```python
import pickle
import numpy as np
from sklearn.cluster import KMeans
import sklearn as sk
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
import cv2
from matplotlib import pyplot as plt
import colorsys
from sklearn.cluster import KMeans, MeanShift, DBSCAN,
AgglomerativeClustering
from sklearn import metrics
from sklearn.metrics import accuracy_score, classification_report
import math
import copy

def load_dataset():
  image_pickle_file_path = 'images.pkl'
  label_pickle_file_path = 'label.pkl'

  with open(image_pickle_file_path, 'rb') as file:
    images = pickle.load(file)

  with open(label_pickle_file_path, 'rb') as file:
    labels = pickle.load(file)

  images = images.reshape(images.shape[0], -1)

  return images, labels

images, labels = load_dataset()

# nthImageToRGB function converts the nth image from an array into the
RGB format
def arrayToRGB(image):
    imageWith3Channels = image.reshape(499,499,3)
#     plt.imshow(imageWith3Channels)
#     plt.axis('off')  # Turn off axis labels
#     plt.show()
    return imageWith3Channels

def nthImageRGBToHSV(image):
    hsvImage = cv2.cvtColor(arrayToRGB(image), cv2.COLOR_BGR2HSV)
#     cv2.imshow('HSV image', hsvImage)
#     cv2.waitKey(0)
```

```
#     cv2.destroyAllWindows()
    return hsvImage

def featureExtractorFromPixels(image):
    myImage = nthImageRGBToHSV(image)
    featureVectorsOfPixelsInMyImage = [] # (x,y,h,s,v,h,s,v,h,s,v) of
each pixel, in a specific image
    for x in range(len(myImage)):
        for y in range(len(myImage[x])):
    #         print(x,y,myImage[x][y])
            featureVectorsOfPixelsInMyImage += [[x,y,myImage[x][y]
[0],myImage[x][y][1],myImage[x][y][2]]]
    return featureVectorsOfPixelsInMyImage

def standardize(array):
    scaler = sk.preprocessing.StandardScaler()
    array_standardized =
scaler.fit_transform(featureExtractorFromPixels(array))
    return array_standardized

def pixelsToRegions(image):
    cluteringAlgo = KMeans(n_clusters=5,random_state=42)
    # standardization
    image_standardized = standardize(image)
        # Fit the model and predict clusters
    predictedLabels = cluteringAlgo.fit_predict(image_standardized)
    return predictedLabels

# predictions => predictedRegionForEachPixel
def regionBasedFeatureVectorGenerator(image,predictions):
    # for every region do
    allRegionBasedFeaturesOfAnImage = []
    for i in range(max(predictions)+1):
        pixelLevelFeaturesOfAnImage =
np.array(featureExtractorFromPixels(image))
        # perform masking; select those regions clustered as 0, 1,
2, ... separately, and create a regionLevel feature
        # vector for each region
        ithRegionPixelLevelFeatures =
pixelLevelFeaturesOfAnImage[predictions==i]
        # selecting h,s,v
        HSVColumns = ithRegionPixelLevelFeatures[:,2:5]
        averageHSVColumns = np.mean(HSVColumns,axis=0)
        stdHSVColumns = np.std(HSVColumns,axis=0)
        numberOfPixelsInThisRegion = len(ithRegionPixelLevelFeatures)
        XYColumns = ithRegionPixelLevelFeatures[:,0:2]
        averageXYColumns = np.mean(XYColumns,axis=0)
        stdXYColumns = np.std(XYColumns,axis=0)
        # concat different features to make a vector
        # averageXYColumns -> avg x, avg y
```

```
        # stdXYColumns -> std x, std y
        # numberOfPixelsInThisRegion -> int
        # averageHSVColumns -> avg h, avg s, avg v
        # stdHSVColumns -> std h, std s, std v
        ithRegionFeatureVector = np.hstack((averageXYColumns,
stdXYColumns,
numberOfPixelsInThisRegion,averageHSVColumns,stdHSVColumns))
        allRegionBasedFeaturesOfAnImage +=
[list(ithRegionFeatureVector)]
    return allRegionBasedFeaturesOfAnImage

# regionPredictionForEachPixel = pixelsToRegions(X_train[6])
#
print(regionBasedFeatureVectorGenerator(X_train[6],regionPredictionFor
EachPixel))

def classify(datapoints, labels):
    test_size = 0.3
    X_train, X_test, y_train, y_test = train_test_split(datapoints,
labels, test_size=test_size, random_state=42)

    clf = RandomForestClassifier(n_estimators=10, random_state=42)

    clf.fit(X_train, y_train)

    y_pred = clf.predict(X_test)

    accuracy = accuracy_score(y_test, y_pred)
#     precision = precision_score(y_test, y_pred,average='macro')
#     recall = recall_score(y_test, y_pred,average='macro')
#     f1 = f1_score(y_test, y_pred, average='macro')
#     print("confusion_matrix\n",confusion_matrix(y_test, y_pred))

#     print(f"Accuracy: {accuracy * 100:.2f}%")
#     print(f"Precision: {precision * 100:.2f}")
#     print(f"Recall: {recall * 100:.2f}")
#     print(f"F1_Score: {f1 * 100:.2f}")

    return accuracy,y_pred,y_train,np.array(y_test),X_train,X_test

array_3d = np.load('3d_arrayEqualWeightsFixed.npy')#[:50]
#we have used k-means to find regions, Therefore all images have same
number of regions
#but the following array is defined in case the number of regions were
different
number_of_regions_per_image = np.full(array_3d.shape[0] ,
array_3d.shape[1])

print(array_3d.shape)
print(number_of_regions_per_image.shape)
```

```
(560, 5, 11)
(560,)
```

```python
#At first the importance of all regions is equal and maximum
regions_importance = np.zeros(array_3d.shape[:2])

label_pickle_file_path = 'label.pkl'
with open(label_pickle_file_path, 'rb') as file:
    labels = pickle.load(file)

labels = labels

avg_features = np.mean(array_3d, axis=1)
avg_features.shape
```

```
(560, 11)
```

```python
#Standardize data
scaler = sk.preprocessing.StandardScaler()
std_avg = scaler.fit_transform(avg_features)

def clf_info(clf,img_means):
    predictions = clf.predict(img_means)
    probabilities = clf.predict_proba(img_means)

    accuracy = accuracy_score(labels, predictions)
    report = classification_report(labels, predictions)

    print("Accuracy:", accuracy)
    print("Classification Report:\n", report)


def find_least_important(clf,img_idx):
    label = labels[img_idx]
    idx_zero = np.where(regions_importance[img_idx]==0)
    if not idx_zero == idx_zero:
      return
    rate = np.max(regions_importance[img_idx])+1
    img = array_3d[img_idx][idx_zero]
    if rate==array_3d.shape[1]:
      regions_importance[img_idx][idx_zero] = rate
      return

    rgn , ftr = img.shape
    acc = []
    modif_dt = np.zeros(img.shape)
    for r in range(rgn):
      modif_img = np.mean(np.delete(img, r, axis=0),axis=0)
      modif_dt[r] = scaler.transform([modif_img])
    proba = clf.predict_proba(modif_dt)
    max_idx = np.argmax(proba[:,label])
```

```
    matching_idx = np.where((array_3d[img_idx] ==
img[max_idx]).all(axis=1))[0]
    regions_importance[img_idx][matching_idx[0]] =
min(array_3d.shape[1],rate)

    return proba[max_idx][label]


def prob(clf,img):
  return clf.predict_proba(scaler.transform([np.mean(img,axis=0)]))


def get_imp_means():
    imgs, rgns, ftrs = array_3d.shape
    means = np.zeros((imgs, ftrs))
    for idx in range(imgs):
        idx_zero = np.where(regions_importance[idx]==0)
        img = array_3d[idx][idx_zero]
        means[idx] = scaler.transform([np.mean(img,axis=0)])
    return means


def find_least_important_for_all(clf):
    l=[]
    for img_idx in range(array_3d.shape[0]):
      proba=find_least_important(clf, img_idx)
      p = prob(clf,array_3d[img_idx])[0][labels[img_idx]]

def do_task(goal):
  clf = None
  for i in range(array_3d.shape[1]-goal):
    means = get_imp_means()
    clf = RandomForestClassifier(n_estimators=100,max_depth=6,
random_state=42)
    clf.fit(means, labels)
    clf_info(clf,means)
    find_least_important_for_all(clf)
  for i in range(goal):
    find_least_important_for_all(clf)

  return clf


#avg_features_test = avg_features
#std_avg_features_test = scaler.transform(avg_features_test)
clf=do_task(2)
#predictions = clf.predict(std_avg)
#probabilities = clf.predict_proba(std_avg)

#accuracy = accuracy_score(labels, predictions)
#report = classification_report(labels, predictions)
```

```
#print("Accuracy:", accuracy)
#print("Classification Report:\n", report)
```

```
Accuracy: 0.8642857142857143
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.88      0.85        80
           1       0.85      0.89      0.87        80
           2       0.80      0.90      0.85        80
           3       0.79      0.84      0.81        80
           4       0.96      0.80      0.87        80
           5       0.92      0.90      0.91        80
           6       0.96      0.85      0.90        80

    accuracy                           0.86       560
   macro avg       0.87      0.86      0.87       560
weighted avg       0.87      0.86      0.87       560

Accuracy: 0.8982142857142857
Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.88      0.87        80
           1       0.89      0.94      0.91        80
           2       0.91      0.94      0.93        80
           3       0.89      0.89      0.89        80
           4       0.96      0.88      0.92        80
           5       0.85      0.90      0.87        80
           6       0.93      0.88      0.90        80

    accuracy                           0.90       560
   macro avg       0.90      0.90      0.90       560
weighted avg       0.90      0.90      0.90       560

Accuracy: 0.9357142857142857
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.93      0.91        80
           1       0.92      0.95      0.93        80
           2       0.93      0.95      0.94        80
           3       0.95      0.91      0.93        80
           4       0.95      0.93      0.94        80
           5       0.92      0.96      0.94        80
           6       1.00      0.93      0.96        80

    accuracy                           0.94       560
   macro avg       0.94      0.94      0.94       560
```

```
weighted avg       0.94      0.94      0.94       560
```

```python
for i in regions_importance[:20]:
  print(i)
```

```
[1. 3. 2. 5. 4.]
[1. 5. 3. 4. 2.]
[2. 1. 4. 3. 5.]
[2. 5. 4. 3. 1.]
[1. 2. 3. 4. 5.]
[4. 1. 2. 5. 3.]
[4. 5. 3. 2. 1.]
[1. 3. 2. 4. 5.]
[2. 3. 4. 5. 1.]
[2. 1. 5. 3. 4.]
[4. 5. 2. 3. 1.]
[1. 3. 5. 4. 2.]
[4. 5. 2. 1. 3.]
[4. 5. 3. 2. 1.]
[1. 5. 4. 3. 2.]
[1. 2. 3. 5. 4.]
[2. 4. 1. 3. 5.]
[3. 5. 2. 1. 4.]
[3. 5. 1. 2. 4.]
[2. 4. 1. 5. 3.]
```

```python
array_3d = np.load('3d_arrayEqualWeightsFixed.npy')

# selecting the most important region
biggestPossibleRegionScore = len(regions_importance[0])
InitialFeatureVectors =
array_3d[regions_importance==biggestPossibleRegionScore]

# we get the correlations before standardizing. Because when we
standardize, standard deviation of our data
# becomes one, and this leads to division by zero in Pearson's
Correlation calculation.
# also, standardizing does not change the correlation of vectors and
matrices at all.
correlation_matrix = np.corrcoef(InitialFeatureVectors, rowvar=False)
# standardizing our data
scaler = sk.preprocessing.StandardScaler()
InitialFeatureVectorsStandardized =
scaler.fit_transform(InitialFeatureVectors)

# training a classifier on the entire images and deleting 20% of
mislabeled test data

accuracy,y_pred,y_train,y_test,X_train,X_test =
classify(InitialFeatureVectorsStandardized,labels)
```

```
# dividing into 3 categories.

# masking: finding those instances where predictions and labels do not
match
booleanMask = y_pred!=y_test
# Test set labeled wrong
# delete 20% of wrong predictions in the test set
wronglabelsLen80PercentTop = len(X_test[booleanMask]) * 80//100
firstPortion = X_test[booleanMask][:wronglabelsLen80PercentTop]
firstPortionLabels = y_test[booleanMask][:wronglabelsLen80PercentTop]



booleanMask = y_pred==y_test
# Test set labeled right
secondPortion = X_test[booleanMask]
secondPortionLabels = y_test[booleanMask]

# all Train set
thirdPortion = X_train
thirdPortionLabels = y_train

labelsReduced =
np.concatenate((firstPortionLabels,secondPortionLabels,thirdPortionLab
els),axis=0)
InitialFeatureVectorsStandard =
np.concatenate((firstPortion,secondPortion,thirdPortion),axis=0)

# when using these correlations, we have to get the maximum
correlation of a feature with other features.
# therefore, setting correlations to -1 will make that correlation
redundant as it will be never selected as
# the maximum correlation

# so we must set the correlations on the main diagonal to -1. (range
of correlation:-1 to 1)
# however, when training a classifier, it does not matter if two
features are extremely correlated
# or exactly opposite. Therefore, we will get abs() from these
correlations. That way the min possible correlation
# becomes 0. So we will set those elements on the main diagonal to 0.
np.fill_diagonal(correlation_matrix, 0)
# print(correlation_matrix[0])



# the for loop iterates P times, where P is the number of second
dimension in InitialFeatureVectorsStandard.
# InitialFeatureVectorsStandard is 560*11. So i goes from 0 to 10.
```

```
# storing the number of best features found so far
# adding a column of ones to BestMfeaturesFoundSoFar
# because if we define BestMfeaturesFoundSoFar=[], we cannot
concatenate an array of size 1*
BestMfeaturesFoundSoFar = np.array([])

# at first, BestMfeaturesFoundSoFar is of size 560*1 so
BestMfeaturesFoundSoFar[0] is of size 1 in the first iteration
S = 11 # you cannot set this number to more than the number of
features

# select best S features in each region
for k in range(S):

    accuracylist = np.array([])
    for i in range((InitialFeatureVectorsStandard.shape)[1]):

        ithFeatureOfImages = (InitialFeatureVectorsStandard[:,i])
[:,np.newaxis]
        # now we will train a Classifier using the ith feature in our
images
        accuracyForThisFeature,y_pred,y_train,y_test,X_train,X_test  =
classify(ithFeatureOfImages,labelsReduced)
        # storing accuracies in a list
        accuracylist = np.append(accuracylist, accuracyForThisFeature)

    # set initial selectedCorrelations to all zero
    selectedCorrelations =
np.zeros((InitialFeatureVectorsStandard.shape)[1])
    # max correlations for each feature
    maxCorrelations = np.zeros((InitialFeatureVectorsStandard.shape)
[1])

    # lets exclude those indices that are already in
BestMfeaturesFoundSoFar
#     mask = np.ones_like(accuracylist, dtype=bool)
    if len(BestMfeaturesFoundSoFar)!=0:
        # setting maxCorrelations to empty array. because we are going
to append real Max Correlations to it.
        maxCorrelations = np.array([])
        accuracylist[BestMfeaturesFoundSoFar.astype(int)] = -100

        # max correlations with features selected so far
        maxCorrelations = np.array([])
        for i in range((InitialFeatureVectorsStandard.shape)[1]):
            abstractOfCorrelationsForFeatureI =
np.abs(correlation_matrix[i])
            # select only those correlations with elements already in
BestMfeaturesFoundSoFar
            selectedCorrelations =
```

```
abstractOfCorrelationsForFeatureI[BestMfeaturesFoundSoFar.astype(int)]
#             print(selectedCorrelations)
            maxCorrelations =
np.append(maxCorrelations,np.max(selectedCorrelations))
#         print(maxCorrelations)
#         print()

    # finding the best accuracy and the feature leading to that


    # if we have a denominator which is very negative, it means that
this denominator belongs to
    # a column that we have already selected for our "best features
set".
    # however, if we divide two negative numbers, the product becomes
positive. Therefore, we must
    # set one of these negative numbers to negative, so that our
division becomes negative and therefore,
    # not selected once again

    numerators = 2*(accuracylist*(1-maxCorrelations))
    denominators = accuracylist+(1-maxCorrelations)
    denominators[denominators<(-50)] = 99
    # combined as in F1-score
    bestFeatureBasedOnAccuracy = np.argmax(numerators/denominators)

    # adding the best feature's index to BestMfeaturesFoundSoFar
    BestMfeaturesFoundSoFar = np.append(BestMfeaturesFoundSoFar,
bestFeatureBasedOnAccuracy)

    datapoints =
InitialFeatureVectorsStandard[:,BestMfeaturesFoundSoFar.astype(int)]
    finalAccuracy,y_pred,y_train,y_test,X_train,X_test =
classify(datapoints,labelsReduced)
    # break the loop as soon as we get the accuracy of more than 70%
    if finalAccuracy>0.7:
        break


print(BestMfeaturesFoundSoFar)
print(finalAccuracy)

[ 5.  2.  7. 10.  6.  0.  1.]
0.7469879518072289
```

- the algorithm stops as soon as we get an accuracy of 70% or more

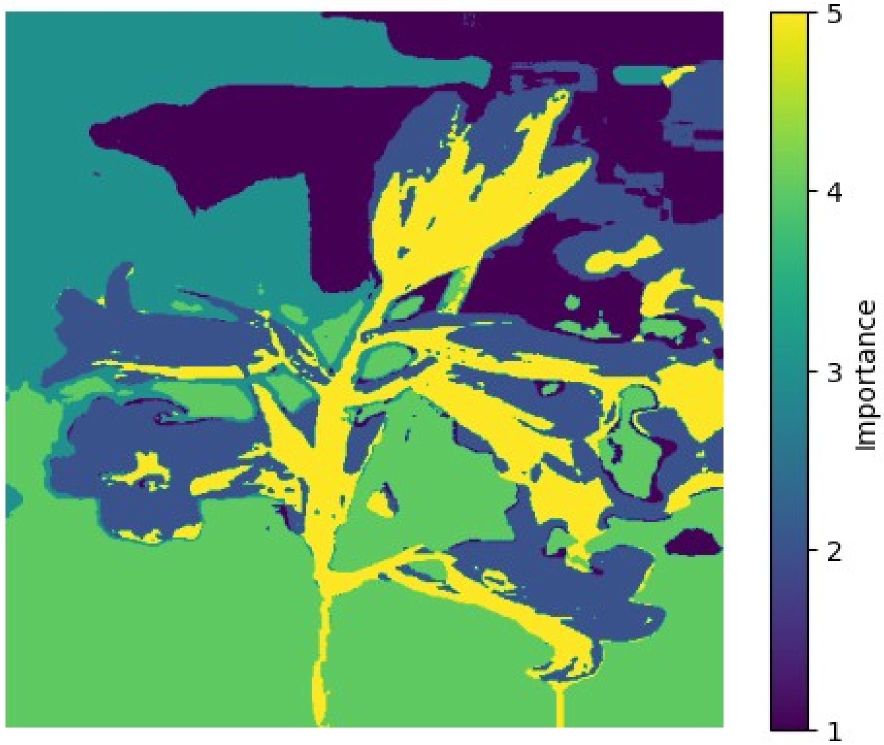
the order of features are as below

- averageX, averageY, stdX, stdY, numberOfPixelsInThisRegion,averageH, averageS, averageV ,stdH , stdS, stdV

- so if our selected features are [0, 7, 5, 8, 6, 10]
- it means that we have chosen averageX, averageV, averageH, stdH, averageS, stdV

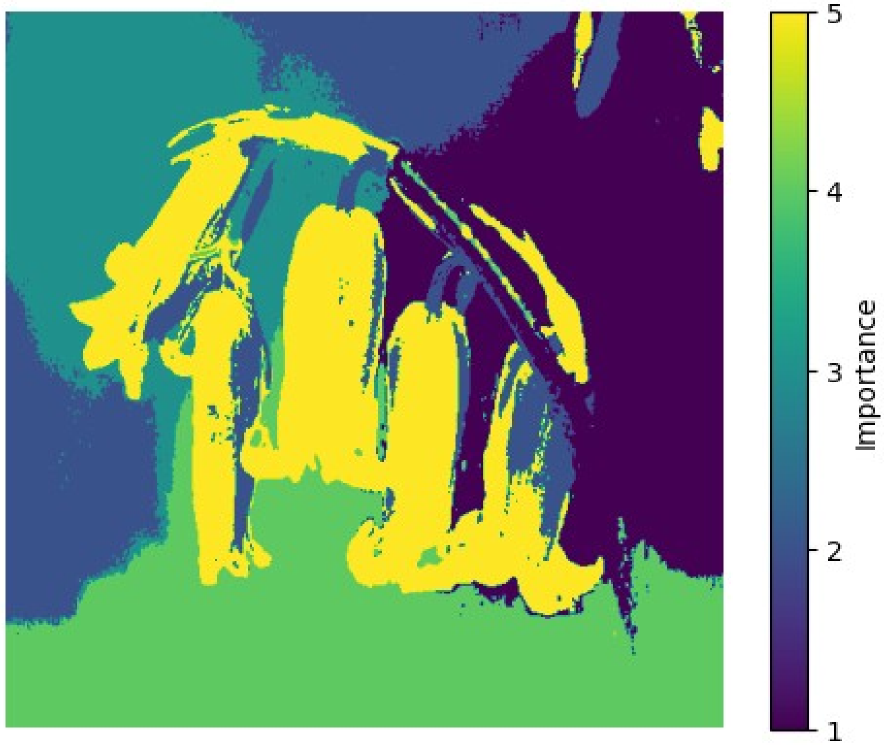
```
def regionImportanceTester(k):
    ithImageTest = k
    myImage = images[ithImageTest]
    plt.imshow(arrayToRGB(myImage))
    plt.axis('off')  # Turn off axis labels
    plt.show()

    regionPredictionForEachPixel = pixelsToRegions(myImage)
    regionBasedFeatureVectorsOfAnImage = 
regionBasedFeatureVectorGenerator(myImage,regionPredictionForEachPixel
)

    regionPredictionForEachPixel2 = 
copy.deepcopy(regionPredictionForEachPixel)
    for i in range(max(regionPredictionForEachPixel2)+1):
        
regionPredictionForEachPixel2[regionPredictionForEachPixel2==i]= -
1*regions_importance[ithImageTest][i]
    regionPredictionForEachPixel2 *= -1

    plt.imshow(regionPredictionForEachPixel2.reshape(499,499))
    cbar = 
plt.colorbar(ticks=np.unique(regionPredictionForEachPixel2), 
label='Importance')
    cbar.set_ticklabels(np.unique(regionPredictionForEachPixel2))

    plt.axis('off')  # Turn off axis labels
    plt.show()

regionImportanceTester(1)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



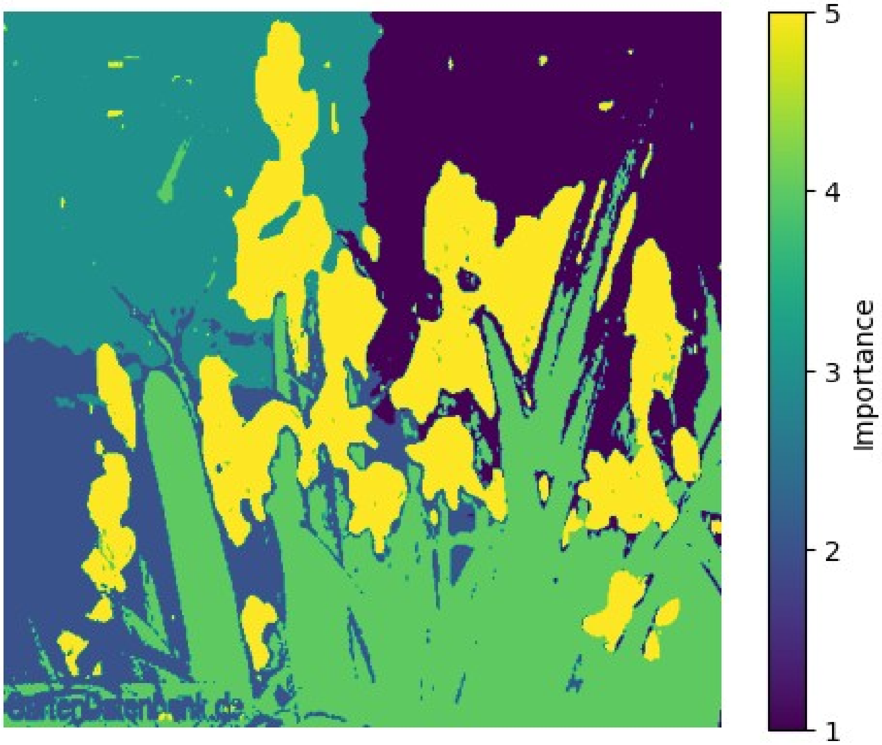

```
regionImportanceTester(15)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



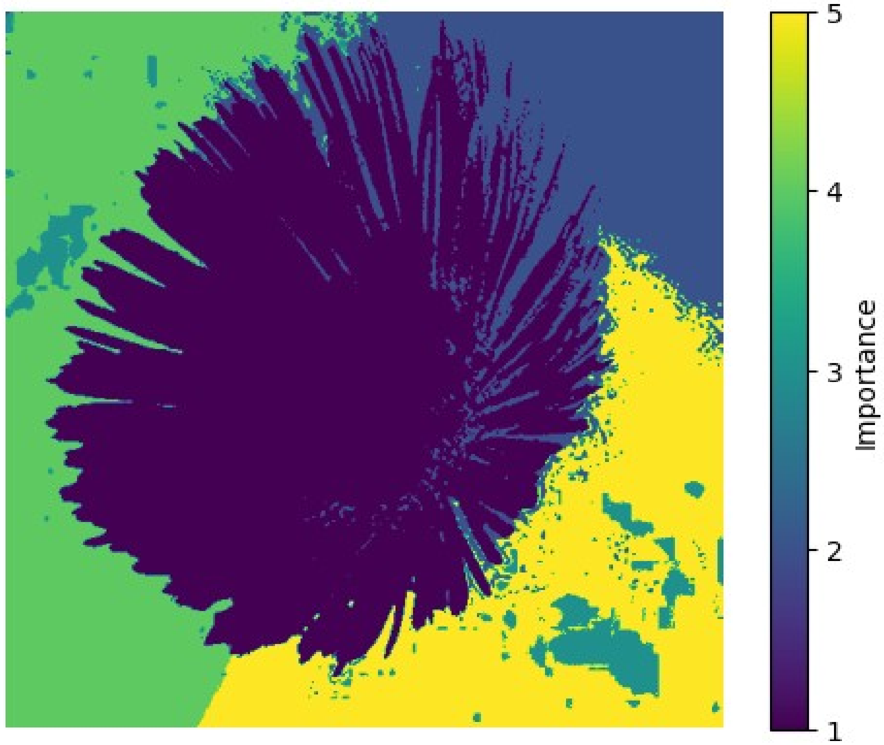

```
regionImportanceTester(50)
```


```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



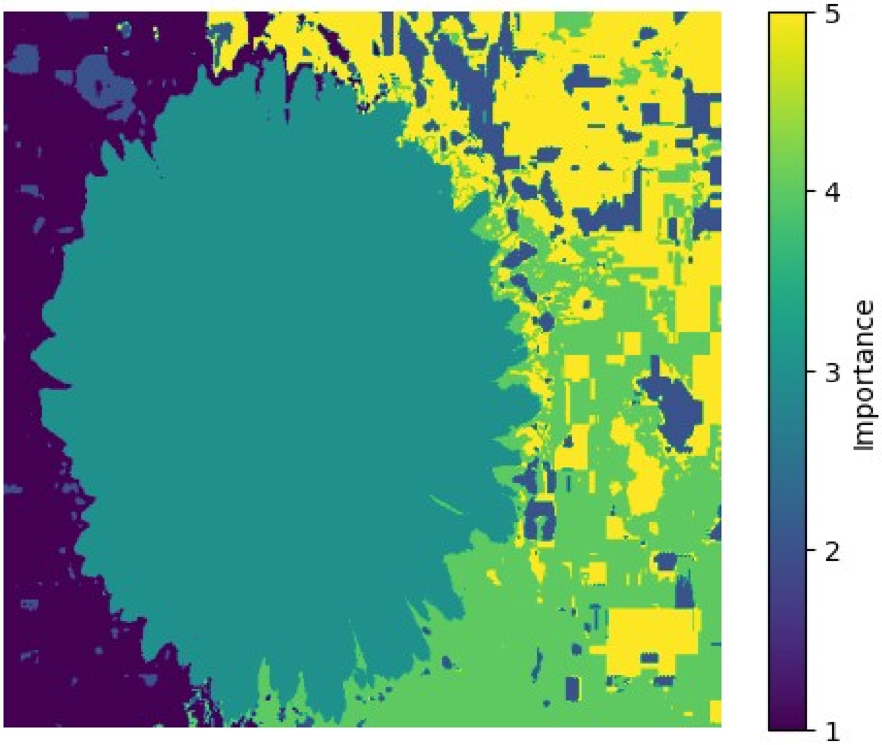

```
regionImportanceTester(100)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



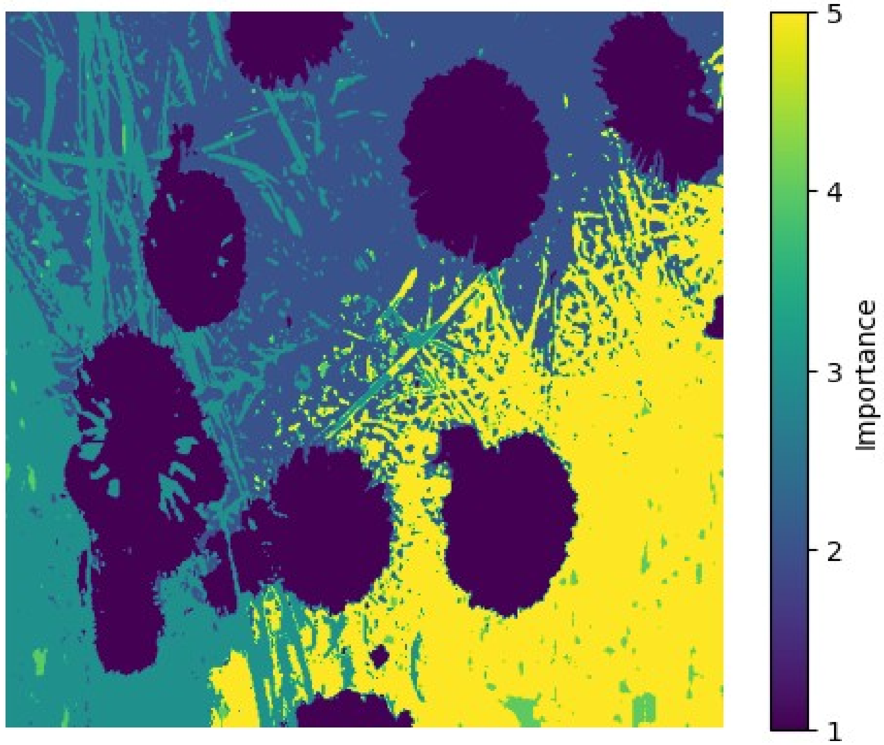

```
regionImportanceTester(102)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



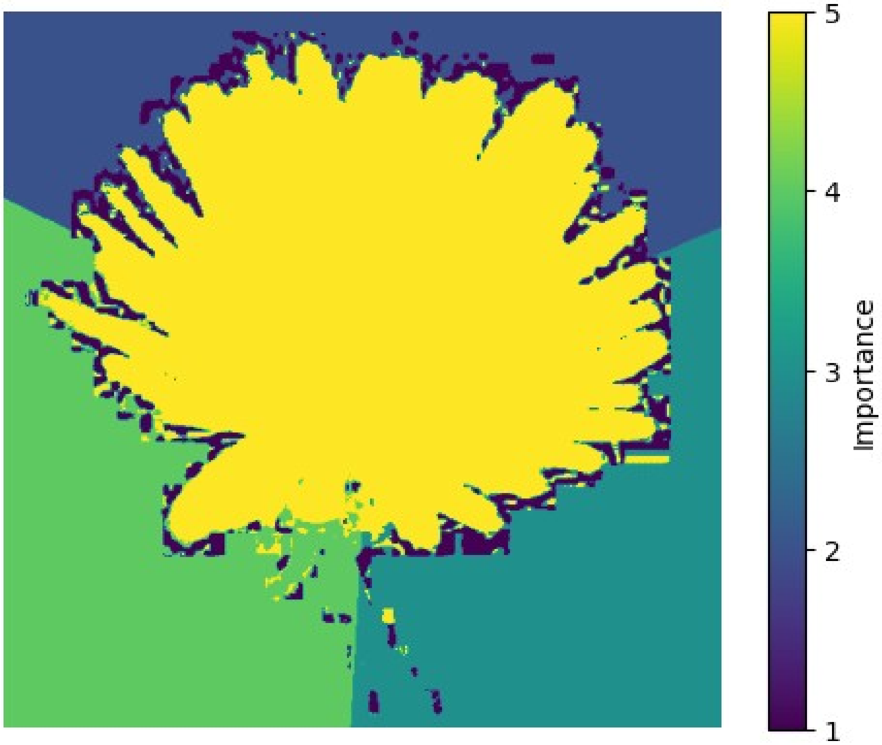

```
regionImportanceTester(156)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



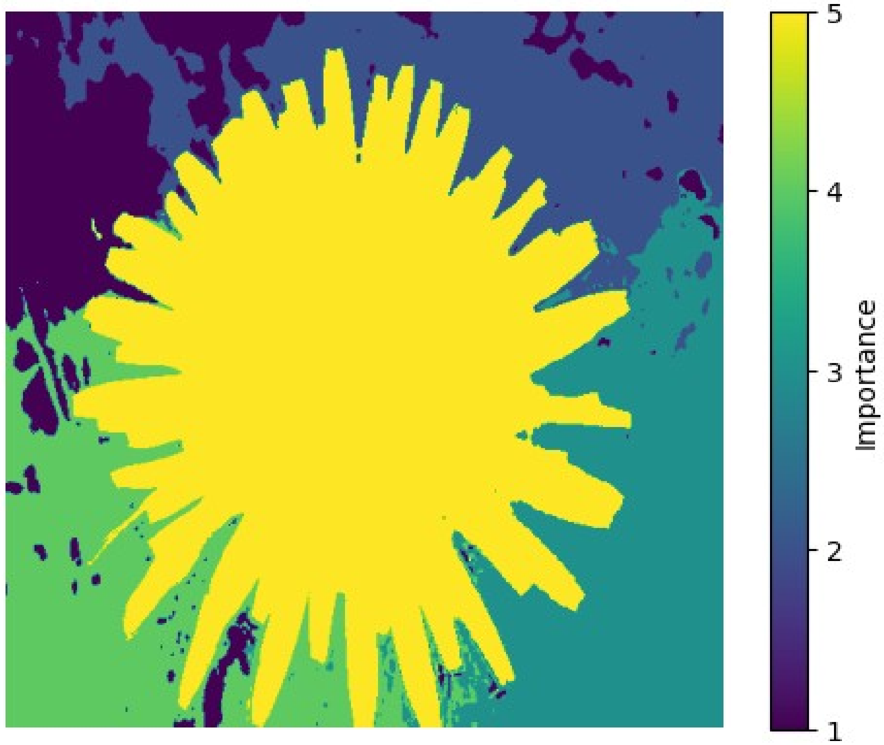

```
regionImportanceTester(200)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



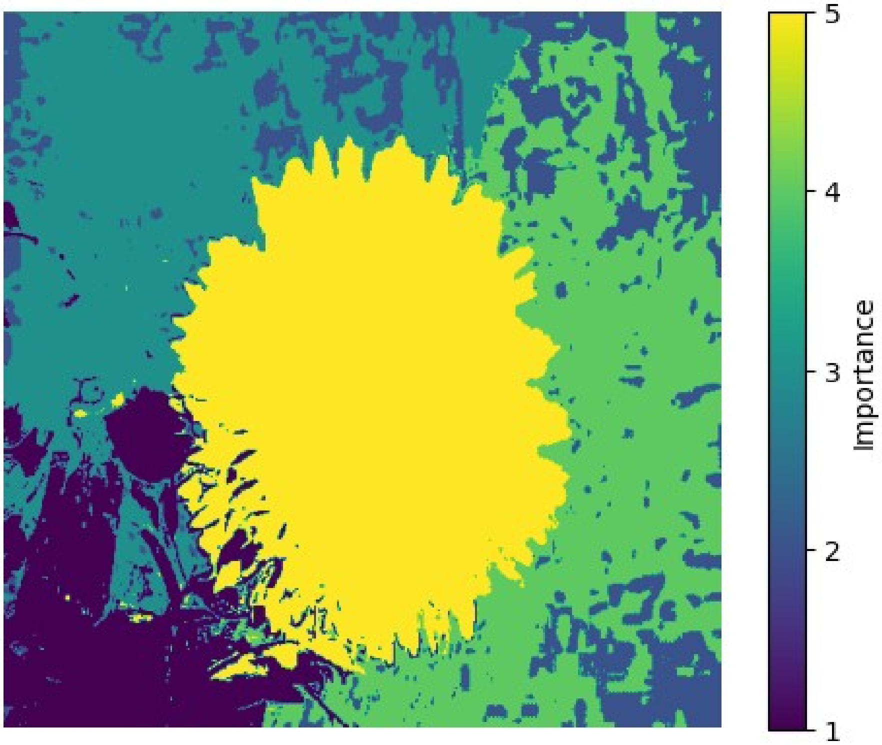

```
regionImportanceTester(201)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



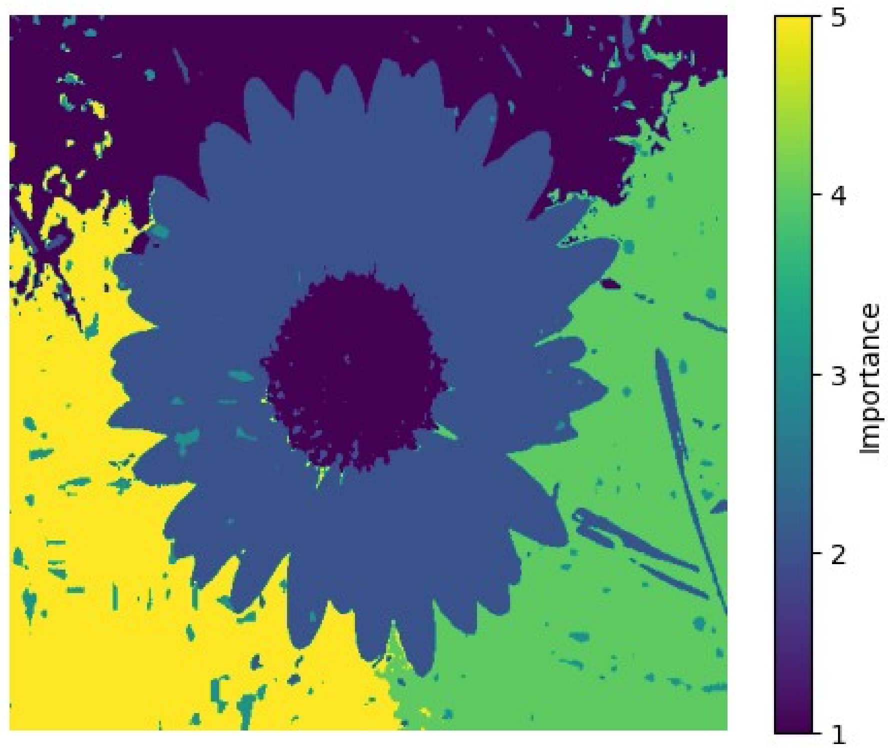

```
regionImportanceTester(204)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



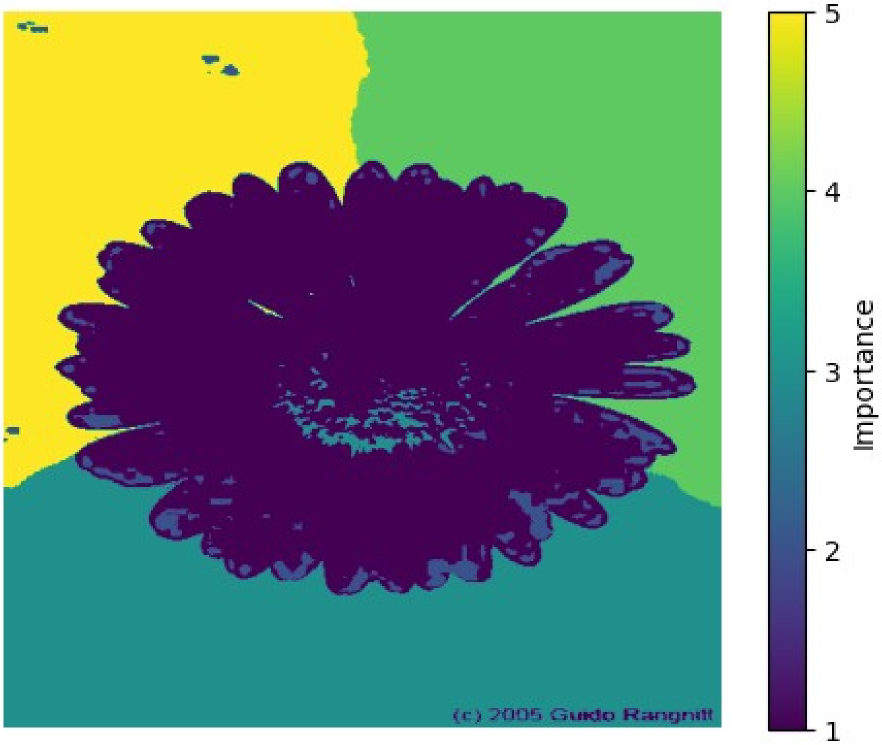

```
regionImportanceTester(257)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



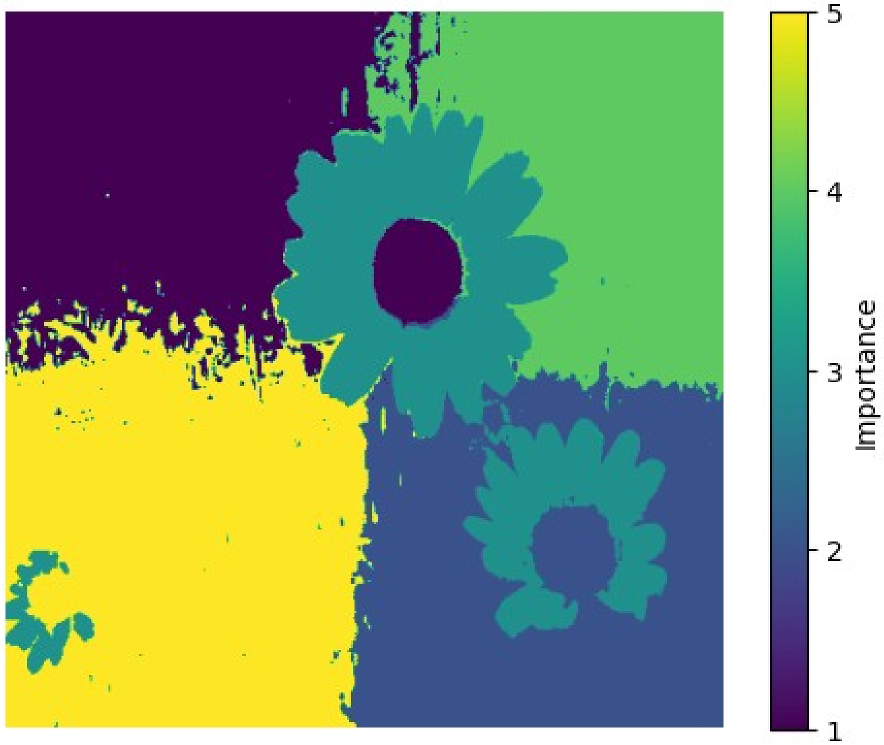

```
regionImportanceTester(270)
```


```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



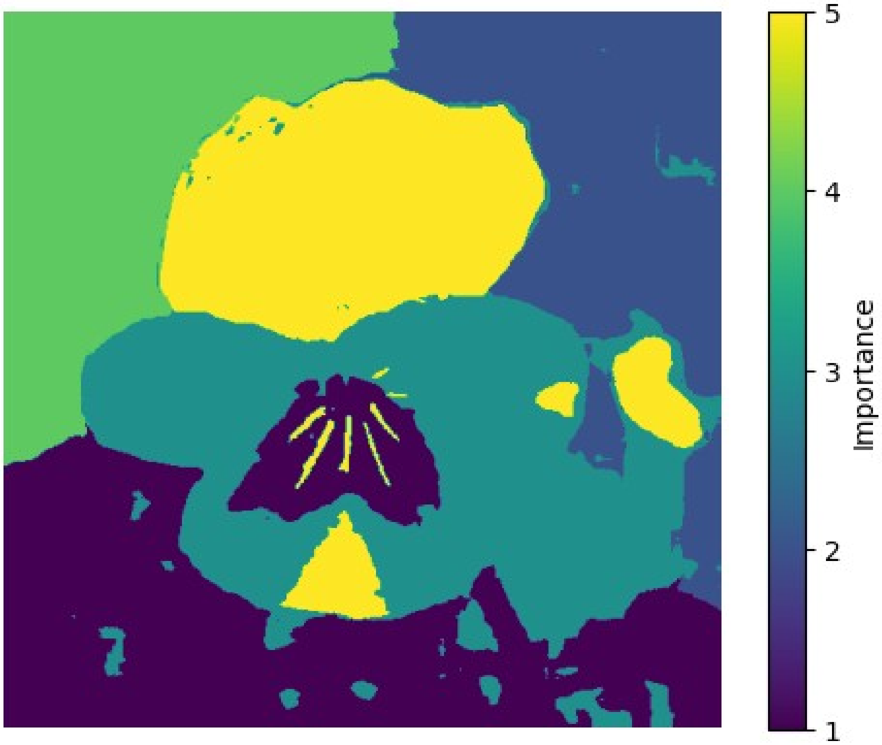

```
regionImportanceTester(310)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



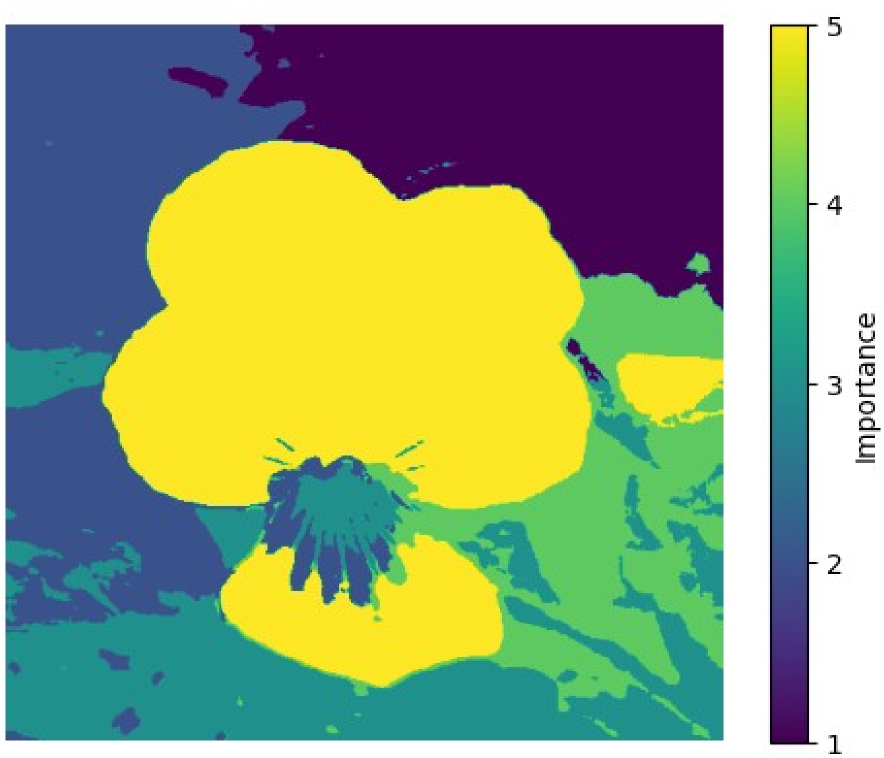

```
regionImportanceTester(350)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



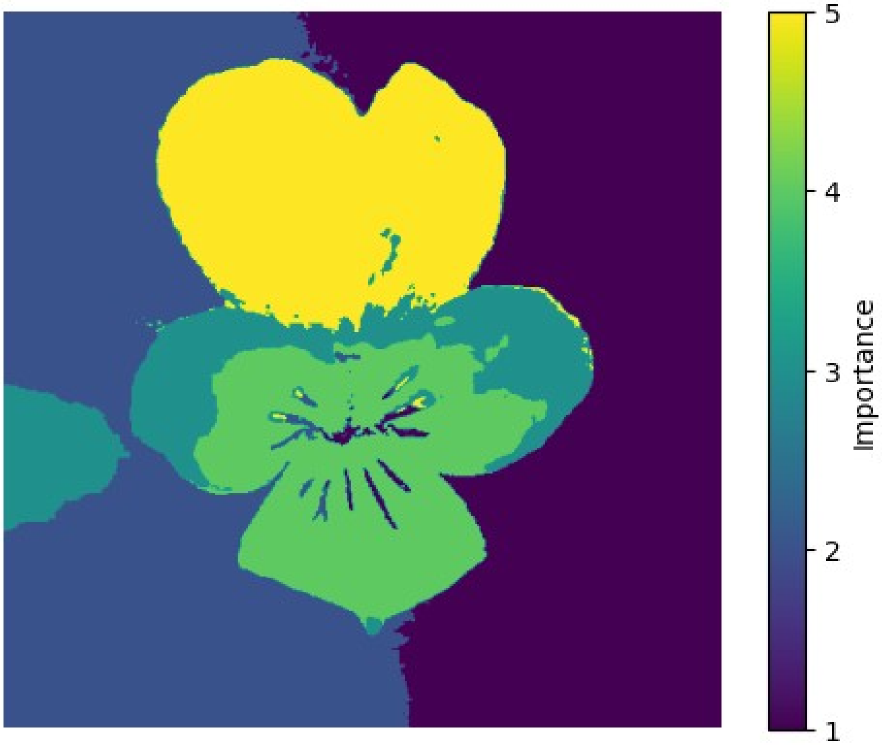

```
regionImportanceTester(351)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



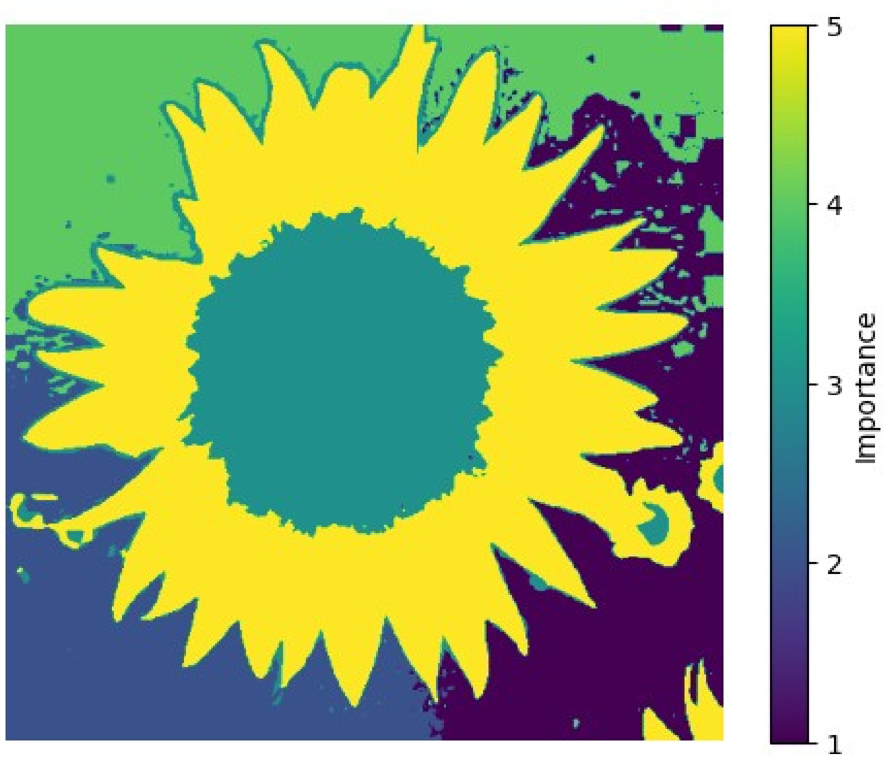

```
regionImportanceTester(352)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



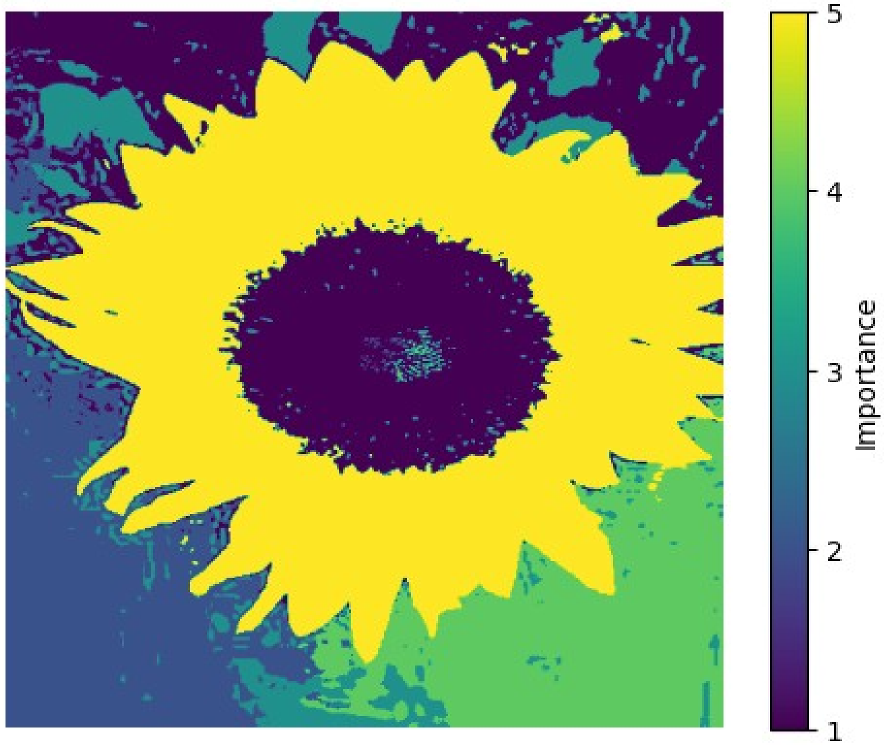

```
regionImportanceTester(400)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



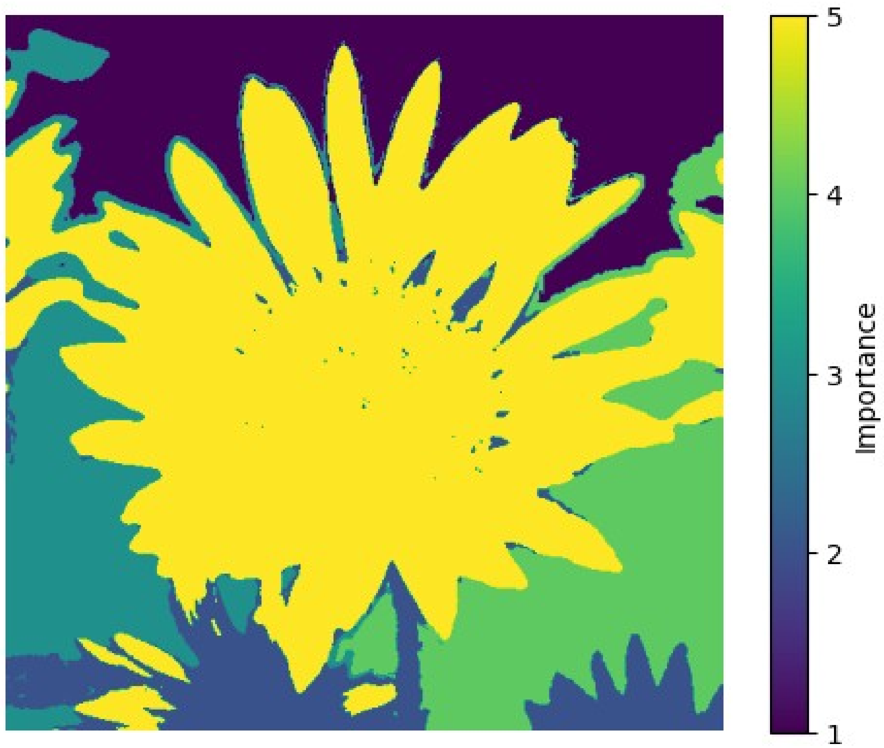

```
regionImportanceTester(402)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



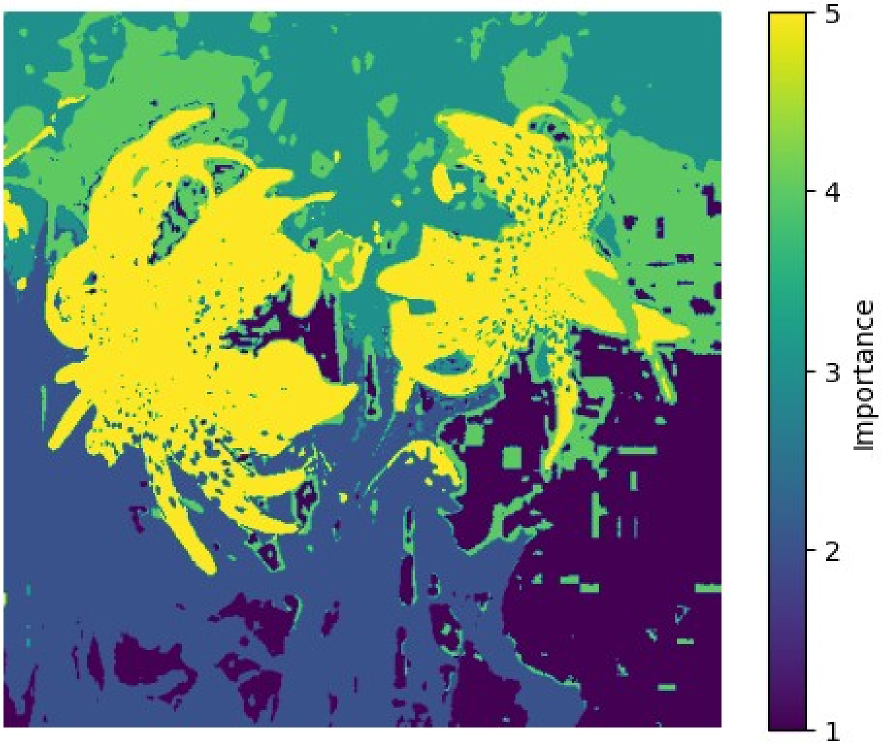

```
regionImportanceTester(450)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



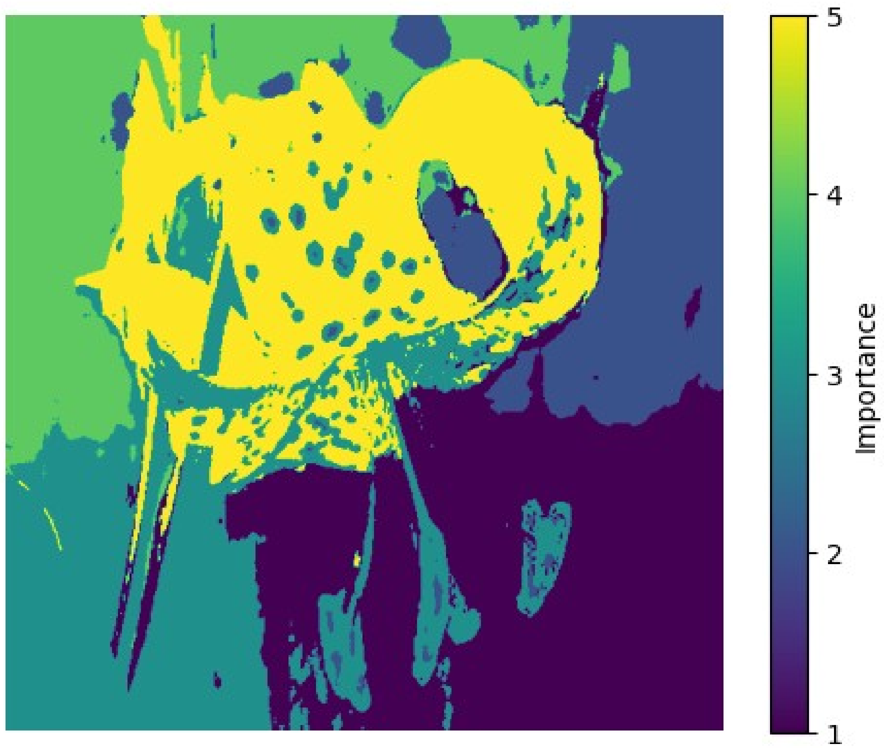

```
regionImportanceTester(501)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



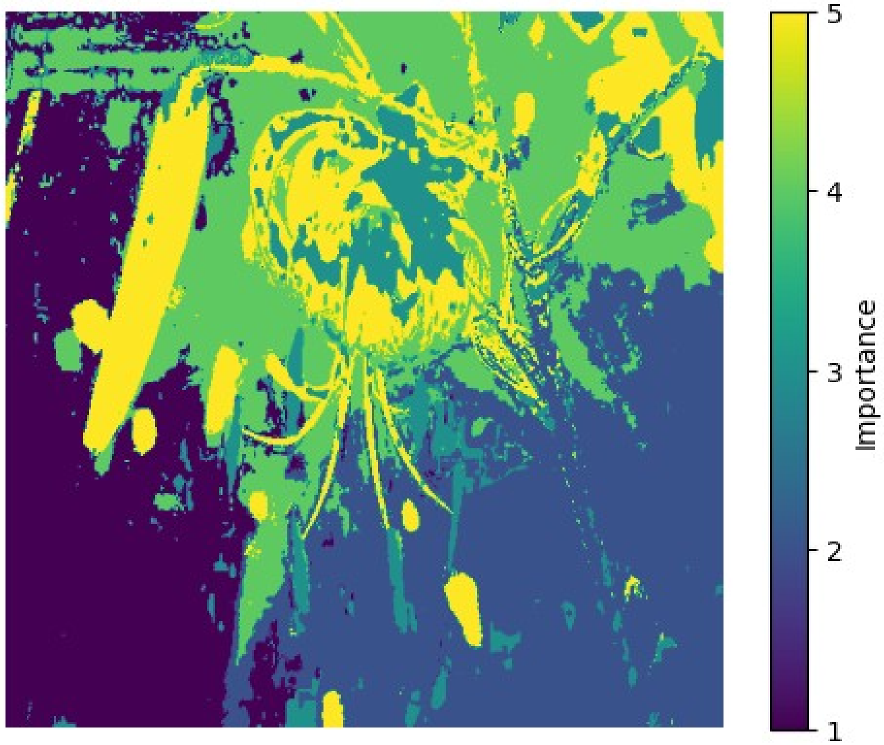

```
regionImportanceTester(503)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```




```
regionImportanceTester(540)
```

```
C:\Users\ASUS\AppData\Roaming\Python\Python39\site-packages\sklearn\
cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init`
will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



5
4
3
2
1
Importance