

PRACTICAL-4

Use Naive bayes, K-nearest, and Decision tree classification algorithms to build classifiers on any two datasets. Pre-process the datasets using techniques specified in Q2. Compare the Accuracy, Precision, Recall and F1 measure reported for each dataset using the abovementioned classifiers under the following situations:

i. Using Holdout method (Random sampling):

- a) Training set = 80% Test set = 20%
- b) Training set = 66.6% (2/3rd of total), Test set = 33.3%

ii. Using Cross-Validation:

- a) 10-fold
- b) 5-fold

Output:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import CategoricalNB
from sklearn.metrics import confusion_matrix, classification_report

fruits = pd.read_csv("/content/fruit_classification_dataset.csv")
#Data Pre-processing
le = LabelEncoder()
fruits['shape'] = le.fit_transform(fruits['shape'])
fruits['color'] = le.fit_transform(fruits['color'])
fruits['taste'] = le.fit_transform(fruits['taste'])
fruits['fruit_name'] = le.fit_transform(fruits['fruit_name'])

#KNN with test-size of 20%

x=fruits.drop('fruit_name',axis=1)
y=fruits['fruit_name']
X_train,X_test,Y_train,Y_test = train_test_split(x,y,test_size = 0.2)

k = 5
knn_classifier = KNeighborsClassifier(n_neighbors=k)
knn_classifier.fit(X_train,Y_train)

y_pred = knn_classifier.predict(X_test)
y_preddec = le.inverse_transform(y_pred)
Y_testdec = le.inverse_transform(Y_test)
print(y_pred)
print(classification_report(Y_testdec,y_preddec))
```

| | [1 1 6 ... 11 17 11] | | | | |
|---------------|-----------------------|--------|----------|---------|--|
| | precision | recall | f1-score | support | |
| ... | | | | | |
| apple | 1.00 | 1.00 | 1.00 | 83 | |
| banana | 1.00 | 1.00 | 1.00 | 97 | |
| blueberry | 1.00 | 1.00 | 1.00 | 110 | |
| cherry | 1.00 | 1.00 | 1.00 | 85 | |
| coconut | 0.93 | 0.88 | 0.90 | 107 | |
| custard apple | 1.00 | 1.00 | 1.00 | 103 | |
| dragon fruit | 1.00 | 1.00 | 1.00 | 106 | |
| grape | 1.00 | 1.00 | 1.00 | 112 | |
| guava | 0.98 | 0.99 | 0.99 | 106 | |
| kiwi | 1.00 | 1.00 | 1.00 | 97 | |
| lychee | 1.00 | 1.00 | 1.00 | 94 | |
| mango | 0.98 | 0.94 | 0.96 | 104 | |
| orange | 1.00 | 1.00 | 1.00 | 100 | |
| papaya | 1.00 | 1.00 | 1.00 | 95 | |
| pear | 0.99 | 0.98 | 0.99 | 114 | |
| pineapple | 0.87 | 0.93 | 0.90 | 95 | |
| plum | 1.00 | 1.00 | 1.00 | 102 | |
| pomegranate | 0.94 | 0.98 | 0.96 | 105 | |
| strawberry | 1.00 | 1.00 | 1.00 | 83 | |
| watermelon | 1.00 | 1.00 | 1.00 | 102 | |
| accuracy | | | 0.98 | 2000 | |
| macro avg | 0.98 | 0.99 | 0.98 | 2000 | |
| weighted avg | 0.98 | 0.98 | 0.98 | 2000 | |

```

# Naive Bayes for test size 20%

nb = CategoricalNB()
categorical_features = ['shape', 'color', 'taste']
X_train_cat = X_train[categorical_features]
X_test_cat = X_test[categorical_features]

nb.fit(X_train_cat, Y_train)
y_nbpred = nb.predict(X_test_cat)
y_nbpred_dec = le.inverse_transform(y_nbpred)
Y_test_dec = le.inverse_transform(Y_test)
print(classification_report(Y_test_dec, y_nbpred_dec))

```

| | precision | recall | f1-score | support | |
|---------------|-----------|--------|----------|---------|--|
| ... | | | | | |
| apple | 0.00 | 0.00 | 0.00 | 83 | |
| banana | 1.00 | 1.00 | 1.00 | 97 | |
| blueberry | 1.00 | 1.00 | 1.00 | 110 | |
| cherry | 0.51 | 1.00 | 0.67 | 85 | |
| coconut | 1.00 | 1.00 | 1.00 | 107 | |
| custard apple | 0.50 | 1.00 | 0.67 | 103 | |
| dragon fruit | 1.00 | 1.00 | 1.00 | 106 | |
| grape | 1.00 | 1.00 | 1.00 | 112 | |
| guava | 1.00 | 1.00 | 1.00 | 106 | |
| kiwi | 0.00 | 0.00 | 0.00 | 97 | |
| lychee | 1.00 | 1.00 | 1.00 | 94 | |
| mango | 1.00 | 1.00 | 1.00 | 104 | |
| orange | 1.00 | 1.00 | 1.00 | 100 | |
| papaya | 1.00 | 1.00 | 1.00 | 95 | |
| pear | 1.00 | 1.00 | 1.00 | 114 | |
| pineapple | 0.49 | 1.00 | 0.66 | 95 | |
| plum | 1.00 | 1.00 | 1.00 | 102 | |
| pomegranate | 0.56 | 1.00 | 0.72 | 105 | |
| strawberry | 0.00 | 0.00 | 0.00 | 83 | |
| watermelon | 0.00 | 0.00 | 0.00 | 102 | |
| accuracy | | | 0.82 | 2000 | |
| macro avg | 0.70 | 0.80 | 0.74 | 2000 | |
| weighted avg | 0.72 | 0.82 | 0.76 | 2000 | |

```
#KNN with test-size of 33%
```

```
x=fruits.drop('fruit_name',axis=1)
y=fruits['fruit_name']
X_train,X_test,Y_train,Y_test = train_test_split(x,y,test_size = 1/3)
```

```
k = 5
knn_classifier = KNeighborsClassifier(n_neighbors=k)
knn_classifier.fit(X_train,Y_train)
```

```
y_pred = knn_classifier.predict(X_test)
y_preddec = le.inverse_transform(y_pred)
Y_testdec = le.inverse_transform(Y_test)
print(y_pred)
print(classification_report(Y_testdec,y_preddec))
```

| | precision | recall | f1-score | support |
|---------------|-----------|--------|----------|---------|
| apple | 1.00 | 1.00 | 1.00 | 173 |
| banana | 1.00 | 1.00 | 1.00 | 179 |
| blueberry | 1.00 | 1.00 | 1.00 | 162 |
| cherry | 1.00 | 1.00 | 1.00 | 177 |
| coconut | 0.93 | 0.87 | 0.90 | 177 |
| custard apple | 1.00 | 1.00 | 1.00 | 185 |
| dragon fruit | 1.00 | 1.00 | 1.00 | 184 |
| grape | 1.00 | 1.00 | 1.00 | 156 |
| guava | 0.99 | 0.99 | 0.99 | 143 |
| kiwi | 1.00 | 1.00 | 1.00 | 146 |
| lychee | 1.00 | 1.00 | 1.00 | 164 |
| mango | 0.94 | 0.96 | 0.95 | 155 |
| orange | 1.00 | 1.00 | 1.00 | 157 |
| papaya | 1.00 | 1.00 | 1.00 | 185 |
| pear | 0.99 | 0.99 | 0.99 | 174 |
| pineapple | 0.87 | 0.93 | 0.90 | 167 |
| plum | 1.00 | 1.00 | 1.00 | 166 |
| pomegranate | 0.96 | 0.94 | 0.95 | 165 |
| strawberry | 1.00 | 1.00 | 1.00 | 158 |
| watermelon | 1.00 | 1.00 | 1.00 | 161 |
| accuracy | | | 0.98 | 3334 |
| macro avg | 0.98 | 0.98 | 0.98 | 3334 |
| weighted avg | 0.98 | 0.98 | 0.98 | 3334 |

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```
# Naive Bayes for test size 33%
```

```
nb = CategoricalNB()
categorical_features = ['shape', 'color', 'taste']
X_train_cat = X_train[categorical_features]
X_test_cat = X_test[categorical_features]

nb.fit(X_train_cat, Y_train)
y_nbpred = nb.predict(X_test_cat)
y_nbpred_dec = le.inverse_transform(y_nbpred)
Y_test_dec = le.inverse_transform(Y_test)
print(classification_report(Y_test_dec,y_nbpred_dec))
```

| | | precision | recall | f1-score | support |
|-----|---------------|-----------|--------|----------|---------|
| ... | | | | | |
| | apple | 0.00 | 0.00 | 0.00 | 173 |
| | banana | 1.00 | 1.00 | 1.00 | 179 |
| | blueberry | 1.00 | 1.00 | 1.00 | 162 |
| | cherry | 0.53 | 1.00 | 0.69 | 177 |
| | coconut | 1.00 | 1.00 | 1.00 | 177 |
| | custard apple | 0.00 | 0.00 | 0.00 | 185 |
| | dragon fruit | 1.00 | 1.00 | 1.00 | 184 |
| | grape | 1.00 | 1.00 | 1.00 | 156 |
| | guava | 1.00 | 1.00 | 1.00 | 143 |
| | kiwi | 0.00 | 0.00 | 0.00 | 146 |
| | lychee | 1.00 | 1.00 | 1.00 | 164 |
| | mango | 1.00 | 1.00 | 1.00 | 155 |
| | orange | 1.00 | 1.00 | 1.00 | 157 |
| | papaya | 1.00 | 1.00 | 1.00 | 185 |
| | pear | 1.00 | 1.00 | 1.00 | 174 |
| | pineapple | 0.53 | 1.00 | 0.70 | 167 |
| | plum | 1.00 | 1.00 | 1.00 | 166 |
| | pomegranate | 0.49 | 1.00 | 0.66 | 165 |
| | strawberry | 0.00 | 0.00 | 0.00 | 158 |
| | watermelon | 0.47 | 1.00 | 0.64 | 161 |
| | accuracy | | | 0.80 | 3334 |
| | macro avg | 0.70 | 0.80 | 0.73 | 3334 |
| | weighted avg | 0.70 | 0.80 | 0.74 | 3334 |

