In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier

from sklearn.metrics import classification_report, accuracy_score


import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
df = pd.read_csv("abalone.data")
df.head()
```

Out[2]:

	M	0.455	0.365	0.095	0.514	0.2245	0.101	0.15	15
0	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
1	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
2	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
3	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7
4	I	0.425	0.300	0.095	0.3515	0.1410	0.0775	0.120	8

In [3]:

```
cols = ["Sex","Length","Diameter","Height","WholeWeight","ShuckedWeight","VisceraWeight
```

In [4]:

```
df = pd.read_csv("abalone.data", header=None, names = cols)
df.head()
```

Out[4]:

	Sex	Length	Diameter	Height	WholeWeight	ShuckedWeight	VisceraWeight	ShellWeight	R
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	

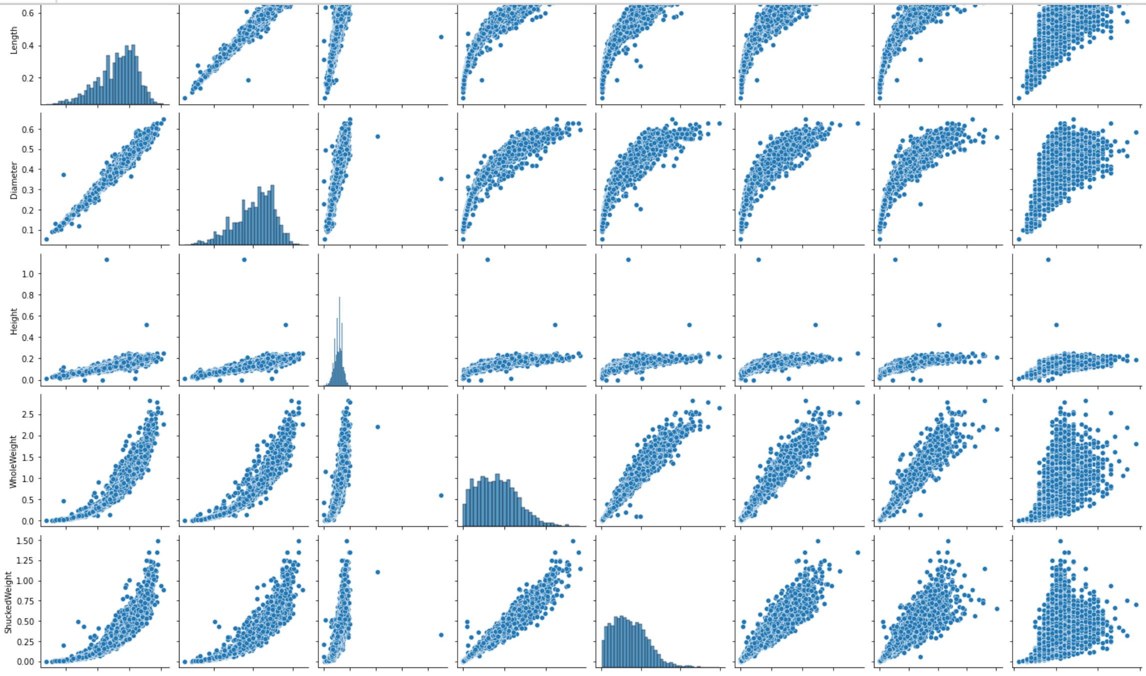
In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Sex            4177 non-null   object 
 1   Length         4177 non-null   float64
 2   Diameter       4177 non-null   float64
 3   Height         4177 non-null   float64
 4   WholeWeight    4177 non-null   float64
 5   ShuckedWeight  4177 non-null   float64
 6   VisceraWeight  4177 non-null   float64
 7   ShellWeight    4177 non-null   float64
 8   Rings          4177 non-null   int64  
dtypes: float64(7), int64(1), object(1)
memory usage: 293.8+ KB
```

In [6]:

```
sns.pairplot(df)
```



In [7]:

```
x = df.iloc[:,1:].values
x
```

Out[7]:

```
array([[ 0.455 ,  0.365 ,  0.095 , ...,  0.101 ,  0.15  , 15.    ],
       [ 0.35  ,  0.265 ,  0.09  , ...,  0.0485,  0.07  ,  7.    ],
       [ 0.53  ,  0.42  ,  0.135 , ...,  0.1415,  0.21  ,  9.    ],
       ...,
       [ 0.6   ,  0.475 ,  0.205 , ...,  0.2875,  0.308 ,  9.    ],
       [ 0.625 ,  0.485 ,  0.15  , ...,  0.261 ,  0.296 , 10.    ],
       [ 0.71  ,  0.555 ,  0.195 , ...,  0.3765,  0.495 , 12.    ]])
```

In [8]:

```
from sklearn.cluster import KMeans
```

In [9]:

```
wcss = []

for i in range(1,11):
    kmeans = KMeans(n_clusters=i, random_state=1)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)
```

In [10]:

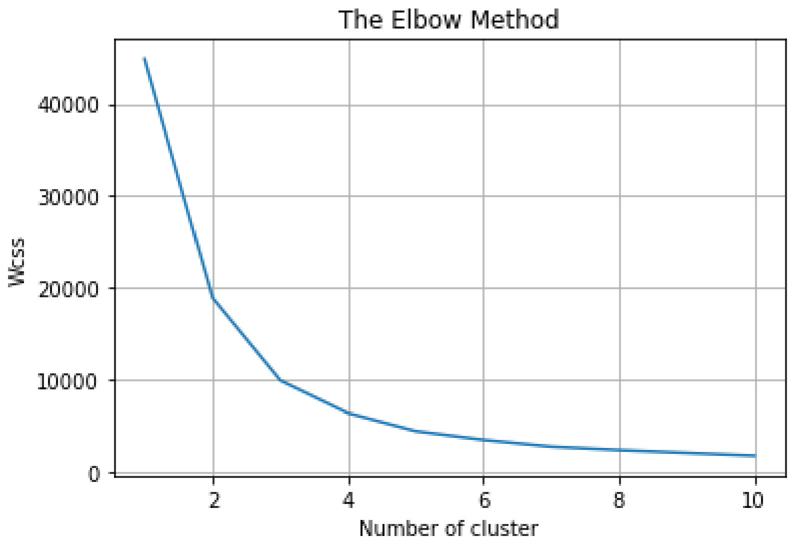
```
wcss
```

Out[10]:

```
[44860.378975952,
 18861.998927978846,
 9889.828962494752,
 6340.081927459619,
 4384.82991662735,
 3438.389737637842,
 2706.8677666982144,
 2331.3658828700895,
 2021.483195630447,
 1717.8814779488623]
```

In [11]:

```
plt.plot(range(1,11), wcss)
plt.title("The Elbow Method")
plt.xlabel("Number of cluster")
plt.ylabel("Wcss")
plt.grid(True)
plt.show()
```



In [12]:

```
kmeans = KMeans(n_clusters=3, random_state=1)
ykmeans = kmeans.fit_predict(x)
```

In [13]:

```
ykmeans
```

Out[13]:

```
array([1, 2, 0, ..., 0, 0, 0])
```

In [14]:

```
kmeans.cluster_centers_
```

Out[14]:

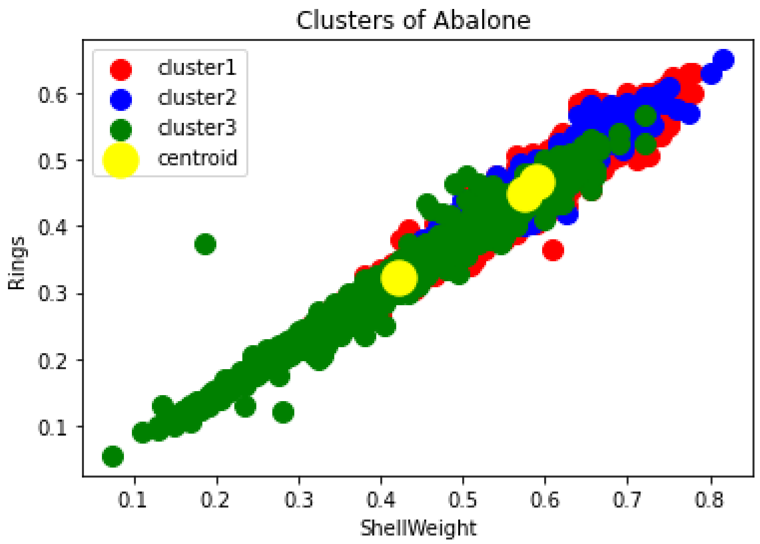
```
array([[ 0.57364035,  0.44874342,  0.15363377,  1.00693048,  0.44330066,
         0.22172434,  0.28465482, 10.4127193 ],
       [ 0.58873469,  0.46642857,  0.16835714,  1.13776327,  0.4316051 ,
         0.23970306,  0.36281939, 16.46122449],
       [ 0.42099147,  0.32127576,  0.10659559,  0.4323742 ,  0.198199  ,
         0.09335714,  0.12139446,  6.88415068]])
```

In [15]:

```
plt.scatter(x[ykmeans==0,0], x[ykmeans==0,1], s=100, c="red", label="cluster1")
plt.scatter(x[ykmeans==1,0], x[ykmeans==1,1], s=100, c="blue", label="cluster2")
plt.scatter(x[ykmeans==2,0], x[ykmeans==2,1], s=100, c="green", label="cluster3")

plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], s=300, c="yello

plt.title("Clusters of Abalone ")
plt.xlabel("ShellWeight")
plt.ylabel("Rings")
plt.legend()
plt.show()
```



In [16]:

```
df["Target"]= ykmeans
```

In [17]:

```
df.head()
```

Out[17]:

	Sex	Length	Diameter	Height	WholeWeight	ShuckedWeight	VisceraWeight	ShellWeight	R
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	

In [18]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 10 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Sex            4177 non-null   object 
 1   Length         4177 non-null   float64
 2   Diameter       4177 non-null   float64
 3   Height         4177 non-null   float64
 4   WholeWeight    4177 non-null   float64
 5   ShuckedWeight  4177 non-null   float64
 6   VisceraWeight  4177 non-null   float64
 7   ShellWeight    4177 non-null   float64
 8   Rings          4177 non-null   int64  
 9   Target         4177 non-null   int32  
dtypes: float64(7), int32(1), int64(1), object(1)
memory usage: 310.1+ KB
```

In [19]:

```
df.isna().sum()
```

Out[19]:

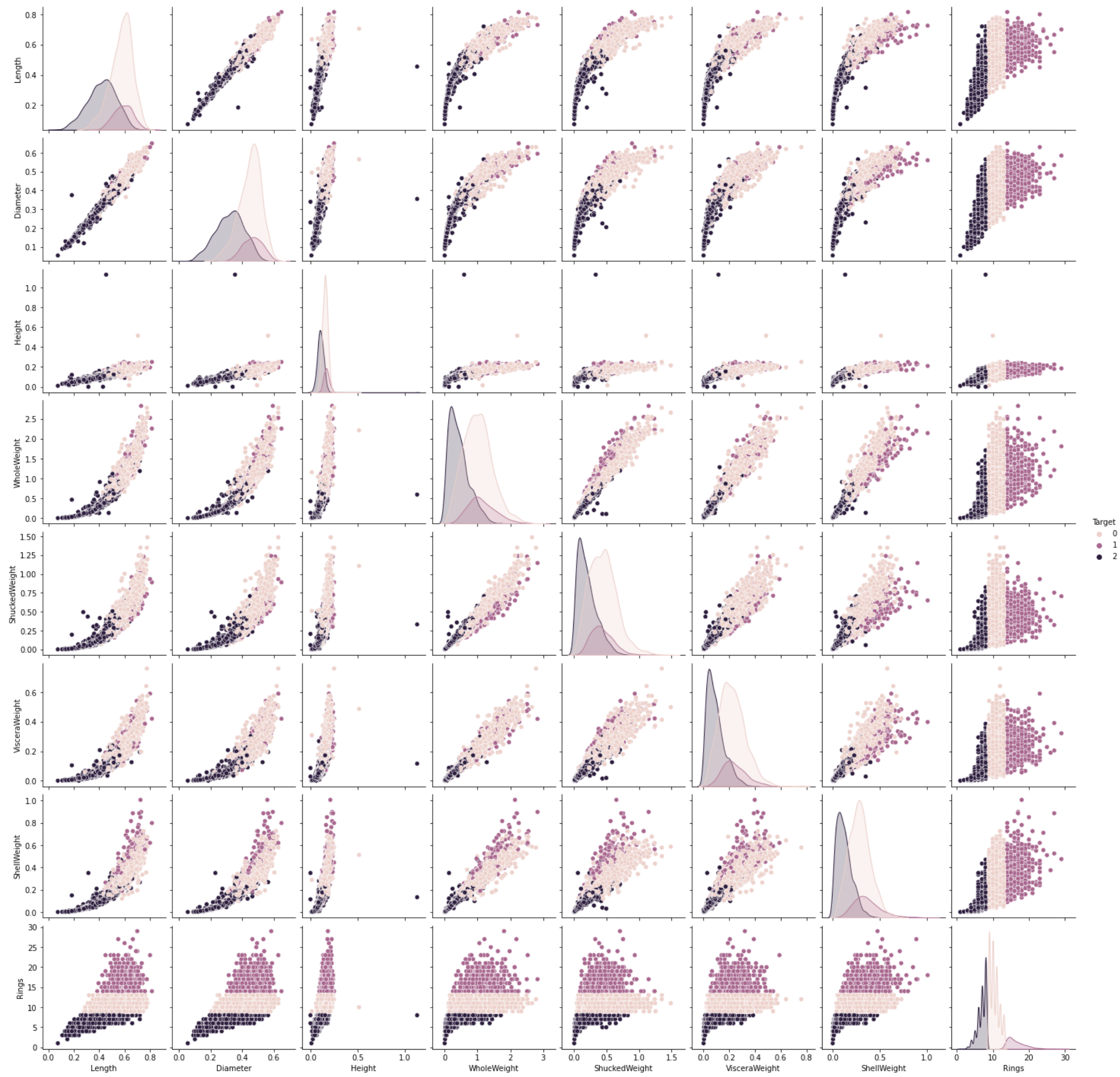
```
Sex              0
Length           0
Diameter         0
Height           0
WholeWeight      0
ShuckedWeight    0
VisceraWeight    0
ShellWeight      0
Rings            0
Target           0
dtype: int64
```

In [20]:

```python
sns.pairplot(df, hue="Target")
```

Out[20]:

```
<seaborn.axisgrid.PairGrid at 0xf36c455fd0>
```



In [21]:

```python
x = df.iloc[:,1:].values
y = df.iloc[:, -1].values
```

In [22]:

```
x
```

Out[22]:

```
array([[ 0.455,  0.365,  0.095, ...,  0.15 , 15.   ,  1.   ],
       [ 0.35 ,  0.265,  0.09 , ...,  0.07 ,  7.   ,  2.   ],
       [ 0.53 ,  0.42 ,  0.135, ...,  0.21 ,  9.   ,  0.   ],
       ...,
       [ 0.6  ,  0.475,  0.205, ...,  0.308,  9.   ,  0.   ],
       [ 0.625,  0.485,  0.15 , ...,  0.296, 10.   ,  0.   ],
       [ 0.71 ,  0.555,  0.195, ...,  0.495, 12.   ,  0.   ]])
```

In [23]:

```
y
```

Out[23]:

```
array([1, 2, 0, ..., 0, 0, 0])
```

In [24]:

```
xtrain,xtest,ytrain,ytest= train_test_split(x,y, test_size=0.3, random_state=1, stratif
```

In [25]:

```
def mymodel(model):
    model.fit(xtrain,ytrain)
    ypred = model.predict(xtest)
    print(classification_report(ytest,ypred))
```

In [26]:

```
logreg = LogisticRegression()
knn = KNeighborsClassifier()
dt = DecisionTreeClassifier()
svm = SVC()
rf = RandomForestClassifier()
```

In [27]:

```
models = []
models.append(("KNN     -:", KNeighborsClassifier()))
models.append(("Logreg  -:", LogisticRegression()))
models.append(("SVM     -:", SVC()))
models.append(("DT      -:", DecisionTreeClassifier()))
models.append(("RF      -:", RandomForestClassifier()))
models.append(("Ada     -:", AdaBoostClassifier(n_estimators=100)))
models.append(("gbc     -:", GradientBoostingClassifier(n_estimators=100)))
accuracy=[]

for name, model in models:
    model.fit(xtrain, ytrain)
    ypred = model.predict(xtest)
    ac = accuracy_score(ytest, ypred)
    accuracy.append(round(ac*100))

    print(name)
    print(classification_report(ytest, ypred))
    print()


print(f"Avg. Ensemble Acurracy-: {np.array(accuracy).mean()} %")
```

```
KNN     -:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254


Logreg  -:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254


SVM     -:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254
```

```
DT      -:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254


RF      -:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254


Ada     -:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254


gbc     -:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254


Avg. Ensemble Acurracy-: 100.0 %
```

Hyper Parameter Tuning

In [28]:

```
logregs = []

logregs.append(("LogregLin        :- ", LogisticRegression(solver = 'liblinear')))
logregs.append(("LogregLbf        :- ", LogisticRegression(solver = 'lbfgs')))
logregs.append(("LogregNcg        :- ", LogisticRegression(solver = 'newton-cg')))

for name, model in logregs:
    print(name)
    mymodel(model)
    print("\n\n\n")

```

```
LogregLin        :- 
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254





LogregLbf        :- 
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254





LogregNcg        :- 
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254
```

In [29]:

```
mymodel(logreg)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254
```

In [30]:

```python
svms = []
svms.append(("SVMlin            :- ", SVC(kernel = 'linear')))
svms.append(("SVMpol           :- ", SVC(kernel = 'poly')))
svms.append(("SVMrbf            :- ", SVC(kernel = 'rbf')))

for name, model in svms:
    print(name)
    mymodel(model)
    print("\n\n\n")
```

```
SVMlin            :- 
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254




SVMpol           :- 
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254




SVMrbf            :- 
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254
```

In [31]:

```
mymodel(svm)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       685
           1       1.00      1.00      1.00       147
           2       1.00      1.00      1.00       422

    accuracy                           1.00      1254
   macro avg       1.00      1.00      1.00      1254
weighted avg       1.00      1.00      1.00      1254
```

Cross Validation Score

In [32]:

```
from sklearn.model_selection import cross_val_score
```

In [33]:

```
for name, model in models:
    print(name)
    cvs = cross_val_score(model,x,y,cv=5,scoring='accuracy')
    print(cvs.mean())
    print("\n\n\n")
```

```
KNN     -:
1.0




Logreg  -:
1.0




SVM     -:
1.0




DT      -:
1.0




RF      -:
1.0




Ada     -:
1.0




gbc     -:
1.0
```

Results

- This model gives 100% accuracy.
- Some HyperParameterTuning has been done even though not necessary
- the mean accuracy of the model is also 100%

In [ ]:

```
```