PRABAL_GHOSH_AM.SC.P2CSC20040_ML_FINAL_LAB_

1.Perform preprocessing on any suitable dataset. ¶

I am using brest cancer data set

SET5

In [110]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
%matplotlib inline
```

In [111]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# roc curve and auc score
from sklearn.datasets import make_classification # Generate a random n-class c
lassification problem. This initially creates clusters of points normally dist
ributed (std=1) about vertices of an n_informative -dimensional hypercube with
sides of length 2*class_sep and assigns an equal number of clusters to each cl
ass.
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn import svm
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
```

In [112]:
```
from sklearn.preprocessing import StandardScaler
```

In [113]:
```
plt.style.use('seaborn')
```

In [114]:
```
from sklearn.metrics import confusion_matrix, classification_report,accuracy_s
core
```

In [115]:
```
from sklearn.metrics import plot_precision_recall_curve,plot_roc_curve
```

In [116]:
```
df = pd.read_csv("C:\\Users\\Prabal Ghosh\\Desktop\\Machine learning final lab exam\\BreastCancer.csv")
```

In [117]:
```
df.tail()
```

Out[117]:

	Id	Cl.thickness	Cell.size	Cell.shape	Marg.adhesion	Epith.c.size	Bare.nuclei	Bl.cron
694	776715	3	1	1	1	3	2.0	
695	841769	2	1	1	1	2	1.0	
696	888820	5	10	10	3	7	3.0	
697	897471	4	8	6	4	3	4.0	
698	897471	4	8	8	5	4	5.0	

In [118]:
```
df.shape
```

Out[118]:
```
(699, 11)
```

In [119]:
```
df['Class'].unique()
```

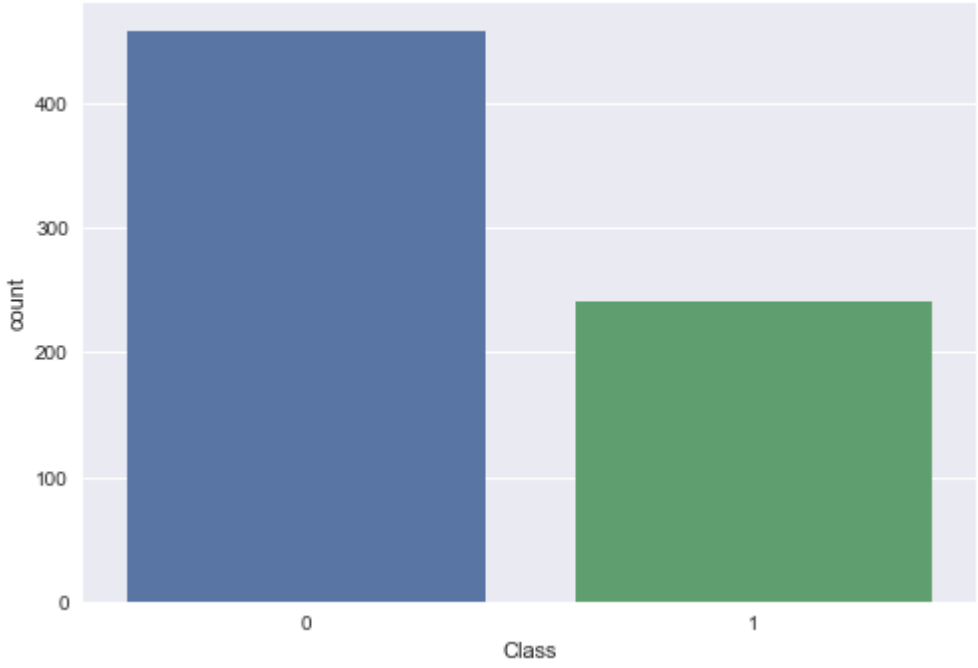
Out[119]:
```
array([0, 1], dtype=int64)
```

In [120]:
```
len(df)
```

Out[120]:
```
699
```

In [121]:
```
sns.countplot(x='Class',data=df)
```

Out[121]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1e4c85b5e50>
```



In [122]:
```
df.dropna(axis=0,how='any' ,thresh=None, inplace=True)
```

In [123]:
```
df.shape
```

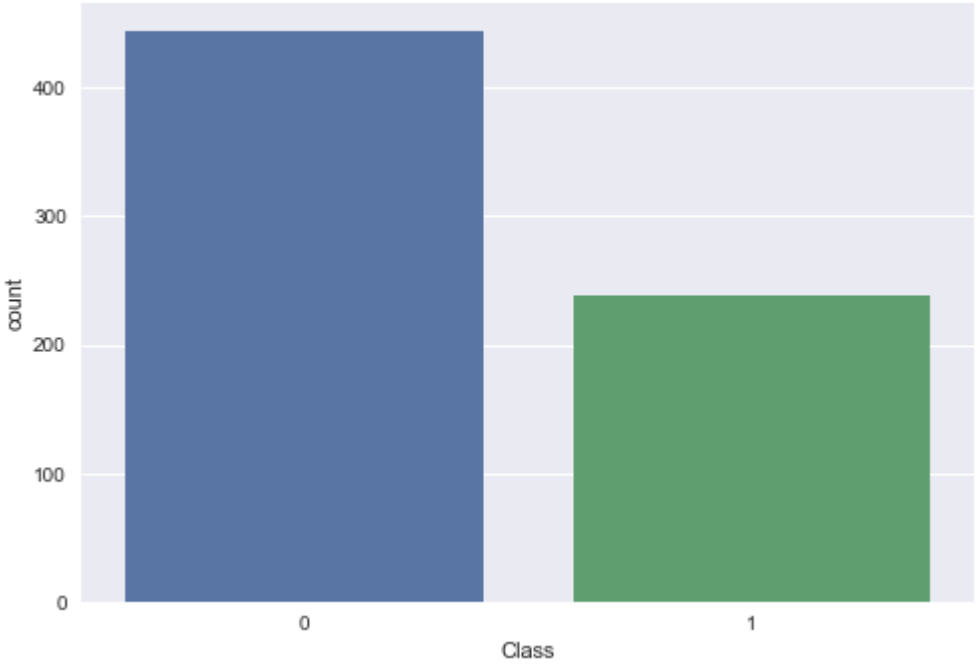
Out[123]:
```
(683, 11)
```

In [124]:
```
len(df)
```

Out[124]:
```
683
```

In [125]:
```
sns.countplot(x='Class',data=df)
```

Out[125]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1e4c85af1c0>
```



In [126]:
```
df.drop(columns=['Id'],inplace=True)
```

In [127]:
```
df.tail()
```

Out[127]:

	Cl.thickness	Cell.size	Cell.shape	Marg.adhesion	Epith.c.size	Bare.nuclei	Bl.cromatin	No
694	3	1	1	1	3	2.0	1	
695	2	1	1	1	2	1.0	1	
696	5	10	10	3	7	3.0	8	
697	4	8	6	4	3	4.0	10	
698	4	8	8	5	4	5.0	10	

In [128]:
```
df.shape
```

Out[128]:
```
(683, 10)
```

In [ ]:
```

```

In [129]:
```
df.iloc[:,0:9]
```

Out[129]:

	Cl.thickness	Cell.size	Cell.shape	Marg.adhesion	Epith.c.size	Bare.nuclei	Bl.cromatin	No
0	5	1	1	1	2	1.0	3	
1	5	4	4	5	7	10.0	3	
2	3	1	1	1	2	2.0	3	
3	6	8	8	1	3	4.0	3	
4	4	1	1	3	2	1.0	3	
...	...	...	...	...	...	...	...	
694	3	1	1	1	3	2.0	1	
695	2	1	1	1	2	1.0	1	
696	5	10	10	3	7	3.0	8	
697	4	8	6	4	3	4.0	10	
698	4	8	8	5	4	5.0	10	

683 rows × 9 columns

In [130]:
```
df.iloc[:,9]
```

Out[130]:
```
0      0
1      0
2      0
3      0
4      0
      ..
694    0
695    0
696    1
697    1
698    1
Name: Class, Length: 683, dtype: int64
```

In [131]:
```
data_X=df.iloc[:,0:9]
class_label=df.iloc[:,9]
```

2. Using this preprocessed dataset, Generate a model based on SVC.

In [132]:
```
# train and test split
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(data_X, class_label, test_
size=0.2, random_state=1)


# random_state =1 ......so every time it will generate same train and test set
```

In [133]:
```
X_train
```

Out[133]:

	Cl.thickness	Cell.size	Cell.shape	Marg.adhesion	Epith.c.size	Bare.nuclei	Bl.cromatin	No
575	5	1	2	1	2	1.0	3	
440	10	4	3	10	4	10.0	10	
123	5	3	5	1	8	10.0	5	
51	5	3	3	4	2	4.0	3	
318	1	1	1	1	5	1.0	3	
...	...	...	...	...	...	...	...	
148	3	1	1	3	8	1.0	5	
661	4	1	1	1	2	1.0	3	
74	10	6	4	1	3	4.0	3	
242	2	1	1	1	2	1.0	3	
38	5	4	4	9	2	10.0	5	

546 rows × 9 columns

In [134]:
```
X_test
```

Out[134]:

	Cl.thickness	Cell.size	Cell.shape	Marg.adhesion	Epith.c.size	Bare.nuclei	Bl.cromatin	No
444	5	1	1	6	3	1.0	2	
24	1	1	1	1	2	1.0	3	
195	4	1	1	1	2	1.0	3	
49	7	8	7	2	4	8.0	3	
375	1	1	1	1	2	1.0	1	
...	...	...	...	...	...	...	...	
90	1	1	1	1	2	1.0	3	
377	1	1	1	1	1	1.0	2	
374	3	1	2	1	2	1.0	2	
408	2	3	2	2	2	2.0	3	
270	8	4	7	1	3	10.0	3	

137 rows × 9 columns

In [135]:
```
Y_train
```

Out[135]:
```
575    0
440    1
123    1
51     1
318    0
      ..
148    0
661    0
74     1
242    0
38     1
Name: Class, Length: 546, dtype: int64
```

In [136]:
```
Y_test
```

Out[136]:
```
444    0
24     0
195    0
49     1
375    0
      ..
90     0
377    0
374    0
408    0
270    1
Name: Class, Length: 137, dtype: int64
```

In [ ]:

LINEAR SVM

In [137]:
```
from sklearn.svm import SVC
classifier_svm = SVC(C=100,random_state=1)  # linear svm applied
classifier_svm.fit(X_train,Y_train)
```

Out[137]:
```
SVC(C=100, random_state=1)
```

In [138]:
```
print(classifier_svm.support_vectors_)
```

```
[[ 6.  9.  7.  5.  5.  8.  4.  2.  1.]
 [ 6.  8.  8.  1.  3.  4.  3.  7.  1.]
 [ 5.  3.  4.  3.  4.  5.  4.  7.  1.]
 [ 3.  3.  2.  6.  3.  3.  3.  5.  1.]
 [ 4.  4.  4.  4.  6.  5.  7.  3.  1.]
 [ 8.  2.  1.  1.  5.  1.  1.  1.  1.]
 [ 6.  3.  3.  3.  3.  2.  6.  1.  1.]
 [ 1.  1.  1.  1.  2. 10.  3.  1.  1.]
 [ 5.  1.  2. 10.  4.  5.  2.  1.  1.]
 [ 6.  3.  3.  5.  3. 10.  3.  5.  3.]
 [ 5.  4.  4.  5.  7. 10.  3.  2.  1.]
 [ 4.  4.  2.  1.  2.  5.  2.  1.  2.]
 [ 8.  3.  3.  1.  2.  2.  3.  2.  1.]
 [ 4.  3.  1.  1.  2.  1.  4.  8.  1.]
 [ 8.  4.  6.  3.  3.  1.  4.  3.  1.]
 [ 3.  1.  3.  1.  3.  4.  1.  1.  1.]
 [ 5.  2.  2.  2.  2.  2.  3.  2.  2.]
 [ 5.  7.  7.  1.  5.  8.  3.  4.  1.]
 [ 5.  4.  5.  1.  8.  1.  3.  6.  1.]
 [ 8.  4.  4.  5.  4.  7.  7.  8.  2.]
 [ 3.  1.  1.  1.  2.  5.  5.  1.  1.]
 [ 4.  2.  4.  3.  2.  2.  2.  1.  1.]
 [ 4.  2.  3.  5.  3.  8.  7.  6.  1.]
 [ 5.  6.  6.  2.  4. 10.  3.  6.  1.]
 [ 7.  4.  7.  4.  3.  7.  7.  6.  1.]
 [ 3.  4.  4. 10.  5.  1.  3.  3.  1.]
 [ 8.  7.  4.  4.  5.  3.  5. 10.  1.]
 [ 2.  5.  3.  3.  6.  7.  7.  5.  1.]
 [ 7.  5.  3.  7.  4. 10.  7.  5.  5.]
 [ 8. 10.  4.  4.  8. 10.  8.  2.  1.]
 [ 6.  3.  4.  1.  5.  2.  3.  9.  1.]
 [10.  4.  5.  4.  3.  5.  7.  3.  1.]
 [ 3.  4.  5.  2.  6.  8.  4.  1.  1.]
 [ 5.  3.  5.  5.  3.  3.  4. 10.  1.]
 [ 6.  3.  2.  1.  3.  4.  4.  1.  1.]
 [10. 10.  6.  3.  3. 10.  4.  3.  2.]
 [ 9. 10. 10.  1. 10.  8.  3.  3.  1.]
 [ 5.  4.  6.  7.  9.  7.  8. 10.  1.]
 [ 5.  3.  3.  3.  2.  3.  4.  4.  1.]
 [ 8. 10. 10.  1.  3.  6.  3.  9.  1.]
 [ 5.  3.  3.  1.  3.  3.  3.  3.  3.]
 [ 4.  1.  1.  3.  1.  5.  2.  1.  1.]
 [10.  6.  6.  3.  4.  5.  3.  6.  1.]
 [ 5.  2.  3.  4.  2.  7.  3.  6.  1.]
 [ 3.  3.  6.  4.  5.  8.  4.  4.  1.]
 [ 2.  3.  4.  4.  2.  5.  2.  5.  1.]
 [ 8.  6.  4.  3.  5.  9.  3.  1.  1.]
 [ 9.  1.  2.  6.  4. 10.  7.  7.  2.]
 [ 9.  5.  8.  1.  2.  3.  2.  1.  5.]
 [ 6.  5.  5.  8.  4. 10.  3.  4.  1.]
 [10.  5.  5.  3.  6.  7.  7. 10.  1.]
 [ 7.  3.  2. 10.  5. 10.  5.  4.  4.]
 [ 4.  6.  6.  5.  7.  6.  7.  7.  3.]
 [ 5. 10. 10.  5.  4.  5.  4.  4.  1.]
 [ 5.  5.  5.  6.  3. 10.  3.  1.  1.]
 [ 6.  1.  3.  1.  4.  5.  5. 10.  1.]
 [ 8.  3.  5.  4.  5. 10.  1.  6.  2.]
```

```
[10.  6.  3.  6.  4. 10.  7.  8.  4.]
[ 7.  4.  6.  4.  6.  1.  4.  3.  1.]
[ 7.  4.  4.  3.  4. 10.  6.  9.  1.]
[ 7.  8.  3.  7.  4.  5.  7.  8.  2.]]
```

In [139]:
```
Y_pred = classifier_svm.predict(X_test)
```

In [140]:
```
print(classification_report(Y_test,Y_pred))
```

```
              precision    recall  f1-score   support

           0       0.99      0.98      0.98        90
           1       0.96      0.98      0.97        47

    accuracy                           0.98       137
   macro avg       0.97      0.98      0.98       137
weighted avg       0.98      0.98      0.98       137
```

In [141]:
```
# ADDED BY ME
accuracy_score(y_true=Y_test, y_pred=Y_pred)
```

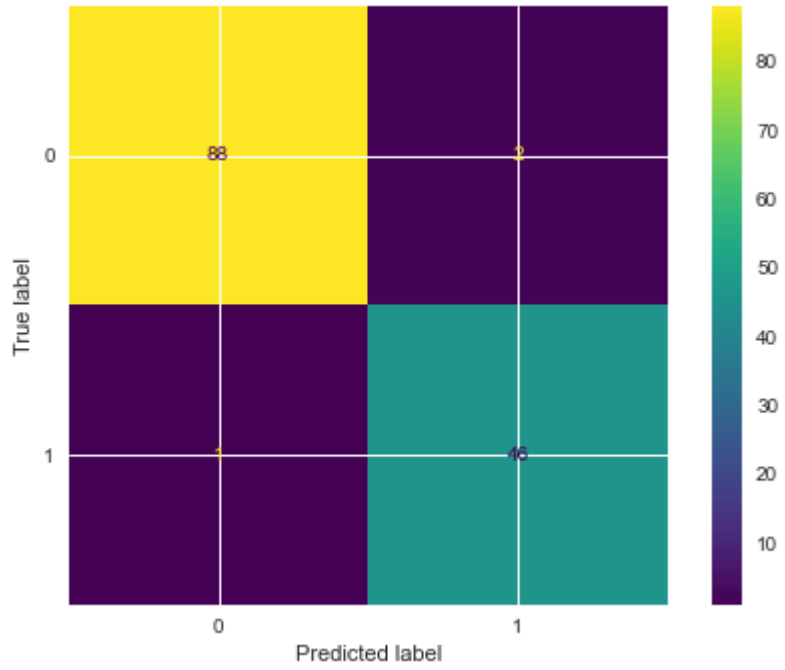
Out[141]:
```
0.9781021897810219
```

In [142]:
```
# ADDED BY ME
confusion_matrix(Y_test,Y_pred)
```

Out[142]:
```
array([[88,  2],
       [ 1, 46]], dtype=int64)
```

In [143]:
```
# ADDED BY ME
from sklearn.metrics import plot_confusion_matrix
plot_confusion_matrix(classifier_svm,X_test,Y_test)
```

Out[143]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1e4c85a9b
b0>
```



3. Use this model to predict the class of test set using various values of C parameter of SVC.

In [144]:
```
# now i will choose c=10

from sklearn.svm import SVC
classifier_svm = SVC(C=10,random_state=1)  # linear svm applied
classifier_svm.fit(X_train,Y_train)
```

Out[144]:
```
SVC(C=10, random_state=1)
```

In [145]:
```
print(classifier_svm.support_vectors_)
```

```
[[ 1.  1.  1.  1.  2.  1.  1.  1.  8.]
 [ 6.  9.  7.  5.  5.  8.  4.  2.  1.]
 [ 6.  8.  8.  1.  3.  4.  3.  7.  1.]
 [ 5.  3.  4.  3.  4.  5.  4.  7.  1.]
 [ 3.  3.  2.  6.  3.  3.  3.  5.  1.]
 [ 4.  4.  4.  4.  6.  5.  7.  3.  1.]
 [ 8.  2.  1.  1.  5.  1.  1.  1.  1.]
 [ 6.  3.  3.  3.  3.  2.  6.  1.  1.]
 [ 1.  1.  1.  1.  2. 10.  3.  1.  1.]
 [ 5.  1.  2. 10.  4.  5.  2.  1.  1.]
 [ 6.  3.  3.  5.  3. 10.  3.  5.  3.]
 [ 5.  4.  4.  5.  7. 10.  3.  2.  1.]
 [ 4.  4.  2.  1.  2.  5.  2.  1.  2.]
 [ 8.  3.  3.  1.  2.  2.  3.  2.  1.]
 [ 4.  3.  1.  1.  2.  1.  4.  8.  1.]
 [ 8.  4.  6.  3.  3.  1.  4.  3.  1.]
 [ 3.  1.  3.  1.  3.  4.  1.  1.  1.]
 [ 5.  2.  2.  2.  2.  2.  3.  2.  2.]
 [ 5.  7.  7.  1.  5.  8.  3.  4.  1.]
 [ 1.  1.  1.  2.  1.  3.  1.  1.  7.]
 [ 3.  4.  5.  3.  7.  3.  4.  6.  1.]
 [ 5.  4.  5.  1.  8.  1.  3.  6.  1.]
 [ 8.  4.  4.  5.  4.  7.  7.  8.  2.]
 [ 3.  1.  1.  1.  2.  5.  5.  1.  1.]
 [ 4.  2.  4.  3.  2.  2.  2.  1.  1.]
 [ 5.  3.  3.  4.  2.  4.  3.  4.  1.]
 [ 4.  2.  3.  5.  3.  8.  7.  6.  1.]
 [ 5.  6.  6.  2.  4. 10.  3.  6.  1.]
 [ 7.  4.  7.  4.  3.  7.  7.  6.  1.]
 [ 3. 10.  3. 10.  6. 10.  5.  1.  4.]
 [ 3.  4.  4. 10.  5.  1.  3.  3.  1.]
 [10.  5.  5.  6.  3. 10.  7.  9.  2.]
 [ 8.  7.  4.  4.  5.  3.  5. 10.  1.]
 [ 6. 10. 10.  2.  8. 10.  7.  3.  3.]
 [ 2.  5.  3.  3.  6.  7.  7.  5.  1.]
 [10.  4.  3.  1.  3.  3.  6.  5.  2.]
 [ 8. 10.  4.  4.  8. 10.  8.  2.  1.]
 [ 6.  3.  4.  1.  5.  2.  3.  9.  1.]
 [10. 10. 10.  1.  6.  1.  2.  8.  1.]
 [10.  4.  5.  4.  3.  5.  7.  3.  1.]
 [ 3.  4.  5.  2.  6.  8.  4.  1.  1.]
 [ 5.  3.  5.  5.  3.  3.  4. 10.  1.]
 [ 6.  3.  2.  1.  3.  4.  4.  1.  1.]
 [ 5.  7.  4.  1.  6.  1.  7. 10.  3.]
 [10. 10.  6.  3.  3. 10.  4.  3.  2.]
 [ 9. 10. 10.  1. 10.  8.  3.  3.  1.]
 [ 5.  4.  6.  7.  9.  7.  8. 10.  1.]
 [ 5.  3.  3.  3.  2.  3.  4.  4.  1.]
 [ 5.  3.  2.  8.  5. 10.  8.  1.  2.]
 [ 8. 10. 10.  1.  3.  6.  3.  9.  1.]
 [ 7.  2.  4.  1.  3.  4.  3.  3.  1.]
 [ 5.  3.  3.  1.  3.  3.  3.  3.  3.]
 [ 4.  1.  1.  3.  1.  5.  2.  1.  1.]
 [ 4. 10.  8.  5.  4.  1. 10.  1.  1.]
 [10.  6.  6.  3.  4.  5.  3.  6.  1.]
 [ 4.  8.  6.  4.  3.  4. 10.  6.  1.]
 [ 3.  3.  6.  4.  5.  8.  4.  4.  1.]
```

```
[ 2.  3.  4.  4.  2.  5.  2.  5.  1.]
[ 8.  6.  4.  3.  5.  9.  3.  1.  1.]
[ 9.  1.  2.  6.  4. 10.  7.  7.  2.]
[ 8.  2.  4.  1.  5.  1.  5.  4.  4.]
[ 9.  5.  8.  1.  2.  3.  2.  1.  5.]
[ 6.  5.  5.  8.  4. 10.  3.  4.  1.]
[ 5.  5.  5.  2.  5. 10.  4.  3.  1.]
[10.  5.  5.  3.  6.  7.  7. 10.  1.]
[ 7.  3.  2. 10.  5. 10.  5.  4.  4.]
[ 8.  7.  8.  5. 10. 10.  7.  2.  1.]
[ 4.  6.  6.  5.  7.  6.  7.  7.  3.]
[ 5. 10. 10.  5.  4.  5.  4.  4.  1.]
[ 5.  5.  5.  6.  3. 10.  3.  1.  1.]
[ 8.  3.  5.  4.  5. 10.  1.  6.  2.]
[10.  6.  3.  6.  4. 10.  7.  8.  4.]
[ 7.  4.  6.  4.  6.  1.  4.  3.  1.]
[ 7.  8.  3.  7.  4.  5.  7.  8.  2.]
[10.  6.  4.  1.  3.  4.  3.  2.  3.]]
```

In [146]:
```
Y_pred = classifier_svm.predict(X_test)
```

In [147]:
```
print(classification_report(Y_test,Y_pred))
```

```
              precision    recall  f1-score   support

           0       0.99      1.00      0.99        90
           1       1.00      0.98      0.99        47

    accuracy                           0.99       137
   macro avg       0.99      0.99      0.99       137
weighted avg       0.99      0.99      0.99       137
```

In [148]:
```
# ADDED BY ME
accuracy_score(y_true=Y_test, y_pred=Y_pred)
```

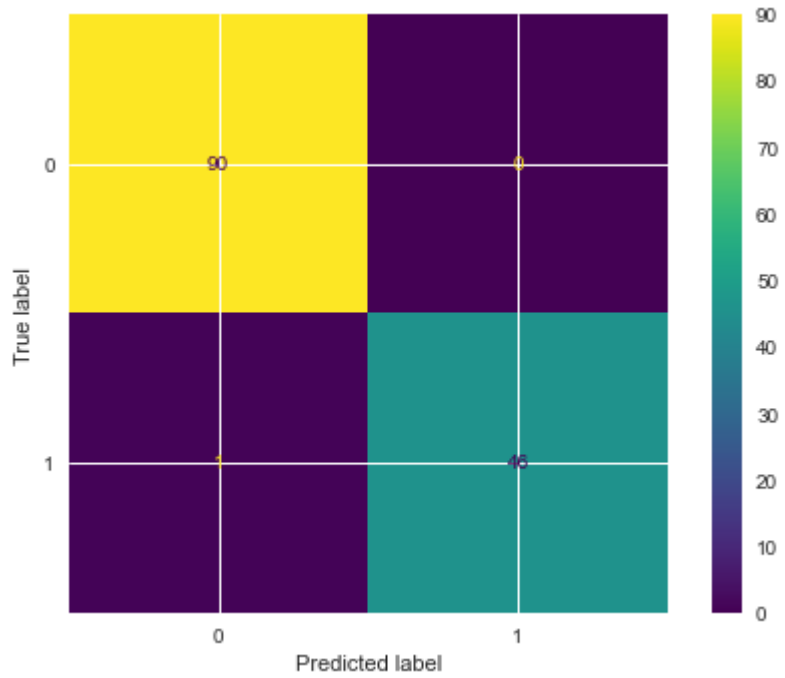
Out[148]:
```
0.9927007299270073
```

In [149]:
```
# ADDED BY ME
confusion_matrix(Y_test,Y_pred)
```

Out[149]:
```
array([[90,  0],
       [ 1, 46]], dtype=int64)
```

In [150]:
```
# ADDED BY ME
from sklearn.metrics import plot_confusion_matrix
plot_confusion_matrix(classifier_svm,X_test,Y_test)
```

Out[150]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1e4c72147
30>
```

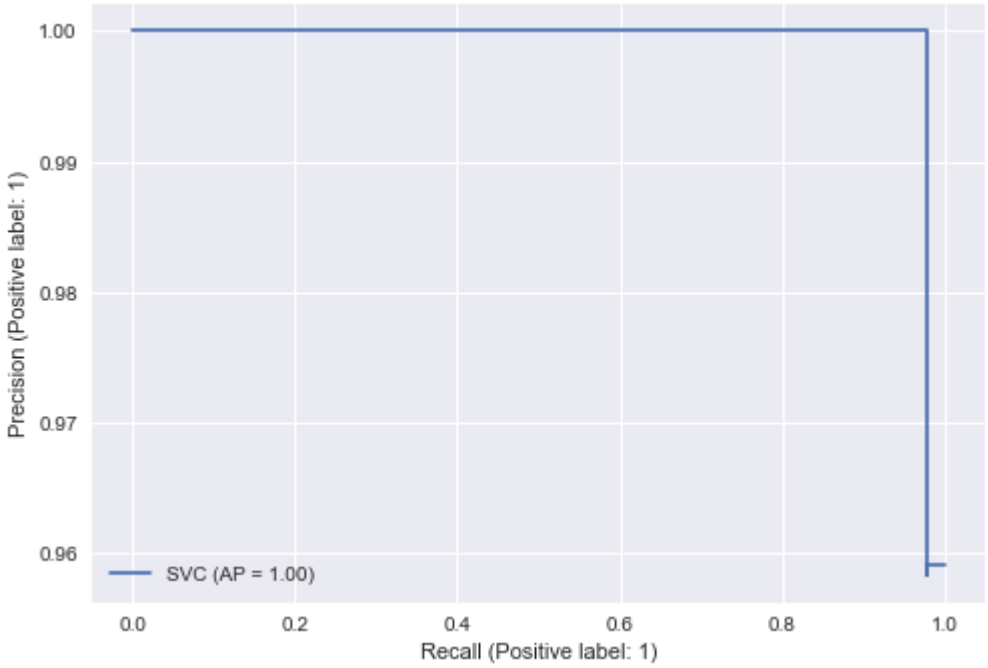


In [ ]:

In [ ]:

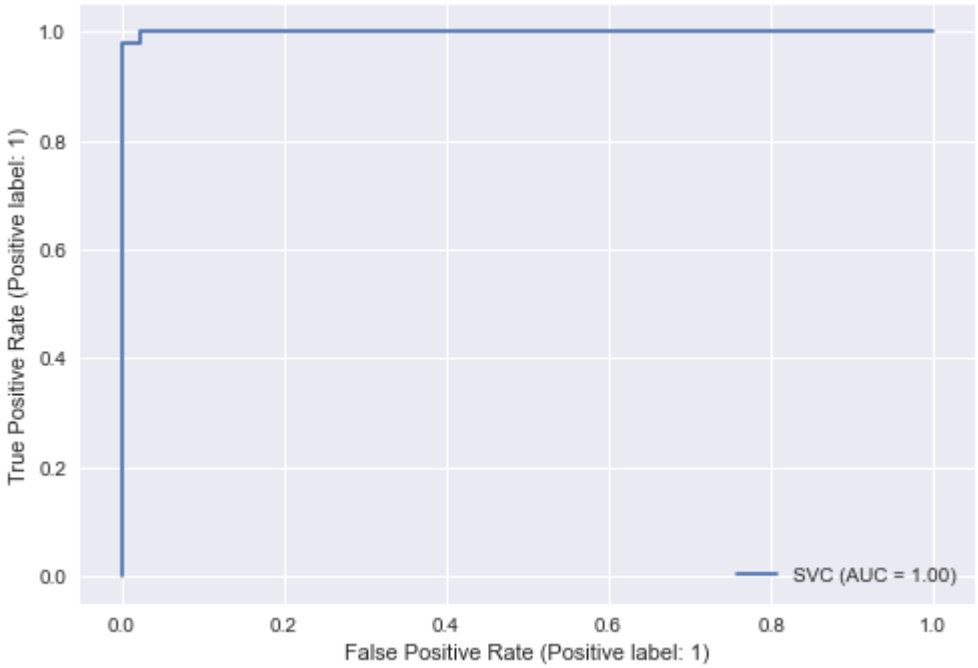
In [151]:
```
# ADDED BY ME
plot_precision_recall_curve(classifier_svm,X_test,Y_test)
```

Out[151]:
```
<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x1e4
c8606b80>
```



In [152]:
```
# ADDED BY ME
plot_roc_curve(classifier_svm,X_test,Y_test)
```

Out[152]:
```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1e4c74dbc40>
```



In [ ]:

In [ ]:

4. Perform PCA on the dataset, project the data onto the new principal components, apply SVC on this data and compare the result.

In [153]:
```
from sklearn.preprocessing import StandardScaler
```

In [154]:
```
scaler=StandardScaler()
```

In [155]:
```
scaled_df_features = scaler.fit_transform(data_X)
```

In [156]:
```
scaled_df_features
```

Out[156]:
```
array([[ 0.19790469, -0.70221201, -0.74177362, ..., -0.18182716,
        -0.61292736, -0.34839971],
       [ 0.19790469,  0.27725185,  0.26278299, ..., -0.18182716,
        -0.28510482, -0.34839971],
       [-0.51164337, -0.70221201, -0.74177362, ..., -0.18182716,
        -0.61292736, -0.34839971],
       ...,
       [ 0.19790469,  2.23617957,  2.2718962 , ...,  1.86073779,
         2.33747554,  0.22916583],
       [-0.15686934,  1.58320366,  0.93248739, ...,  2.67776377,
         1.02618536, -0.34839971],
       [-0.15686934,  1.58320366,  1.6021918 , ...,  2.67776377,
         0.37054027, -0.34839971]])
```

In [163]:
```
#PCA
#Perform PCA on the  scaled_df_features data set with 2 components.
```

In [157]:
```
from sklearn.decomposition import PCA
```

In [158]:
```
pca_model = PCA(n_components=2)
```

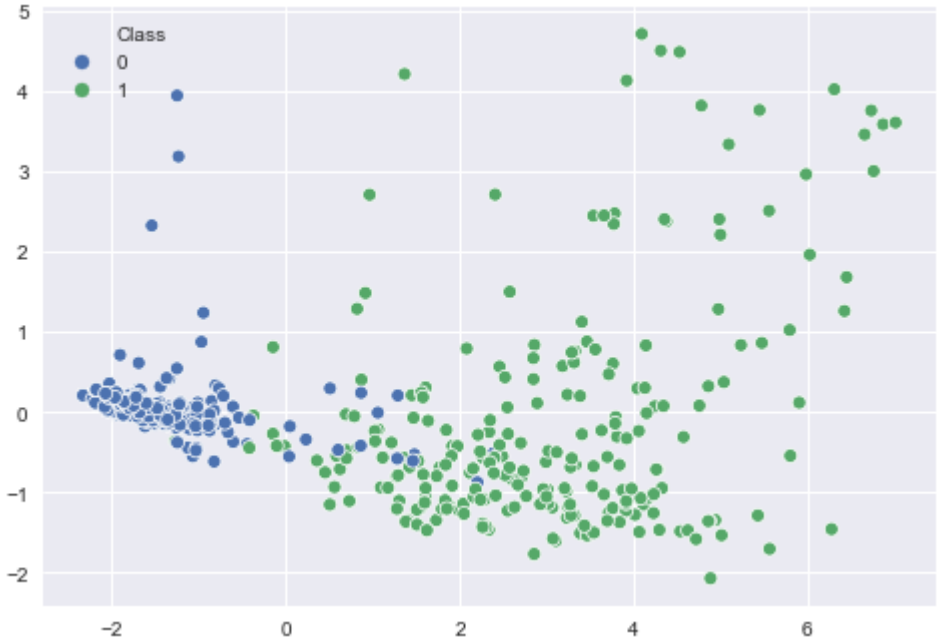
In [159]:
```
pca_scaled_df_features = pca_model.fit_transform(scaled_df_features)
```

In [160]:
```
pca_scaled_df_features.shape
```

Out[160]:
```
(683, 2)
```

In [162]:
```
sns.scatterplot(pca_scaled_df_features[:,0],pca_scaled_df_features[:,1],hue=cl
ass_label)
```

Out[162]: <matplotlib.axes._subplots.AxesSubplot at 0x1e4c88259a0>



In [164]:
```
#How much variance is explained by 2 principal components.
np.sum(pca_model.explained_variance_ratio_)
```

Out[164]: 0.7417162482831758

In [165]:
```
pca_components = pca_model.components_
```

In [166]:
```
principal_br_Df = pd.DataFrame(data = pca_scaled_df_features
             , columns = ['principal component 1', 'principal component 2'])
```

In [167]:
```
principal_br_Df.tail()
```

Out[167]:

	principal component 1	principal component 2
678	-1.723605	0.184232
679	-2.074148	0.231929
680	3.789261	-0.142209
681	2.240007	-1.091287
682	2.632462	-1.184698

In [207]:
```
df_comp = pd.DataFrame(pca_components,index=['PC1','PC2'],columns=data_X.colum
ns)
```

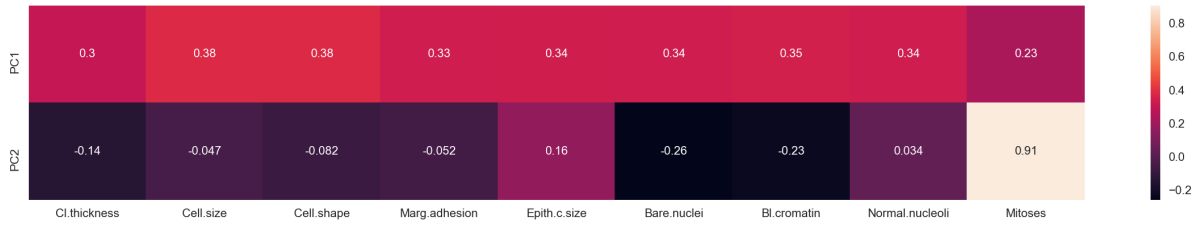
In [208]:
```
df_comp
```

Out[208]:

	Cl.thickness	Cell.size	Cell.shape	Marg.adhesion	Epith.c.size	Bare.nuclei	Bl.cromatin	N
PC1	0.302063	0.380793	0.377583	0.332724	0.336234	0.335068	0.345747	
PC2	-0.140801	-0.046640	-0.082422	-0.052094	0.164404	-0.261261	-0.228077	

In [209]:
```
plt.figure(figsize=(20,3),dpi=150)
sns.heatmap(df_comp,annot=True)
```

Out[209]: <matplotlib.axes._subplots.AxesSubplot at 0x1e4c91ad9a0>



In [ ]:
```
```

In [176]:
```
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
```

In [177]:
```
X_train_pca, X_test_pca, y_train_pca, y_test_pca = train_test_split(scaled_df_
features,class_label, test_size=0.20, random_state=1)
```

In [178]:
```
X_test_pca
```

Out[178]:
```
array([[ 0.19790469, -0.70221201, -0.74177362, ..., -0.59034015,
        -0.61292736, -0.34839971],
       [-1.22119144, -0.70221201, -0.74177362, ..., -0.18182716,
        -0.61292736, -0.34839971],
       [-0.15686934, -0.70221201, -0.74177362, ..., -0.18182716,
        -0.61292736, -0.34839971],
       ...,
       [-0.51164337, -0.70221201, -0.40692142, ..., -0.59034015,
        -0.61292736, -0.34839971],
       [-0.8664174 , -0.0492361 , -0.40692142, ..., -0.18182716,
        -0.61292736, -0.34839971],
       [ 1.26222679,  0.27725185,  1.2673396 , ..., -0.18182716,
         2.00965299,  0.22916583]])
```

In [179]:
```
y_test_pca.tail()
```

Out[179]:
```
90     0
377    0
374    0
408    0
270    1
Name: Class, dtype: int64
```

In [180]:
```
classifier_svm_pca = SVC()
classifier_svm_pca.fit(X_train_pca,y_train_pca)
```

Out[180]:
```
SVC()
```

In [181]:
```
#Making the predictions
preds = classifier_svm_pca.predict(X_test_pca)
```

In [182]:
```
from sklearn.metrics import confusion_matrix, classification_report,accuracy_s
core
```

In [183]:
```
# ADDED BY ME
accuracy_score(y_true=y_test_pca, y_pred=preds)
```

Out[183]:
```
1.0
```

In [185]:
```
cf = pd.DataFrame(confusion_matrix(y_test_pca,preds),columns=['True','False'],
index=['True','False'])
cf
```

Out[185]:

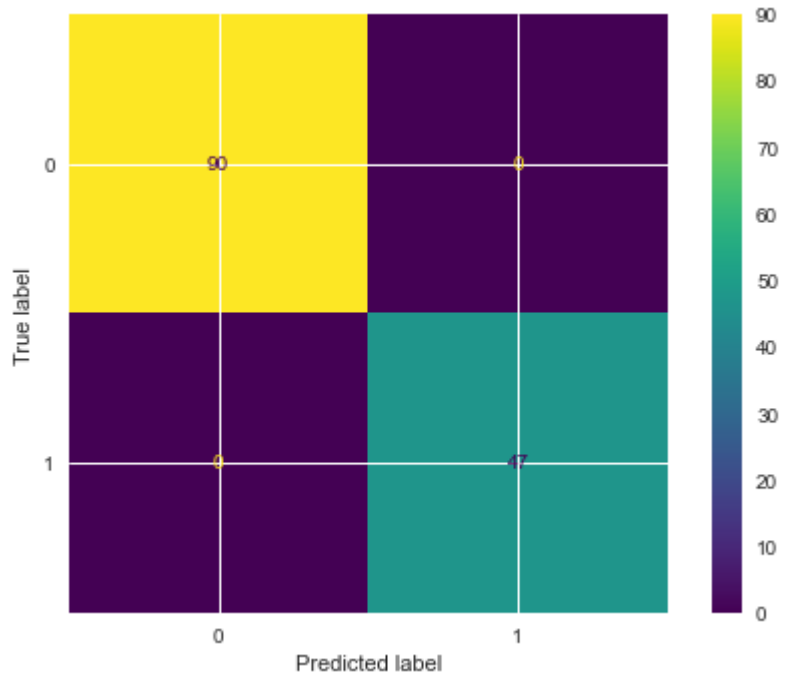
	True	False
True	90	0
False	0	47

In [186]:
```
# ADDED BY ME
confusion_matrix(y_test_pca,preds)
```

Out[186]:
```
array([[90,  0],
       [ 0, 47]], dtype=int64)
```

In [187]:
```
# ADDED BY ME
from sklearn.metrics import plot_confusion_matrix
plot_confusion_matrix(classifier_svm_pca,X_test_pca,y_test_pca)
```

Out[187]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1e4c73d9dc0>
```

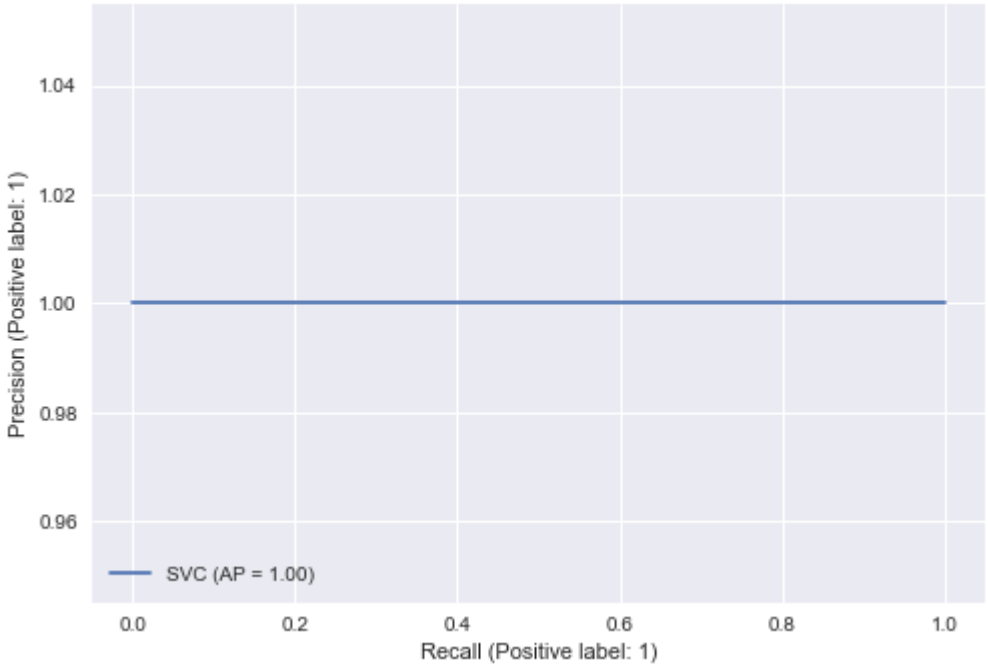


In [188]:
```
print(classification_report(y_test_pca,preds))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        90
           1       1.00      1.00      1.00        47

    accuracy                           1.00       137
   macro avg       1.00      1.00      1.00       137
weighted avg       1.00      1.00      1.00       137
```

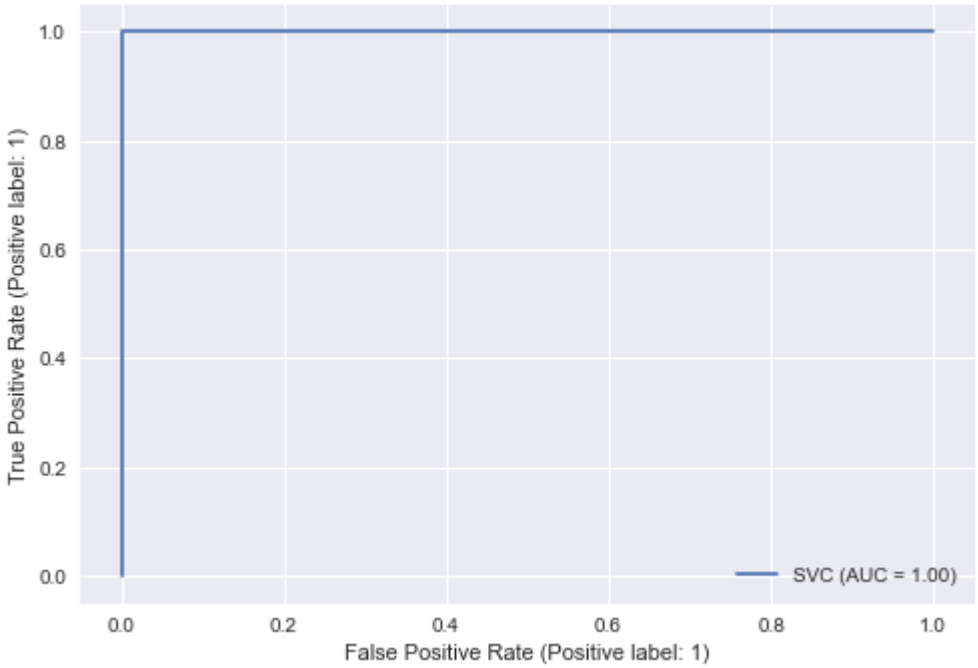
In [189]:
```
# ADDED BY ME
plot_precision_recall_curve(classifier_svm_pca,X_test_pca,y_test_pca)
```

Out[189]:
```
<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x1e4
c9037df0>
```



In [190]:
```
# ADDED BY ME
plot_roc_curve(classifier_svm_pca,X_test_pca,y_test_pca)
```

Out[190]:
```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1e4c8712460>
```



In [ ]:

In [ ]:

5. Compare the result with KNN classifier in terms of accuracy by constructing a confusion matrix.

In [191]:
```
model_knn = KNeighborsClassifier(n_neighbors=4)
```

In [192]:
```
model_knn.fit(X_train, Y_train)

# predict probabilities
pred_prob2 = model_knn.predict_proba(X_test)
```

In [193]:
```
fpr2, tpr2, thresh2 = roc_curve(Y_test, pred_prob2[:,1], pos_label=1)
print(fpr2)
```

```
[0.         0.         0.         0.         0.01111111 1.        ]
```

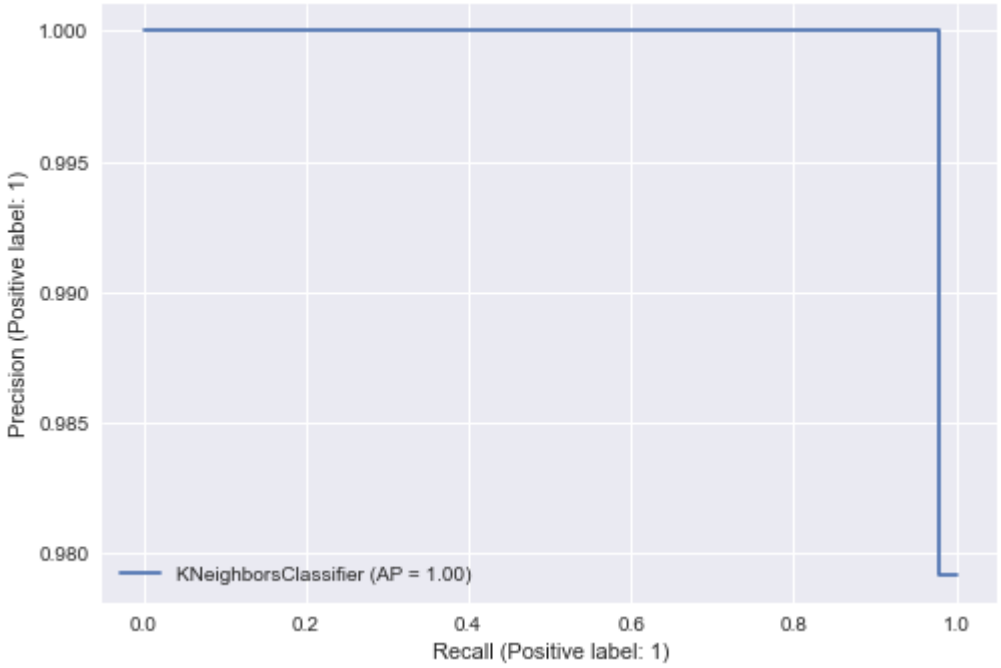
In [194]:
```
auc_score2 = roc_auc_score(Y_test, pred_prob2[:,1])

print(auc_score2)
```

```
0.9998817966903074
```

In [196]:
```
from sklearn.metrics import plot_precision_recall_curve,plot_roc_curve
plt.style.use('seaborn')
```

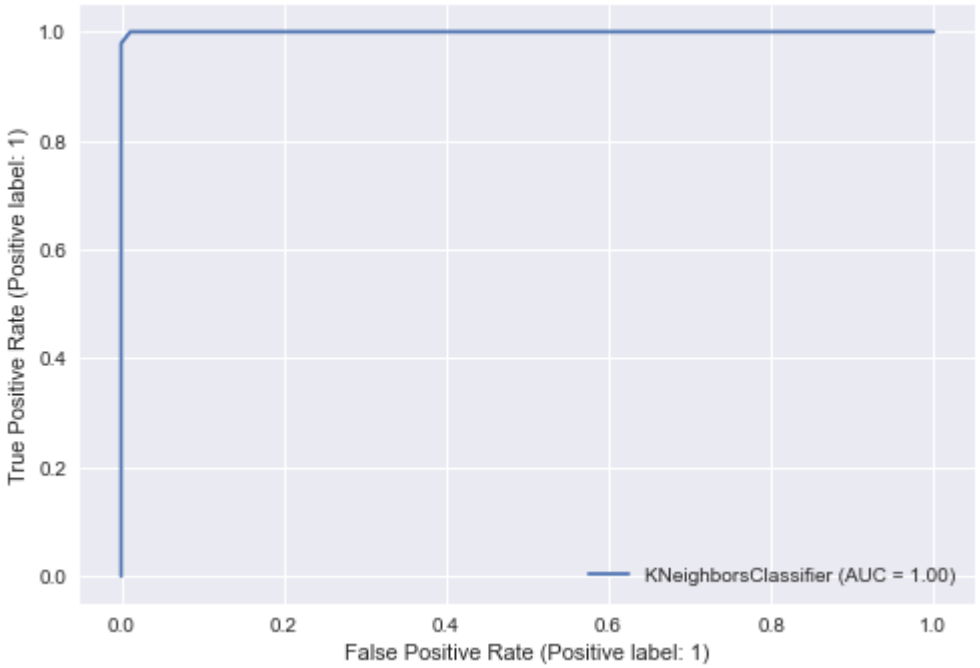
In [197]:
```
# ADDED BY ME
plot_precision_recall_curve(model_knn,X_test,Y_test)
```

Out[197]:
```
<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x1e4
c7442130>
```



In [198]:
```
# ADDED BY ME
plot_roc_curve(model_knn,X_test,Y_test)
```

Out[198]:
```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1e4c87cc6a0>
```



In [199]:
```
# ADDED BY ME
pred_y_KNN=model_knn.predict(X_test)
pred_y_KNN
```

Out[199]:
```
array([0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1,
       0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0,
       1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 1], dtype=int64)
```

In [203]:
```
# ADDED BY ME
accuracy_score(y_true=Y_test, y_pred=pred_y_KNN)
```

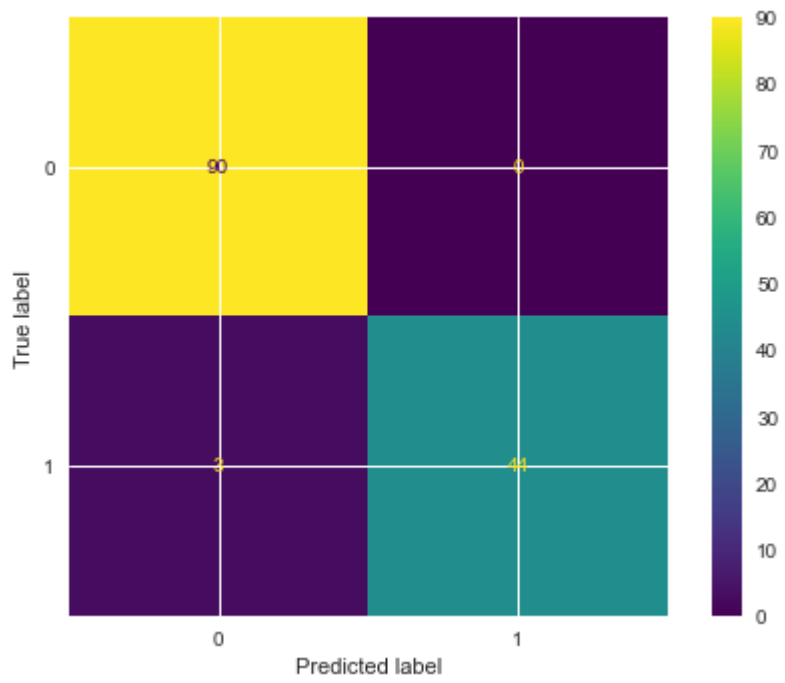
Out[203]:
```
0.9781021897810219
```

In [200]:
```
# ADDED BY ME
confusion_matrix(Y_test,pred_y_KNN)
```

Out[200]:
```
array([[90,  0],
       [ 3, 44]], dtype=int64)
```

In [201]:
```
# ADDED BY ME
plot_confusion_matrix(model_knn,X_test,Y_test)
```

Out[201]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1e4ca3707
f0>
```



In [202]:
```
# ADDED BY ME
print(classification_report(Y_test,pred_y_KNN))
```

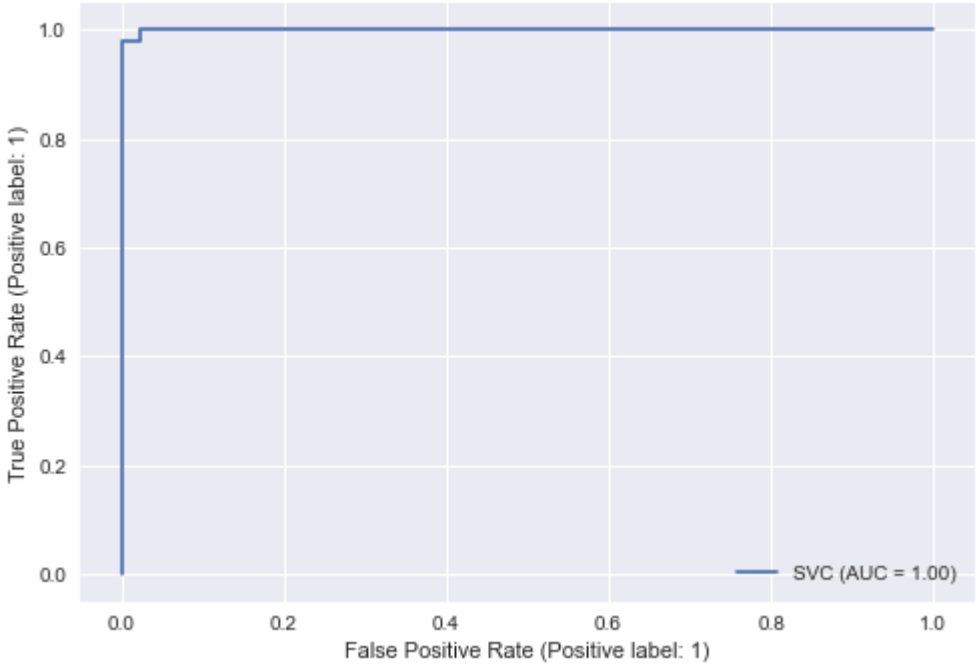
```
              precision    recall  f1-score   support

           0       0.97      1.00      0.98        90
           1       1.00      0.94      0.97        47

    accuracy                           0.98       137
   macro avg       0.98      0.97      0.98       137
weighted avg       0.98      0.98      0.98       137
```

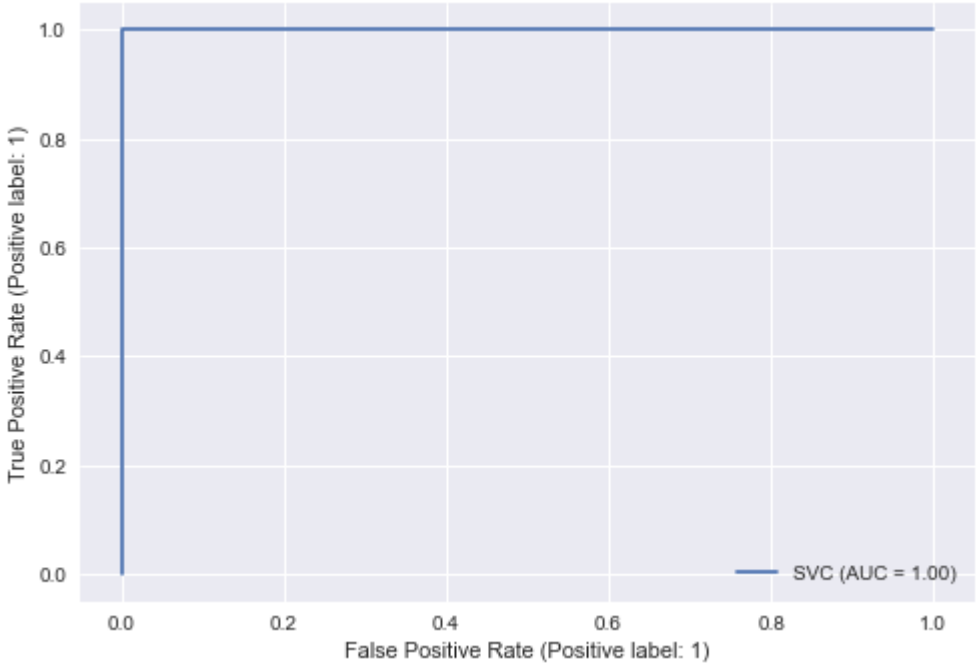
6.Compare the result with KNN classifier using ROC curve

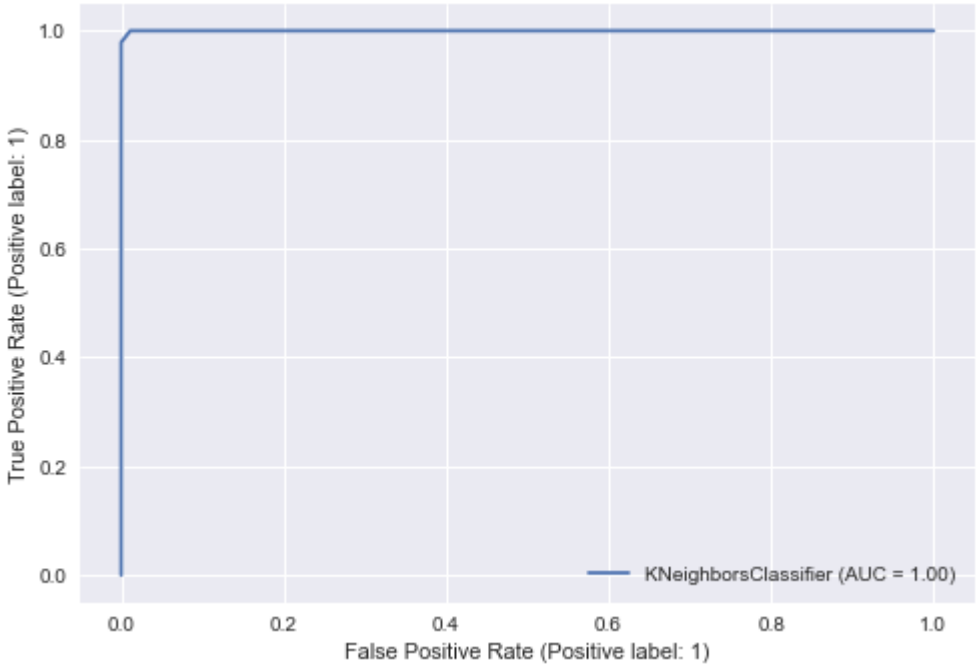
already allthese roc and auc calculation done by me in every classifier model

In [204]:
```
# normal LINEAR SVM
plot_roc_curve(classifier_svm,X_test,Y_test)
# LINEAR SVM AFTER PCA
plot_roc_curve(classifier_svm_pca,X_test_pca,y_test_pca)

# KNN
plot_roc_curve(model_knn,X_test,Y_test)
```

Out[204]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1e4ca47aa90>






True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)
KNeighborsClassifier (AUC = 1.00)
0.0
0.2
0.4
0.6
0.8
1.0

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: