



Alexandria University- Faculty of Engineering  
Computer and Systems Engineering Department

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# Pattern Recognition

## Lab 2

### Image Segmentation

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[colab link](#)

## Downloading dataset and understanding the format:

- We uploaded the dataset on google drive mount the dataset folder to our colab
- Every image in the dataset is in the format of jpg with dimensions (321 \* 481 \* 3) or (481 \* 321 \* 3) so reading the image in RGB and show it using cv2.

- The ground truth from .mat files we get from 4 to 8 ground truths for each image

And each one has a segmentation 2D array and boundaries 2D array.

### Functions:

- `read_images(directory)`
- `read_groundTruth(directory)`

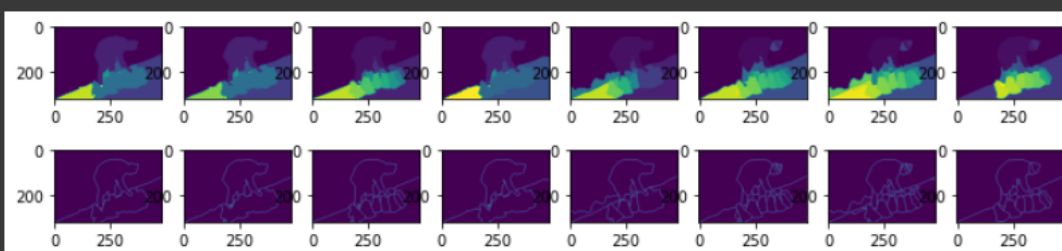
## Visualization of images and ground truth:

- Each image is shown by cv2
- Each ground truth has two 2D arrays Segmentation and Boundaries, we show them using “`image.fromarray()`”

```
[37] view_image(trainImg[131])
```



```
[38] view_segmentation(groundTruthList[131])
```



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### Functions:

- `view_image(image)`
- `view_segmentation(segment)`  $\Rightarrow$  to show all segmentations and boundaries of the ground truth of image
- `view_single_sigmentation(array)`
- `convert_to_seg(one_d_array, shape)`  $\Rightarrow$  convert 2D array to 1D array with specific shape

### Helpful Functions to Kmeans:

- `save_clustered_colored_pic(centroids, labels, shape, filename)`  $\Rightarrow$  save coloured image after Kmeans
- `plot_clustered_colored_pic(centroids, labels, shape)`  $\Rightarrow$  plot coloured image after Kmeans.

## K-means clustering :

### 1. Functions :

- a. **assignToCluster(pixel, centroids)** -> this function is responsible for calculating the distance (euclidean distance) between the current pixel sent to the function and the centroids to return the index of the cluster that this pixel must be assigned to.
- b. **updateCentroids(clusters)** -> this function calculates the new centroid by looping on the list of pixels of each cluster and dividing their sum with the number of pixels in this cluster to be at this point the new centroid.
- c. **generateCentroids** -> this function is responsible for generating a random index to be accessed in the array for setting the starting centroids, this is used in random start condition as well.
- d. **kMeans** -> this function run the main algorithm and by the end of this function it returns the clusters with pixels assigned to each cluster and the finals centroids to each cluster

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2. Different values for K: [link of all pics](#)

a. K = 3:



F\_measure : [0.055978936610462694, 0.03942545073257343,  
0.0024435587988665274, 0.07264711357669414, 0.0017976218195010804]

Avg : 0.034458536307619574

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```
cond_entropy : [0.331913440770064, 0.3521251358642472,  
0.4351051417421084, 0.41285169373298247, 0.43748263922243386]
```

```
Avg :0.393895610266367
```

b. K = 5:



---

**F\_measure** : [0.015023909252915652, 0.010478642890284173,  
0.1075699677562719, 0.16568837573164644, 0.0042403097293638]

**Avg** : 0.0606002410720964

**cond\_entropy** : [0.2816467279171293, 0.3043151414472042,  
0.38293073104214737, 0.3601868993641797, 0.3829453945735835]

**Avg** : 0.3424049788688488

c.  $K = 7$ :





**F\_measure** : [0.08550478960057355, 0.0057295735786745605,  
0.024578717229613953, 0.05255476140044795,  
0.0037633030774904676]

**Avg** : 0.03442622897736009

**cond\_entropy** : [0.1770049881712876, 0.19678643536588725,  
0.27510449382796837, 0.2548346286083342, 0.2723112446757974]

**Avg** : 0.23520835812985497

d.  $K = 9$





F\_measure : [0.03009238657495649, 0.006874172489071815,  
0.00924496447275736, 0.05029791293691038, 0.00551625015274811]

Avg : 0.020405137325288834

cond\_entropy : [0.15251851351092788, 0.17167529176737492,  
0.24856193173348012, 0.22827399282643263, 0.24316333385043035]

Avg : 0.20883861273772916

F\_measure : [0.1391445877503677, 0.018408138702360872,  
0.180074895795193, 0.17970258297894665, 0.028463308856557547]

Avg : 0.10915870281668516

cond\_entropy : [0.4646057174607904, 0.8391907450409402,  
0.412572461634212, 0.41303652916958095, 0.6307371573471492]

Avg : 0.5520285221305345



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e.  $K = 11$



```
F_measure : [0.10993520484306529, 0.004448728180146626,  
0.022344768872259443, 0.01100262632267883,  
0.018857465006236755]
```

```
Avg : 0.03331775864487739
```

```
cond_entropy : [0.12870283013549752, 0.14807460503000783,  
0.22443654999691612, 0.204400741566176, 0.2185521517236978]
```

```
Avg : 0.18483337569045905
```



```
F_measure : [0.18495673222611994, 0.048097505030044216,  
0.17448322891263005, 0.17477964431167836, 0.14555607888196812]
```

```
Avg : 0.14557463787248812
```

```
cond_entropy : [0.4493864674345097, 0.8129523940127532,  
0.39821866489645696, 0.3991972810556999, 0.613133631629338]
```

```
Avg : 0.5345776878057517
```

### 3.Evaluation:

- Functions:
  - F\_measure for each image with all ground truths using  $\Rightarrow$ 
    - `calc_F_measure(true, pred)`
  - Conditional\_entropy for each image with all ground truths using  $\Rightarrow$

- 
- `calc_entropy(true, pred)`
  - `calculate(matrix)` using it inside `calc_entropy` to calculate it for only one ground truth
- Examples on images (like above)
  - Average of data set:
    - F\_measure K=3 : 0.14896335403379882
    - Conditional\_entropy k=3 : 0.5558454686749122
  - F\_measure K=5 : 0.107965610545471
  - Conditional\_entropy k=5 : 0.47229517195741605
  - F\_measure K=7 : 0.09554371541713111
  - Conditional\_entropy k=7 : 0.42081322565779333
  - F\_measure K=9 : 0.1649822116470378
  - Conditional\_entropy k=9 : 0.3931504672347952
  - F\_measure K=11 : 0.07699169876861764
  - Conditional\_entropy k=11 : 0.18347021804290442

#### 4. Good and bad results

Good results With k = 3

F-measure : 0.4758089660107171



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F-measure : 0.523036143428053



Bad results :

F-measure : 0.0006416522926151907



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F-measure : 0.0028738596714602545



With  $k = 5$

Best Results :

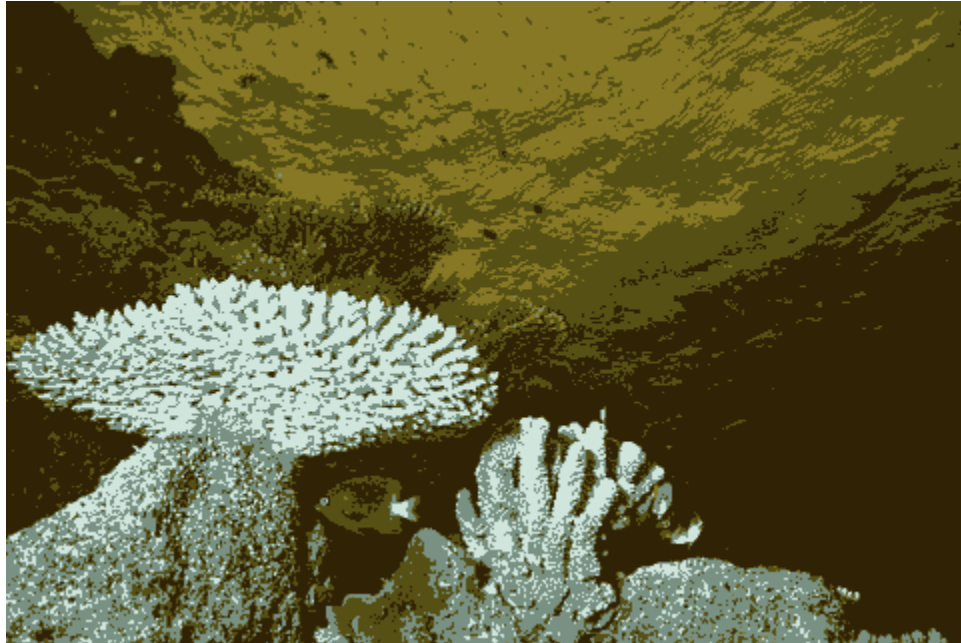
F\_measure : 0.2827962457307048



---

Bad results:

F\_measure : 0.005530685157229402



With  $k = 7$

Best Results :

F\_measure : 0.22725002307335948



---

Bad results :

F\_measure : 0.03442622897736009



With  $k = 9$

Best Results :

F\_measure : 0.3599914411009442





---

Bad results :

F\_measure : 0.020405137325288834



With  $k = 11$

Best Results :

F\_measure : 0.19391086543907352





---

Bad results:

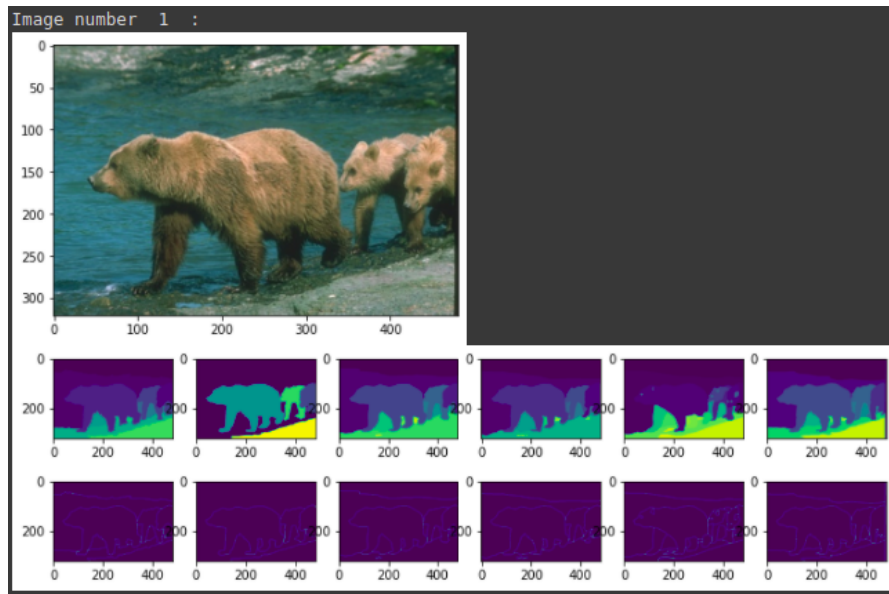
F\_measure : 0.03331775864487739



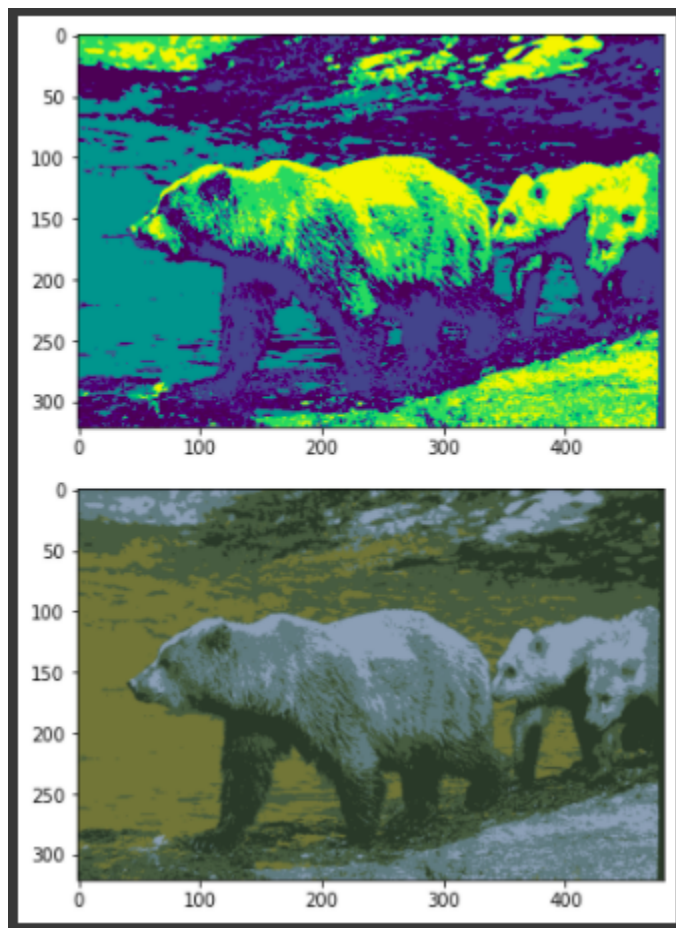
## Big Picture:

1. First Five pictures of the training set were selected along side it's ground truth segmentation(s)
  2. Reshaping the images and calling the implemented k means and built-in spectral clustering
  3. Converting the labels into segmentation and visualize it
- 
- A. K Means segmentation with original ground truth
    - a. Comment :
      - i. K means clustering had some regions correct and mixed another regions with different clusters but overall it was close

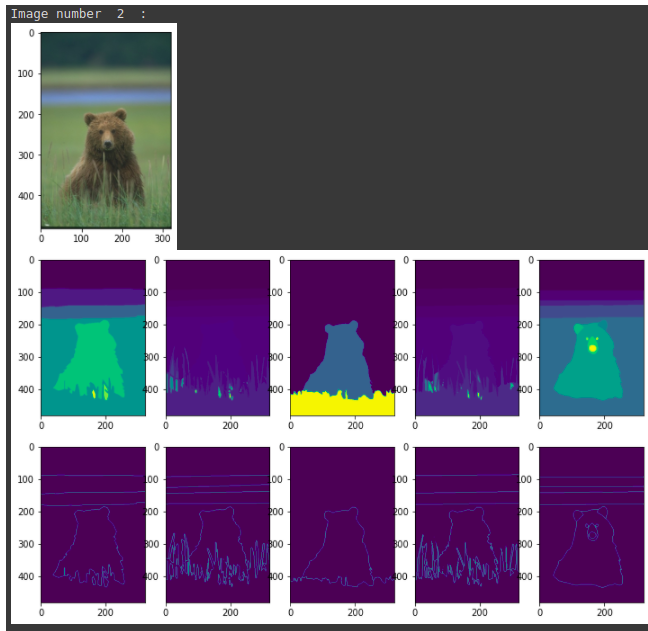
- Image 1 with its ground truth



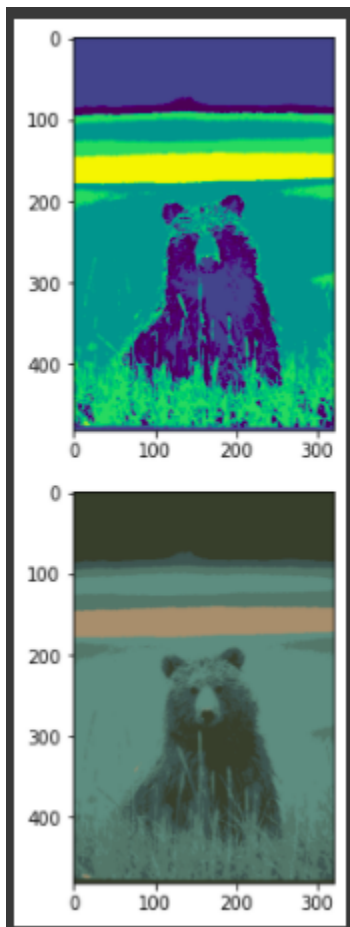
- Image 1 Segmentation



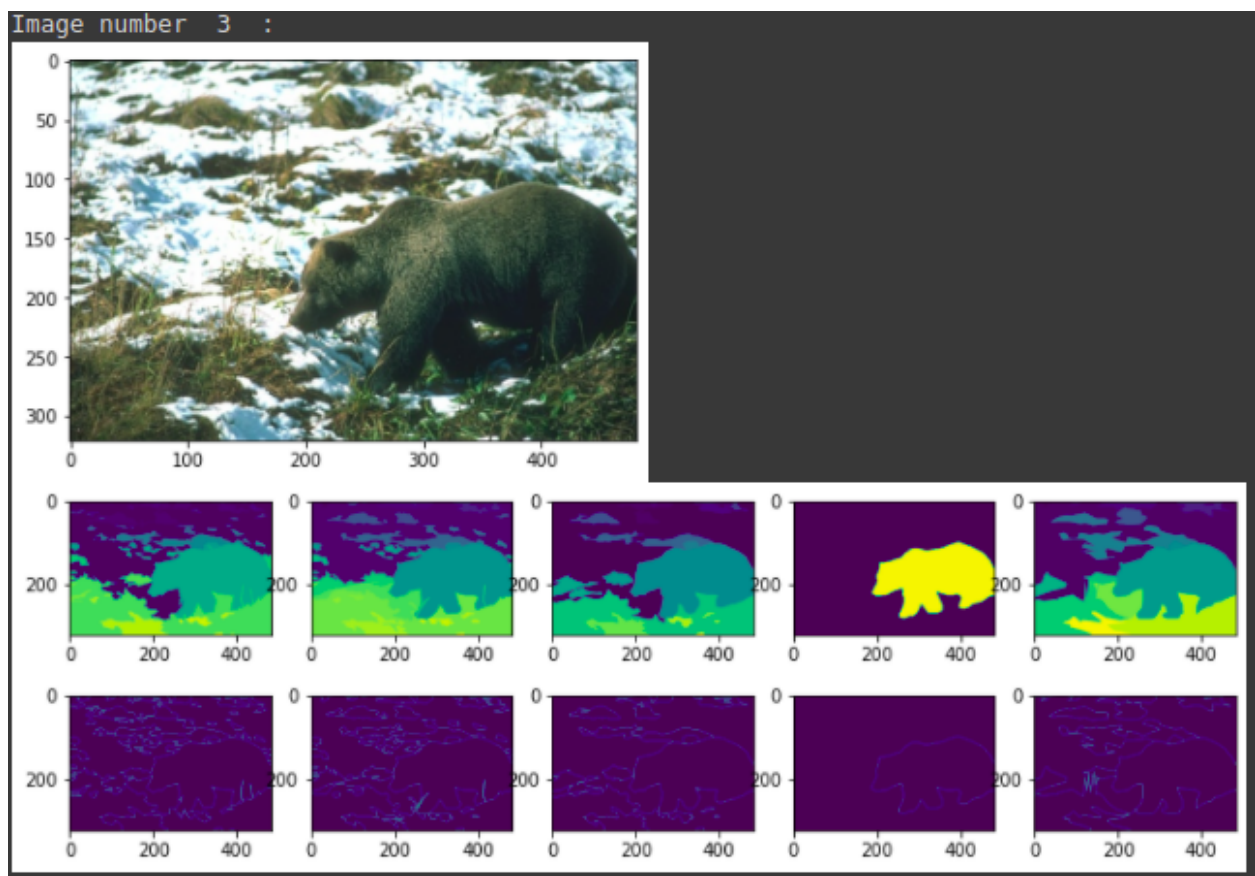
- Image 2 with it's ground truth



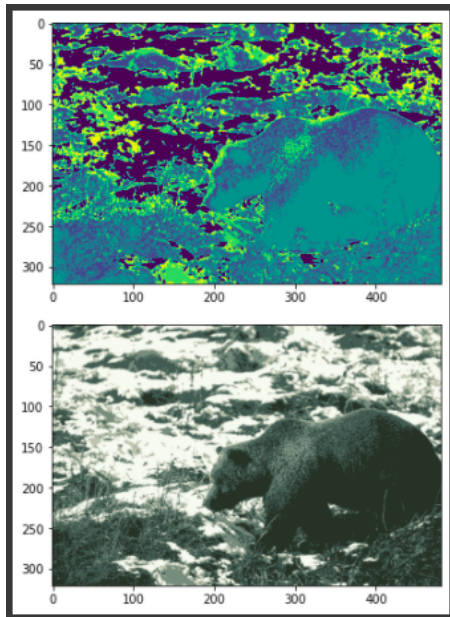
➤ Image 2 Segmentation



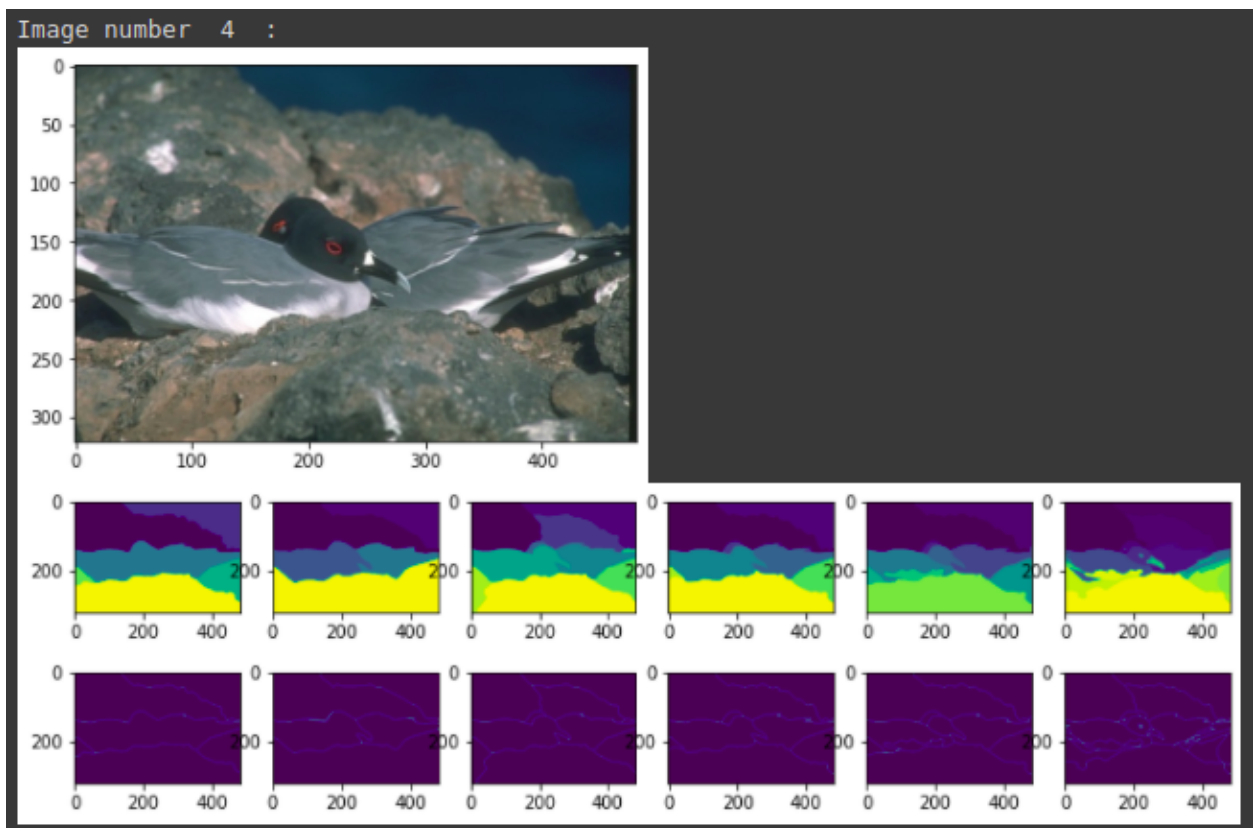
- Image 3 with it's ground truth



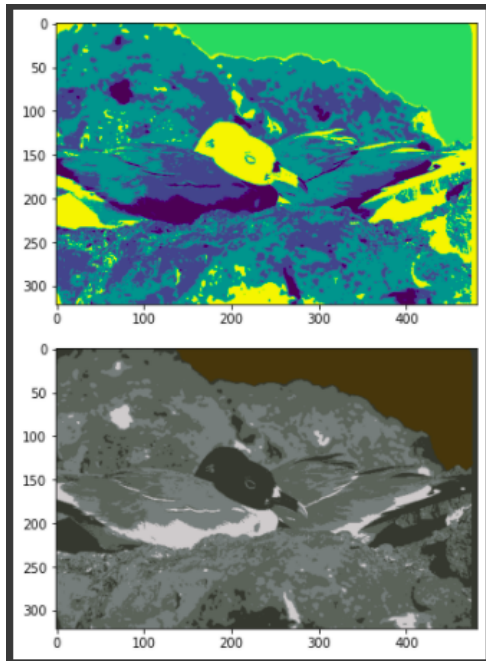
- Image 3 Segmentation



- Image 4 with it's ground truth

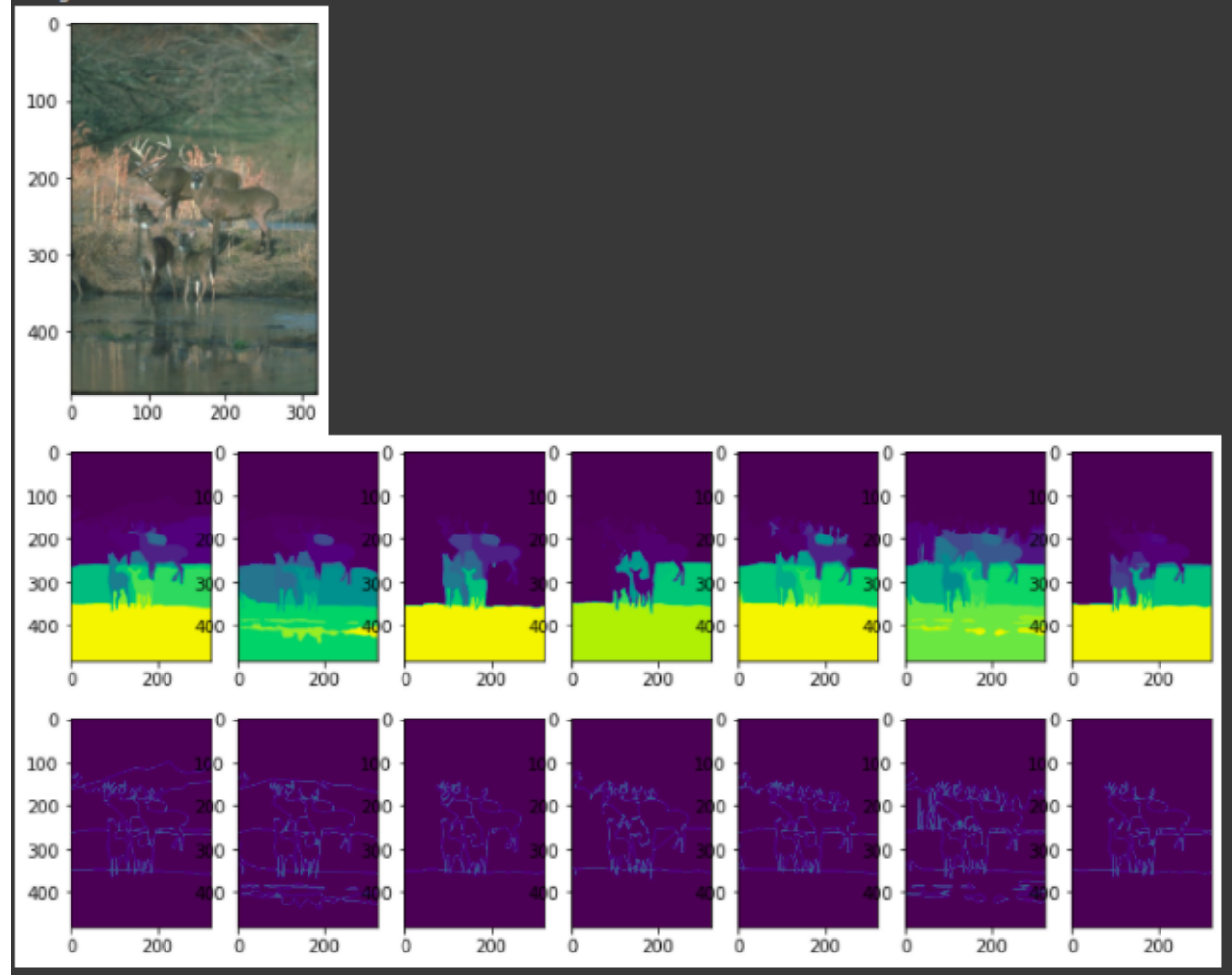


- Image 4 Segmentation



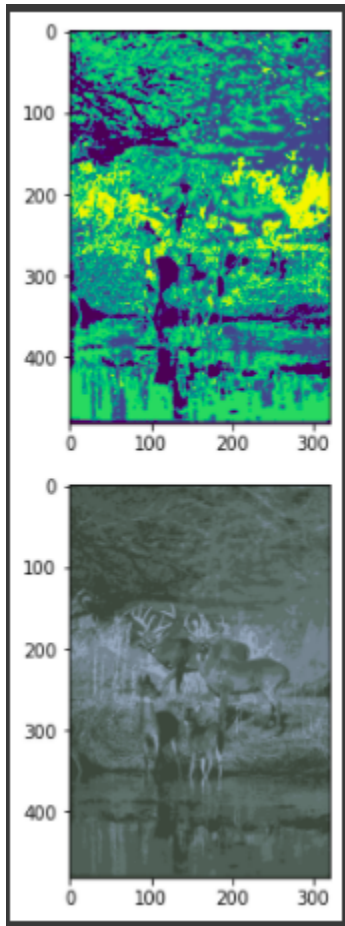
- Image 5 with it's ground truth

Image number 5 :



➤ Image 5 Segmentation

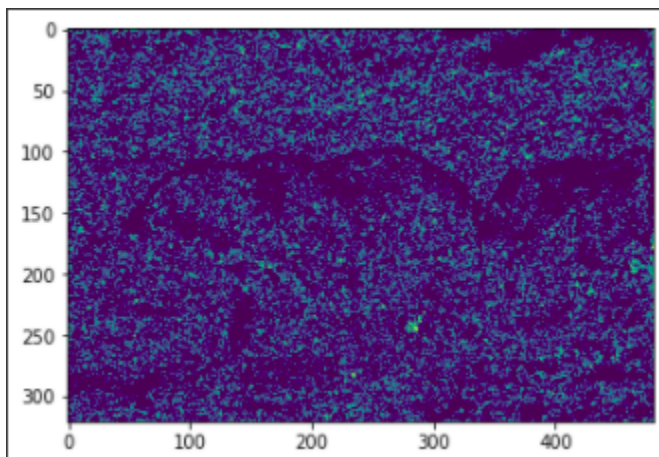




B. Spectral Clustering Segmentation with original ground truth

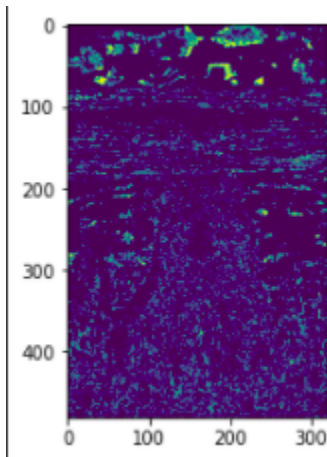
a. Comment :

- i. N-cut didn't classify any object correct and had everything mixed together
- Image 1 Segmentation

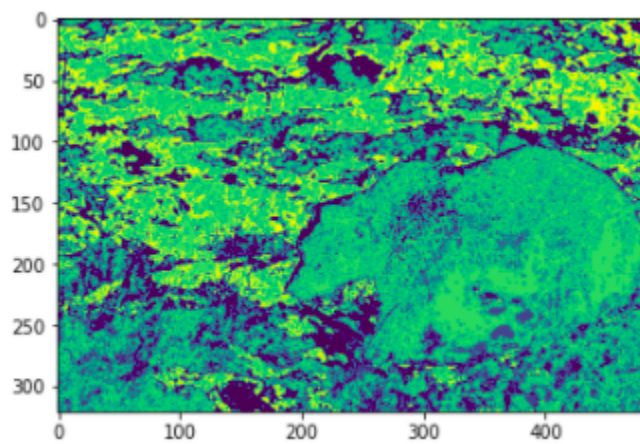


- Image 2 Segmentation

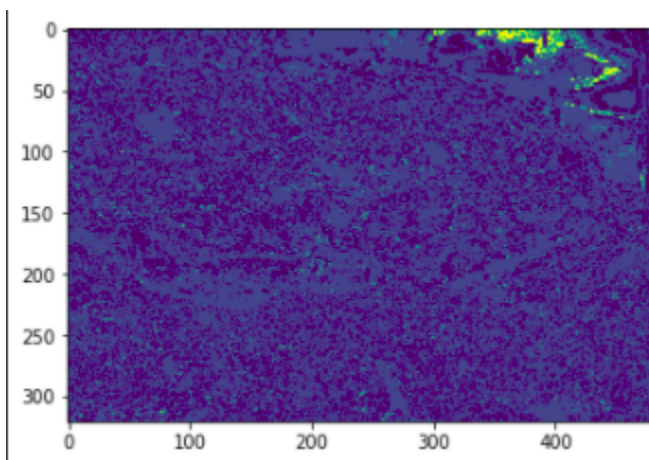




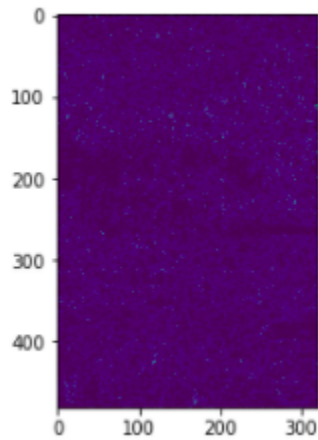
- Image 3 Segmentation



- Image 4 Segmentation



- Image 5 Segmentation



C. Comparing Kmeans & spectral clustering segmentations

a. Comment :

- i. K means is much better than normalized cut and the classification in the N-cut were so far behind and mixed objects together