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Pattern Recognition

Image Segmentation System

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Overview:

This project focuses on applying image segmentation using Kmeans and spectral clustering. The clustering is done using the values of the RGB vector for each pixel. In the last part of the project, we take into consideration the spatial aspect as well as the colors to compare the results.

1. **Reading the dataset on Colab:**

Reading from Google Drive

```
[ ] # Code to read file into Colaboratory:
    ! pip install -U -q PyDrive
    from pydrive.auth import GoogleAuth
    from pydrive.drive import GoogleDrive
    from google.colab import auth
    from oauth2client.client import GoogleCredentials
    # Authenticate and create the PyDrive client.
    auth.authenticate_user()
    gauth = GoogleAuth()
    gauth.credentials = GoogleCredentials.get_application_default()
    drive = GoogleDrive(gauth)
```

Upload the dataset

```
[ ] link = 'https://drive.google.com/file/d/1gDh0lyglElhgxjXLkEJALhVsEYXSZ1Kw/view?usp=sharing' # The shareable link
    # to get the id part of the file
    id = link.split("/")[-2]
    downloaded = drive.CreateFile({'id':id})
    downloaded.GetContentFile('BSR_bsds500.tgz')
```

Unzipping

```
[ ] import tarfile
    !tar -xvf  'BSR_bsds500.tgz' -C '/content/'
```

The zip file was uploaded on google drive and a connection between colab notebook and google drive is set and the zip file is downloaded.

The necessary imports are then made which will be used throughout the project.

Imports

```
[ ] from scipy import io
    import scipy
    import os
    from PIL import Image as im
    import matplotlib.pyplot as plt
    import matplotlib.image as mpimg
    import numpy as np
    import math
    import random
    from sklearn.metrics.pairwise import euclidean_distances
    import cv2 as cv
    from google.colab.patches import cv2_imshow
    from skimage import data, color
    from skimage.transform import resize
    from sklearn.neighbors import NearestNeighbors
```

2. Reading Dataset

Read the data

```
[ ] root = '/content/BSR/BSDS500/data/'
    gt_PATH = os.path.join(root,'groundTruth/')
    data_PATH = os.path.join(root,'images/')
    ground_truth = []
    dataset = []

    # read only test data we can change this later
    for sub_dir_name in ['test']:
        sub_pth = os.path.join(gt_PATH,sub_dir_name)
        for filename in os.listdir(sub_pth):
            mat_file = io.loadmat(os.path.join(sub_pth,filename))
            ground_truth.append(mat_file['groundTruth'])

            # not the best way but to perserve the index order !!
            img_file = mpimg.imread(os.path.join(os.path.join(data_PATH,sub_dir_name),filename.split('.')[0]+".jpg"))
            dataset.append(img_file)
```

3. Visualizing images and ground truth

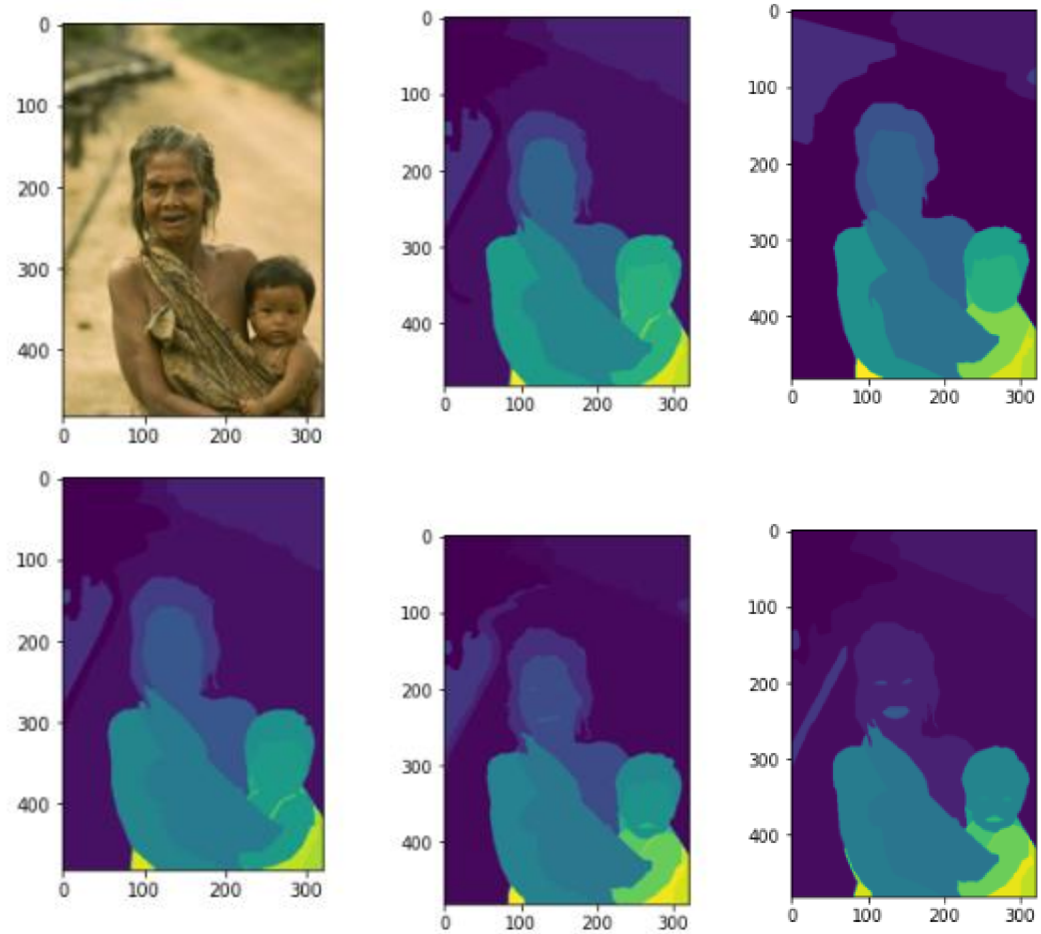
Function to generate all the available ground truth for an image

```
[ ]  def get_GT(index):
       n = len(ground_truth[index][0])
       results = []

       for i in range(n):
         results.append(ground_truth[index][0][i][0][0][0])
       return results
```

Visualize the available ground truth of an image

```
[ ]  def show_GT(index):
       gt = get_GT(index)

       fig = plt.figure(figsize=(25, 15))
       rows = 1
       columns = len(gt)
       for i in range(len(gt)):
         fig.add_subplot(rows, columns, i+1)
         plt.imshow(gt[i])
         plt.title("Ground Truth "+ str(i+1))
```

```
[ ]  def view_image_only(n):
       fig1=plt.figure()
       plt.imshow(dataset[n])
```


0
100
200
300
400
0 100 200 300

4. Implementing Kmeans

K-Means Implementation

```
[ ]  def Kmeans(dataset,k):
       #define constants in this function which determine its accuracy
       max_iterations=20
       tolerance=0.0001
       max_repetition=3

       #reshaping image to 1D instead of 2D
       dataset2=np.array(dataset)
       dataset2=dataset2.reshape(dataset2.shape[0]*dataset2.shape[1],dataset2.shape[2])

       flag=1 #flag to make sure all clusters are not empty
       iterate=0 #keep track how many times we repeat the reclustering to set a limit
       empty=[] #array to keep track of empty clusters

       while(flag==1):
         iterate+=1
         #initialize variables
         centroids=[]
         flag=0
```

```
#choosing a random centroids from the dataset
for i in range(k):
  if np.unique(dataset2, axis=0).shape[0]>=k: #if there is more than (k) colors, let's pick different k centroids
    ready=0
    while ready==0:
      ready=1
      c=random.choice(dataset2)
      for centroid in centroids:
        for e in range(dataset2.shape[-1]):
          if c[e]==centroid[e]:
            ready+=1
        if ready==c.shape[0]+1:
          ready=0
    else: #if the image doesn't contain k unique colors, we will ignore the condition of different centroids
      c=random.choice(dataset2)
  centroids.append(c)
```

```
#starting the clustering algorithm
for i in range(max_iterations):
  #preparing the clusters array
  clusters=[]
  for j in range(k):
    clusters.append([])
  #cluster assignment (adding the index of the pixel not the pixel itself in the cluster)
  for d in range(dataset2.shape[0]):
    min=math.inf
    for m in range(k):
      distance=np.linalg.norm(centroids[m]-dataset2[d])
      if(distance<min):
        min=distance
        j=m
    clusters[j].append(d)
  #check if any clusters is empty
  for m in range(k):
    if len(clusters[m])==0:
      empty.append(m)
      flag=1
```

```
    #if a cluster is empty choose another random k points and repeat the clustering
    if flag==1 and iterate<=max_repetition:
      flag=0
      break
    #if the reclustering is executed more than 10 times, assign a random centroid for the empty clusters only
    if flag==1 and iterate>max_repetition:
      flag=0
      for e in empty:
        np.append(centroids[e],random.choice(dataset2))
      empty=[] #reset empty array
    #centroids update
    centroids_copy=np.array(centroids)
    for m in range(k):
      ind=np.array(clusters[m])
      centroids[m]=dataset2[ind].mean(axis=0)
    #tolerance check
    sum=0.0
    for m in range(k):
      sum+=pow(np.linalg.norm(centroids[m]-centroids_copy[m]),2)
    if sum<tolerance:
      break
for i in range(k):
  dataset2[clusters[i]]=[i]
dataset2=dataset2[:,0].reshape((dataset.shape[0],dataset.shape[1]))
return dataset2
```

K-means function starts with k random different centroids from the image and starts assigning pixels to clusters using the minimum distance between the pixel and the centroid. After this we calculate the mean of each cluster and update the centroids. We test if the centroids haven't moved significantly. This means that we can return this clusters and label them. If they have moved, we repeat the same loop again.

If an empty cluster is found, we choose another random k centroids. If this has been repeated for more than 3 times, we will assign a random point to the centroid corresponding to the empty cluster and continue on for a max number of times specified by max iterations variable.

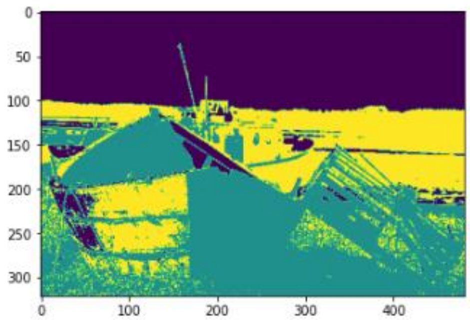
5. Coloring Labeled Images

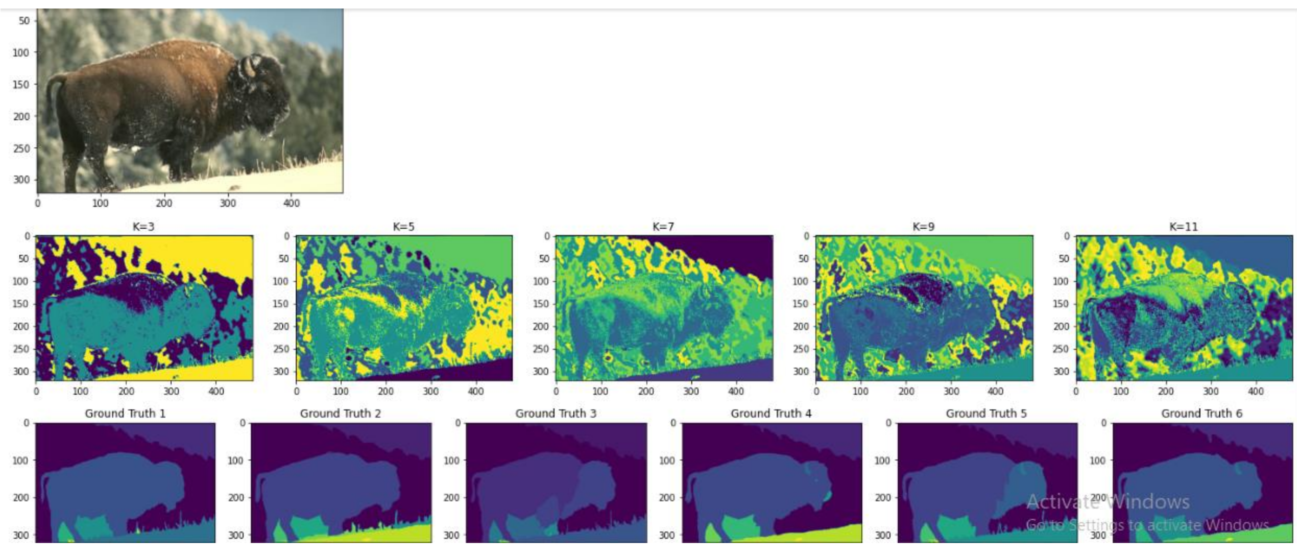
```
[ ] def color_clustered_image(image,k):
      image=np.array(image,dtype=np.int64)
      colors=[[255,255,0],[0,255,255],[255,0,255],[255,255,255],[0,0,0],[0,0,255],[0,255,0],[255,0,0],[50,0,50],[50,255,0],[0,50,0]]
      for row in image:
        for pixel in row:
          pixel=colors[pixel.round()]
      return image
```

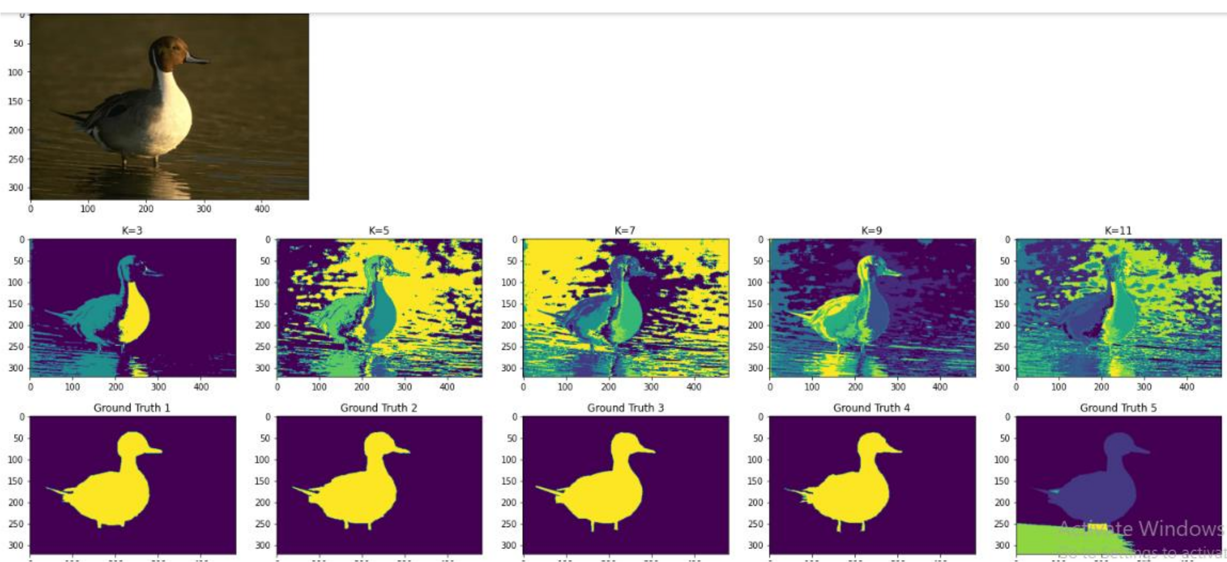
```
[ ] def apply_kmeans(n,k):
      image=dataset[n]
      clustered_image=Kmeans(image,k)
      colored_clustered_image=color_clustered_image(clustered_image,k)
      return colored_clustered_image
```

```
[ ] def show_img(img):
      fig=plt.figure()
      plt.imshow(img)
```

```
[ ] n=5
    k=3
    img=apply_kmeans(n,k)
    show_img(img)
```







6. Spectral Clustering

Building 5NN Similarity matrix

K-NN Similarity Function

```
[ ] def nn_similarity(n,dataset):
      data=np.array(dataset)
      data=data.reshape(data.shape[0]*data.shape[1],data.shape[2])
      dist_matrix=euclidean_distances(data,data)
      A=np.zeros(dist_matrix.shape)
      for i in range(dist_matrix.shape[0]):
        ind=dist_matrix[i,:].argsort()
        temp=dist_matrix[i,ind]
        y=temp[n]
        vectorizer = np.vectorize(lambda x: 1 if x <= y and x!=0 else 0)
        A[i]=np.vectorize(vectorizer)(dist_matrix[i])
      return A
```

It can be substituted using nn_neighbors from sklearn which produces the same results. To minimize the running time, we used the sklearn function for testing.

We also built a resizing function to minimize the dimensions of the image because of the limited RAM resources.

Resizing Function

```
[ ] def resize_img(img):
      return resize(img, (img.shape[0] // 4, img.shape[1] // 4,3),anti_aliasing=True)
```

Normalized Cut Function:

Normalization Function

```
[ ] def normalization(vec):
      results = []
      for i in range(vec.shape[0]):
        norm=np.linalg.norm(vec[i])
        results.append(vec[i]/norm)
      return np.array(results)
```

Normalized Cut function

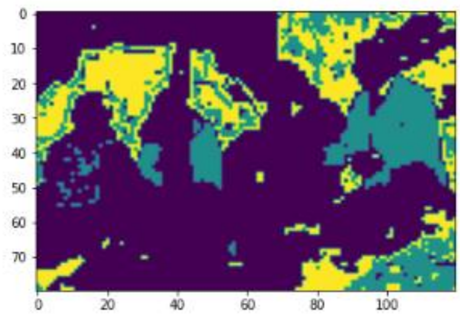
```
[ ] def normalized_cut(nn_neigbors,k,img):
      #reshape img to 1D instead of 2D
      img2=img.reshape(img.shape[0]*img.shape[1],img.shape[2])

      # build K-NN graph for the samples
      nbrs = NearestNeighbors(n_neighbors=(nn_neigbors+1), algorithm='auto').fit(img2)
      A = nbrs.kneighbors_graph(img2).toarray()

      # reject the self neighbour for the point -> zeroing the diagonal
      np.fill_diagonal(A,0)

      # build degree matrix --> nn_neigbors*I
      delta = np.identity(A.shape[0]) * nn_neigbors

      # Laplacian Matrix
      A = delta - A

      # compute the eigen_values and eigen vectors and pick the k vectors corresponding to the smallest k eigen values
      eigen_val, eigen_vec = np.linalg.eig(np.dot(np.linalg.inv(delta),A))
      idx = np.real(eigen_val).argsort()[1:k+1]
      eigen_vec = np.real(eigen_vec[:,idx])

      # normalization
      normalized_eigen_vec = normalization(eigen_vec)

      #return new coordinates
      img2=normalized_eigen_vec.reshape(img.shape[0],img.shape[1],k)
      return img2
```

We calculate the A matrix using 5NN graph. We set the k for 6 then we set the diagonal by zeros. We then calculate the degree matrix and the Laplacian matrix and calculate the eigen vectors for delta^{-1} * L and take the smallest K vectors. We normalize these values then return the new normalized vectors.

We pass these new coordinates to the K-means and map the colors once again.

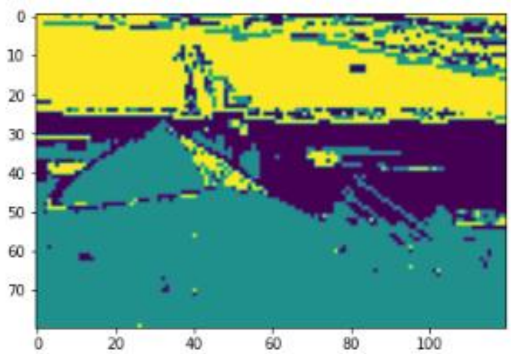
```
def apply_our_spectral(k,n):
  img=normalized_cut(5,k,resize_img(dataset[n]))
  img=Kmeans(img,k)
  img=color_clustered_image(img,k)
  return img
```

```
n=21
k=3
img=apply_our_spectral(k,n)
show_img(img)
```



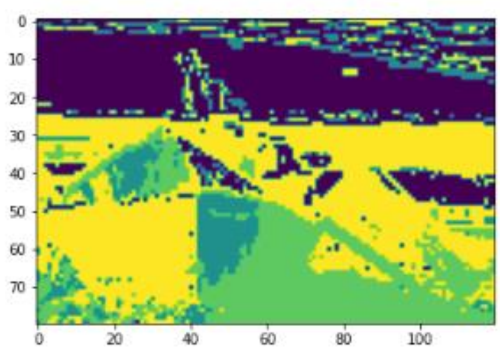

```
[ ] view_image_only(21)
```


```
[ ] n=5
    k=3
    img=apply_our_spectral(k,n)
    show_img(img)
```




```
[ ] view_image_only(5)
```

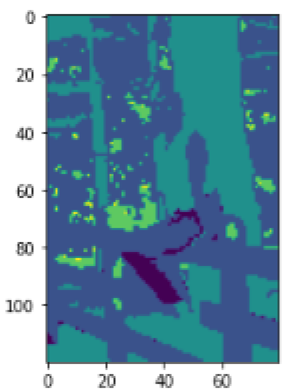

```
[ ] n=5
    k=5
    img=apply_our_spectral(k,n)
    show_img(img)
```

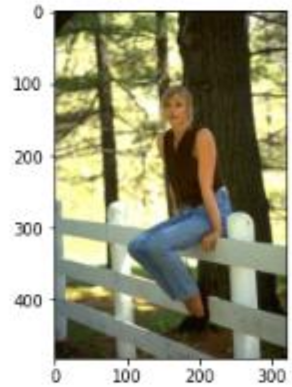



```
[ ] view_image_only(5)
```

```
[ ]  n=1
     k=5
     img=apply_our_spectral(k,n)
     show_img(img)
```

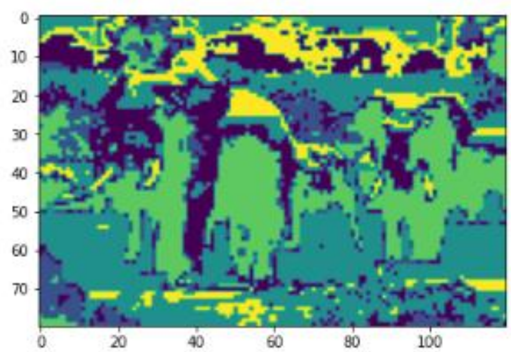
```
[ ]  view_image_only(1)
```

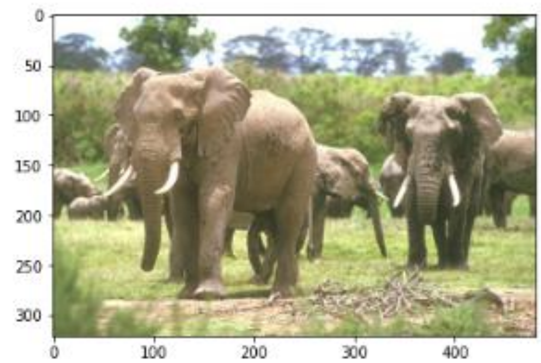





```
[ ]  n=35
     k=5
     img=apply_our_spectral(k,n)
     show_img(img)
```

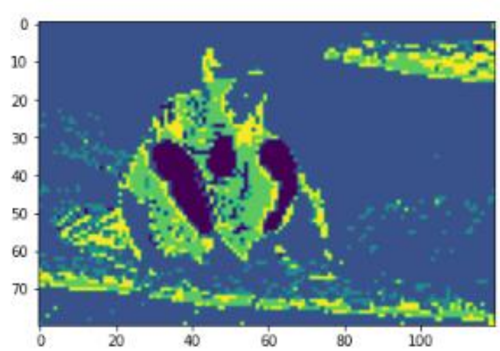
```
[ ]  view_image_only(35)
```






```
n=9
k=5
img=apply_our_spectral(k,n)
show_img(img)
```

```
view_image_only(9)
```



7. Adding Spatial Attributes

```
[ ] def add_x_y(data):
      x_max = data.shape[1]
      y_max = data.shape[0]
      coord = np.array([ [x,y] for x in range(x_max) for y in range(y_max)]).reshape((y_max,x_max,2))

      return np.concatenate((data,coord),axis=2)
```

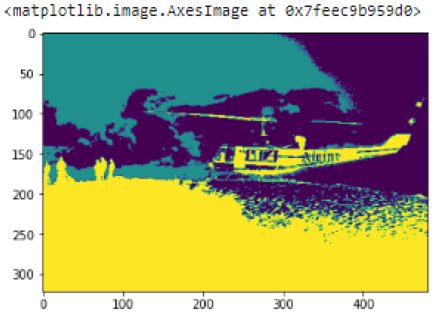
Attribute Scaling

```
[ ] def scale_arr(image):
      arr=image.reshape(image.shape[0]*image.shape[1],image.shape[2])
      min=arr.min(axis=0)
      max=arr.max(axis=0)
      diff=max-min
      arr=(arr-min)/ diff
      arr=arr.reshape(image.shape)
      return arr
```

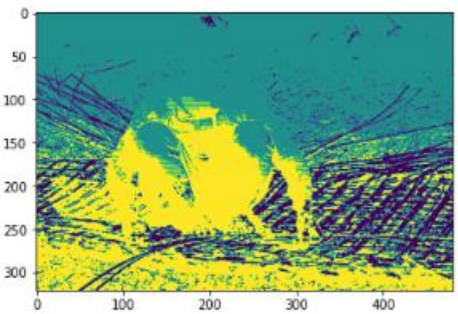
Adding (x,y) attributes to the vector and then scaling attributes to avoid biasing in low values for x, y or high values.

```
[ ] n=30
    k=3
    image=add_x_y(dataset[n])
    image=scale_arr(image)
    clustered_image=Kmeans(image,k)
    clustered_image=color_clustered_image( clustered_image ,k)
    fig=plt.figure()
    plt.imshow(clustered_image)
```

<matplotlib.image.AxesImage at 0x7feec9b959d0>




```
[ ] view_image_only(n)
```


0
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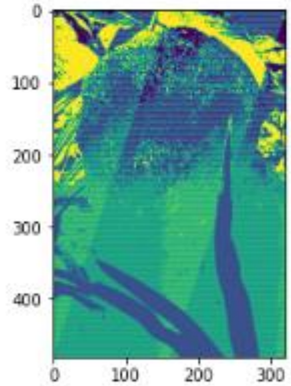
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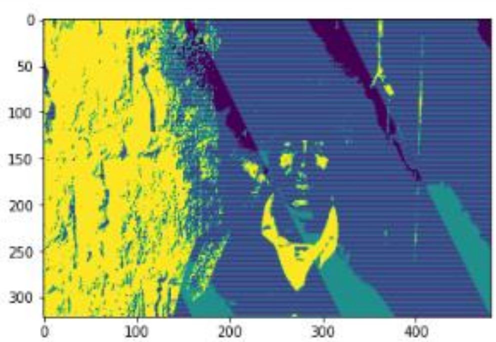
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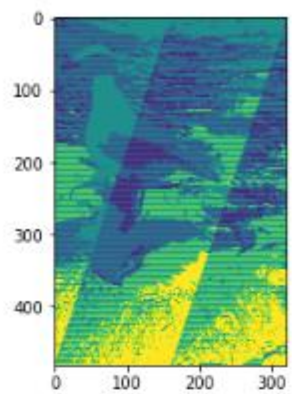
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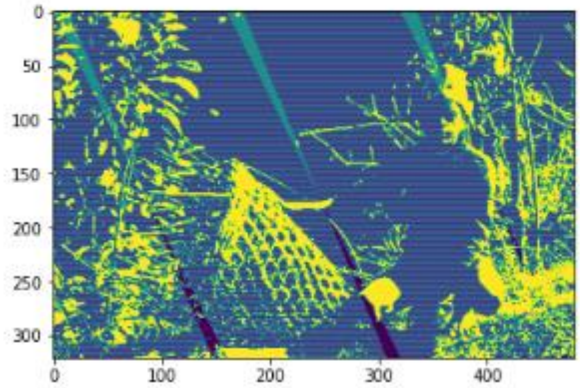
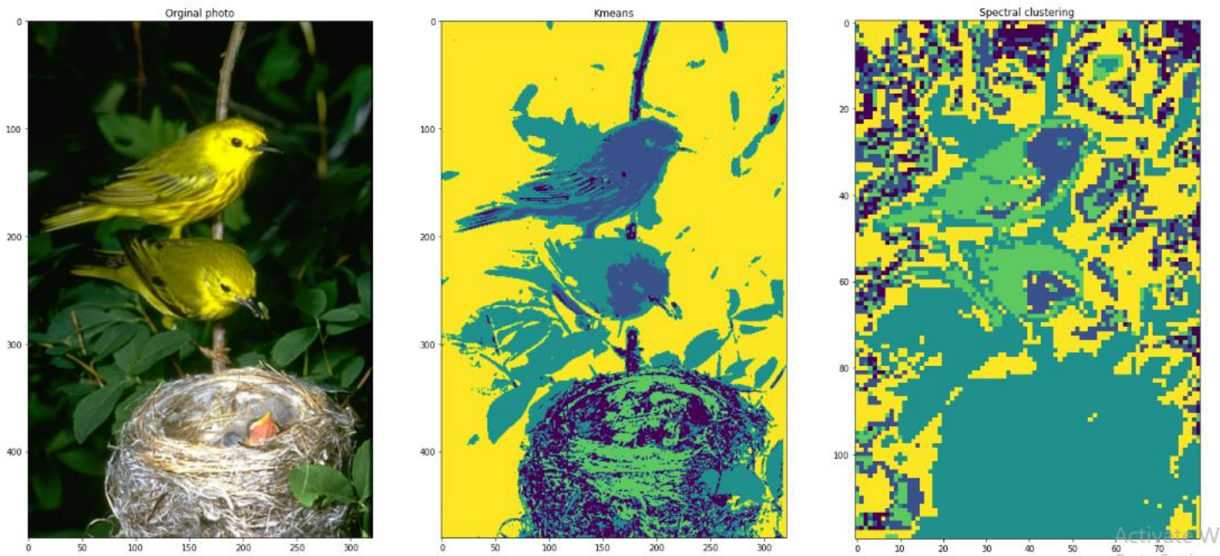
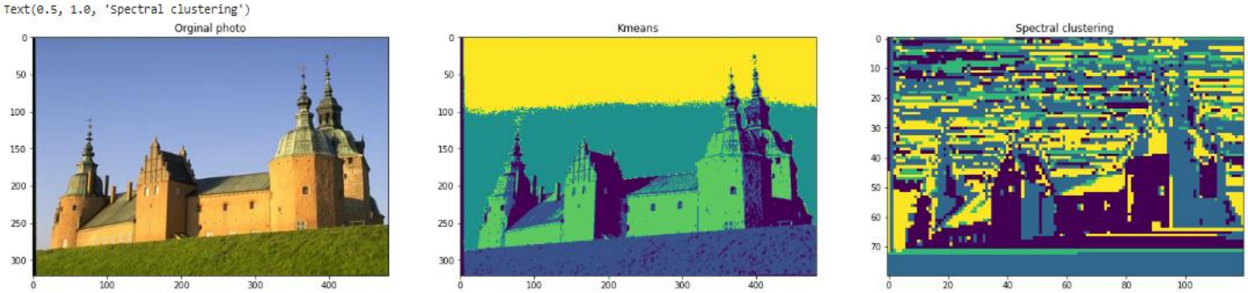


8. Comparing the results (Big Picture)

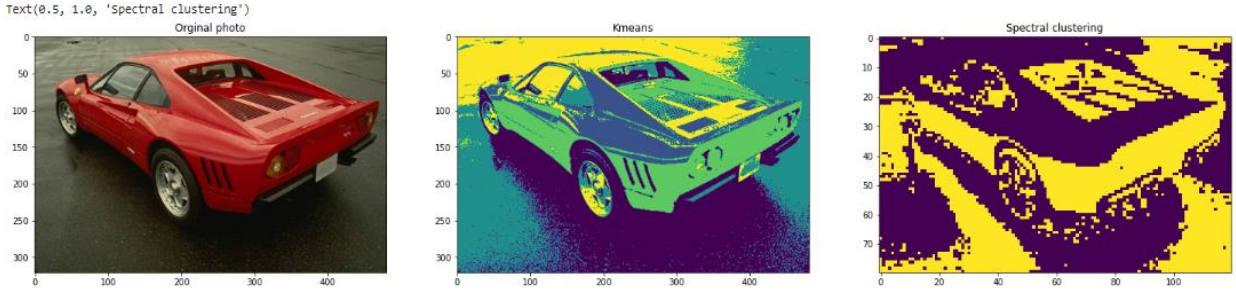
```
n=11
k=5
img = apply_kmeans(n,k)
img2=apply_our_spectral(k,n)

fig = plt.figure(figsize=(25, 15))

fig.add_subplot(1, 3, 1)
plt.imshow(dataset[n])
plt.title("Orginal photo")
fig.add_subplot(1, 3, 2)
plt.imshow(img)
plt.title("Kmeans")
fig.add_subplot(1, 3, 3)
plt.imshow(img2)
plt.title("Spectral clustering")
```



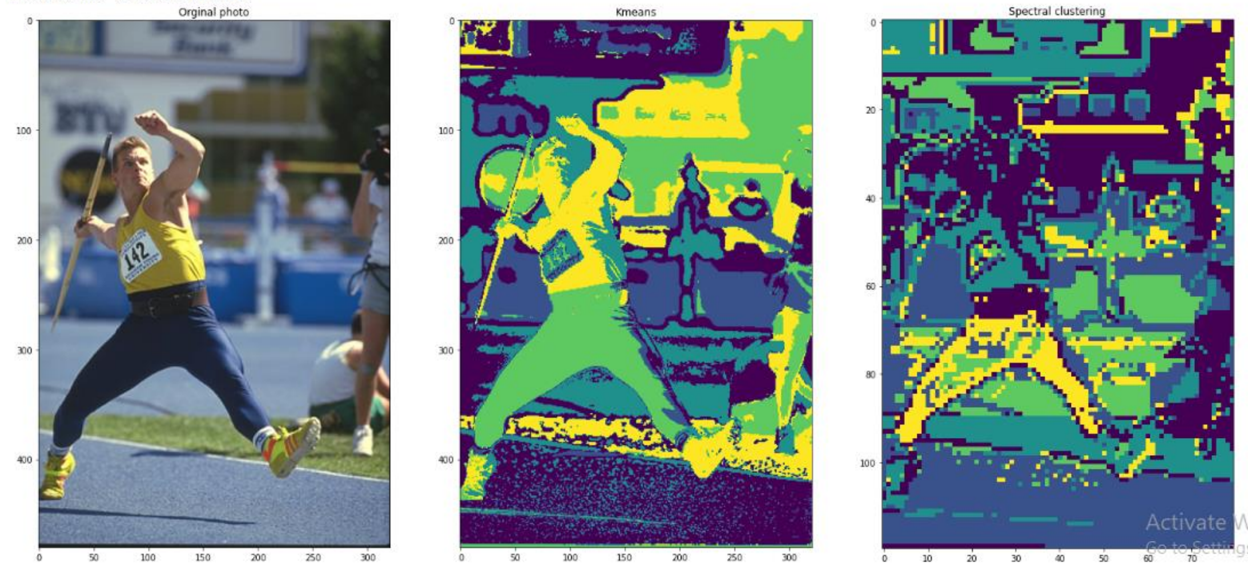

```
Text(0.5, 1.0, 'Spectral clustering')
```

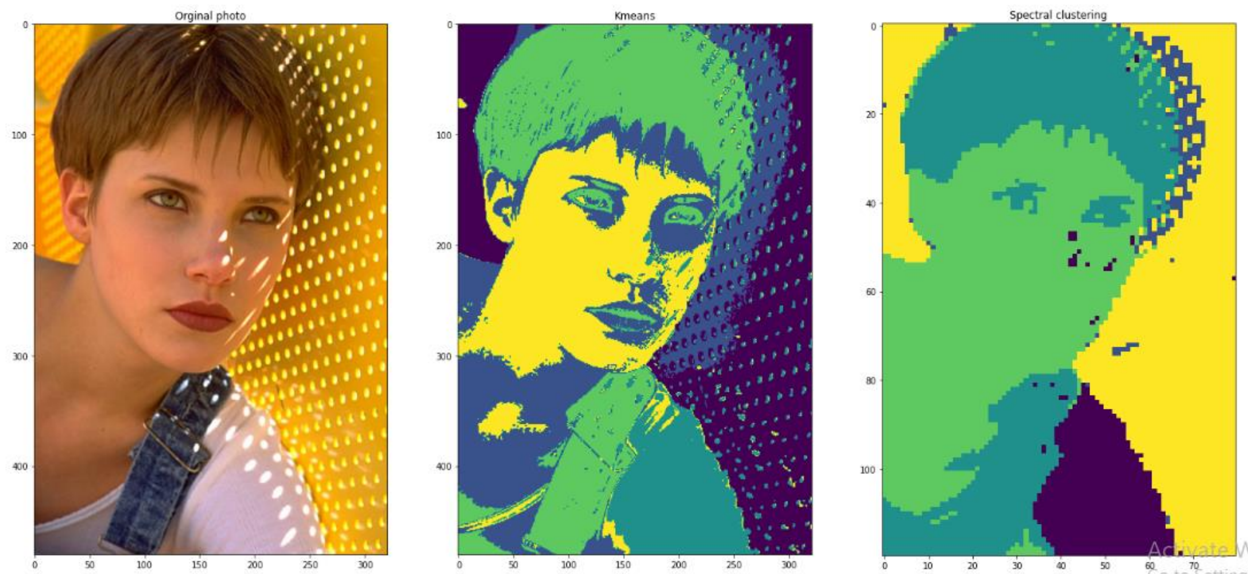



```
Text(0.5, 1.0, 'Spectral clustering')
```

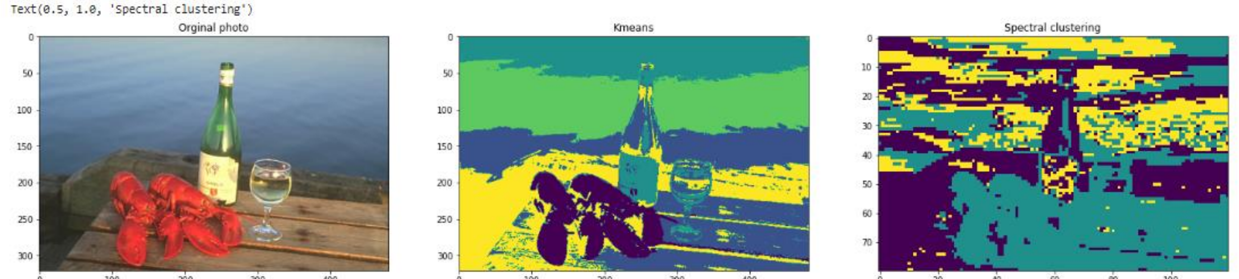


```
Text(0.5, 1.0, 'Spectral clustering')
```






```
Text(0.5, 1.0, 'Spectral clustering')
```



9. Evaluating Results

We used two measures: Fmeasure and Entropy

Evaulations

```
def evaluation(cluster, groundtruth):

  clustering_labels = cluster
  groud_truth_labels = groundtruth.flatten()

  # K x 3 Matrix for every cluster counting the the TP
  contingency_mat = contingency_matrix (groud_truth_labels, clustering_labels)
  ## rows->>> predicted. , cols->>> ground_truth
  contingency_mat = contingency_mat.T
  precision = np.zeros((contingency_mat.shape[0],1))
  recall = np.zeros((contingency_mat.shape[0],1))
  ##rows represent predicted clusters with kmeans
  ## coloumns represents ground truth classes
  ## preision Tp"of max no."" / segma(col)
  ## precision  Tp "of max no."" / segma(row)
  for i in range(contingency_mat.shape[0]):
    index_max = np.argmax(contingency_mat[i])
    precision[i] = contingency_mat[i][index_max]/np.sum(contingency_mat[i])
    recall[i] = contingency_mat[i][index_max]/np.sum(contingency_mat[:,index_max])
  F_score = (2*precision*recall) / (precision + recall)
  F_score_total = np.mean(F_score)


  count_per_cluster = np.sum(contingency_mat,axis =1)#total number of pixels per cluster
  count_total = np.sum(count_per_cluster)
  cont_entropy = np.where(np.copy(contingency_mat) == 0, 1, np.copy(contingency_mat))
  entropy_mat = np.zeros((cont_entropy.shape[0],1))
  for i in range(cont_entropy.shape[0]):
    entropy_mat[i] = count_per_cluster[i]*np.sum(-contingency_mat[i]*np.log10(cont_entropy[i]/np.sum(contingency_mat[i])))/np.sum(contingency_mat[i])
  entropy = np.sum(entropy_mat)/count_total
  return round(F_score_total,6),round(entropy,6)
```

```
[ ] def show_evaluation(clusters,gt):

      f_measures_means = []
      entropy_means = []
      for i in range(len(clusters)):
        f_measures_sum = 0
        entropy_sum = 0
        for j in range(len(gt)):
          clusters[i],gt[j] = equal_clusters(clusters[i],gt[j])
          f_measures_sum += evaluation(clusters[i],gt[j])[0]
          entropy_sum += evaluation(clusters[i],gt[j])[1]
        f_measures_means.append(f_measures_sum/len(gt))
        entropy_means.append(f_measures_sum/len(gt))

      table = PrettyTable()
      table.add_column("K",[3,5,7,9,11])
      table.add_column("F_measures mean",f_measures_means)
      table.add_column("Conditional Entropy mean",entropy_means)
      print(table)
```

```python
def test_kmeans(start,end):
  k = [3,5,7,9,11]
  clusters = []

  for sample in range(start,end+1,1):

    ci = []
    view_image_only(sample)
    for ki in k:
      ci.append(Kmeans(dataset[sample],ki))

    # Segmentations and GroundTruth Visualization
    show_clusters(ci,sample)
    show_GT(sample)
    show_evaluation(ci,get_GT(sample))
    clusters.append(ci)
```

K	F_measures mean	Conditional Entropy mean
3	0.6918658	0.1059342
5	0.7385424	0.060845
7	0.39375940000000004	0.23875100000000002
9	0.7138458	0.0595402
11	0.5548676	0.19130019999999998

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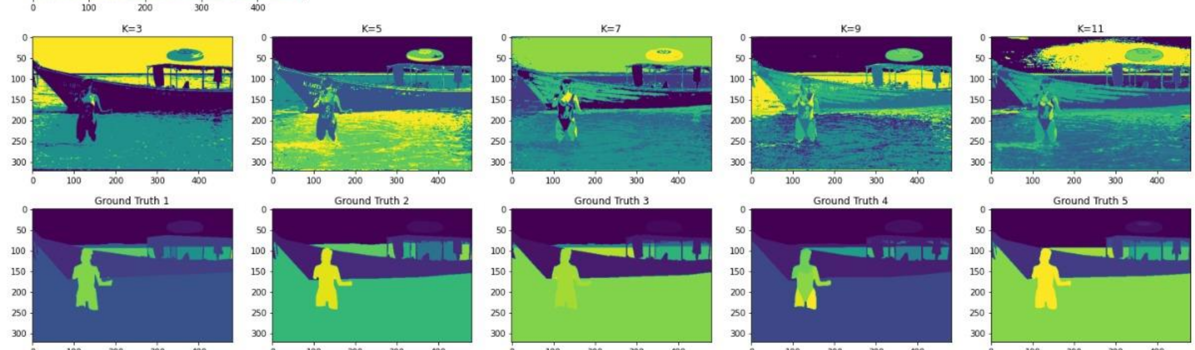

K	F_measures mean	Conditional Entropy mean
3	0.6192296666666666	0.31837150000000003
5	0.44299483333333334	0.4206706666666667
7	0.4051076666666667	0.4222810000000001
9	0.39286883333333334	0.4412585
11	0.30720333333333334	0.4585515

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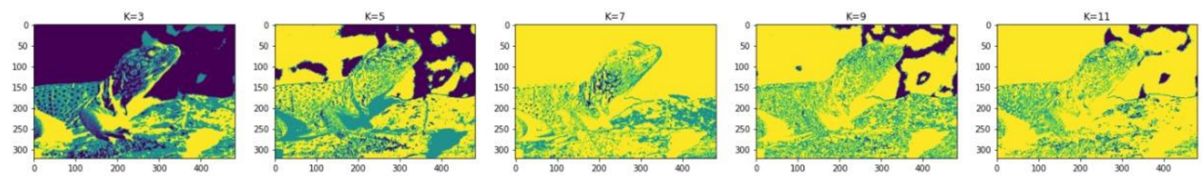
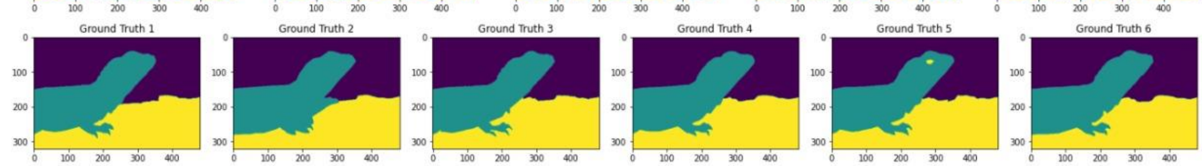
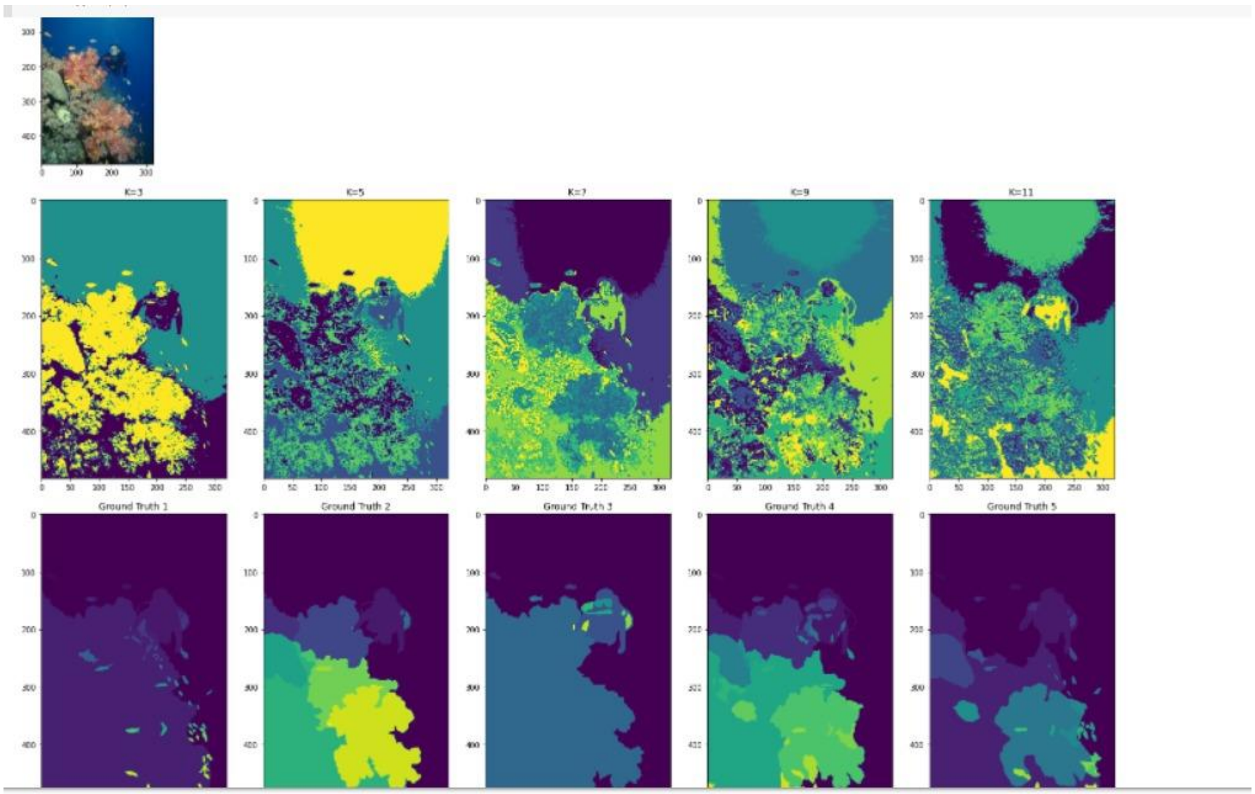




K	F_measures mean	Conditional Entropy mean
3	0.4415808	0.2367282
5	0.409729	0.24577419999999997
7	0.4073722	0.25787
9	0.3768132	0.25629399999999997
11	0.3888932	0.2557522



K	F_measures mean	Conditional Entropy mean
3	0.7055020000000001	0.1279560000000001
5	0.5409271999999999	0.24355279999999996
7	0.7025838	0.13174999999999998
9	0.407718	0.27648160000000005
11	0.48608019999999996	0.2457282

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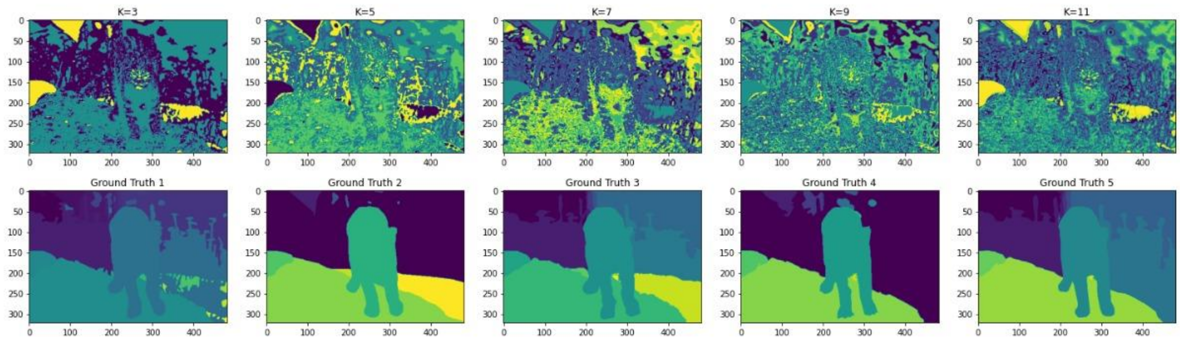
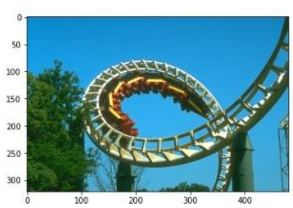
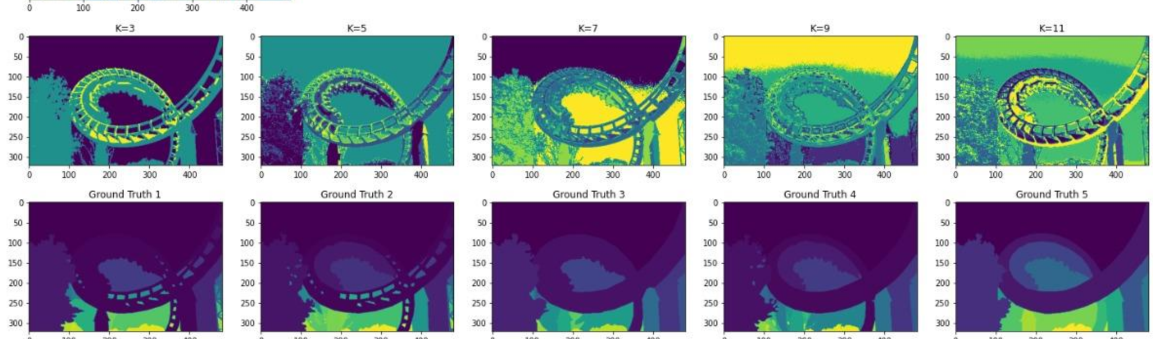
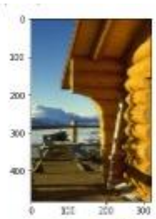


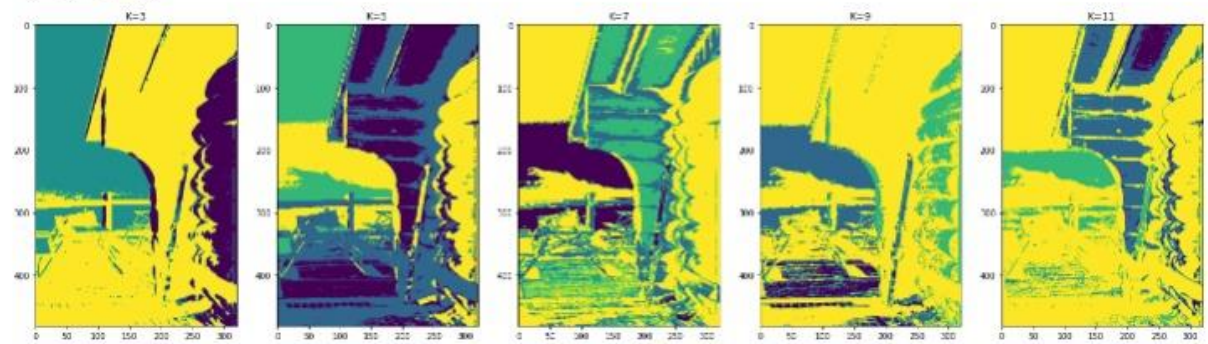
K	F_measures mean	Conditional Entropy mean
3	0.5649398000000001	0.3217314
5	0.49695900000000004	0.3704858
7	0.6665528000000001	0.2353538
9	0.3375978	0.4279116
11	0.3516108000000001	0.42966679999999996

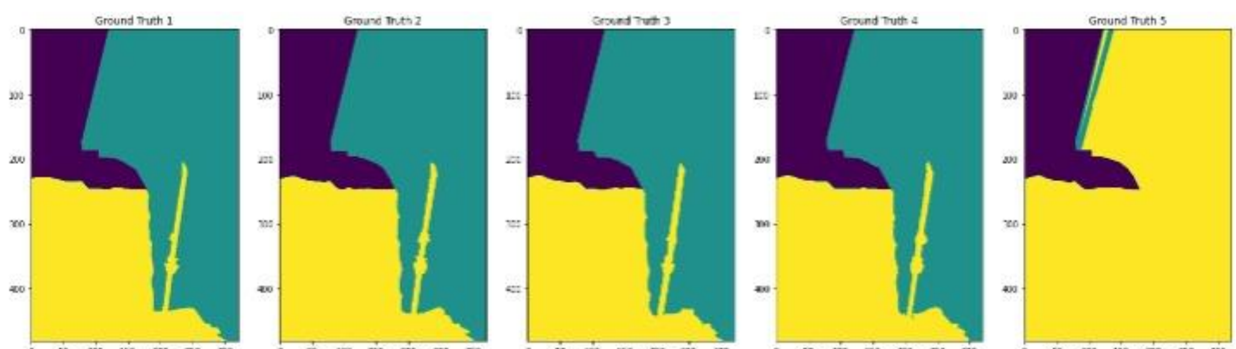




K	F_measures mean	Conditional Entropy mean
3	0.63146	0.23281739999999998
5	0.48582380000000003	0.28848900000000005
7	0.42846600000000007	0.326974
9	0.42725359999999996	0.3221718
11	0.3625758	0.334625







Colab link:

https://colab.research.google.com/drive/1w5kXbAaOp9td6FtIKd2Z-jQ1iszCoxVW?usp=sharing#scrollTo=9aUu8wMEd8D7