	f1-score	support
0 1	0.72 0.62	0.62 0.72	0.67 0.67	21 18
accuracy macro avg weighted avg	0.67 0.67	0.67 0.67	0.67 0.67 0.67	39 39 39

In [37]:

```
dtcscores=cross_val_score(dtc,x,y,cv=5)
print(dtcscores)
print(dtcscores mean() dtcscores std())
```

```
| PIIII (ULCOCOTED . MEAN (), ULCOCOTED . DLU ())
[0.48571429 0.77142857 0.31428571 0.55882353 0.55882353]
0.5378151260504203 0.14706314519460217
In [38]:
rf=RandomForestClassifier()
rf.fit(x train,y train)
rf.score(x_train,y_train)
predrf=rf.predict(x_test)
print(accuracy_score(y_test,predrf))
print(confusion_matrix(y_test,predrf))
print(classification_report(y_test,predrf))
0.8974358974358975
[[17 4]
 [ 0 18]]
             precision
                        recall f1-score support
           0
                  1.00
                           0.81
                                     0.89
                                                  21
           1
                 0.82
                           1.00
                                     0.90
                                                 18
                                                  39
                                      0.90
   accuracy
                0.91 0.90
0.92 0.90
                                   0.90
   macro avg
                                                  39
                                                 39
weighted avg
In [39]:
rfscores=cross_val_score(rf,x,y,cv=5)
print(rfscores)
print(rfscores.mean(),rfscores.std())
           0.8
                      0.37142857 0.91176471 0.58823529]
0.6142857142857143 0.21380370901101162
In [40]:
from sklearn.ensemble import AdaBoostClassifier
ad=AdaBoostClassifier()
ad.fit(x_train,y_train)
ad.score(x_train,y_train)
predad=ad.predict(x_test)
print(accuracy_score(y_test,predad))
print(confusion_matrix(y_test,predad))
print(classification_report(y_test,predad))
0.7948717948717948
[[13 8]
 [ 0 18]]
             precision recall f1-score support
                  1.00
                           0.62
                                     0.76
           1
                  0.69
                           1.00
                                     0.82
                                                 18
                                      0.79
                                                  39
   accuracy
               0.85
                0.85 0.81
0.86 0.79
                                  0.79
   macro avg
                                                  39
                                                 39
weighted avg
```

In [41]:

```
adscores=cross_val_score(ad,x,y,cv=5)
print(adscores.mean(),adscores.std())
```

[0.42857143 0.71428571 0.48571429 0.79411765 0.58823529] 0.6021848739495799 0.13660629920681341

```
In [43]:
#RandomForestClassifier is the best model among all models
import joblib
joblib.dump(rf,'sonar.pkl')
Out[43]:
['sonar.pkl']
In []:
```