```python
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # this is used for the plot the graph
import os
from sklearn.model_selection import train_test_split, cross_val_score,
GridSearchCV
from sklearn import metrics
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.cluster import KMeans
from sklearn.model_selection import KFold
from sklearn import model_selection

import itertools

import warnings
warnings.filterwarnings('ignore')

from google.colab import drive
drive.mount('drive')


def draw_confusion_matrix(y, yhat, classes):
    '''
        Draws a confusion matrix for the given target and predictions
        Adapted from scikit-learn and discussion example.
    '''
    plt.cla()
    plt.clf()
    matrix = confusion_matrix(y, yhat, labels=classes)
    plt.imshow(matrix, interpolation='nearest', cmap=plt.cm.Blues)
    plt.title("Confusion Matrix")
    plt.colorbar()
    num_classes = len(classes)
    plt.xticks(np.arange(num_classes), classes, rotation=90)
    plt.yticks(np.arange(num_classes), classes)

    fmt = 'd'
    thresh = matrix.max() / 2.
    for i, j in itertools.product(range(matrix.shape[0]),
range(matrix.shape[1])):
        plt.text(j, i, format(matrix[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if matrix[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

```
    plt.tight_layout()
    plt.show()


rice_data = pd.read_csv("/content/drive/MyDrive/CSSI - Intermediate
Course - Data Science/Final Project/Rice_MSC_Dataset.csv")
rice_data.head()
```

```
Mounted at drive

   AREA  PERIMETER  MAJOR_AXIS  MINOR_AXIS  ECCENTRICITY   EQDIASQ
SOLIDITY  \
0  7805    437.915    209.8215     48.0221        0.9735   99.6877
0.9775
1  7503    340.757    138.3361     69.8417        0.8632   97.7400
0.9660
2  5124    314.617    141.9803     46.5784        0.9447   80.7718
0.9721
3  7990    437.085    201.4386     51.2245        0.9671  100.8622
0.9659
4  7433    342.893    140.3350     68.3927        0.8732   97.2830
0.9831

   CONVEX_AREA  EXTENT  ASPECT_RATIO  ...  ALLdaub4L  ALLdaub4a
ALLdaub4b  \
0         7985  0.3547        4.3693  ...   113.9924    65.0610
59.5989
1         7767  0.6637        1.9807  ...   105.7055    64.3685
62.2084
2         5271  0.4760        3.0482  ...   109.7155    62.6423
58.7439
3         8272  0.6274        3.9325  ...   116.5405    64.9069
60.2562
4         7561  0.6006        2.0519  ...   107.7502    64.7071
61.3549

   ALLdaub4Y  ALLdaub4Cb  ALLdaub4Cr  ALLdaub4XX  ALLdaub4YY
ALLdaub4ZZ  \
0   104.8552     67.8779     63.0828      0.3673      0.3793
0.4733
1    96.8375     65.5371     63.5832      0.3014      0.3144
0.3641
2   100.2352     68.9753     59.8342      0.3233      0.3445
0.4448
3   107.2560     67.3298     63.2237      0.3880      0.4020
0.4904
4    98.8704     66.2048     63.5378      0.3184      0.3303
0.3928

     CLASS
```

```
0  Basmati
1  Arborio
2  Jasmine
3  Basmati
4  Arborio

[5 rows x 107 columns]
```

```
#rice_data = rice_data.drop(columns=["CLASS"])
rice_data
```

```
        AREA  PERIMETER  MAJOR_AXIS  MINOR_AXIS  ECCENTRICITY
EQDIASQ  \
0       7805    437.915    209.8215     48.0221        0.9735
99.6877
1       7503    340.757    138.3361     69.8417        0.8632
97.7400
2       5124    314.617    141.9803     46.5784        0.9447
80.7718
3       7990    437.085    201.4386     51.2245        0.9671
100.8622
4       7433    342.893    140.3350     68.3927        0.8732
97.2830
...      ...        ...         ...         ...           ...        ..
.
74995   5551    285.911    114.1695     62.9079        0.8345
84.0699
74996   7696    322.703    121.3900     81.1375        0.7438
98.9892
74997   7579    339.295    136.3125     71.2866        0.8524
98.2338
74998  15174    489.502    200.9486     97.6282        0.8740
138.9969
74999  12931    452.635    185.5138     90.2651        0.8736
128.3131

       SOLIDITY  CONVEX_AREA  EXTENT  ASPECT_RATIO  ...  ALLdaub4L
ALLdaub4a  \
0        0.9775         7985  0.3547        4.3693  ...   113.9924
65.0610
1        0.9660         7767  0.6637        1.9807  ...   105.7055
64.3685
2        0.9721         5271  0.4760        3.0482  ...   109.7155
62.6423
3        0.9659         8272  0.6274        3.9325  ...   116.5405
64.9069
4        0.9831         7561  0.6006        2.0519  ...   107.7502
64.7071
...         ...          ...     ...           ...  ...        ...
...
```

```
74995    0.9846         5638  0.6418        1.8149  ...   103.9529
64.9225
74996    0.9868         7799  0.7309        1.4961  ...   108.9778
65.4571
74997    0.9805         7730  0.6399        1.9122  ...   106.0881
64.1869
74998    0.9766        15537  0.7903        2.0583  ...   119.2037
63.3545
74999    0.9760        13249  0.7640        2.0552  ...   121.4198
63.5424

       ALLdaub4b  ALLdaub4Y  ALLdaub4Cb  ALLdaub4Cr  ALLdaub4XX
ALLdaub4YY  \
0        59.5989   104.8552     67.8779     63.0828      0.3673
0.3793
1        62.2084    96.8375     65.5371     63.5832      0.3014
0.3144
2        58.7439   100.2352     68.9753     59.8342      0.3233
0.3445
3        60.2562   107.2560     67.3298     63.2237      0.3880
0.4020
4        61.3549    98.8704     66.2048     63.5378      0.3184
0.3303
...          ...        ...         ...         ...         ...
...
74995    62.4355    95.2780     65.5114     64.4457      0.2895
0.2997
74996    59.9502   100.2301     67.5089     63.6028      0.3335
0.3426
74997    61.3876    97.1585     66.2445     63.0596      0.3028
0.3164
74998    64.8200   109.3027     63.3122     63.5967      0.3970
0.4215
74999    65.2355   111.4580     63.0129     63.9117      0.4162
0.4414

       ALLdaub4ZZ      CLASS
0          0.4733    Basmati
1          0.3641    Arborio
2          0.4448    Jasmine
3          0.4904    Basmati
4          0.3928    Arborio
...           ...        ...
74995      0.3455    Arborio
74996      0.4257  Karacadag
74997      0.3761    Arborio
74998      0.4469     Ipsala
74999      0.4626     Ipsala

[75000 rows x 107 columns]
```

```
rice_data = rice_data.drop(rice_data.iloc[:, 16:106], axis=1)
rice_data.head()
```

```
   AREA  PERIMETER  MAJOR_AXIS  MINOR_AXIS  ECCENTRICITY   EQDIASQ
SOLIDITY  \
0  7805    437.915    209.8215     48.0221        0.9735   99.6877
0.9775
1  7503    340.757    138.3361     69.8417        0.8632   97.7400
0.9660
2  5124    314.617    141.9803     46.5784        0.9447   80.7718
0.9721
3  7990    437.085    201.4386     51.2245        0.9671  100.8622
0.9659
4  7433    342.893    140.3350     68.3927        0.8732   97.2830
0.9831

   CONVEX_AREA  EXTENT  ASPECT_RATIO  ROUNDNESS  COMPACTNESS
SHAPEFACTOR_1  \
0         7985  0.3547        4.3693     0.5114       0.4751
0.0269
1         7767  0.6637        1.9807     0.8120       0.7065
0.0184
2         5271  0.4760        3.0482     0.6505       0.5689
0.0277
3         8272  0.6274        3.9325     0.5256       0.5007
0.0252
4         7561  0.6006        2.0519     0.7944       0.6932
0.0189

   SHAPEFACTOR_2  SHAPEFACTOR_3  SHAPEFACTOR_4    CLASS
0         0.0062         0.2257         0.9863  Basmati
1         0.0093         0.4992         0.9888  Arborio
2         0.0091         0.3236         0.9865  Jasmine
3         0.0064         0.2507         0.9859  Basmati
4         0.0092         0.4806         0.9860  Arborio
```

```
from sklearn.compose import ColumnTransformer

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

from sklearn.base import BaseEstimator, TransformerMixin

rice_data_target = rice_data["CLASS"]
rice_data = rice_data.drop(["CLASS"], axis = 1)

numerical_features = list(rice_data)

pipeline = ColumnTransformer([
        ('std_scaler', StandardScaler(), numerical_features)
```

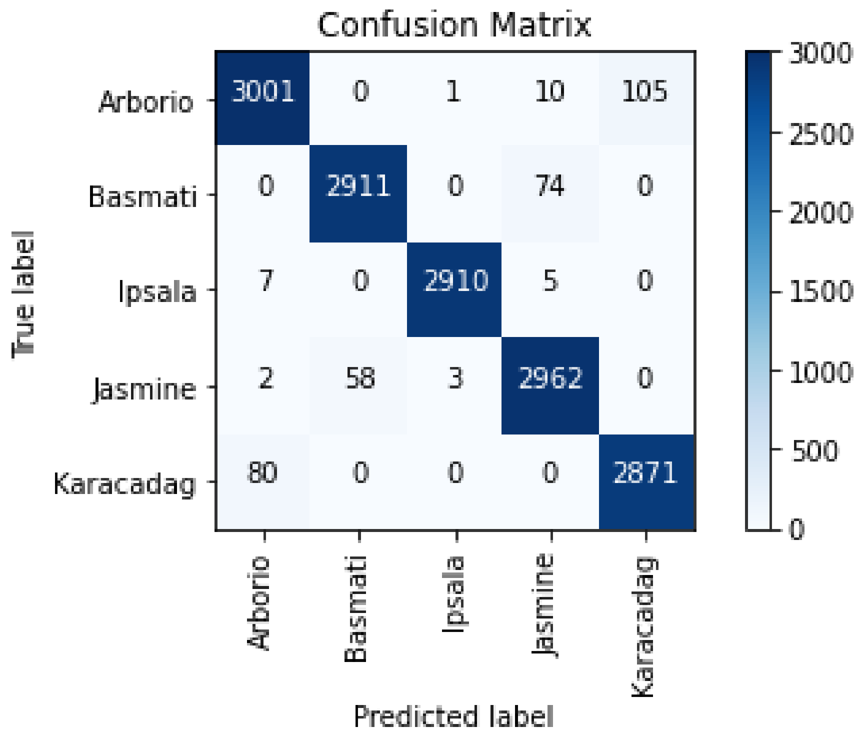
```
    ])

rice_data_prepared = pipeline.fit_transform(rice_data)

X_train, X_test, y_train, y_test =
train_test_split(rice_data_prepared, rice_data_target, test_size =
0.2)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(60000, 16) (15000, 16) (60000,) (15000,)
```

```
#Logistic Regression w/o Penalty

log_reg = LogisticRegression(multi_class="multinomial",
solver="lbfgs", penalty='none') #maybe make into knn or svm
log_reg.fit(X_train, y_train)

y_pred = log_reg.predict(X_test)
log_score = log_reg.predict_proba(X_test)

print("%-12s %f" % ('Accuracy:',
metrics.accuracy_score(y_test,y_pred)))
print("%-12s %f" % ('Precision:',
metrics.precision_score(y_test,y_pred,labels=None, pos_label=1,
average='macro', sample_weight=None)))
print("%-12s %f" % ('Recall:',
metrics.recall_score(y_test,y_pred,labels=None, pos_label=1,
average='macro', sample_weight=None)))
print("%-12s %f" % ('F1 Score:',
metrics.f1_score(y_test,y_pred,labels=None, pos_label=1,
average='macro', sample_weight=None)))
```

```
Accuracy:    0.977000
Precision:   0.977167
Recall:      0.977190
F1 Score:    0.977166
```

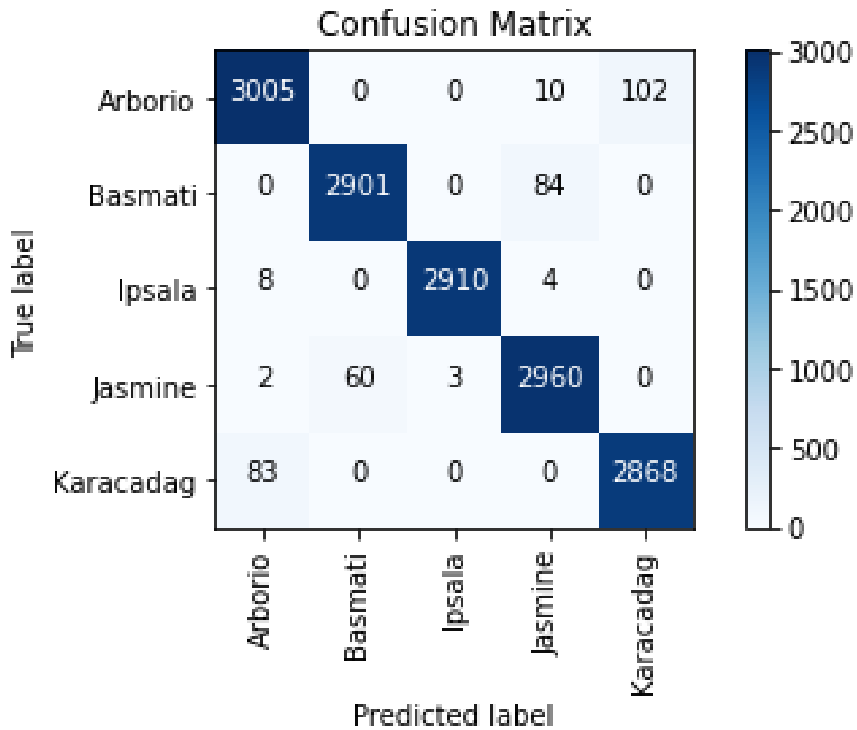
```
draw_confusion_matrix(y_test, y_pred, ['Arborio', 'Basmati', 'Ipsala',
'Jasmine', 'Karacadag'])
#rice_data.head(10)
```




```
#Logistic Regression w/ l2 Penalty

log_reg = LogisticRegression(multi_class="multinomial",
solver="lbfgs", penalty='l2')
log_reg.fit(X_train, y_train)

y_pred = log_reg.predict(X_test)
log_score = log_reg.predict_proba(X_test)

print("%-12s %f" % ('Accuracy:',
metrics.accuracy_score(y_test,y_pred)))
print("%-12s %f" % ('Precision:',
metrics.precision_score(y_test,y_pred,labels=None, pos_label=1,
average='macro', sample_weight=None)))
print("%-12s %f" % ('Recall:',
metrics.recall_score(y_test,y_pred,labels=None, pos_label=1,
average='macro', sample_weight=None)))
print("%-12s %f" % ('F1 Score:',
metrics.f1_score(y_test,y_pred,labels=None, pos_label=1,
average='macro', sample_weight=None)))

draw_confusion_matrix(y_test, y_pred, ['Arborio', 'Basmati', 'Ipsala',
'Jasmine', 'Karacadag'])
```

```
Accuracy:    0.976267
Precision:   0.976459
```

```
Recall:      0.976441
F1 Score:    0.976437
```



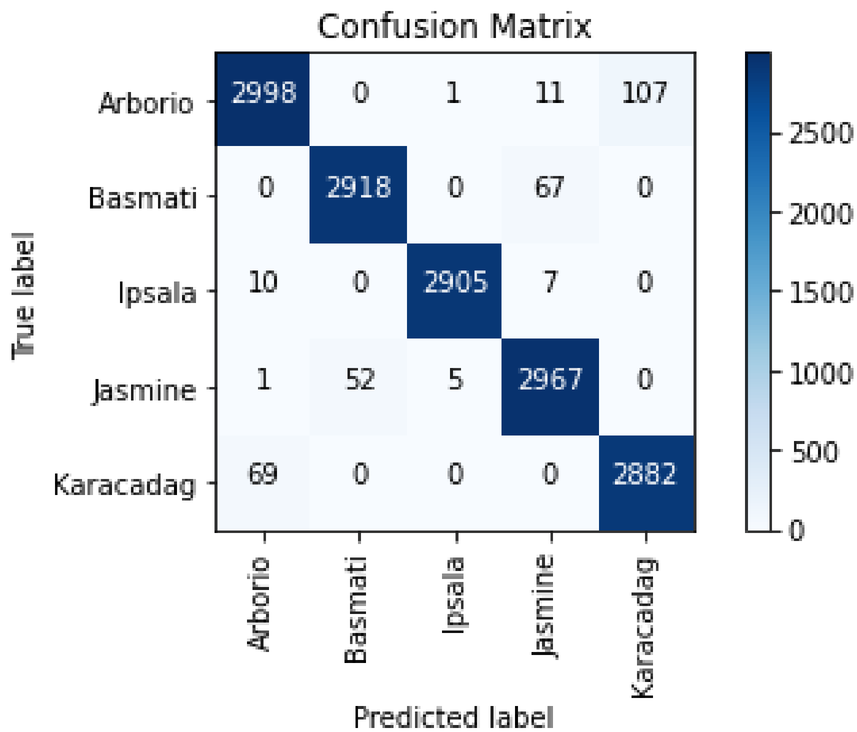

```
'''
#KNN Optimizer
k_values = [1,2,3,5,7,9,10,20,200]
for k in k_values:
  knnclass = KNeighborsClassifier(n_neighbors=k)
  knnclass.fit(X_train, y_train)
  y_pred = knnclass.predict(X_test)
  print(k, "%-12s %f" % ('Accuracy:',
metrics.accuracy_score(y_test,y_pred)))
'''
```

{"type":"string"}

```
#KNN

knnclass = KNeighborsClassifier(n_neighbors=5)
knnclass.fit(X_train, y_train)
y_pred = knnclass.predict(X_test)

print("%-12s %f" % ('Accuracy:',
metrics.accuracy_score(y_test,y_pred)))
print("%-12s %f" % ('Precision:',
metrics.precision_score(y_test,y_pred,labels=None, pos_label=1,
average='macro', sample_weight=None)))
print("%-12s %f" % ('Recall:',
```

```
metrics.recall_score(y_test,y_pred,labels=None, pos_label=1,
average='macro', sample_weight=None)))
print("%-12s %f" % ('F1 Score:',
metrics.f1_score(y_test,y_pred,labels=None, pos_label=1,
average='macro', sample_weight=None)))

draw_confusion_matrix(y_test, y_pred, ['Arborio', 'Basmati', 'Ipsala',
'Jasmine', 'Karacadag'])
```

```
Accuracy:    0.978000
Precision:   0.978158
Recall:      0.978201
F1 Score:    0.978158
```




```
#K Fold of Top 2
kfold = model_selection.KFold(n_splits=10, random_state=42,
shuffle=True)

# replace the two models below with what you picked
knn_model_kfold = KNeighborsClassifier(n_neighbors=5)
log_model_kfold = LogisticRegression(multi_class="multinomial",
solver="lbfgs", penalty='none')

# Finally we pull it all together. We call cross val score to generate
an accuracy performance score for our model
# we define our learning model, data, labels, and cross-val splitting
strategy (all defined previously)
```

```
knn_results_kfold = model_selection.cross_val_score(knn_model_kfold,
X_train, y_train, cv=kfold)
log_results_kfold = model_selection.cross_val_score(log_model_kfold,
X_train, y_train, cv=kfold)

# Because we're collecting results from all runs, we take the mean
value
print("For KNN Classifier our mean accuracy across folds is: %.2f%%" %
(knn_results_kfold.mean()*100.0))
print("For Logistic Regression our mean accuracy across folds is: %.2f
%%" % (log_results_kfold.mean()*100.0))
```

```
For KNN Classifier our mean accuracy across folds is: 97.92%
For Logistic Regression our mean accuracy across folds is: 97.76%
```