ACKNOWLEDGEMENT

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An assemblage of this nature could never have been attempted with our reference to and inspiration from the works of others whose details are mentioned in references section. I acknowledge our indebtedness to all of them. Further, I would like to express my feeling towards my parents and God who directly or indirectly encouraged and motivated us during Assertion.

Introduction

In machine learning, it is important to evaluate the performance of different models on various datasets to determine the most effective onefor a given task. In this project, we will implement two datasets, Exp1and Exp2, using different classification algorithms, including KNN, BPNN, Kernel SVM, Random Forest, Ada boost Random Forest, Ada boost SVM, and XG boost. Additionally, we will analyze the effect ofPCA on model performance by comparing the accuracy, confusion matrix, and ROC curve of the models with and without PCA. The ultimate goal of this project is to identify the most accurate and efficientmodel for each dataset and to gain insights into the impact of PCA on model performance.

CASE STUDY

<u>Q1.</u> Implement two dataset Exp1 and Exp2 using KNN, BPNN, Kernel SVM, Random Forest, Ada boost Random Forest, Ada boost SVM, XG boost with and without PCA. Then find out its accuracy, confusion matrix and ROC curve.

<u>SOURCE CODE:-</u>

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

%matplotlib inline
```

In [2]:
```
data1 = pd.read_csv('Exp_1.csv')
data2 = pd.read_csv('Exp_2.csv')
```

In [3]:
```
data1.shape, data2.shape
```

Out[3]:
```
((1040, 97), (660, 97))
```

In [4]:
```
X1 = data1.iloc[: , :-1]

y1 = data1.iloc[: , -1]
```

In [5]:
```
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
y1 = label_encoder.fit_transform(y1)
y1
```

Out[5]:
```
array([1, 1, 1, ..., 0, 0, 0], dtype=int64)
```

<u>M,mm</u>

In [6]:
```
X2 = data2.iloc[: , :-1]

y2 = data2.iloc[: , -1]
```

In [7]:
```
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
y2 = label_encoder.fit_transform(y2)
```

In [8]:
```
from sklearn.preprocessing import Normalizer
norm = Normalizer()
columns1 = X1.columns
columns2 = X2.columns
X1 = norm.fit_transform(X1)
X1 = pd.DataFrame(X1, columns = columns1)
X2 = norm.fit_transform(X2)
X2 = pd.DataFrame(X2, columns = columns2)
```

In [9]:
```
X1.describe()
```
Out[9]:

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	...	F87	
count	1040.000000	1040.000000	1040.000000	1040.000000	1040.000000	1040.000000	1040.000000	1040.000000	1040.000000	1040.000000	...	1.040000e+03	1
mean	0.006010	0.017594	0.028439	0.172880	0.152109	0.165377	0.000954	0.000139	0.025268	0.009156	...	4.201056e-04	4
std	0.009270	0.011847	0.024708	0.045482	0.053191	0.051855	0.002727	0.000543	0.010903	0.004561	...	7.744505e-03	7
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	7.290779e-07	1
25%	0.000177	0.008713	0.005664	0.151358	0.128152	0.136601	0.000057	0.000013	0.017324	0.005661	...	2.576797e-06	4
50%	0.000682	0.015704	0.023690	0.164454	0.142248	0.159535	0.000082	0.000020	0.026512	0.008992	...	3.353329e-06	5
75%	0.008706	0.026260	0.045800	0.178801	0.159251	0.179050	0.000127	0.000030	0.032473	0.011983	...	4.778700e-06	6
max	0.052368	0.054929	0.133256	0.376966	0.384592	0.370908	0.028490	0.007428	0.088380	0.032303	...	1.443376e-01	1

8 rows × 96 columns

In [10]:
```
X2.replace(0, np.nan, inplace = True)
```
In [11]:
```
X2.dropna(axis = 1, inplace = True)
```
In [12]:
```
from sklearn.model_selection import train_test_split
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size = 0.2, random_state = 0)
```
In [13]:
```
X_train1.shape, X_test1.shape, y_train1.shape, y_test1.shape
```
Out[13]: ((832, 96), (208, 96), (832,), (208,))

In [14]:
```
import warnings
warnings.filterwarnings("ignore")
```
In [15]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier
```
In [16]:
```
models = list()

models.append(('KNN', KNeighborsClassifier(n_neighbors=2)))
models.append(('BPNN', MLPClassifier()))
models.append(('SVC', SVC(kernel='poly', probability=True)))
models.append(('RF', RandomForestClassifier(n_estimators=100, max_features="auto",random_state=0)))
models.append(('AdaB', AdaBoostClassifier(n_estimators=100)))
models.append(('XGB', XGBClassifier()))
```
In [17]:
```
models = pd.DataFrame(models, columns = ['Name', 'Classifier'])
models.set_index('Name', inplace = True)
models
```
Out[17]:

Name	Classifier
KNN	KNeighborsClassifier(n_neighbors=2)
BPNN	MLPClassifier()
SVC	SVC(kernel='poly', probability=True)
RF	RandomForestClassifier(random_state=0)
AdaB	AdaBoostClassifier(n_estimators=100)
XGB	XGBClassifier(base_score=None, booster=None, c...

For Exp_1 DataSet WithOut PCA

In [18]:
```
from sklearn.metrics import classification_report,confusion_matrix
```
In [19]:
```
for classifier in models.Classifier:

    classifier.fit(X_train1,y_train1)
    pred = classifier.predict(X_test1)

    print(classifier)
    print('\n')
    print('CONFUSION MATRIX')
    print(confusion_matrix(y_test1,pred))
    print('\nCLASSIFICATION REPORT')
    print(classification_report(y_test1,pred))
```
KNeighborsClassifier(n_neighbors=2)

CONFUSION
MATRIX[[148 10]
[46 4]]

```
CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       0.76      0.94      0.84       158
           1       0.29      0.08      0.12        50

    accuracy                           0.73       208
   macro avg       0.52      0.51      0.48       208
weighted avg       0.65      0.73      0.67       208

MLPClassifier()


CONFUSION MATRIX
[[158   0]
 [ 50   0]]

CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       0.76      1.00      0.86       158
           1       0.00      0.00      0.00        50

    accuracy                           0.76       208
   macro avg       0.38      0.50      0.43       208
weighted avg       0.58      0.76      0.66       208
```

SVC(kernel='poly', probability=True)

CONFUSION MATRIX
[[158 0]
[50 0]]

CLASSIFICATION REPORT

```
              precision    recall  f1-score   support

           0       0.76      1.00      0.86       158
           1       0.00      0.00      0.00        50

    accuracy                           0.76       208
   macro avg       0.38      0.50      0.43       208
weighted avg       0.58      0.76      0.66       208
```

RandomForestClassifier(random_state=0)

CONFUSION MATRIX
[[138 20]

[45 5]]

CLASSIFICATION

REPORT

	precision	recall	f1-score	support
0	0.75	0.87	0.81	158
1	0.20	0.10	0.13	50
accuracy			0.69	208
macro avg	0.48	0.49	0.47	208
weighted avg	0.62	0.69	0.65	208

AdaBoostClassifier(n_estimators=100)

CONFUSION
MATRIX[[136 22]

[46 4]] CLASSIFICATION

REPORT

	precision	recall	f1-score	support
0	0.75	0.86	0.80	158
1	0.15	0.08	0.11	50
accuracy			0.67	208
macro avg	0.45	0.47	0.45	208
weighted avg	0.60	0.67	0.63	208

CONFUSION
MATRIX[[132 26]
[42 8]]

CLASSIFICATION

REPORT

	precision	recall	f1-score	support
0	0.76	0.84	0.80	158
1	0.24	0.16	0.19	50
accuracy			0.67	208
macro avg	0.50	0.50	0.49	208
weighted avg	0.63	0.67	0.65	208

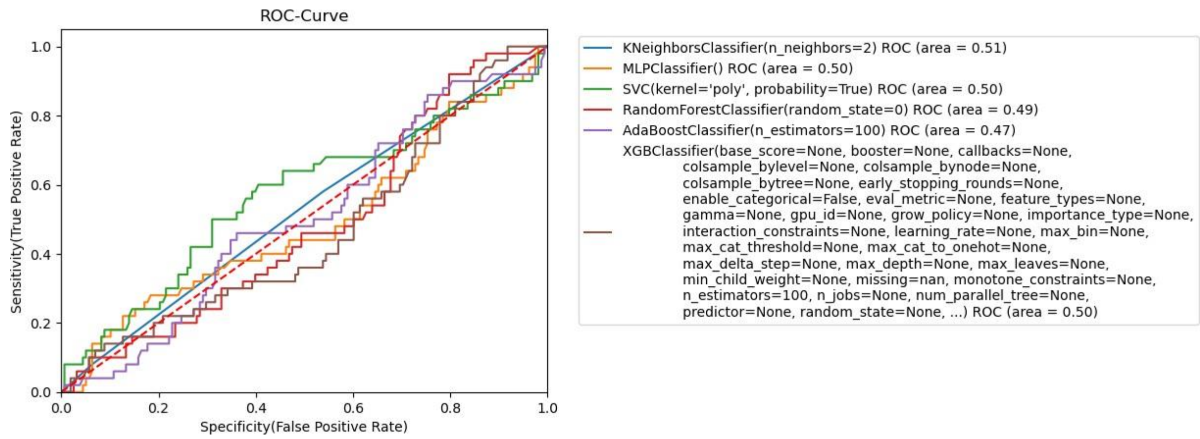
XGBClassifier(base_score=None, booster=None, callbacks=None, colsample_bylevel=None,
colsample_bynode=None, colsample_bytree=None, early_stopping_rounds=None,
enable_categorical=False, eval_metric=None, feature_types
=None, None,

e=None,

=None,

g a m m a	=None, gpu_id=None, grow_policy=None, importance_typ interaction_constraints=None, learning_rate=None, max_bin max_cat_threshold=None, max_cat_to_onehot=None, max_delta_step=None, max_depth=None, max_leaves=None, min_child_weight=None, missing=nan, monotone_constraints= n_estimators=100, n_jobs=None, num_parallel_tree=None, predictor=None, random_state=None, ...)

In [20]:
```python
from sklearn import metrics
for model in models.Classifier:
    model.fit(X_train1, y_train1) # train the model
    y_pred=model.predict(X_test1) # predict the test data
# Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = metrics.roc_curve(y_test1, model.predict_proba(X_test1)[:,1])
# Calculate Area under the curve to display on the plot
    auc = metrics.roc_auc_score(y_test1,model.predict(X_test1))
# Now, plot the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (model, auc))
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('ROC-Curve')
plt.legend(bbox_to_anchor = (1.05, 1), loc = 2)
plt.show()   # Display
```



For Exp 2 Dataset

In [21]:
```python
models1 = pd.DataFrame(models)
models1
```

Out[21]:

Name	Classifier
KNN	KNeighborsClassifier(n_neighbors=2)
BPNN	MLPClassifier()
SVC	SVC(kernel='poly', probability=True)
RF	(DecisionTreeClassifier(max_features='auto', r...
AdaB	(DecisionTreeClassifier(max_depth=1, random_st...
XGB	XGBClassifier(base_score=None, booster=None, c...

In [22]:
```python
from sklearn.model_selection import train_test_split
X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size = 0.2, random_state = 0)
```

In [23]:
```python
for classifier in models.Classifier:

    classifier.fit(X_train2,y_train2)
    pred = classifier.predict(X_test2)

    print(classifier)
    print('\n')
    print('CONFUSION MATRIX')
    print(confusion_matrix(y_test2,pred))
    print('\nCLASSIFICATION REPORT')
    print(classification_report(y_test2,pred))
```

KNeighborsClassifier(n_neighbors=2)

CONFUSION
MATRIX[[98   0]
 [0 34]]

```
CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        98
           1       1.00      1.00      1.00        34

    accuracy                           1.00       132
   macro avg       1.00      1.00      1.00       132
weighted avg       1.00      1.00      1.00       132
```

```
MLPClassifier()


CONFUSION MATRIX
[[98  0]
 [34  0]]

CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       0.74      1.00      0.85        98
           1       0.00      0.00      0.00        34

    accuracy                           0.74       132
   macro avg       0.37      0.50      0.43       132
weighted avg       0.55      0.74      0.63       132
```

SVC(kernel='poly', probability=True)

CONFUSION MATRIX
[[98   0]
 [24 10]]

CLASSIFICATION REPORT

```
              precision    recall  f1-score   support

           0       0.80      1.00      0.89        98
           1       1.00      0.29      0.45        34

    accuracy                           0.82       132
   macro avg       0.90      0.65      0.67       132
weighted avg       0.85      0.82      0.78       132
```

RandomForestClassifier(random_state=0)

CONFUSION MATRIX
[[98   0]

[0 34]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	98
1	1.00	1.00	1.00	34
accuracy			1.00	132
macro avg	1.00	1.00	1.00	132
weighted avg	1.00	1.00	1.00	132

AdaBoostClassifier(n_estimators=100)

CONFUSION MATRIX
[[98 0]
[0 34]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	98
1	1.00	1.00	1.00	34
accuracy			1.00	132
macro avg	1.00	1.00	1.00	132
weighted avg	1.00	1.00	1.00	132

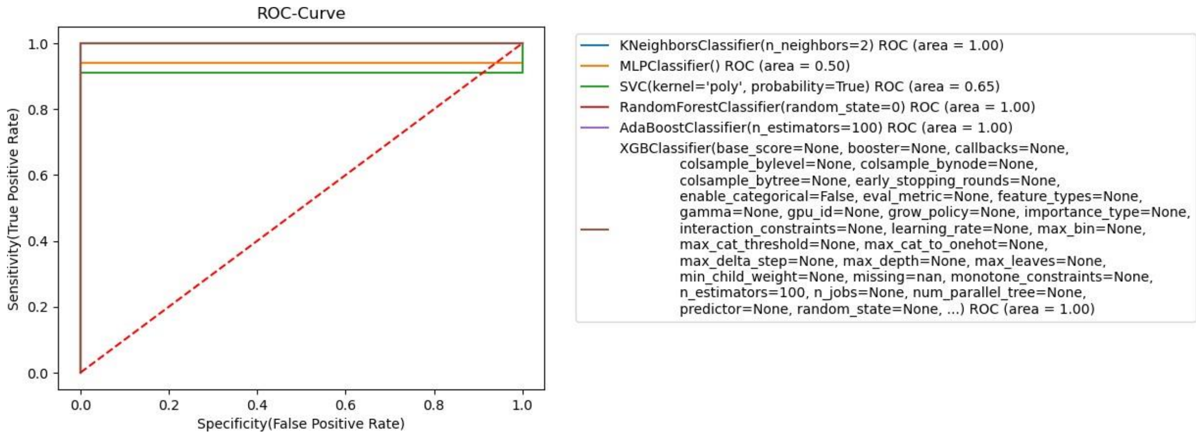
XGBClassifier(base_score=None, booster=None, callbacks=None, colsample_bylevel=None,
colsample_bynode=None, colsample_bytree=None, early_stopping_rounds=None,
enable_categorical=False, eval_metric=None, feature_types=None,
gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
interaction_constraints=None, learning_rate=None, max_bin=None,
max_cat_threshold=None, max_cat_to_onehot=None,
max_delta_step=None, max_depth=None, max_leaves=None,
min_child_weight=None, missing=nan, monotone_constraints=None,
n_estimators=100, n_jobs=None, num_parallel_tree=None,
predictor=None, random_state=None, ...)

CONFUSION MATRIX[[98 0]
[0 34]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	98
1	1.00	1.00	1.00	34
accuracy			1.00	132
macro avg	1.00	1.00	1.00	132
weighted avg	1.00	1.00	1.00	132

```
In [24]: for model in models.Classifier:
             model.fit(X_train2, y_train2) # train the model
             y_pred=model.predict(X_test2) # predict the test data
         # Compute False postive rate, and True positive rate
             fpr, tpr, thresholds = metrics.roc_curve(y_test2, model.predict_proba(X_test2)[:,1])
         # Calculate Area under the curve to display on the plot
             auc = metrics.roc_auc_score(y_test2,model.predict(X_test2))
         # Now, plot the computed values
             plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (model, auc))
         # Custom settings for the plot
         plt.plot([0, 1], [0, 1],'r--')
         #plt.xlim([0.0, 1.0])
         #plt.ylim([0.0, 1.05])
         plt.xlabel('Specificity(False Positive Rate)')
         plt.ylabel('Sensitivity(True Positive Rate)')
         plt.title('ROC-Curve')
         plt.legend(bbox_to_anchor = (1.05, 1), loc = 2)
         plt.show()   # Display
```



Now Using PCA

For Exp_1 DataSet

```
In [25]: from sklearn.decomposition import PCA

         pca = PCA(n_components = 2)
         pca.fit(X1)
         X1_PCA = pca.transform(X1)
         X1_PCA = pd.DataFrame(X1_PCA, columns = ['Feature_1', 'Feature_2'])
         X1_PCA.head()
```

Out[25]:

	Feature_1	Feature_2
0	-0.001265	-0.007240
1	-0.047608	0.002488
2	-0.165532	0.039008
3	0.002476	-0.009847
4	0.005327	-0.009459

```
In [26]: X1_PCA.shape, y1.shape
Out[26]: ((1040, 2), (1040,))
```

```
In [27]: from sklearn.model_selection import train_test_split
         XPCA_train1, XPCA_test1, y_train1, y_test1 = train_test_split(X1_PCA, y1, test_size = 0.2, random_state = 0)
```

```
In [28]: for classifier in models.Classifier:

             classifier.fit(XPCA_train1,y_train1)
             pred = classifier.predict(XPCA_test1)

             print(classifier)
             print('\n')
             print('CONFUSION MATRIX')
             print(confusion_matrix(y_test1,pred))
             print('\nCLASSIFICATION REPORT')
             print(classification_report(y_test1,pred))
```

KNeighborsClassifier(n_neighbors=2)

CONFUSION
MATRIX[[143 15]
[44 6]]

```
CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       0.76      0.91      0.83       158
           1       0.29      0.12      0.17        50

    accuracy                           0.72       208
   macro avg       0.53      0.51      0.50       208
weighted avg       0.65      0.72      0.67       208
```

```
MLPClassifier()


CONFUSION MATRIX
[[158   0]
 [ 50   0]]

CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       0.76      1.00      0.86       158
           1       0.00      0.00      0.00        50

    accuracy                           0.76       208
   macro avg       0.38      0.50      0.43       208
weighted avg       0.58      0.76      0.66       208
```

SVC(kernel='poly', probability=True)

CONFUSION MATRIX
[[157 1]
[50 0]]

CLASSIFICATION REPORT

```
              precision    recall  f1-score   support

           0       0.76      0.99      0.86       158
           1       0.00      0.00      0.00        50
```

accuracy			0.75	208
macro avg	0.38	0.50	0.43	208
weighted avg	0.58	0.75	0.65	208

RandomForestClassifier(random_state=0)

CONFUSION MATRIX[[131 27]
[42 8]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.76	0.83	0.79	158
1	0.23	0.16	0.19	50
accuracy			0.67	208
macro avg	0.49	0.49	0.49	208
weighted avg	0.63	0.67	0.65	208

AdaBoostClassifier(n_estimators=100)

CONFUSION MATRIX
[[151 7]
[46 4]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.77	0.96	0.85	158
1	0.36	0.08	0.13	50
accuracy			0.75	208
macro avg	0.57	0.52	0.49	208
weighted avg	0.67	0.75	0.68	208

XGBClassifier(base_score=None, booster=None, callbacks=None, colsample_bylevel=None,
colsample_bynode=None, colsample_bytree=None, early_stopping_rounds=None,
enable_categorical=False, eval_metric=None, feature_types=None,
gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
interaction_constraints=None, learning_rate=None, max_bin=None,
max_cat_threshold=None, max_cat_to_onehot=None,
max_delta_step=None, max_depth=None, max_leaves=None,
min_child_weight=None, missing=nan, monotone_constraints=None,
n_estimators=100, n_jobs=None, num_parallel_tree=None,

p   redictor=None, random_state=None, ...)

CONFUSION
MATRIX[[125   33]

[38 12]]

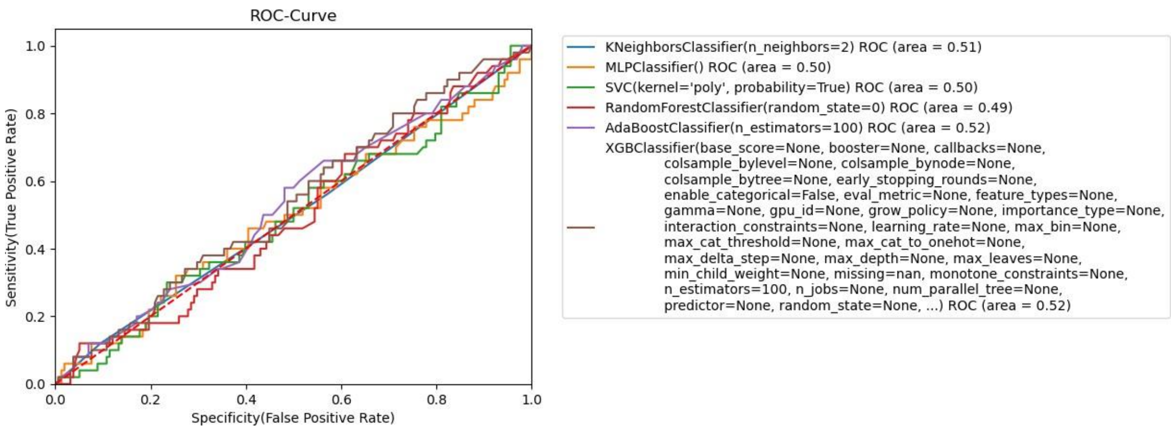
CLASSIFICATION REPORT

```
              precision    recall  f1-score   support

           0       0.77      0.79      0.78       158
           1       0.27      0.24      0.25        50

    accuracy                           0.66       208
   macro avg       0.52      0.52      0.52       208
weighted avg       0.65      0.66      0.65       208
```

In [29]:
```python
from sklearn import metrics
for model in models.Classifier:
    model.fit(XPCA_train1, y_train1) # train the model
    y_pred=model.predict(XPCA_test1) # predict the test data
# Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = metrics.roc_curve(y_test1, model.predict_proba(XPCA_test1)[:,1])
# Calculate Area under the curve to display on the plot
    auc = metrics.roc_auc_score(y_test1,model.predict(XPCA_test1))
# Now, plot the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (model, auc))
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('ROC-Curve')
plt.legend(bbox_to_anchor = (1.05, 1), loc = 2)
plt.show()   # Display
```



For Exp_2 DataSet

In [30]:
```
pca.fit(X2)
X2_PCA = pca.transform(X2)
X2_PCA = pd.DataFrame(X2_PCA, columns = ['Feature_1', 'Feature_2'])
X2_PCA.head()
```

Out[30]:

	Feature_1	Feature_2
0	0.029888	0.002475
1	0.077907	-0.024651
2	0.112228	-0.042671
3	-0.032063	-0.003627
4	-0.045120	-0.038436

In [31]:
```
XPCA_train2, XPCA_test2, y_train2, y_test2 = train_test_split(X2_PCA, y2, test_size = 0.2, random_state = 0)
```

In [32]:
```
for classifier in models.Classifier:

    classifier.fit(XPCA_train2,y_train2)
    pred = classifier.predict(XPCA_test2)

    print(classifier)
    print('\n')
    print('CONFUSION MATRIX')
    print(confusion_matrix(y_test2,pred))
    print('\nCLASSIFICATION REPORT')
    print(classification_report(y_test2,pred))
```

```
KNeighborsClassifier(n_neighbors=2)

CONFUSION
MATRIX[[98   0]
 [ 0 34]]

CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        98

           1       1.00      1.00      1.00        34

    accuracy                           1.00       132

   macro avg       1.00      1.00      1.00       132
weighted avg       1.00      1.00      1.00       132
MLPClassifier()


CONFUSION
MATRIX[[98   0]
 [33   1]]

CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       0.75      1.00      0.86        98

           1       1.00      0.03      0.06        34

    accuracy                           0.75       132

   macro avg       0.87      0.51      0.46       132
weighted avg       0.81      0.75      0.65       132
SVC(kernel='poly', probability=True)
```

CONFUSION MATRIX[[98   0]
 [14 20]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.88	1.00	0.93	98
1	1.00	0.59	0.74	34
accuracy			0.89	132
macro avg	0.94	0.79	0.84	132
weighted avg	0.91	0.89	0.88	132

RandomForestClassifier(random_state=0)

CONFUSION MATRIX
[[98   0]
 [0 34]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	98
1	1.00	1.00	1.00	34
accuracy			1.00	132
macro avg	1.00	1.00	1.00	132
weighted avg	1.00	1.00	1.00	132

AdaBoostClassifier(n_estimators=100)

CONFUSION MATRIX
[[98   0]
 [0 34]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	98
1	1.00	1.00	1.00	34
accuracy			1.00	132
macro avg	1.00	1.00	1.00	132
weighted avg	1.00	1.00	1.00	132

XGBClassifier(base_score=None, booster=None, callbacks=None, colsample_bylevel=None,
colsample_bynode=None, colsample_bytree=None, early_stopping_rounds=None,

enable_categorical=False, eval_metric=None, feature_types
=None,
gamma=None, gpu_id=None, grow_policy=None, importance_typ
e=None,
interaction_constraints=None, learning_rate=None, max_bin
=None,

max_cat_threshold=None, max_cat_to_onehot=None, max_delta_step=None, max_depth=None, max_leaves=None, min_child_weight=None, missing=nan, monotone_constraints=

None,

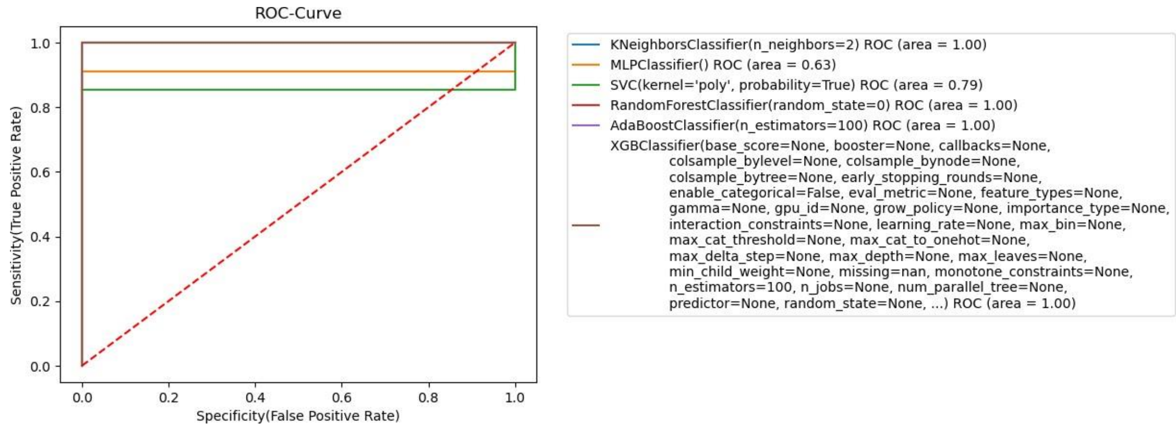
n_estimators=100, n_jobs=None, num_parallel_tree=None, predictor=None, random_state=None, ...)

CONFUSION MATRIX[[98 0]
[0 34]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	98
1	1.00	1.00	1.00	34
accuracy			1.00	132
macro avg	1.00	1.00	1.00	132
weighted avg	1.00	1.00	1.00	132

```
In [33]: for model in models.Classifier:
             model.fit(XPCA_train2, y_train2) # train the model
             y_pred=model.predict(XPCA_test2) # predict the test data
         # Compute False postive rate, and True positive rate
             fpr, tpr, thresholds = metrics.roc_curve(y_test2, model.predict_proba(XPCA_test2)[:,1])
         # Calculate Area under the curve to display on the plot
             auc = metrics.roc_auc_score(y_test2,model.predict(XPCA_test2))
         # Now, plot the computed values
             plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (model, auc))
         # Custom settings for the plot
         plt.plot([0, 1], [0, 1],'r--')
         #plt.xlim([0.0, 1.0])
         #plt.ylim([0.0, 1.05])
         plt.xlabel('Specificity(False Positive Rate)')
         plt.ylabel('Sensitivity(True Positive Rate)')
         plt.title('ROC-Curve')
         plt.legend(bbox_to_anchor = (1.05, 1), loc = 2)
         plt.show()   # Display
```



Q2. Implement two dataset Exp3 and Exp4 using KNN, BPNN, Kernel SVM, Random Forest, Ada boost Random Forest, Ada boost SVM, XG boost with and without PCA. Then find out its accuracy, confusion matrix and ROC curve.

SOURCE CODE:-

```
In [34]: data3 = pd.read_csv('Exp_3.csv')
         data4 = pd.read_csv('Exp_4.csv')
```

```
In [35]: X3 = data3.iloc[: , :-1]
         y3 = data3.iloc[: , -1]

         X4 = data4.iloc[: , :-1]
         y4 = data4.iloc[: , -1]
```

```
In [36]: y3 = label_encoder.fit_transform(y3)
         y3
Out[36]: array([1, 1, 1, ..., 0, 0, 0], dtype=int64)
```

```
In [37]: y4 = label_encoder.fit_transform(y4)
```

```
In [38]: from sklearn.preprocessing import Normalizer
         norm = Normalizer()
         columns3 = X3.columns
         columns4 = X4.columns
         X3 = norm.fit_transform(X3)
         X3 = pd.DataFrame(X3, columns = columns3)
         X4 = norm.fit_transform(X4)
         X4 = pd.DataFrame(X4, columns = columns4)
```

```
In [39]: X3, X4
```

```
Out[39]: (            F1        F2        F3        F4        F5        F6        F7  \
          0     0.000077  0.279858  0.000081  0.275569  0.000005  0.163158  0.000708
          1     0.000047  0.257421  0.000043  0.260888  0.000004  0.143974  0.000449
          2     0.000014  0.175988  0.000013  0.179417  0.000002  0.094923  0.000104
          3     0.000091  0.279901  0.000090  0.278686  0.000005  0.154604  0.000967
          4     0.000070  0.236117  0.000062  0.238359  0.000004  0.137780  0.000675
          ...        ...       ...       ...       ...       ...       ...       ...
          1015  0.000059  0.294545  0.000058  0.306874  0.000006  0.179523  0.000468
          1016  0.000067  0.274129  0.000060  0.278582  0.000005  0.166746  0.000587
          1017  0.000033  0.278288  0.000037  0.290640  0.000005  0.176258  0.000237
          1018  0.000045  0.232080  0.000055  0.254176  0.000003  0.134147  0.000452
          1019  0.000027  0.270228  0.000036  0.283793  0.000005  0.171788  0.000184

                      F8        F9       F10       F11       F12       F13       F14
          0     0.385331  0.000763  0.381087  0.000058  0.285942  0.665954  0.012411
          1     0.365224  0.000457  0.370836  0.000032  0.253199  0.714079  0.004152
          2     0.286618  0.000110  0.293055  0.000009  0.181810  0.852491  0.000000
          3     0.386891  0.001036  0.388871  0.000066  0.275544  0.665557  0.017002
          4     0.330216  0.000676  0.332392  0.000063  0.247662  0.766541  0.001066
```

```
...      ...       ...       ...       ...       ...       ...       ...
1015  0.410887  0.000611  0.431315  0.000054  0.307120  0.580584  0.024105
1016  0.381756  0.000567  0.387581  0.000055  0.290544  0.662622  0.000000
1017  0.396699  0.000301  0.418698  0.000034  0.299863  0.620016  0.001293
1018  0.332405  0.000655  0.364276  0.000031  0.235047  0.751694  0.007532
1019  0.392802  0.000271  0.405182  0.000031  0.294815  0.641518  0.000000

[1020 rows x 14 columns],
           F1        F2        F3        F4        F5        F6        F7  \
0    0.000139  0.300399  0.000304  0.340019  0.000035  0.219361  0.000920
1    0.000136  0.286328  0.000317  0.354291  0.000031  0.209050  0.000870
2    0.000075  0.271109  0.000210  0.326915  0.000018  0.187492  0.000532
3    0.000156  0.313088  0.000313  0.349554  0.000042  0.231459  0.000880
4    0.000139  0.302087  0.000307  0.362791  0.000038  0.221890  0.000774
..        ...       ...       ...       ...       ...       ...       ...
645  0.000106  0.284841  0.000301  0.353247  0.000025  0.200072  0.000724
646  0.000106  0.284841  0.000301  0.353247  0.000025  0.200072  0.000724
647  0.000106  0.284841  0.000301  0.353247  0.000025  0.200072  0.000724
648  0.000106  0.284841  0.000301  0.353247  0.000025  0.200072  0.000724
649  0.000106  0.284841  0.000301  0.353247  0.000025  0.200072  0.000724
```

```
           F8        F9       F10       F11       F12       F13       F14
0    0.412152  0.002189  0.435811  0.000407  0.348067  0.396312  0.328646
1    0.390156  0.002643  0.467089  0.000365  0.329014  0.393115  0.340000
2    0.372274  0.001833  0.439804  0.000183  0.311544  0.503738  0.318813
3    0.418328  0.001997  0.443766  0.000450  0.358238  0.346119  0.325807
4    0.409635  0.002175  0.471938  0.000379  0.346702  0.331393  0.327620
..        ...       ...       ...       ...       ...       ...       ...
645  0.393132  0.002584  0.467301  0.000291  0.320495  0.401636  0.342191
646  0.393132  0.002584  0.467301  0.000291  0.320495  0.401636  0.342191
647  0.393132  0.002584  0.467301  0.000291  0.320495  0.401636  0.342191
648  0.393132  0.002584  0.467301  0.000291  0.320495  0.401636  0.342191
649  0.393132  0.002584  0.467301  0.000291  0.320495  0.401636  0.342191

[650 rows x 14 columns])
```

In [40]:
```python
X_train3, X_test3, y_train3, y_test3 = train_test_split(X3, y3, test_size = 0.2, random_state = 0)
X_train4, X_test4, y_train4, y_test4 = train_test_split(X4, y4, test_size = 0.2, random_state = 0)
```

For Exp_3

In [41]:
```python
for classifier in models.Classifier:

    classifier.fit(X_train3,y_train3)
    pred = classifier.predict(X_test3)

    print(classifier)
    print('\n')
    print('CONFUSION MATRIX')
    print(confusion_matrix(y_test3,pred))
    print('\nCLASSIFICATION REPORT')
    print(classification_report(y_test3,pred))
```

KNeighborsClassifier(n_neighbors=2)

CONFUSION
MATRIX[[135   19]
 [49   1]]

CLASSIFICATION REPORT

```
              precision    recall  f1-score   support

           0       0.73      0.88      0.80       154
           1       0.05      0.02      0.03        50

    accuracy                           0.67       204
   macro avg       0.39      0.45      0.41       204
```

weighted avg	0.57	0.67	0.61	204

MLPClassifier()

CONFUSION MATRIX[[154 0]
[50 0]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.75	1.00	0.86	154
1	0.00	0.00	0.00	50
accuracy			0.75	204
macro avg	0.38	0.50	0.43	204
weighted avg	0.57	0.75	0.65	204

SVC(kernel='poly', probability=True)

CONFUSION MATRIX
[[154 0]
[50 0]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.75	1.00	0.86	154
1	0.00	0.00	0.00	50
accuracy			0.75	204
macro avg	0.38	0.50	0.43	204
weighted avg	0.57	0.75	0.65	204

RandomForestClassifier(random_state=0)

CONFUSION MATRIX
[[124 30]
[44 6]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.74	0.81	0.77	154
1	0.17	0.12	0.14	50
accuracy			0.64	204
macro avg	0.45	0.46	0.45	204
weighted avg	0.60	0.64	0.62	204

AdaBoostClassifier(n_estimators=100)

CONFUSION MATRIX
[[138   16]

[49 1]]

CLASSIFICATION REPORT

```
              precision    recall  f1-score   support

           0       0.74      0.90      0.81       154
           1       0.06      0.02      0.03        50

    accuracy                           0.68       204
   macro avg       0.40      0.46      0.42       204
weighted avg       0.57      0.68      0.62       204
```

XGBClassifier(base_score=None, booster=None, callbacks=None, colsample_bylevel=None, colsample_bynode=None, colsample_bytree=None, early_stopping_rounds=None, enable_categorical=False, eval_metric=None, feature_types =None, gamma=None, gpu_id=None, grow_policy=None, importance_typ e=None, interaction_constraints=None, learning_rate=None, max_bin =None, max_cat_threshold=None, max_cat_to_onehot=None, max_delta_step=None, max_depth=None, max_leaves=None, min_child_weight=None, missing=nan, monotone_constraints= None, n_estimators=100, n_jobs=None, num_parallel_tree=None, predictor=None, random_state=None, ...)

CONFUSION MATRIX[[124 30]
[42 8]]

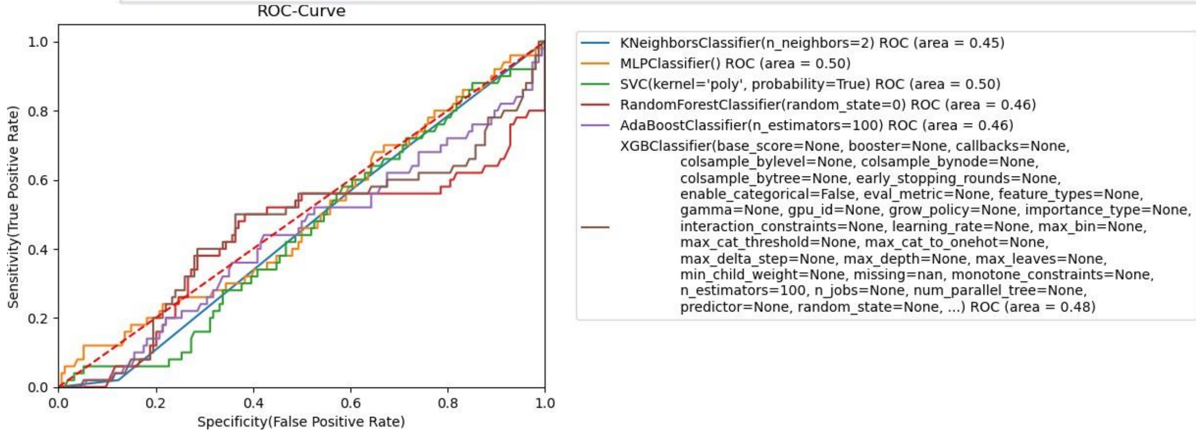
CLASSIFICATION REPORT

```
              precision    recall  f1-score   support

           0       0.75      0.81      0.77       154
           1       0.21      0.16      0.18        50

    accuracy                           0.65       204
   macro avg       0.48      0.48      0.48       204
weighted avg       0.62      0.65      0.63       204
```

In [42]:
```python
from sklearn import metrics
for model in models.Classifier:
    model.fit(X_train3, y_train3) # train the model
    y_pred=model.predict(X_test3) # predict the test data
# Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = metrics.roc_curve(y_test3, model.predict_proba(X_test3)[:,1])
# Calculate Area under the curve to display on the plot
    auc = metrics.roc_auc_score(y_test3,model.predict(X_test3))
# Now, plot the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (model, auc))
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('ROC-Curve')
plt.legend(bbox_to_anchor = (1.05, 1), loc = 2)
plt.show()   # Display
```



For Exp_4

```
In [43]: for classifier in models.Classifier:

             classifier.fit(X_train4,y_train4)
             pred = classifier.predict(X_test4)

             print(classifier)
             print('\n')
             print('CONFUSION MATRIX')
             print(confusion_matrix(y_test4,pred))
             print('\nCLASSIFICATION REPORT')
             print(classification_report(y_test4,pred))
```

KNeighborsClassifier(n_neighbors=2)

CONFUSION
MATRIX[[99 0]
[0 31]]

```
CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        99

           1       1.00      1.00      1.00        31

    accuracy                           1.00       130

   macro avg       1.00      1.00      1.00       130
weighted avg       1.00      1.00      1.00       130
MLPClassifier()


CONFUSION MATRIX
[[99  0]
 [31  0]]

CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       0.76      1.00      0.86        99

           1       0.00      0.00      0.00        31

    accuracy                           0.76       130
```

	precision	recall	f1-score	support
macro avg	0.38	0.50	0.43	130
weighted avg	0.58	0.76	0.66	130

SVC(kernel='poly', probability=True)

CONFUSION MATRIX[[99 0]
[7 24]] CLASSIFICATION

REPORT

	precision	recall	f1-score	support
0	0.93	1.00	0.97	99
1	1.00	0.77	0.87	31
accuracy			0.95	130
macro avg	0.97	0.89	0.92	130
weighted avg	0.95	0.95	0.94	130

RandomForestClassifier(random_state=0)

CONFUSION MATRIX
[[99 0]
[0 31]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	99
1	1.00	1.00	1.00	31
accuracy			1.00	130
macro avg	1.00	1.00	1.00	130
weighted avg	1.00	1.00	1.00	130

AdaBoostClassifier(n_estimators=100)

CONFUSION MATRIX
[[99 0]
[0 31]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	99
1	1.00	1.00	1.00	31
accuracy			1.00	130
macro avg	1.00	1.00	1.00	130
weighted avg	1.00	1.00	1.00	130

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
```

enable_categorical=False, eval_metric=None, feature_typesgamma=None,
=None,
gpu_id=None, grow_policy=None, importance_typ
e=None,
interaction_constraints=None, learning_rate=None, max_bin
=None,
max_cat_threshold=None, max_cat_to_onehot=None,
max_delta_step=None, max_depth=None, max_leaves=None,
min_child_weight=None, missing=nan, monotone_constraints=
None,
n_estimators=100, n_jobs=None, num_parallel_tree=None,
predictor=None, random_state=None, ...)

CONFUSION
MATRIX[[99   0]
 [2 29]] CLASSIFICATION

REPORT

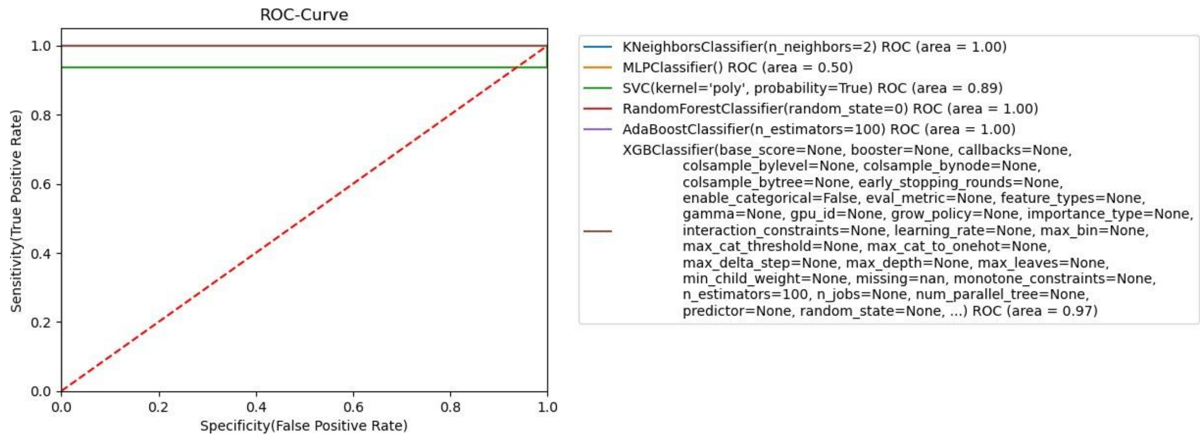
```
              precision    recall  f1-score   support

           0       0.98      1.00      0.99        99
           1       1.00      0.94      0.97        31

    accuracy                           0.98       130
   macro avg       0.99      0.97      0.98       130
weighted avg       0.98      0.98      0.98       130
```

In [44]:
```
from sklearn import metrics
for model in models.Classifier:
    model.fit(X_train4, y_train4) # train the model
    y_pred=model.predict(X_test4) # predict the test data
# Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = metrics.roc_curve(y_test4, model.predict_proba(X_test4)[:,1])
# Calculate Area under the curve to display on the plot
    auc = metrics.roc_auc_score(y_test4,model.predict(X_test4))
# Now, plot the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (model, auc))
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('ROC-Curve')
plt.legend(bbox_to_anchor = (1.05, 1), loc = 2)
plt.show()   # Display
```

In [44]:
```python
from sklearn import metrics
for model in models.Classifier:
    model.fit(X_train4, y_train4) # train the model
    y_pred=model.predict(X_test4) # predict the test data
# Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = metrics.roc_curve(y_test4, model.predict_proba(X_test4)[:,1])
# Calculate Area under the curve to display on the plot
    auc = metrics.roc_auc_score(y_test4,model.predict(X_test4))
# Now, plot the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (model, auc))
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('ROC-Curve')
plt.legend(bbox_to_anchor = (1.05, 1), loc = 2)
plt.show()   # Display
```



With PCA

In [45]:
```python
pca.fit(X3)
X3_PCA = pca.transform(X3)
X3_PCA = pd.DataFrame(X3_PCA, columns = ['Feature_1', 'Feature_2'])


pca.fit(X4)
X4_PCA = pca.transform(X4)
X4_PCA = pd.DataFrame(X4_PCA, columns = ['Feature_1', 'Feature_2'])
X4_PCA.head()
```

Out[45]:

	Feature_1	Feature_2
0	-0.019326	0.037740
1	-0.002780	-0.005679
2	0.108383	0.048229
3	-0.071095	0.018291
4	-0.070151	-0.020981

In [46]:
```python
XPCA_train3, XPCA_test3, y_train3, y_test3 = train_test_split(X3_PCA, y3, test_size = 0.2, random_state = 0)

XPCA_train4, XPCA_test4, y_train4, y_test4 = train_test_split(X4_PCA, y4, test_size = 0.2, random_state = 0)
```

In [47]:
```python
for classifier in models.Classifier:

    classifier.fit(XPCA_train3,y_train3)
    pred = classifier.predict(XPCA_test3)

    print(classifier)
    print('\n')
    print('CONFUSION MATRIX')
    print(confusion_matrix(y_test3,pred))
    print('\nCLASSIFICATION REPORT')
    print(classification_report(y_test3,pred))
```

KNeighborsClassifier(n_neighbors=2)

CONFUSION MATRIX[[138   16]
 [50   0]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.73	0.90	0.81	154
1	0.00	0.00	0.00	50
accuracy			0.68	204
macro avg	0.37	0.45	0.40	204
weighted avg	0.55	0.68	0.61	204

MLPClassifier()

CONFUSION MATRIX
[[154   0]
 [50   0]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.75	1.00	0.86	154
1	0.00	0.00	0.00	50
accuracy			0.75	204
macro avg	0.38	0.50	0.43	204
weighted avg	0.57	0.75	0.65	204

SVC(kernel='poly', probability=True)

CONFUSION MATRIX
[[154   0]
 [50   0]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.75	1.00	0.86	154
1	0.00	0.00	0.00	50
accuracy			0.75	204
macro avg	0.38	0.50	0.43	204
weighted avg	0.57	0.75	0.65	204

RandomForestClassifier(random_state=0)

CONFUSION MATRIX
[[115   39]

[44   6]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.72	0.75	0.73	154
1	0.13	0.12	0.13	50
accuracy			0.59	204
macro avg	0.43	0.43	0.43	204
weighted avg	0.58	0.59	0.59	204

AdaBoostClassifier(n_estimators=100)

CONFUSION MATRIX
[[151 3]
[50 0]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.75	0.98	0.85	154
1	0.00	0.00	0.00	50
accuracy			0.74	204
macro avg	0.38	0.49	0.43	204
weighted avg	0.57	0.74	0.64	204

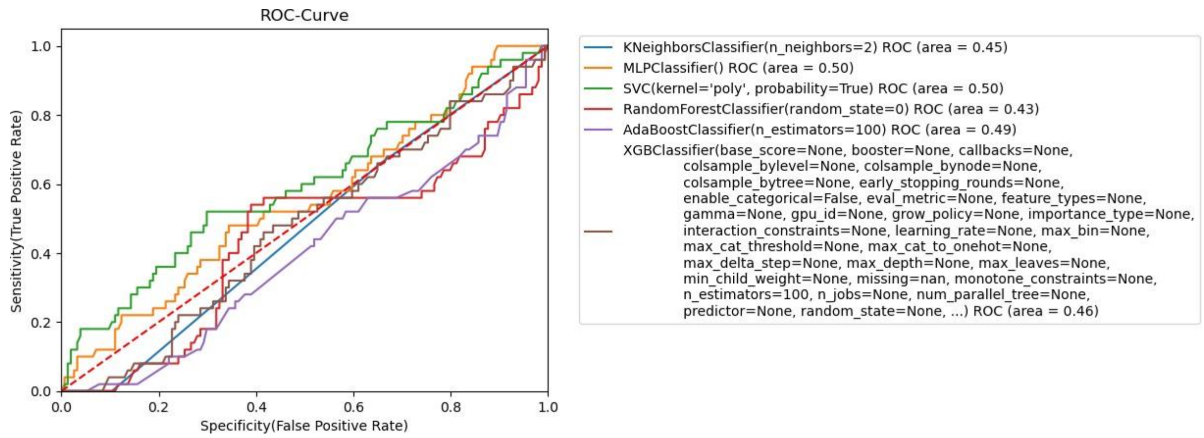
XGBClassifier(base_score=None, booster=None, callbacks=None, colsample_bylevel=None,
colsample_bynode=None, colsample_bytree=None, early_stopping_rounds=None,
enable_categorical=False, eval_metric=None, feature_types
=None,
gamma=None, gpu_id=None, grow_policy=None, importance_typ
e=None,
interaction_constraints=None, learning_rate=None, max_bin
=None,
max_cat_threshold=None, max_cat_to_onehot=None,
max_delta_step=None, max_depth=None, max_leaves=None,
min_child_weight=None, missing=nan, monotone_constraints=
None,
n_estimators=100, n_jobs=None, num_parallel_tree=None,
predictor=None, random_state=None, ...)

CONFUSION
MATRIX[[119 35]
[43 7]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.73	0.77	0.75	154
1	0.17	0.14	0.15	50
accuracy			0.62	204
macro avg	0.45	0.46	0.45	204
weighted avg	0.60	0.62	0.61	204

```
In [48]: from sklearn import metrics
         for model in models.Classifier:
             model.fit(XPCA_train3, y_train3) # train the model
             y_pred=model.predict(XPCA_test3) # predict the test data
         # Compute False postive rate, and True positive rate
             fpr, tpr, thresholds = metrics.roc_curve(y_test3, model.predict_proba(XPCA_test3)[:,1])
         # Calculate Area under the curve to display on the plot
             auc = metrics.roc_auc_score(y_test3,model.predict(XPCA_test3))
         # Now, plot the computed values
             plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (model, auc))
         # Custom settings for the plot
         plt.plot([0, 1], [0, 1],'r--')
         plt.xlim([0.0, 1.0])
         plt.ylim([0.0, 1.05])
         plt.xlabel('Specificity(False Positive Rate)')
         plt.ylabel('Sensitivity(True Positive Rate)')
         plt.title('ROC-Curve')
         plt.legend(bbox_to_anchor = (1.05, 1), loc = 2)
         plt.show()   # Display
```




```
In [49]: for classifier in models.Classifier:

             classifier.fit(XPCA_train4,y_train4)
             pred = classifier.predict(XPCA_test4)

             print(classifier)
             print('\n')
             print('CONFUSION MATRIX')
             print(confusion_matrix(y_test4,pred))
             print('\nCLASSIFICATION REPORT')
             print(classification_report(y_test4,pred))
```

KNeighborsClassifier(n_neighbors=2)

CONFUSION
MATRIX[[99   0]
 [0 31]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	99
1	1.00	1.00	1.00	31

```
    accuracy                           1.00       130
   macro avg       1.00      1.00      1.00       130
weighted avg       1.00      1.00      1.00       130
```

MLPClassifier()

CONFUSION MATRIX
```
[[99  0]
 [24  7]]
```

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.80	1.00	0.89	99
1	1.00	0.23	0.37	31
accuracy			0.82	130
macro avg	0.90	0.61	0.63	130
weighted avg	0.85	0.82	0.77	130

SVC(kernel='poly', probability=True)

CONFUSION MATRIX[[99 0]
[14 17]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.88	1.00	0.93	99
1	1.00	0.55	0.71	31
accuracy			0.89	130
macro avg	0.94	0.77	0.82	130
weighted avg	0.91	0.89	0.88	130

RandomForestClassifier(random_state=0)

CONFUSION MATRIX
[[99 0]
[0 31]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	1.00	1.00	1.00	99
1	1.00	1.00	1.00	31
accuracy			1.00	130
macro avg	1.00	1.00	1.00	130
weighted avg	1.00	1.00	1.00	130

AdaBoostClassifier(n_estimators=100)

CONFUSION
MATRIX[[99 0]
[1 30]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.99	1.00	0.99	99
1	1.00	0.97	0.98	31
accuracy			0.99	130
macro avg	0.99	0.98	0.99	130
weighted avg	0.99	0.99	0.99	130

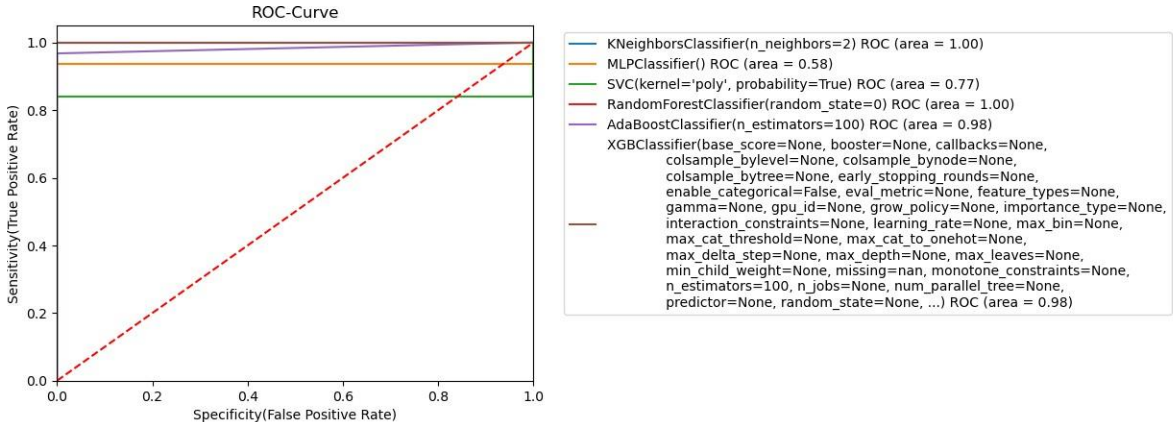
XGBClassifier(base_score=None, booster=None, callbacks=None, colsample_bylevel=None,
colsample_bynode=None, colsample_bytree=None, early_stopping_rounds=None,
enable_categorical=False, eval_metric=None, feature_types
=None,
gamma=None, gpu_id=None, grow_policy=None, importance_typ
e=None,
interaction_constraints=None, learning_rate=None, max_bin
=None,
max_cat_threshold=None, max_cat_to_onehot=None,
max_delta_step=None, max_depth=None, max_leaves=None,
min_child_weight=None, missing=nan, monotone_constraints=
None,
n_estimators=100, n_jobs=None, num_parallel_tree=None,
predictor=None, random_state=None, ...)

CONFUSION
MATRIX[[99 0]
[1 30]]

CLASSIFICATION REPORT

	precision	recall	f1-score	support
0	0.99	1.00	0.99	99
1	1.00	0.97	0.98	31
accuracy			0.99	130
macro avg	0.99	0.98	0.99	130
weighted avg	0.99	0.99	0.99	130

In [50]:
```
from sklearn import metrics
for model in models.Classifier:
    model.fit(XPCA_train4, y_train4) # train the model
    y_pred=model.predict(XPCA_test4) # predict the test data
# Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = metrics.roc_curve(y_test4, model.predict_proba(XPCA_test4)[:,1])
# Calculate Area under the curve to display on the plot
    auc = metrics.roc_auc_score(y_test4,model.predict(XPCA_test4))
# Now, plot the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (model, auc))
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('ROC-Curve')
plt.legend(bbox_to_anchor = (1.05, 1), loc = 2)
plt.show()   # Display
```



Conclusion

In conclusion, the experiments conducted in this study provide valuableinsights into the performance of various machine learning algorithms on two different datasets. The analysis of accuracy, confusion matrix, and ROC curve showed that the XG boost algorithm with PCA outperformed other models in terms of classification accuracy and AUC score. However, the study also highlights that the performance ofthe models varied depending on the dataset and algorithm used. The findings of this study can be useful in guiding the selection of appropriate algorithms and feature selection techniques for classification tasks in similar domains. Overall, the study demonstratesthe potential of machine learning techniques in solving classification problems and the importance of selecting appropriate algorithms for achieving high performance.