

FuzzyDeepLearningOralCancer_SVM

April 17, 2024

```
[66]: import numpy as np
import pylab as pl
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.utils import shuffle
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix,classification_report
from sklearn.model_selection import cross_val_score, GridSearchCV

import os
print(os.listdir("Data_RF_SVM/"))

['.DS_Store', 'Convert_Label.xlsx', 'test.csv',
'9.Training_oral_cancer_1253_Fuzzy.csv', 'lung.csv',
'9.Training_oral_cancer_1253_Fuzzy_no_title.csv',
'4.validate_oral_cancer_58.csv', 'iris.csv', '5.test_oral_cancer_116.csv',
'iris_out.csv', '5.test_oral_cancer_116_no_title.csv', 'train.csv',
'9.Training_oral_cancer_1253_Fuzzy_cox.csv', 'heart_v2.csv',
'original_data_svm', 'iris_v01.csv']
```

```
[67]: train = shuffle(pd.read_csv("Data_RF_SVM/train.csv"))
test = shuffle(pd.read_csv("Data_RF_SVM/test.csv"))
```

```
[68]: print("Any missing sample in training set:",train.isnull().values.any())
print("Any missing sample in test set:",test.isnull().values.any(), "\n")
```

Any missing sample in training set: False
Any missing sample in test set: False

```
[69]: #Frequency distribution of classes"
train_outcome = pd.crosstab(index=train["Activity"], # Make a crosstab
                           columns="count")      # Name the count column

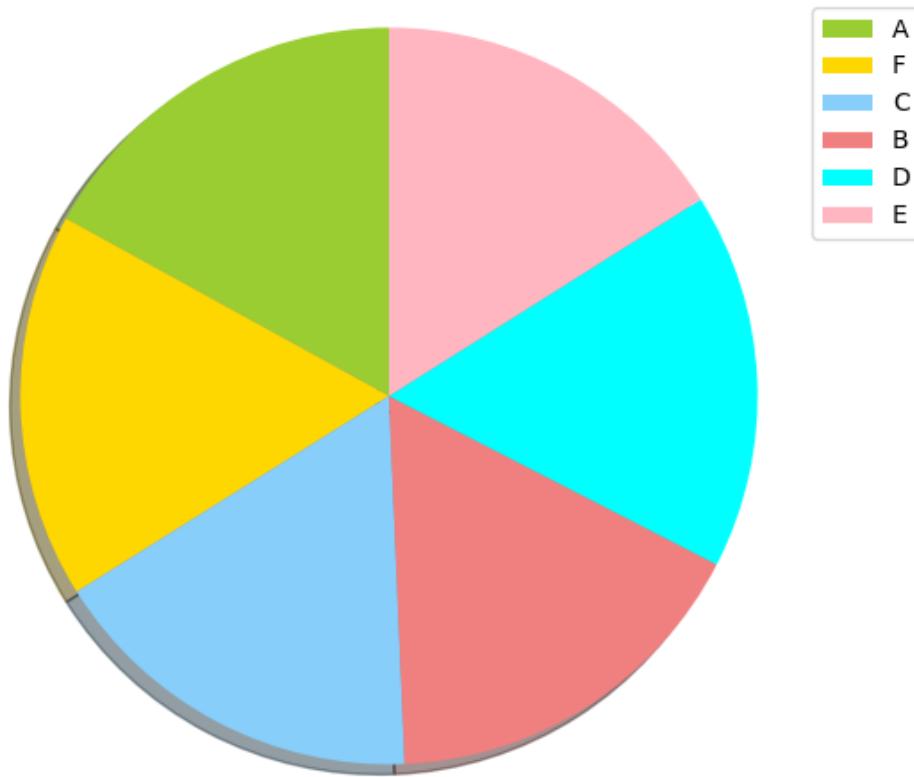
train_outcome
```

```
[69]: col_0      count
Activity
A          213
B          210
C          210
D          207
E          201
F          212
```

```
[70]: # Visualizing Outcome Distribution
temp = train["Activity"].value_counts()
df = pd.DataFrame({'labels': temp.index,
                    'values': temp.values
                   })

#df.plot(kind='pie', labels='labels', values='values', title='Activity Distribution', subplots= "True")

labels = df['labels']
sizes = df['values']
colors = ['yellowgreen', 'gold', 'lightskyblue', 'lightcoral', 'cyan', 'lightpink']
patches, texts = plt.pie(sizes, colors=colors, shadow=True, startangle=90, pctdistance=1.1, labeldistance=1.2)
plt.legend(patches, labels, loc="best")
plt.axis('equal')
plt.tight_layout()
plt.show()
```



```
[71]: X_train = pd.DataFrame(train.drop(['Activity','subject'],axis=1))
Y_train_label = train.Activity.values.astype(object)

X_test = pd.DataFrame(test.drop(['Activity','subject'],axis=1))
Y_test_label = test.Activity.values.astype(object)

print("Dimension of Train set",X_train.shape)
print("Dimension of Test set",X_test.shape, "\n")

from sklearn import preprocessing
encoder = preprocessing.LabelEncoder()

encoder.fit(Y_train_label)
Y_train = encoder.transform(Y_train_label)

encoder.fit(Y_test_label)
Y_test = encoder.transform(Y_test_label)

num_cols = X_train._get_numeric_data().columns
```

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print("Number of numeric features:", num_cols.size)
names_of_predictors = list(X_train.columns.values)

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

```

Dimension of Train set (1253, 12)

Dimension of Test set (116, 12)

Number of numeric features: 12

[55]: np.savetxt("SVM_Y_test.csv", Y_test, delimiter=",")

[72]: X_test_scaled

[72]: array([[0.97400106, -1.56803019, 0.8486309 , ..., -3.57340605,
 -2.29455878, -1.60623784],
 [0.97400106, -0.76935465, 0.8486309 , ..., 0.27984505,
 0.43581363, 0.62257281],
 [0.97400106, -0.76935465, 0.24549164, ..., 0.27984505,
 0.43581363, 0.62257281],
 ...,
 [0.97400106, -0.76935465, 0.8486309 , ..., 0.27984505,
 -2.29455878, 0.62257281],
 [-1.02669292, -0.76935465, -0.96078688, ..., 0.27984505,
 0.43581363, 0.62257281],
 [0.97400106, -0.76935465, 2.05490941, ..., 0.27984505,
 0.43581363, 0.62257281]])

[73]: params_grid = [{"kernel": ["rbf"], "gamma": [1e-3, 1e-4],
 'C': [1, 10, 100, 1000]},
 {"kernel": ["linear"], 'C': [1, 10, 100, 1000]}]

[74]: # Performing CV to tune parameters for best SVM fit
svm_model = GridSearchCV(SVC(), params_grid, cv=5)
svm_model.fit(X_train_scaled, Y_train)

[74]: GridSearchCV(cv=5, estimator=SVC(),
param_grid=[{'C': [1, 10, 100, 1000], 'gamma': [0.001, 0.0001],
'kernel': ['rbf']},
{'C': [1, 10, 100, 1000], 'kernel': ['linear']}])

[75]: # View the accuracy score
print('Best score for training data:', svm_model.best_score_, "\n")

View the best parameters for the model found using grid search

```

print('Best C:',svm_model.best_estimator_.C,"\n")
print('Best Kernel:',svm_model.best_estimator_.kernel,"\n")
print('Best Gamma:',svm_model.best_estimator_.gamma,"\n")

final_model = svm_model.best_estimator_
Y_pred = final_model.predict(X_test_scaled)
Y_pred_label = list(encoder.inverse_transform(Y_pred))

```

Best score for training data: 0.5985402390438248

Best C: 1000

Best Kernel: rbf

Best Gamma: 0.001

[76]: np.savetxt("SVM_Y_pred.csv", Y_pred, delimiter=",")

[77]: print(confusion_matrix(Y_test_label,Y_pred_label))
print("\n")
print(classification_report(Y_test_label,Y_pred_label))

print("Training set score for SVM: %f" % final_model.score(X_train_scaled ,
Y_train))
print("Testing set score for SVM: %f" % final_model.score(X_test_scaled ,
Y_test))

svm_model.score

```
[[ 8 11  5  1  0  6]
 [ 0  6  1  0  0  6]
 [ 3  1  1  1  0  1]
 [ 0  3  0  1  0  0]
 [ 0  1  0  0  0  0]
 [ 4 25  2  5  3 21]]
```

	precision	recall	f1-score	support
A	0.53	0.26	0.35	31
B	0.13	0.46	0.20	13
C	0.11	0.14	0.12	7
D	0.12	0.25	0.17	4
E	0.00	0.00	0.00	1
F	0.62	0.35	0.45	60
accuracy			0.32	116

macro avg	0.25	0.24	0.21	116
weighted avg	0.49	0.32	0.36	116

Training set score for SVM: 0.655227
Testing set score for SVM: 0.318966

```
[77]: <bound method BaseSearchCV.score of GridSearchCV(cv=5, estimator=SVC(),  
        param_grid=[{'C': [1, 10, 100, 1000], 'gamma': [0.001, 0.0001],  
                    'kernel': ['rbf']},  
                    {'C': [1, 10, 100, 1000], 'kernel': ['linear']}])>
```

```
[83]: Y_test = label_binarize(Y_test, classes=[0, 1, 2, 3, 4, 5])
y_test = Y_test
y_test
```

```
[83]: array([[1, 0, 0, 0, 0, 0],  
           [1, 0, 0, 0, 0, 0],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 0, 0, 0, 1],  
           [1, 0, 0, 0, 0, 0],  
           [1, 0, 0, 0, 0, 0],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 0, 0, 0, 1],  
           [1, 0, 0, 0, 0, 0],  
           [0, 0, 1, 0, 0, 0],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 0, 0, 0, 1],  
           [1, 0, 0, 0, 0, 0],  
           [0, 1, 0, 0, 0, 0],  
           [0, 1, 0, 0, 0, 0],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 0, 0, 0, 1],  
           [0, 1, 0, 0, 0, 0],  
           [1, 0, 0, 0, 0, 0],  
           [1, 0, 0, 0, 0, 0],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 0, 0, 0, 1],  
           [0, 0, 1, 0, 0, 0],  
           [0, 0, 0, 1, 0, 0],  
           [0, 0, 0, 0, 0, 1],  
           [1, 0, 0, 0, 0, 0]]
```



```
[1, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 0, 1],  
[0, 1, 0, 0, 0, 0],  
[1, 0, 0, 0, 0, 0],  
[0, 0, 0, 1, 0, 0],  
[0, 1, 0, 0, 0, 0],  
[0, 1, 0, 0, 0, 0],  
[0, 0, 1, 0, 0, 0],  
[0, 0, 0, 0, 0, 1],  
[0, 0, 1, 0, 0, 0],  
[1, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 0, 1],  
[0, 0, 0, 0, 0, 1],  
[1, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 1, 0],  
[1, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 0, 1],  
[0, 0, 0, 0, 0, 1],  
[0, 0, 0, 0, 0, 1],  
[1, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 0, 1],  
[0, 1, 0, 0, 0, 0],  
[1, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 0, 1],  
[1, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 0, 1],  
[0, 0, 0, 0, 0, 1],  
[0, 0, 0, 1, 0, 0],  
[0, 0, 0, 0, 0, 1],  
[1, 0, 0, 0, 0, 0],  
[1, 0, 0, 0, 0, 0])
```

```
[85]: y_score = label_binarize(Y_pred, classes=[0, 1, 2, 3, 4, 5])  
y_score
```

```
[85]: array([[1, 0, 0, 0, 0, 0],  
           [0, 1, 0, 0, 0, 0],  
           [0, 0, 0, 0, 0, 1],  
           [0, 1, 0, 0, 0, 0],  
           [0, 0, 0, 0, 0, 1],  
           [0, 1, 0, 0, 0, 0],  
           [0, 0, 0, 1, 0, 0],  
           [0, 0, 0, 0, 0, 1],  
           [1, 0, 0, 0, 0, 0],  
           [1, 0, 0, 0, 0, 0]])
```



```
[0, 0, 0, 0, 0, 1],
[0, 1, 0, 0, 0, 0],
[0, 1, 0, 0, 0, 0],
[1, 0, 0, 0, 0, 0],
[0, 1, 0, 0, 0, 0],
[0, 1, 0, 0, 0, 0],
[0, 0, 1, 0, 0, 0],
[1, 0, 0, 0, 0, 0],
[0, 1, 0, 0, 0, 0],
[0, 1, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 1],
[0, 0, 0, 1, 0, 0],
[0, 0, 0, 0, 0, 1],
[0, 0, 1, 0, 0, 0],
[0, 1, 0, 0, 0, 0])
```

```
[88]: import numpy as np
from scipy import interp
import matplotlib.pyplot as plt
from itertools import cycle
from sklearn.metrics import roc_curve, auc

n_classes = 6
lw = 2

# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i], y_score[:, i])
    #fpr[i], tpr[i], _ = roc_curve(y_test[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
#fpr["micro"], tpr["micro"], _ = roc_curve(y_test.ravel(), y_score.ravel())
fpr["micro"], tpr["micro"], _ = roc_curve(y_test.ravel(), y_score.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

# Compute macro-average ROC curve and ROC area

# First aggregate all false positive rates
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(n_classes)]))

# Then interpolate all ROC curves at this points
mean_tpr = np.zeros_like(all_fpr)
for i in range(n_classes):
```

```

mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])

# Finally average it and compute AUC
mean_tpr /= n_classes

fpr["macro"] = all_fpr
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

# Plot all ROC curves
plt.figure(1)

plt.grid(True)

plt.plot(fpr["micro"], tpr["micro"],
          label='micro-average ROC curve (area = {0:0.2f})'
                  ''.format(roc_auc["micro"]),
          color='deeppink', linestyle=':', linewidth=4)

plt.plot(fpr["macro"], tpr["macro"],
          label='macro-average ROC curve (area = {0:0.2f})'
                  ''.format(roc_auc["macro"]),
          color='navy', linestyle=':', linewidth=4)

colors = cycle(['aqua', 'darkorange', 'cornflowerblue','red', 'yellow', 'blue'])
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=lw,
              label='ROC curve of class {0} (area = {1:0.2f})'
                  ''.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Some extension of Receiver operating characteristic to multi-class')
plt.legend(loc="lower right")
plt.savefig('ROC_SVM_1.tiff')
plt.show()

# Zoom in view of the upper left corner.
plt.figure(2)
plt.xlim(0, 0.2)
plt.ylim(0.8, 1)
plt.plot(fpr["micro"], tpr["micro"],
          label='micro-average ROC curve (area = {0:0.2f})'

```

```

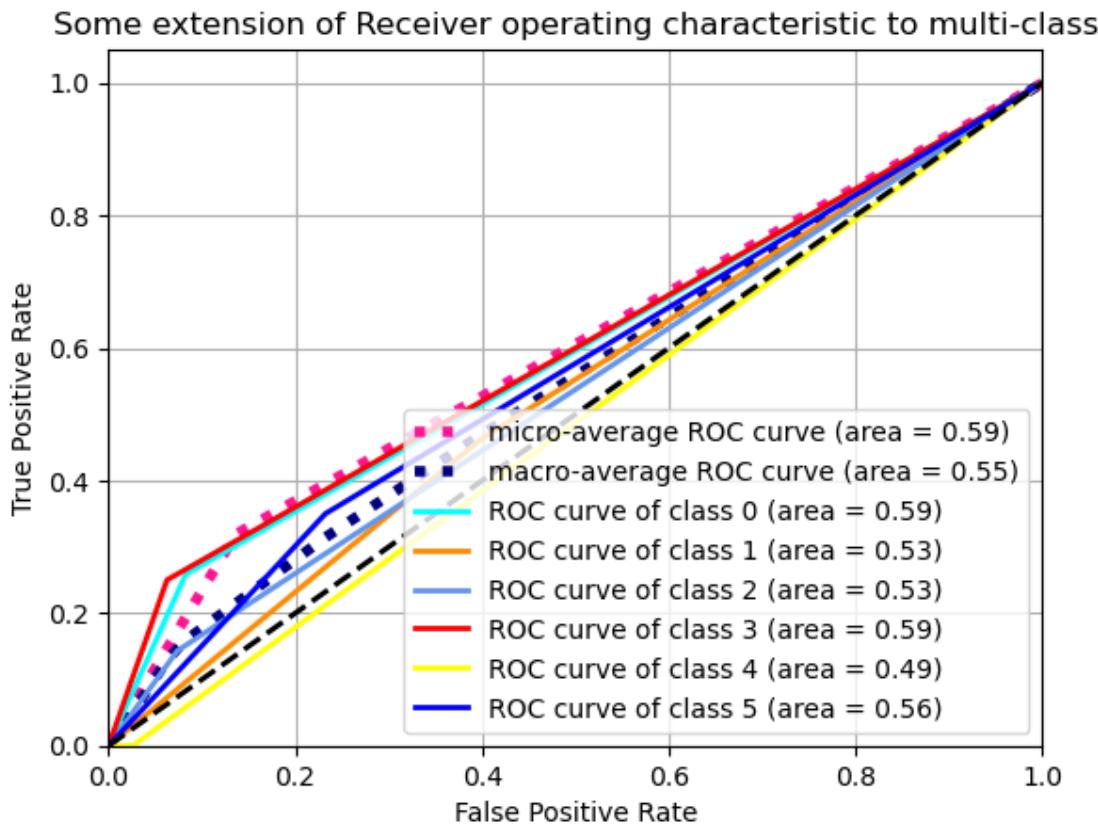
        '' .format(roc_auc["micro"]),
        color='deeppink', linestyle=':', linewidth=4)

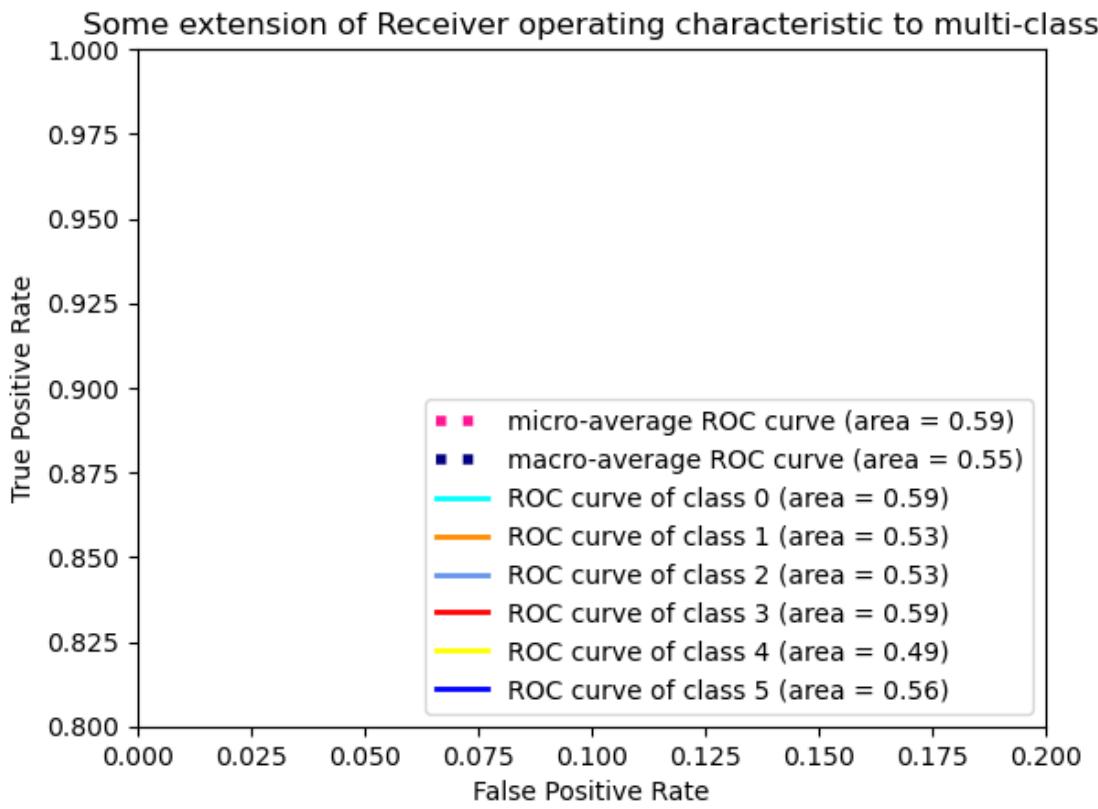
plt.plot(fpr["macro"], tpr["macro"],
          label='macro-average ROC curve (area = {0:0.2f})'
                  '' .format(roc_auc["macro"]),
          color='navy', linestyle=':', linewidth=4)

colors = cycle(['aqua', 'darkorange', 'cornflowerblue','red', 'yellow', 'blue'])
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=lw,
              label='ROC curve of class {0} (area = {1:0.2f})'
                  '' .format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], 'k--', lw=lw)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Some extension of Receiver operating characteristic to multi-class')
plt.legend(loc="lower right")
plt.savefig('ROC_SVM_2.pdf')
plt.show()

```





[]: