INDIAN INSTITUTE OF INFORMATION TECHNOLOGY BHAGALPUR

भारतीय सूचना प्रौद्योगिकी संस्थान भागलपुर
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Machine Learning
CS-307

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Q.1	Objective: Human Activity Recognition through Support Vector Machine by performing multi-class classification. Also you have perform 1.scikit learn for incorporating various kernels to perform multi-class classification. 2. Compare the performance of these kernels through Confusion matrix. 3. Print the value of parameters of the SVM algorithm.
ANS:-	**---:Human Activity Recognition through SVM:---**

```
# Get required libraries
import numpy as np
import pylab as pl
import pandas as pd
import matplotlib.pyplot as plt
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
```

Load The Train And Test Set

```
train = shuffle(pd.read_csv("train.csv"))
test = shuffle(pd.read_csv("test.csv"))
```

Check for Missing Values in the dataset

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

Frequency distribution of classes

```
train_outcome = pd.crosstab(index=train["Activity"],
                    columns="count")

train_outcome
```

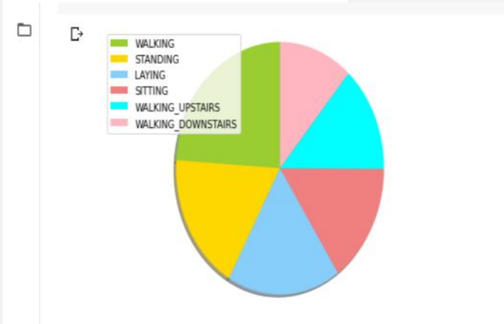
Visualizing Outcome Distribution

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

#df.plot(kind='pie',labels='labels',values='values', title='Activity Ditribution',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()
```

OUTPUT WILL LOOKS LIKE:-



Seperating Predictors and outcome Values from train and test sets

```
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("**********************************************")
```

OUTPUT WILL LOOKS LIKE:--

```
**********************************************
Dimension of Train set (639, 561)
Dimension of Test set (158, 561)

Number of numeric features: 561
********START OF OUR CODE***********
```

```
# Dimension of Train and Test set

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

# Transforming non numerical labels into numerical labels

from sklearn import preprocessing
encoder = preprocessing.LabelEncoder()
#Total Number of Continous and Categorical features in the training set

num_cols = X_train._get_numeric_data().columns
print("Number of numeric features:",num_cols.size)
#list(set(X_train.columns) - set(num_cols))

names_of_predictors = list(X_train.columns.values)

# Scaling the Train and Test feature set

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
from sklearn.decomposition import PCA

pca = PCA(n_components=200)

X_train_scaled = pca.fit_transform(X_train_scaled, Y_train)
print(pca.explained_variance_ratio_.sum())
X_test_scaled = pca.transform(X_test_scaled)

#Hyperparameter tuning using grid search and cross validation

params_grid = [{'kernel': ['rbf'], 'gamma': [1e-2, 1e-3, 1e-4],
             'C': [1, 10, 100]},
            {'kernel': ['linear'], 'C': [1, 10, 100]}]


# Performing CV to tune parameters for best SVM fit
svm_model = GridSearchCV(SVC(), params_grid, cv=8)
svm_model.fit(X_train_scaled, Y_train)

# 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")

OUTPUT :-
```

Best score for training data: 0.9854461371055495
Best C: 100
Best Kernel: rbf
Best Gamma: 0.001

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

# To Making the Confusion Matrix

print(confusion_matrix(Y_test_label,Y_pred_label))
print("\n")
print(classification_report(Y_test_label,Y_pred_label))
plot_confusion(final_model,X_test_scaled , Y_test)

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 ))
print("\n\n\n\n End of our program*************")
```

OUTPUT WILL LOOKS LIKE:---

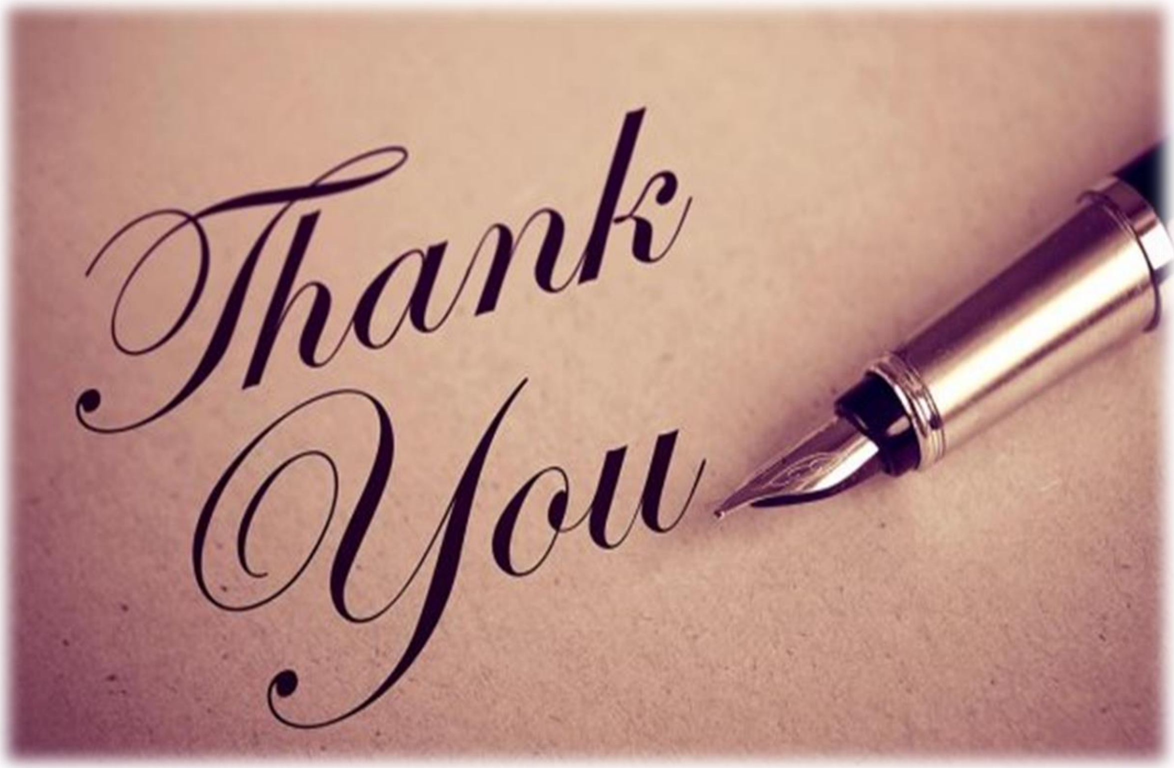
```
[[537   0   0   0   0   0]
 [  3 432  55   0   0   1]
 [  0  23 509   0   0   0]
 [  0   0   0 486   4   6]
 [  0   0   0   8 384  28]
 [  0   0   0  15   2 454]]

               precision    recall  f1-score   support

            LAYING       0.99      1.00      1.00       537
           SITTING       0.95      0.88      0.91       491
          STANDING       0.90      0.96      0.93       532
           WALKING       0.95      0.98      0.97       496
WALKING_DOWNSTAIRS       0.98      0.91      0.95       420
  WALKING_UPSTAIRS       0.93      0.96      0.95       471

       avg / total       0.95      0.95      0.95      2947

Training set score for SVM: 1.000000
Testing  set score for SVM: 0.950797
```


Thank
You