

```

1 pip install mpld3

1 from sklearn.decomposition import PCA
2 from sklearn.utils import shuffle
3
4 from sklearn.preprocessing import LabelEncoder, StandardScaler
5 from sklearn.model_selection import train_test_split
6
7 from sklearn.svm import SVC
8 from sklearn.ensemble import RandomForestClassifier
9 from xgboost import XGBClassifier
10 from sklearn.neighbors import KNeighborsClassifier
11 from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
12
13 import sklearn.metrics as mt
14 from sklearn.metrics import confusion_matrix
15 from sklearn.metrics import recall_score, precision_score, accuracy_score
16 from sklearn.metrics import confusion_matrix, f1_score, classification_report
17 from sklearn.model_selection import cross_val_score
18 from scipy.io import loadmat
19 import numpy as np
20 from sklearn.metrics import mutual_info_score
21 from scipy.stats import kendalltau
22 from scipy.stats import spearmanr
23 import numpy as np
24 import torch
25 import torch.nn as nn
26 import torch.nn.functional as F
27 from scipy.io import loadmat

1 data1 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 1/Subject12Trial1.mat')['data']
2 data2 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 1/Subject12Trial2.mat')['data']
3 data3 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 1/Subject34Trial1.mat')['data']
4 data4 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 1/Subject34Trial2.mat')['data']
5 data5 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 2/Subject12Trial1.mat')['data']
6 data6 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 2/Subject12Trial2.mat')['data']
7 data7 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 2/Subject34Trial1.mat')['data']
8 data8 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 2/Subject34Trial2.mat')['data']
9 data = np.concatenate([data1,data2,data3,data4,data5,data6,data7,data8],axis=2)
10
11 subj1 = data[:30,:,:]
12 subj1 = subj1.reshape(subj1.shape[2],subj1.shape[0],subj1.shape[1])
13 subj2 = data[30:,:,:]
14 subj2 = subj2.reshape(subj2.shape[2],subj2.shape[0],subj2.shape[1])
15 subj = data.reshape(data.shape[2],data.shape[0],data.shape[1])
16 Labels1 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 1/Subject12Trial1Label.mat')['Labels'].T ##Labels
17 Labels2 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 1/Subject12Trial2Label.mat')['Labels'].T
18 Labels3 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 1/Subject34Trial1Label.mat')['Labels'].T
19 Labels4 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 1/Subject34Trial2Label.mat')['Labels'].T
20 Labels5 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 2/Subject12Trial1Label.mat')['Labels'].T
21 Labels6 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 2/Subject12Trial2Label.mat')['Labels'].T
22 Labels7 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 2/Subject34Trial1Label.mat')['Labels'].T
23 Labels8 = loadmat('/content/drive/MyDrive/GRAPH EEG/Experiment 2/Subject34Trial2Label.mat')['Labels'].T
24
25
26 Labels = np.concatenate([Labels1,Labels2,Labels3,Labels4,Labels5,Labels6,Labels7,Labels8], axis=0)
27 subj.shape,Labels.shape

((232, 60, 1000), (232, 1))

1 data_subj1 = data[:30,:,:]
2 data_subj2 = data[30:,:,:]
3 data_concatenate = np.concatenate([data_subj1,data_subj2],axis=2)
4
5 data_labels = np.concatenate([Labels,Labels],axis=0)
6 data_concatenate.shape, data_labels.shape

((30, 1000, 464), (464, 1))

```

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 from sklearn.preprocessing import StandardScaler
4 from sklearn.neighbors import KNeighborsClassifier
5 from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
6 from sklearn.svm import SVC
7 from sklearn.metrics import accuracy_score, classification_report
8 from sklearn.ensemble import RandomForestClassifier
9 from sklearn.neural_network import MLPClassifier
10 from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score, KFold, cross_validate
11 from sklearn.metrics import accuracy_score, classification_report, precision_score, recall_score, f1_score
12
13 # Correct transpose
14 data_concatenate = np.transpose(data_concatenate, (2, 0, 1))
15 print("Transposed shape of data_concatenate:", data_concatenate.shape)
16
17 # Now, reshape to (464, 30 * 1000)
18 X = data_concatenate.reshape(464, 30 * 1000)
19 print("Shape of X after reshaping:", X.shape)
20
21 # Assuming data_labels is (464, 1), we flatten it to (464,)
22 y = data_labels
23 #y = y.ravel()
24
25 # Normalize the data
26 scaler = StandardScaler()
27 X_scaled = scaler.fit_transform(X)
28
29 # Split the data into training and testing sets
30 X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.1, random_state=42)
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✓ Extra Work

```
1 import numpy as np
2 from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
3 from sklearn.model_selection import cross_validate, KFold
4 from sklearn.preprocessing import StandardScaler
5 from sklearn.model_selection import train_test_split
6 from sklearn.utils import compute_sample_weight
7
8 from sklearn.utils.validation import has_fit_parameter
9
10 kf = KFold(n_splits=10, shuffle=True, random_state=42)
11
12 def evaluate_model(model, X_train, y_train, X_test, y_test, kf):
13     scoring = ['accuracy', 'precision', 'recall', 'f1']
14
15     if has_fit_parameter(model, 'sample_weight'):
16         # Use sample weights if the model supports them
17         sample_weight = compute_sample_weight('balanced', y_train)
18         cv_results = cross_validate(model, X_train, y_train, cv=kf, scoring=scoring,
19                                   fit_params={'sample_weight': sample_weight})
20     else:
21         # Otherwise, perform standard cross-validation
22         cv_results = cross_validate(model, X_train, y_train, cv=kf, scoring=scoring)
23
24     # Mean CV scores
25     mean_cv_accuracy = np.mean(cv_results['test_accuracy']) * 100
26     mean_cv_precision = np.mean(cv_results['test_precision']) * 100
27     mean_cv_recall = np.mean(cv_results['test_recall']) * 100
28     mean_cv_f1 = np.mean(cv_results['test_f1']) * 100
29
30     # Max CV scores
31     max_cv_accuracy = np.max(cv_results['test_accuracy']) * 100
32     max_cv_precision = np.max(cv_results['test_precision']) * 100
33     max_cv_recall = np.max(cv_results['test_recall']) * 100
34     max_cv_f1 = np.max(cv_results['test_f1']) * 100
35
36     print(f"Mean CV Accuracy: {mean_cv_accuracy:.2f}%")
37     print(f"Max CV Accuracy: {max_cv_accuracy:.2f}%")
38     print(f"Mean CV Precision: {mean_cv_precision:.2f}%")
39     print(f"Max CV Precision: {max_cv_precision:.2f}%")
40     print(f"Mean CV Recall: {mean_cv_recall:.2f}%")
41     print(f"Max CV Recall: {max_cv_recall:.2f}%")
42     print(f"Mean CV F1-Score: {mean_cv_f1:.2f}%")
43     print(f"Max CV F1-Score: {max_cv_f1:.2f}%")
44
45     # Train and evaluate on the test set
46     model.fit(X_train, y_train)
47     y_pred = model.predict(X_test)
48
49     # Test scores
50     test_accuracy = accuracy_score(y_test, y_pred) * 100
51     test_precision = precision_score(y_test, y_pred, average='binary') * 100
52     test_recall = recall_score(y_test, y_pred, average='binary') * 100
53     test_f1 = f1_score(y_test, y_pred, average='binary') * 100
54
55     print(f"Test Accuracy: {test_accuracy:.2f}%")
56     print(f"Test Precision: {test_precision:.2f}%")
57     print(f"Test Recall: {test_recall:.2f}%")
58     print(f"Test F1-Score: {test_f1:.2f}%")
59
```

```

1 from imblearn.over_sampling import SMOTE
2 from imblearn.pipeline import make_pipeline as make_pipeline_imb
3 from sklearn.neighbors import KNeighborsClassifier
4 from sklearn.decomposition import PCA
5 # Correct transpose
6 data_concatenate = np.transpose(data_concatenate, (2, 0, 1))
7 print("Transposed shape of data_concatenate:", data_concatenate.shape)
8
9 # Now, reshape to (464, 30 * 1000)
10 X = data_concatenate.reshape(464, 30 * 1000)
11 print("Shape of X after reshaping:", X.shape)
12
13 # Assuming data_labels is (464, 1), we flatten it to (464,)
14 y = y.ravel()
15
16 # Normalize the data
17 scaler = StandardScaler()
18 X_scaled = scaler.fit_transform(X)
19
20 # Apply PCA to reduce dimensionality
21 pca = PCA(n_components=0.85) # Keep 95% of variance
22 X_pca = pca.fit_transform(X_scaled)
23 print("Shape of X after PCA:", X_pca.shape)
24
25 # Split the data into training and testing sets
26 X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.10, random_state=42)
27
28 # Apply SMOTE for imbalance handling before model training
29 smote = SMOTE()
30 X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)

    Transposed shape of data_concatenate: (30, 1000, 464)
    Shape of X after reshaping: (464, 30000)
    Shape of X after PCA: (464, 256)

1 svclassifier = SVC(kernel='rbf', random_state=42)
2 evaluate_model(svclassifier, X_train_smote, y_train_smote, X_test, y_test, kf)
3 # svclassifier.fit(X_train_smote, y_train_smote)
4 # predicted_labels = svclassifier.predict(X_test)
5 # print(mt.classification_report(y_test, predicted_labels))

    Mean CV Accuracy: 71.62%
    Max CV Accuracy: 79.55%
    Mean CV Precision: 73.61%
    Max CV Precision: 95.00%
    Mean CV Recall: 69.40%
    Max CV Recall: 81.25%
    Mean CV F1-Score: 70.17%
    Max CV F1-Score: 80.85%
    Test Accuracy: 80.85%
    Test Precision: 85.71%
    Test Recall: 75.00%
    Test F1-Score: 80.00%

1 RFClassifier = RandomForestClassifier(random_state=42)
2 evaluate_model(RFClassifier, X_train_smote, y_train_smote, X_test, y_test, kf)
3 # RFClassifier.fit(X_train_smote, y_train_smote)
4 # predicted_labels = RFClassifier.predict(X_test)
5 # print(mt.classification_report(y_test, RFClassifier.predict(X_test)))

    Mean CV Accuracy: 67.07%
    Max CV Accuracy: 81.40%
    Mean CV Precision: 71.53%
    Max CV Precision: 94.12%
    Mean CV Recall: 59.15%
    Max CV Recall: 69.57%
    Mean CV F1-Score: 63.81%
    Max CV F1-Score: 80.00%
    Test Accuracy: 70.21%
    Test Precision: 72.73%
    Test Recall: 66.67%
    Test F1-Score: 69.57%

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```

1 XGBvlassifier = XGBClassifier(random_state=42,use_label_encoder=False)
2 evaluate_model(XGBvlassifier, X_train_smote, y_train_smote, X_test, y_test, kf)
3 # XGBvlassifier.fit(X_train_smote, y_train_smote)
4 # predicted_labels = XGBvlassifier.predict(X_test)
5 # print(mt.classification_report(y_test,predicted_labels))

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Mean CV Accuracy: 64.71%
Max CV Accuracy: 75.00%
Mean CV Precision: 64.67%
Max CV Precision: 83.33%
Mean CV Recall: 64.03%
Max CV Recall: 77.78%
Mean CV F1-Score: 63.47%

```

```

1 classifier = KNeighborsClassifier(n_neighbors =2)
2 evaluate_model(classifier, X_train_smote, y_train_smote, X_test, y_test, kf)
3 # classifier.fit(X_train, y_train)
4 # y_pred = classifier.predict(X_test)
5 # print(mt.classification_report(y_test,y_pred))

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Mean CV Accuracy: 73.22%
Max CV Accuracy: 86.36%
Mean CV Precision: 66.83%
Max CV Precision: 83.87%
Mean CV Recall: 93.87%
Max CV Recall: 100.00%
Mean CV F1-Score: 77.39%
Max CV F1-Score: 89.66%
Test Accuracy: 87.23%
Test Precision: 84.62%
Test Recall: 91.67%
Test F1-Score: 88.00%

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1 LDAclassifier = LinearDiscriminantAnalysis()
2 evaluate_model(LDAclassifier, X_train_smote, y_train_smote, X_test, y_test, kf)

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Mean CV Accuracy: 71.84%
Max CV Accuracy: 84.09%
Mean CV Precision: 69.22%
Max CV Precision: 86.36%
Mean CV Recall: 72.66%
Max CV Recall: 92.59%
Mean CV F1-Score: 70.70%
Max CV F1-Score: 87.72%
Test Accuracy: 78.72%
Test Precision: 79.17%
Test Recall: 79.17%
Test F1-Score: 79.17%

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```

1 pca.fit(X_scaled)
2 var= pca.explained_variance_ratio_
3 var1=np.cumsum(np.round(pca.explained_variance_ratio_, decimals=4)*100)
4 plt.figure(figsize=(8, 4))
5 plt.plot(range(256),var1,'ro-', linewidth=1)
6 plt.title('Cumulative Explained Variance')
7 plt.ylabel('Cumulative explained variance ratio')
8 plt.xlabel('Principal components')
9 plt.show()

```

