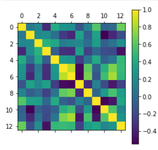
WINE CLASSIFICATION PROJECT

In [7]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_wine
from sklearn.model_selection import train_test_split
```

In [20]:
```
wine_data=load_wine()
X_train,X_test,y_train,y_test=train_test_split(wine_data.data,wine_data.target,test_size=0.5,random_state=42)
df_x_train=pd.DataFrame(X_train,columns=wine_data.feature_names)
```

DATA UNDERSTANDING

In [11]:
```
#plotting a graph to understand data
plt.matshow(df_x_train.corr())
plt.colorbar()
plt.show()
```



DATA PREPARATION

Transforming raw data that was collected into a form that can be used for modeling.

In [4]:
```
#training dataset
X_train,X_test,y_train,y_test=train_test_split(wine_data.data,wine_data.target,test_size=0.5,random_state=42)
```

In [12]:
```
df_x_train.head()
```

Out[12]:

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	proanthocyanins	color_intensity	hue	od280/od315_of_diluted_wines	proline
0	12.70	3.87	2.40	23.0	101.0	2.83	2.55	0.43	1.95	2.57	1.19	3.13	463.0
1	11.84	0.89	2.58	18.0	94.0	2.20	2.21	0.22	2.35	3.05	0.79	3.08	520.0
2	14.22	3.99	2.51	13.2	128.0	3.00	3.04	0.20	2.08	5.10	0.89	3.53	760.0
3	12.60	1.34	1.90	18.5	88.0	1.45	1.36	0.29	1.35	2.45	1.04	2.77	562.0
4	12.16	1.61	2.31	22.8	90.0	1.78	1.69	0.43	1.56	2.45	1.33	2.26	495.0

In [13]:
```
#describing and formatting data to five decimal places
#feature identification
df_x_train.describe().style.format("{:.5f}")
```

Out[13]:

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	proanthocyanins	color_intensity	hue	od280/od315_of_diluted_wines	pro
count	89.00000	89.00000	89.00000	89.00000	89.00000	89.00000	89.00000	89.00000	89.00000	89.00000	89.00000	89.00000	89.00
mean	12.96011	2.43472	2.37000	19.69551	99.68539	2.30393	2.00202	0.37360	1.57461	5.16461	0.94467	2.54899	730.85
std	0.87890	1.10208	0.25634	3.63005	13.33536	0.67975	1.04548	0.13405	0.56620	2.32526	0.23536	0.73836	306.43
min	11.03000	0.89000	1.36000	10.60000	70.00000	1.10000	0.47000	0.13000	0.42000	1.74000	0.48000	1.27000	278.00
25%	12.29000	1.64000	2.25000	18.00000	88.00000	1.70000	1.20000	0.26000	1.25000	3.21000	0.78000	1.75000	495.00
50%	12.96000	1.97000	2.38000	20.00000	100.00000	2.20000	1.84000	0.37000	1.53000	5.00000	0.95000	2.77000	630.00
75%	13.72000	3.26000	2.54000	22.00000	108.00000	2.88000	2.89000	0.48000	1.87000	6.75000	1.08000	3.16000	920.00
max	14.83000	5.65000	3.23000	30.00000	139.00000	3.88000	5.08000	0.66000	3.58000	10.80000	1.71000	3.71000	1547.00

Feature Scaling: To have a same scale for the smallest and largest value for a given feature.

In [14]:
```
from sklearn import preprocessing
scaler = preprocessing.StandardScaler().fit(X_train)
X_scaled = scaler.transform(X_train)
X_scaled
```

Out[14]:
```
array([[-0.29763036,  1.30971359,  0.11769613, ...,  1.04824751,
         0.79134959, -0.87905518],
       [-1.28167477, -1.40957746,  0.82387293, ..., -0.66090388,
         0.72324853, -0.69198999],
       [ 1.44161091,  1.41921525,  0.54924862, ..., -0.23361603,
         1.33615805,  0.09565289],
       ...,
       [ 1.62468894, -0.51531396,  0.03923204, ...,  1.0909763 ,
         0.61428684,  2.67846516],
       [-0.30907274, -0.82556864, -0.43155249, ...,  0.06548546,
        -0.66601304, -0.77403613],
       [-0.70955593,  0.01394403,  0.3530884 , ..., -0.61817509,
         1.13185488, -0.96110131]])
```

In [15]:
```
#importing necessary libraries
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn import linear_model
from sklearn import svm
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import plot_roc_curve
```

IMPLEMENTING THREE CLASSIFICATION MODELS

In [9]:
```
#Performing comparative study on three classification models in order to choose most suitable model
```

Implementing Naive Bayes Model

In [41]:
```
pipe=make_pipeline(GaussianNB())
pipe.fit(X_train,y_train)
```

Out[41]:
```
Pipeline(steps=[('gaussiannb', GaussianNB())])
```

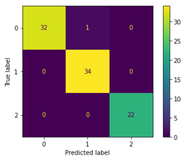
In [42]:
```
pipe.score(X_train,y_train),pipe.score(X_test,y_test)
```

Out[42]:
```
(0.9775280898876404, 0.9887640449438202)
```

In [43]:
```
#evaluation
confusion_matrix(y_test,pipe.predict(X_test))
```

Out[43]:
```
array([[32,  1,  0],
       [ 0, 34,  0],
       [ 0,  0, 22]], dtype=int64)
```

In [65]:
```
clf = GaussianNB()
clf.fit(X_train, y_train)
GaussianNB()
plot_confusion_matrix(clf, X_test, y_test)
plt.show()
```



Implementing SVM Model

In [60]:
```
pipe=make_pipeline(svm.SVC())
pipe.fit(X_train,y_train)
```

Out[60]:
```
Pipeline(steps=[('svc', SVC())])
```

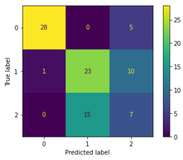
In [61]:
```
pipe.score(X_train,y_train),pipe.score(X_test,y_test)
```

Out[61]:
```
(0.7640449438202247, 0.651685393258427)
```

In [62]:
```
#evaluation
confusion_matrix(y_test,pipe.predict(X_test))
```

Out[62]:
```
array([[28,  0,  5],
       [ 1, 23, 10],
       [ 0, 15,  7]], dtype=int64)
```

In [63]:
```
#visualization
clf = SVC(random_state=0)
clf.fit(X_train, y_train)
SVC(random_state=0)
plot_confusion_matrix(clf, X_test, y_test)
plt.show()
```



Implementing Logistic Regression

In [56]:
```
pipe=make_pipeline(linear_model.LogisticRegression())
pipe.fit(X_scaled,y_train) #using scaled data here
```

Out[56]:
```
Pipeline(steps=[('logisticregression', LogisticRegression())])
```

In [57]:
```
pipe.score(X_scaled,y_train),pipe.score(X_test,y_test)
```

Out[57]:
```
(1.0, 0.3707865168539326)
```

In [58]:
```
#evaluation
confusion_matrix(y_test,pipe.predict(X_test))
```

Out[58]:
```
array([[33,  0,  0],
       [34,  0,  0],
       [22,  0,  0]], dtype=int64)
```

In [59]:
```
clf = LogisticRegression(random_state=0)
clf.fit(X_scaled, y_train)
LogisticRegression(random_state=0)
plot_confusion_matrix(clf, X_test, y_test)
plt.show()
```