Assignment 1: Superpixels and Image Segmentation.

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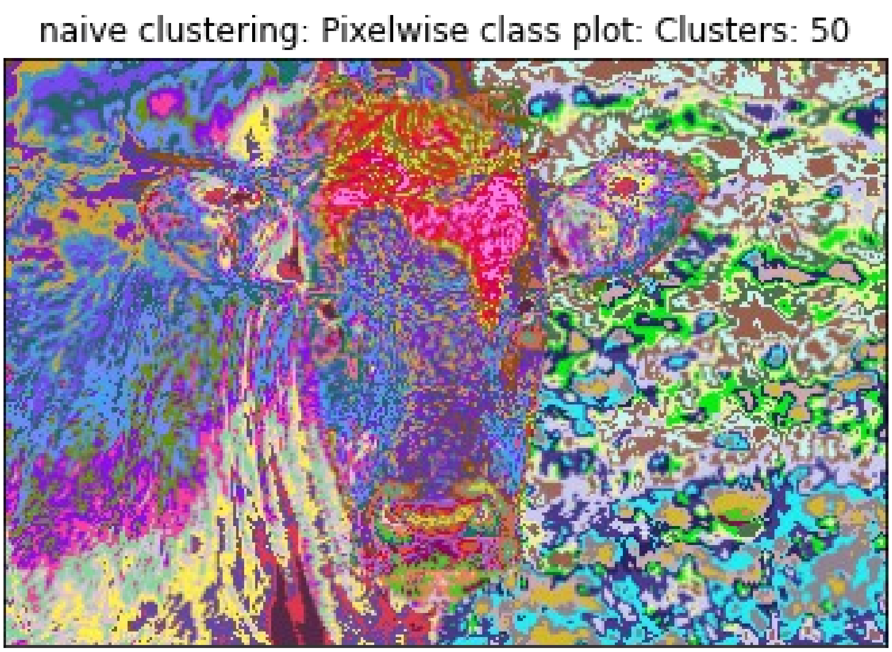
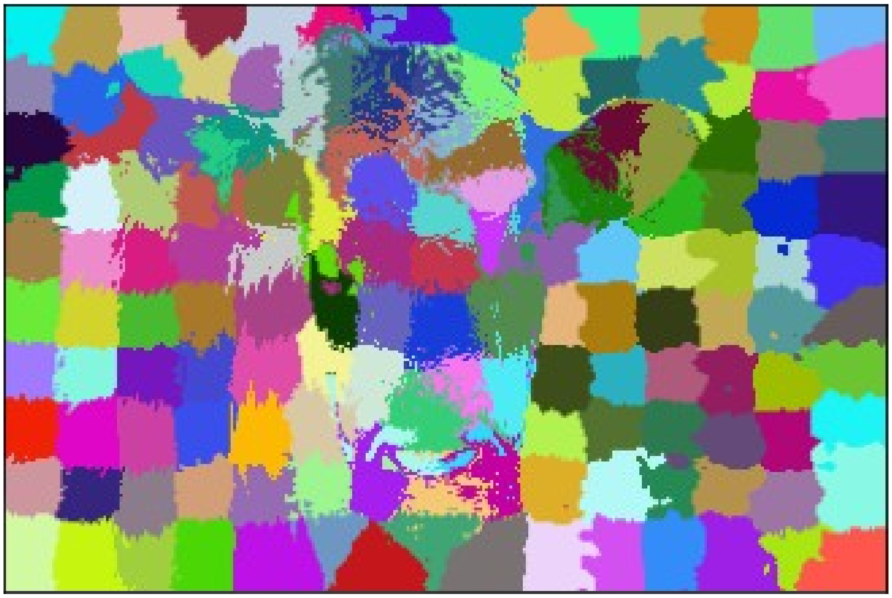
Link to Google Drive :
https://colab.research.google.com/drive/1zTEH4JB50L0LNoMFQXPew-BL1RH7oHGL

Please submit a PDF containing all outputs to gradescope by **October 5, 11:59pm**

In this assignment, you will learn about superpixels. You will first generate superpixels by clustering pixels via k-means. This will generate a superpixel map such as the following:



You will then implement a better superpixel algorithm: SLIC, which lets you generate superpixel maps like the following:



You will then build a segmentation network by training a deep neural network on your superpixels. This part is fairly open-ended, feel free to try any model you can think of (GNN, CNN, Transformer, etc.).

To give an example, for a CNN-based system that reformulates segmentation as superpixel image classification, there are basically three steps in the training stage:

1. Dilate and save each superpixel region from SLIC output into image of size 224X224, alongwith the ground truth segments label.
2. Build a couple of convolution layers to extract the deep features from each Superpixel patch image. Let the last layer be Fully connected layers.
3. Define the segmentation loss as multi-class classification loss and train a convolutional neural network based classifier.

Then, during inference, you would combine the classifier's predicted labels to form the whole input image's Superpixel segmentation results.

Part 1: Superpixels

For this first part of the assignment, you will implement 2 superpixels methods: k-means pixel clustering, and SLIC.

Data

First, we download the MSRC labeled imaged database.

```
!wget http://download.microsoft.com/download/A/1/1/A116CD80-5B79-407E-B5CE-3D5C6ED8B0D5/msrc_objcategimagedatabase_v1.zip
!unzip --qq msrc_objcategimagedatabase_v1.zip
```

```
--2023-10-05 20:14:56--
http://download.microsoft.com/download/A/1/1/A116CD80-5B79-407E-B5CE-
3D5C6ED8B0D5/msrc_objcategimagedatabase_v1.zip
Resolving download.microsoft.com (download.microsoft.com)...
23.46.189.29, 2600:1401:4000:481::317f, 2600:1401:4000:49d::317f
Connecting to download.microsoft.com (download.microsoft.com)|
23.46.189.29|:80... connected.
HTTP request sent, awaiting response... 302 Moved Temporarily
Location: https://download.microsoft.com/download/A/1/1/A116CD80-5B79-
407E-B5CE-3D5C6ED8B0D5/msrc_objcategimagedatabase_v1.zip [following]
--2023-10-05 20:14:56--
https://download.microsoft.com/download/A/1/1/A116CD80-5B79-407E-B5CE-
3D5C6ED8B0D5/msrc_objcategimagedatabase_v1.zip
Connecting to download.microsoft.com (download.microsoft.com)|
23.46.189.29|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 44119839 (42M) [application/octet-stream]
Saving to: ‘msrc_objcategimagedatabase_v1.zip’

msrc_objcategimaged 100%[===================>]  42.08M  24.9MB/s    in
1.7s

2023-10-05 20:14:58 (24.9 MB/s) - ‘msrc_objcategimagedatabase_v1.zip’
saved [44119839/44119839]
```

For the first part of this assignment, we will only use the following images. We define the list below as `im_list`.

```
im_list = ['MSRC_ObjCategImageDatabase_v1/1_22_s.bmp',
           'MSRC_ObjCategImageDatabase_v1/1_27_s.bmp',
           'MSRC_ObjCategImageDatabase_v1/3_3_s.bmp',
           'MSRC_ObjCategImageDatabase_v1/3_6_s.bmp',
           'MSRC_ObjCategImageDatabase_v1/6_5_s.bmp',
           'MSRC_ObjCategImageDatabase_v1/7_19_s.bmp']
```

We provide the following functions as helpers for plotting your results. Please pay attention to their signatures and outputs.

```
#All important functions to plot
%matplotlib inline
import cv2
import matplotlib.pyplot as plt
import numpy as np
import matplotlib.patches as mpatches

def plot_image(im, title, xticks = [], yticks = [], isCv2 = True):
    """
    im :Image to plot
```

```
    title : Title of image
    xticks : List of tick values. Defaults to nothing
    yticks :List of tick values. Defaults to nothing
    cv2 :Is the image cv2 image? cv2 images are BGR instead of RGB.
Default True
    """
    plt.figure()
    if isCv2:
        im = im[:,:,::-1]
    plt.imshow(im)
    plt.title(title)
    plt.xticks(xticks)
    plt.yticks(yticks)

def superpixel_plot(im,seg,title = "Superpixels"):
    """
    Given an image (nXmX3) and pixelwise class mat (nXm),
    1. Consider each class as a superpixel
    2. Calculate mean superpixel value for each class
    3. Replace the RGB value of each pixel in a class with the mean
value

    Inputs:
    im: Input image
    seg: Segmentation map
    title: Title of the plot

    Output: None
    Creates a plot
    """
    clust = np.unique(seg)
    mapper_dict = {i: im[seg == i].mean(axis = 0)/255. for i in clust}

    seg_img =  np.zeros((seg.shape[0],seg.shape[1],3))
    for i in clust:
        seg_img[seg == i] = mapper_dict[i]

    plot_image(seg_img,title)

    return None

def rgb_segment(seg,n = None,plot = True,title=None,legend =
True,color = None):
    """
    Given a segmentation map, get the plot of the classes
    """
    #This clust gives unique labels
    clust = np.unique(seg)

    if n is None:
```

```
        n = len(clust)

    if color is None:
        cm = plt.cm.get_cmap('hsv',n+1)
        # mapper_dict = {i:np.array(cm(i/n)) for i in clust}
        mapper_dict = {i:np.random.rand(3,) for i in clust}
    # elif color == 'mean':
        #TODO..get the mean color of cluster center and assign that to
mapper_dict
    seg_img =  np.zeros((seg.shape[0],seg.shape[1],3))
    for i in clust:
          seg_img[seg == i] = mapper_dict[i][:3]
    # mapper_dict = {i: seg_img[seg == i].mean/255. for i in clust}
      #     cluster_color = np.mean(seg_img[seg], axis=(0, 1))
      #     mean_color_cluster.append(cluster_color)
    if plot:
        plot_image(seg_img,title = title)
    if legend:
        # get the colors of the values, according to the
        # colormap used by imshow
        patches = [ mpatches.Patch(color=mapper_dict[i], label=" :
{l}".format(l=i) ) for i in range(n) ]
        # put those patched as legend-handles into the legend
        plt.legend(handles=patches, bbox_to_anchor=(1.05, 1), loc=2,
borderaxespad=0. )
        plt.grid(True)
        plt.show()

    return seg_img
```

For example, the following code uses `plot_image` to plot the 6 images we are using for this assignment.

```
for i in im_list:
    plot_image(cv2.imread(i),i.split("/")[-1])
```

1_22_s.bmp

1_27_s.bmp

3_3_s.bmp

3_6_s.bmp

6_5_s.bmp

7_19_s.bmp

Question 1: Perform k-means on image pixels `(r, g, b, x, y)`. (40 points)

The k-means clustering algorithm is an unsupervised algorithm which, for some items and for some specified number of clusters represented by cluster centers, minimizes the distance between items and their associated cluster centers. It does so by iteratively assigning items to a cluster and recomputing the cluster center based on the assigned items.

Complete the pixel clustering function. It should take input an image (shape = `(n, m, 3)`) and number of clusters. Each pixel should be represented by a vector with 3 values: `(r, g, b, x, y)`.

Then, let our provided code plot the pixelwise and superpixel plots for the cow image (`1_22_s.bmp`), using your `cluster_pixels` implementation with the provided values for the number of clusters: `5, 10, 25, 50, 150`.

```
from sklearn.cluster import KMeans
import numpy as  np

def cluster_rgbxy(im,k):
    """
    Given image im and asked for k clusters, return nXm size 2D array
    segmap[0,0] is the class of pixel im[0,0,:]
    """
    # assert 1==2," NOT IMPLEMENTED"
    #segmap is nXm. Each value in the 2D array is the cluster assigned
to that pixel

    Image_rgb = im.reshape((-1, 3))
    height, width, _ = im.shape

    x, y = np.meshgrid(np.arange(width), np.arange(height))
    xy = np.column_stack((x.reshape(-1), y.reshape(-1)))

    # After we get r,g,b,x,y we stack them in a feature matrix
    features = np.column_stack((Image_rgb, xy))
    # Performing k-means clustering algorithm on r,g,b,x,y
    kmeans = KMeans(n_clusters=k, random_state=0).fit(features)
    # give labels to each pixel
    labels = kmeans.labels_
    #Reshape the labels back to the original image shape
    segmap = labels.reshape(im.shape[:2])


    return segmap

im = cv2.imread(im_list[0])
for k in [5, 10, 25, 50, 150]:
    clusters = cluster_rgbxy(im,k)
    _ = rgb_segment(clusters,n = k, title =  "naive clustering:
Pixelwise class plot: Clusters: " + str(k),legend = False)
    superpixel_plot(im,clusters,title =  "naive clustering: Superpixel
plot: Clusters: "+ str(k))
```

```
/home/mayank/.local/lib/python3.8/site-packages/sklearn/cluster/
_kmeans.py:1416: 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)
/home/mayank/.local/lib/python3.8/site-packages/sklearn/cluster/_kmean
s.py:1416: 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
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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)
```
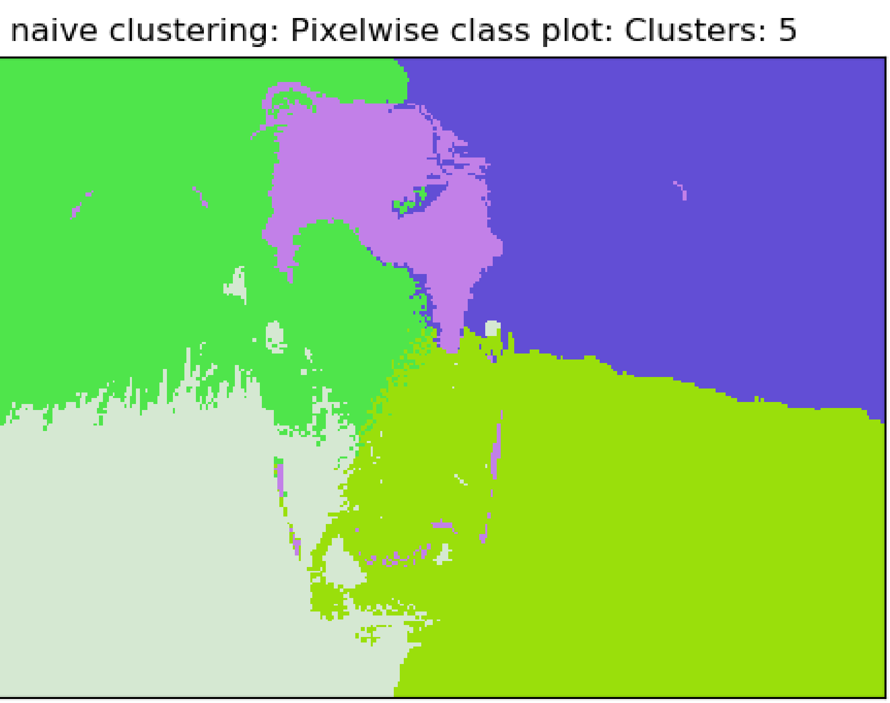
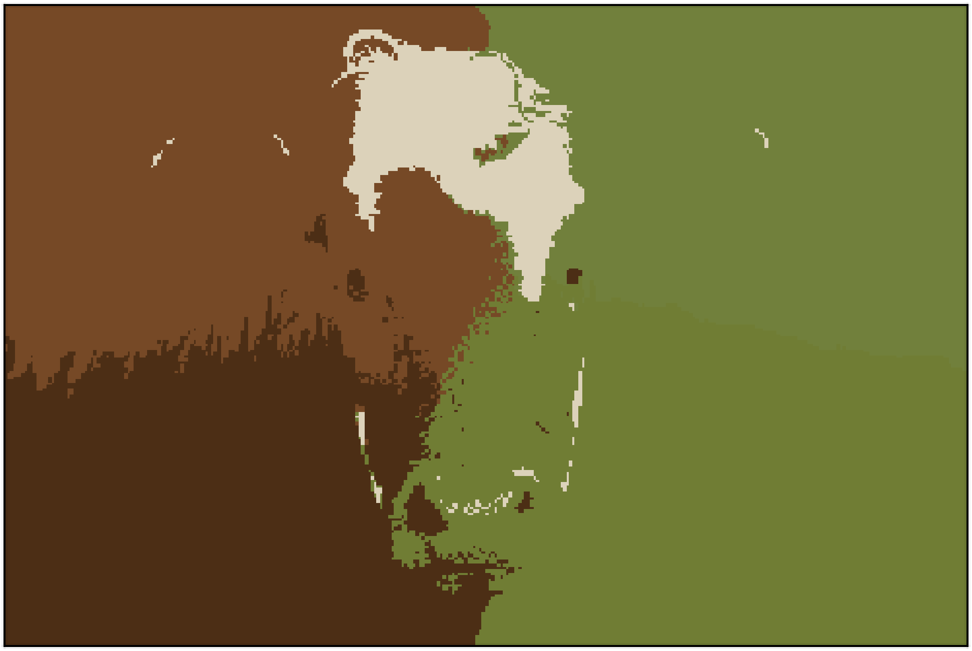



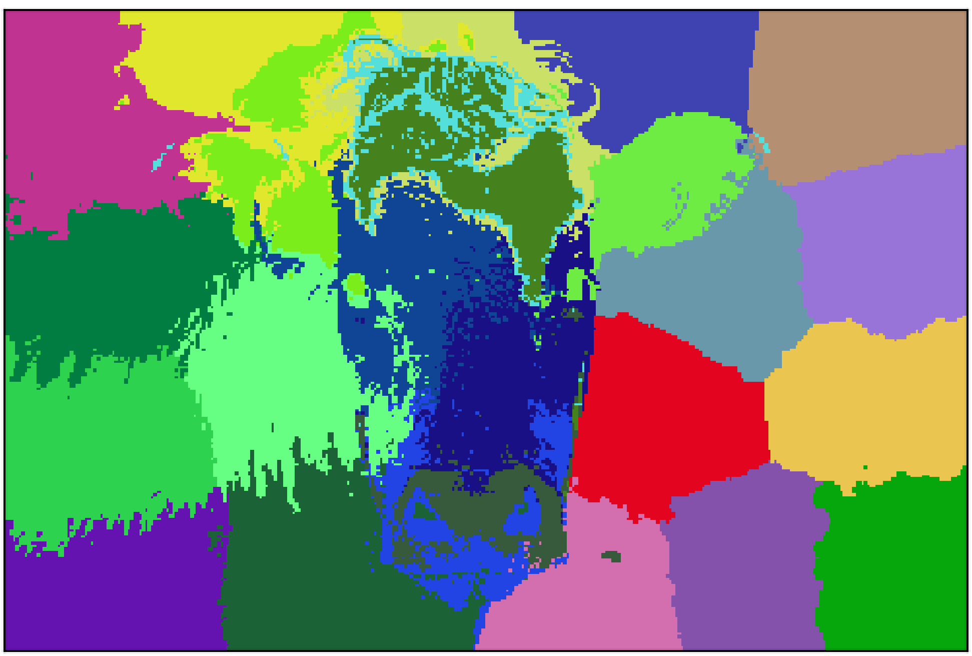
naive clustering: Superpixel plot: Clusters: 5



naive clustering: Pixelwise class plot: Clusters: 10

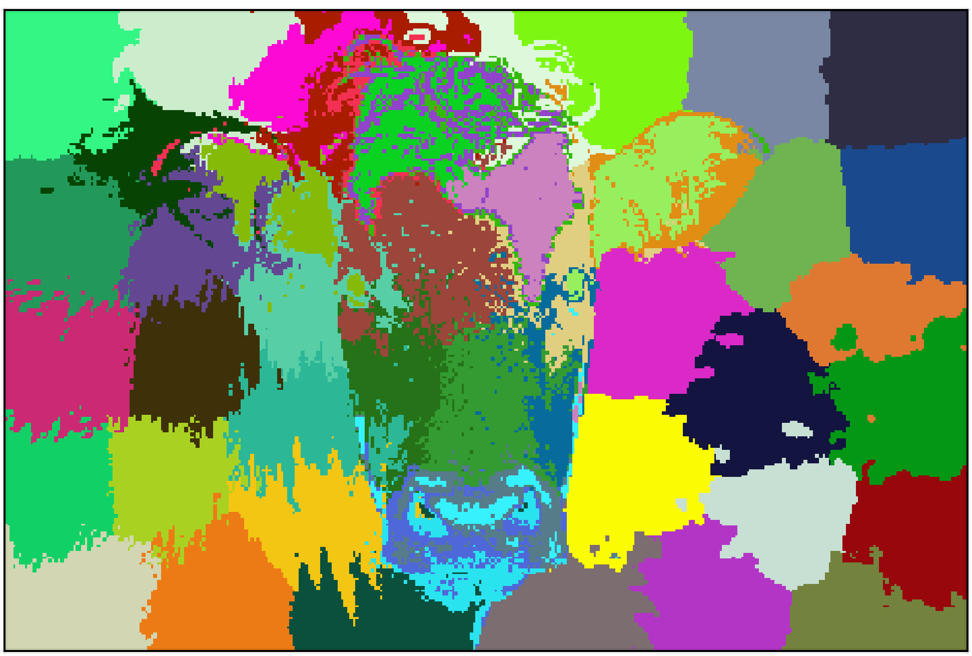
naive clustering: Superpixel plot: Clusters: 10

naive clustering: Pixelwise class plot: Clusters: 25



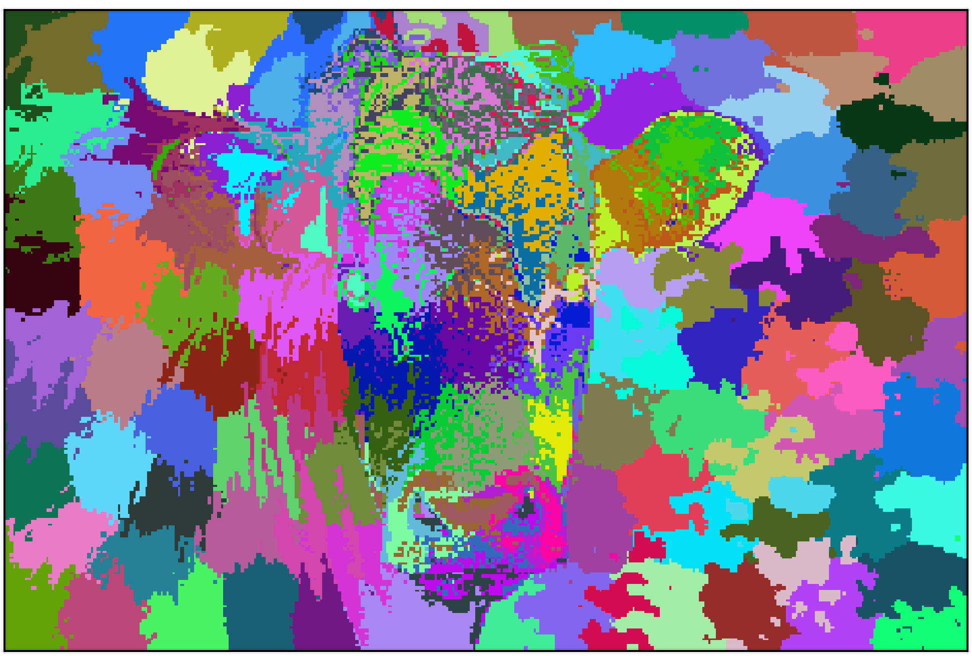
naive clustering: Superpixel plot: Clusters: 25

naive clustering: Pixelwise class plot: Clusters: 50



naive clustering: Superpixel plot: Clusters: 50

naive clustering: Pixelwise class plot: Clusters: 150



naive clustering: Superpixel plot: Clusters: 150

Pick your favorite superpixel **k** value and plot results for all 6 images in `im_list`.

```
# TODO: plot for 6 images with chosen k value

# My pick is K=50
k=50
for i in im_list:
    im=cv2.imread(i)
    clusters = cluster_rgbxy(im,k)
    _ = rgb_segment(clusters,n = k, title =  "naive clustering: 
Pixelwise class plot: Clusters: " + str(k),legend = False)
    superpixel_plot(im,clusters,title =  "naive clustering: Superpixel 
plot: Clusters: "+ str(k))


/home/mayank/.local/lib/python3.8/site-packages/sklearn/cluster/
_kmeans.py:1416: FutureWarning: The default value of `n_init` will 
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly 
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/home/mayank/.local/lib/python3.8/site-packages/sklearn/cluster/_kmean
s.py:1416: 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)
/home/mayank/.local/lib/python3.8/site-packages/sklearn/cluster/_kmean
s.py:1416: FutureWarning: The default value of `n_init` will change
from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to
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/home/mayank/.local/lib/python3.8/site-packages/sklearn/cluster/_kmean
s.py:1416: FutureWarning: The default value of `n_init` will change
from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to
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s.py:1416: 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)
```
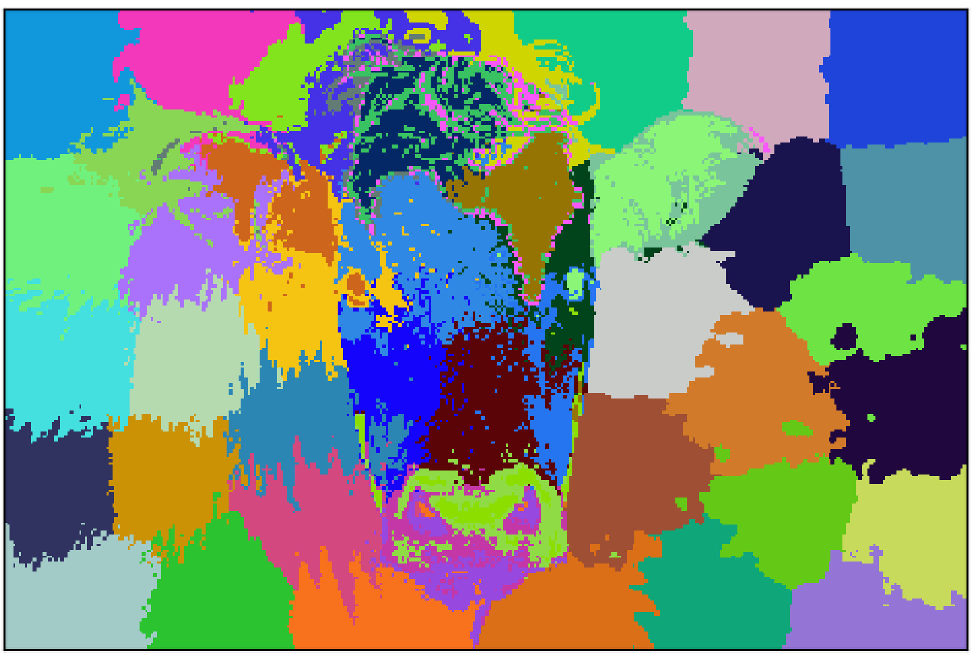
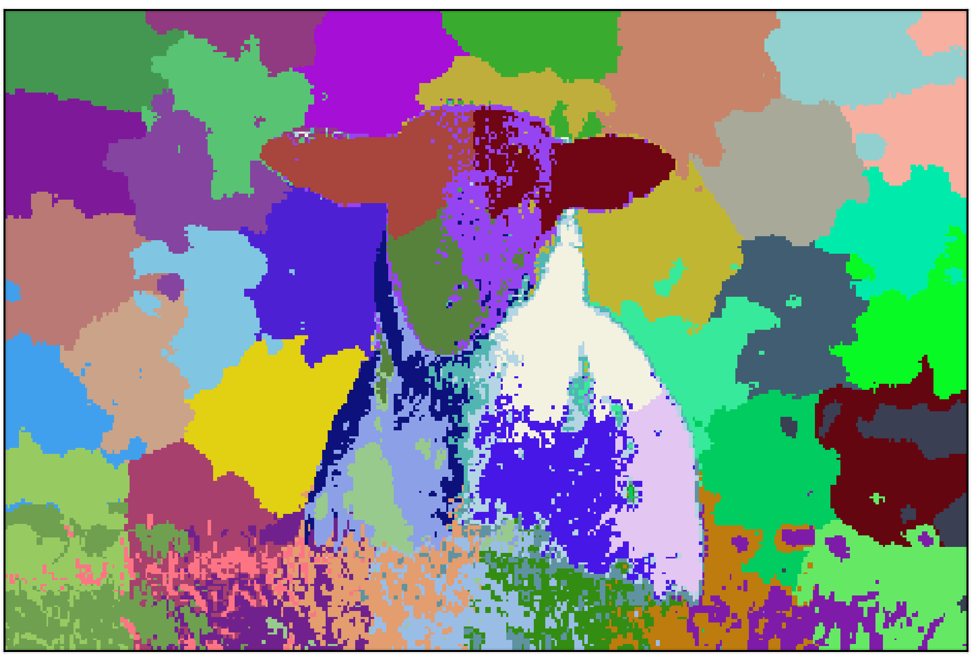

naive clustering: Pixelwise class plot: Clusters: 50



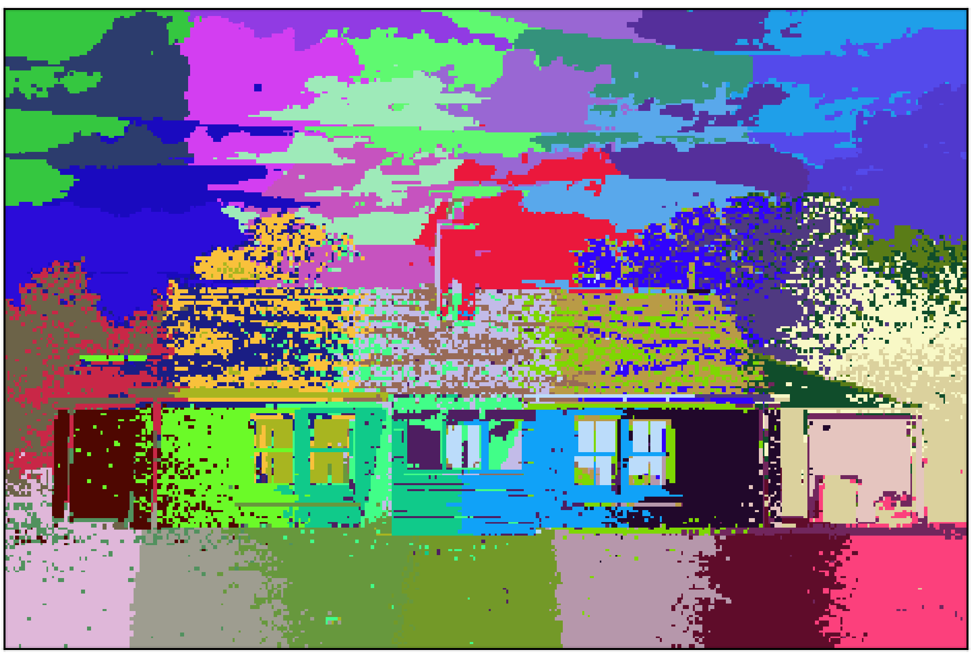
naive clustering: Superpixel plot: Clusters: 50

naive clustering: Pixelwise class plot: Clusters: 50



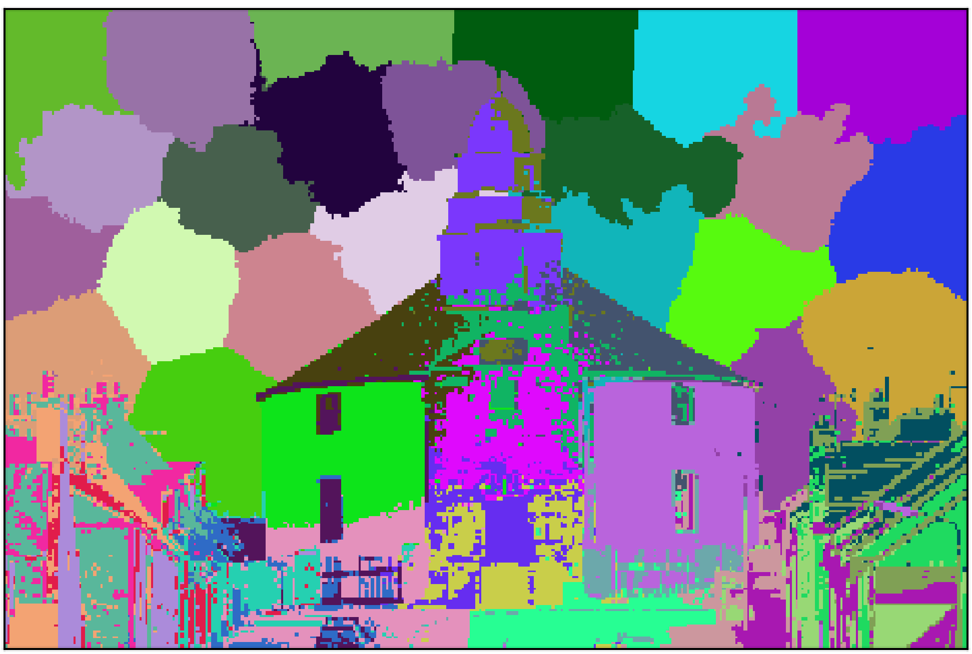
naive clustering: Superpixel plot: Clusters: 50

naive clustering: Pixelwise class plot: Clusters: 50



naive clustering: Superpixel plot: Clusters: 50

naive clustering: Pixelwise class plot: Clusters: 50

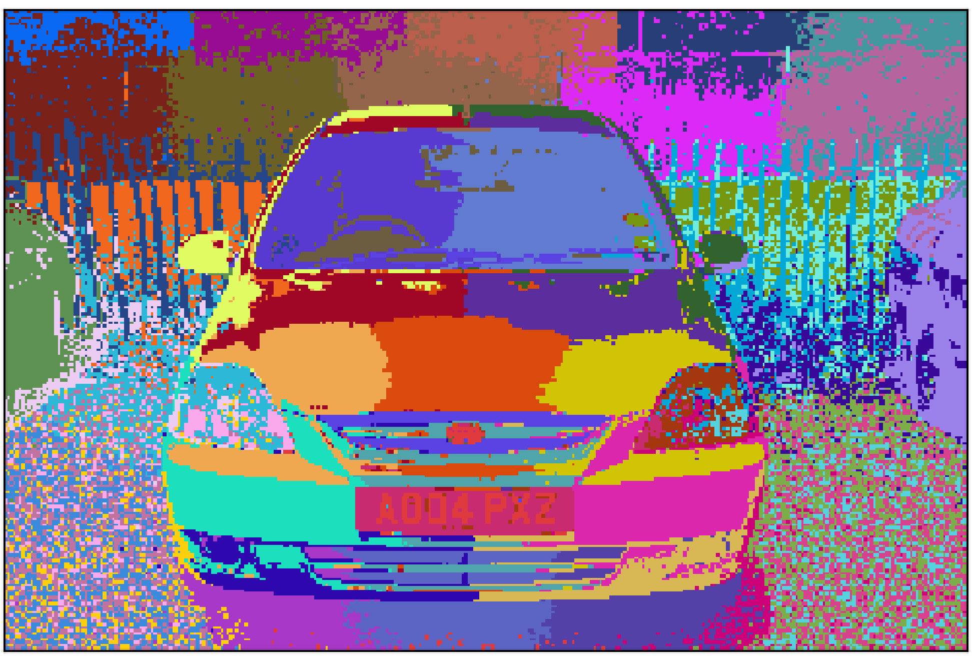


naive clustering: Superpixel plot: Clusters: 50

naive clustering: Pixelwise class plot: Clusters: 50

naive clustering: Superpixel plot: Clusters: 50

naive clustering: Pixelwise class plot: Clusters: 50



naive clustering: Superpixel plot: Clusters: 50

Question 2: Replicate SLIC and Show Results for 6 Images (50 points)

It doesn't look like we have a very favourable outcome with superpixels being implemented with simple clustering. Can we do better? Have a look at the SLIC paper here. Incorporate S and m and redefine your distance metric as per the paper.

Finding an existing implementation of SLIC and using it for your assigment would be considered cheating.

```
from skimage.util import img_as_float
from skimage import io, color
import math
import time
import copy
import cv2

# A class to initialize the super pixels, of the form - [l,a,b,h,w].
class SuperPixel(object):
    def __init__(self, h, w, l=0, a=0, b=0):
        self.update( h, w,l, a, b)
        self.pixels = []
    def update(self, h, w ,l, a, b):

        self.h = h
        self.w = w
        self.l = l
        self.a = a
        self.b = b
```

```python
# Function which returns an object of class SuperPixel
def make_SuperPixel(h, w,image):
    return SuperPixel( h, w,image[h,w][0],image[h,w][1],image[h,w][2])

# Functions for Simple Linear Iterative Clustering (SLIC)
def get_lab(image):
  image_lab = cv2.cvtColor(image,
cv2.COLOR_BGR2LAB).astype(np.float64)
  return image_lab

def initializing_cluster_centers(S, image, image_height, image_width,
clusters):
    # Initializing clusters by sampling pixels at an equally sampled
regular grid (distanced by S)
    h = S // 2
    w = S // 2
    while h < image_height:
        while w < image_width:
          clusters.append(make_SuperPixel(h, w,image))
          w= w+S
        w = S // 2
        h =  S + h
    return clusters


def get_cluster_gradient(h,w,image,image_width,image_height):
    #Calculating gradient of the cluster
    gradient=np.linalg.norm(image[h+1, w] - image[h-1,w])**2 +
np.linalg.norm(image[h, w+1] - image[h, w-1])**2
    return gradient

def relocating_cluster_center_to_lowgradients(clusters,
image,image_width,image_height):
    # for each cluster c, reassign cluster to the pixel having
smallest gradient value.
    # Step 1: compute gradient wrt cluster-center c.h, c.w in 3X3
neighborhood of cluster center.
    # Step 2: Similarly, compute gradient for each pixel in 3X3
spatial neighborhood of cluster c.
    # Step 3. Reassign cluster-center to the pixel (x,y) having the
lowest gradient.
    for i in clusters:
      minimum_gradient =
get_cluster_gradient(i.h,i.w,image,image_width,image_height)
      for j in range(-1,2):
          for k in range(-1,2):
            Height_new = i.h + j
            Width_new = i.w + k
            new_cluster_grad =
```

```
get_cluster_gradient(Height_new,Width_new,image,image_width,image_heig
ht)
            if new_cluster_grad<minimum_gradient:

i.update(Height_new,Width_new,image[Height_new,Width_new]
[0],image[Height_new,Width_new][1],image[Height_new,Width_new][2])
              minimum_gradient = new_cluster_grad
    return None

def assign_pixels_2_cluster(clusters, S, image, image_height,
image_width, cluster_dict, dis,segmap,m):

    # Comparing each pixel to cluster center within 2S pixel distance
and assign to nearest cluster using the "distance metric"
    # (involving both color and spatial dimensions of pixel and
cluster

  for idx, i in enumerate(clusters):
    for h in range(i.h-2*S,i.h+2*S):
      if h<0 or h>=image_height: continue
      for w in range(i.w-2*S,i.w+2*S):
          if w<0 or w>=image_width: continue
          l,a,b = image[h,w]
          distance_color = math.sqrt(math.pow(l-i.l,2)+math.pow(a-
i.a,2)+math.pow(b-i.b,2))
          distance_spatial = math.sqrt(math.pow(h-i.h,2)+math.pow(w-
i.w,2))
          D = distance_color + (distance_spatial*m/S)
          if D < dis[h,w]:
            if (h,w) not in cluster_dict:
              cluster_dict[(h,w)] = i
              i.pixels.append((h,w))
            else:
              cluster_dict[(h,w)].pixels.remove((h,w))
              cluster_dict[(h,w)] = i
              i.pixels.append((h,w))
            dis[h,w] = D
            segmap[h,w]=idx
  return segmap

def update_clusters(clusters):
  # For each cluster, update the cluster center with mean of the
pixels assigned (c.pixels)
  for i in clusters:
    H = W = count = 0
    for pix in i.pixels:
      H = H + pix[0]
      W = W + pix[1]
      count = count + 1
      H_mean = H//count
```

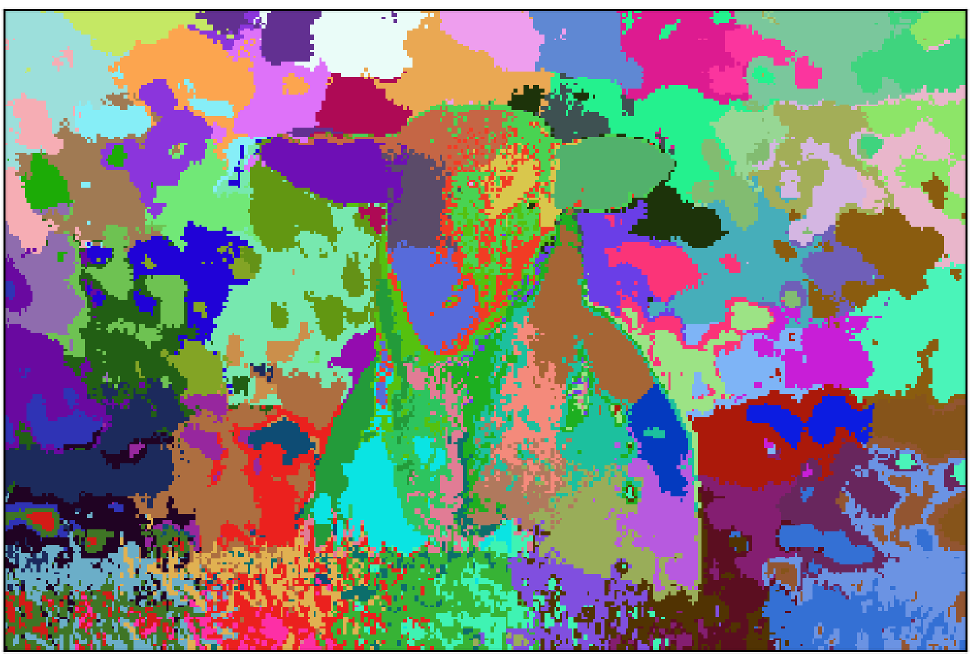
```
      W_mean = W//count
      i.update(H_mean,W_mean,image[H_mean,W_mean]
[0],image[H_mean,W_mean][1],image[H_mean,W_mean][2])
  return None


def SLIC(im,k):
    """
    Input arguments:
    im: image input
    k: number of cluster segments
    Compute
    S: As described in the paper
    m: As described in the paper (use the same value as in the paper)
    follow the algorithm..

    returns:
    segmap: 2D matrix where each value corresponds to the image
pixel's cluster number

    """
    #I have set m=10 according to the paper
    m=10# compactness factor, more the m, more spatial proximity so
more compact[1,20]
    N = image_height * image_width  # number of pixels in the image
    S = int(math.sqrt(N /k)) # Average size of each superpixel
    clusters = []
    # cluster_dict contain cluster-assignment for each pixel.
    cluster_dict = {}
    #Initializing cluster centers
    clusters = initializing_cluster_centers(S, image, image_height,
image_width, clusters)
    # Move centers to position in 3x3 window with smallest gradient.
    relocating_cluster_center_to_lowgradients(clusters,
image,image_width,image_height)
    #initialiatize segmentation map
    segmap=np.zeros(image.shape[:2])
    # Distance between pixels and cluster is initialized as infinity
at the beginning.
    distance = np.full((image_height, image_width), np.inf)
    segmap=assign_pixels_2_cluster(clusters, S, image, image_height,
image_width, cluster_dict, distance,segmap,m)
    # old_clusters = copy.deepcopy(clusters)
    update_clusters(clusters)
    # return segmap
    return segmap
```

```
## TODO: Call our plot functions with your SLIC results for all 6
images

k=100
for i in im_list:
  image_RGB=cv2.imread(i)
  image_height=image_RGB.shape[0]
  image_width=image_RGB.shape[1]
  image= get_lab(image_RGB)
  clusters = SLIC(image, k)
  _ = rgb_segment(clusters,n = k, title =  "SLIC superpixel
clustering: Pixelwise class plot: Clusters: " + str(k),legend = False)
  superpixel_plot(image_RGB,clusters,title =  "SLIC superpixel
clustering: Superpixel plot: Clusters: "+ str(k))
```

SLIC superpixel clustering: Pixelwise class plot: Clusters: 100

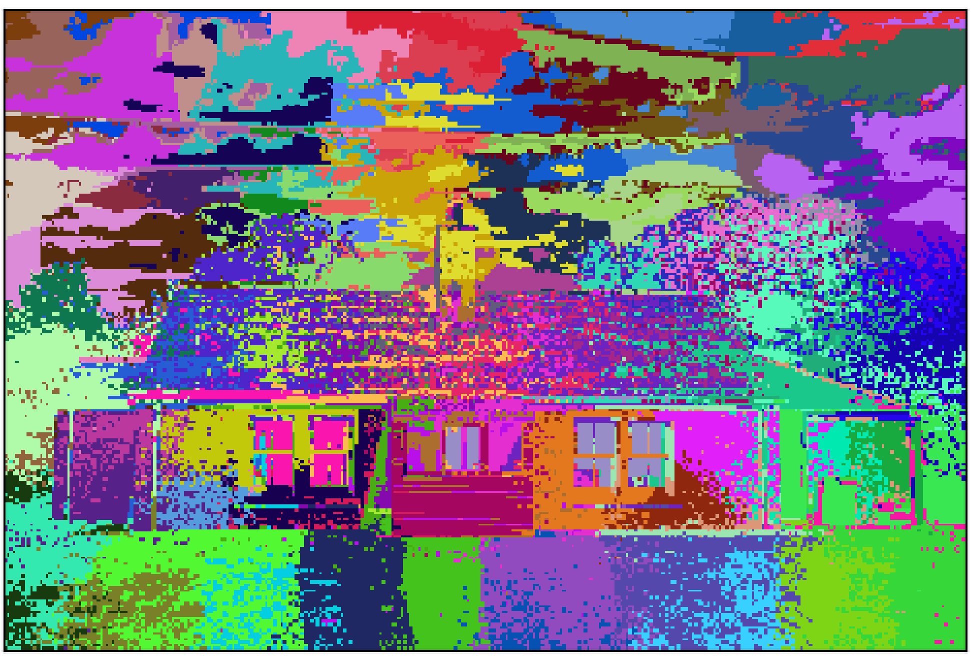
SLIC superpixel clustering: Superpixel plot: Clusters: 100

SLIC superpixel clustering: Pixelwise class plot: Clusters: 100



SLIC superpixel clustering: Superpixel plot: Clusters: 100

SLIC superpixel clustering: Pixelwise class plot: Clusters: 100



SLIC superpixel clustering: Superpixel plot: Clusters: 100

SLIC superpixel clustering: Pixelwise class plot: Clusters: 100

SLIC superpixel clustering: Superpixel plot: Clusters: 100

SLIC superpixel clustering: Pixelwise class plot: Clusters: 100

SLIC superpixel clustering: Superpixel plot: Clusters: 100

SLIC superpixel clustering: Pixelwise class plot: Clusters: 100

With SLIC implemented, plot results for all 6 images.

Question 3: What advantage did the SLIC give compared to `(r, g, b, x, y)`? Please answer in 3 sentences or fewer. (10 points)

Your Answer:

CIELAB color space used in SLIC is widely considered as perceptually uniform for small color distances compared to (r,g,b,x,y). In addition we get compact superpixels, improved efficiency and better segmentation.

Bonus Question 4: Enforce connectivity (20 points, OPTIONAL)

There are many superpixels which are very small and disconnected from each other. Merge them with larger superpixels

O(N) algorithm:

1. Set minimum size of superpixel
2. If region smaller than threshold, assign to nearest cluster

Plot results for the 6 images.

Part 2: Segmentation

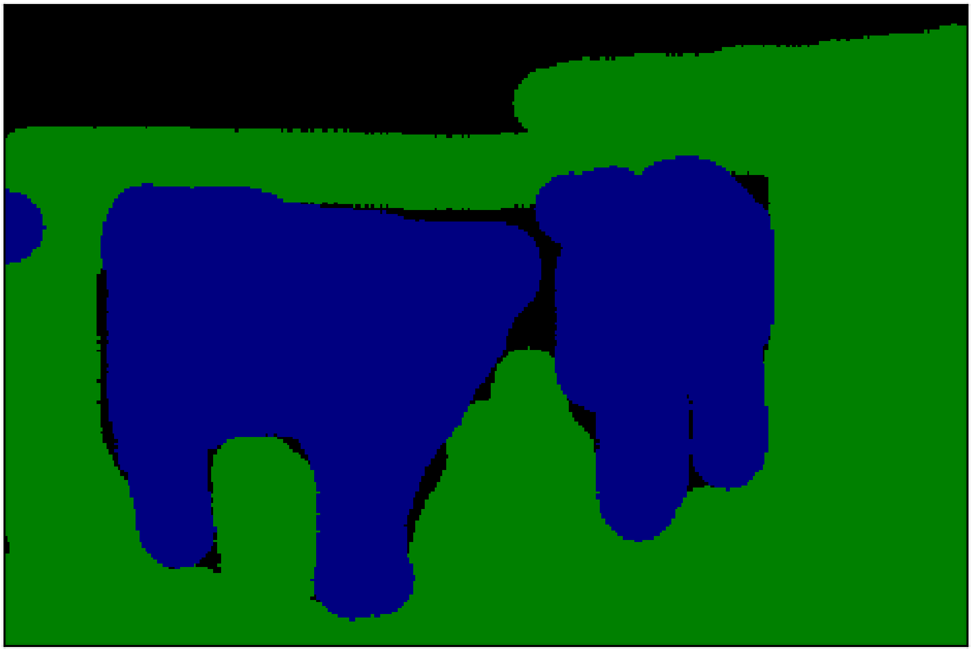
For this part, you will use your best superpixels to build an image segmentation system. Alternatively, you can use SLIC from some library, as we demonstrate in the Data section that follows.

Data

This is mostly the same as the last part, except now we also need to consider the annotated ground truth segmentation maps.

```python
#  plot a sample image and its ground truth segments
image_sample = cv2.imread('MSRC_ObjCategImageDatabase_v1/1_19_s.bmp')
seg_sample = cv2.imread('MSRC_ObjCategImageDatabase_v1/1_19_s_GT.bmp')
plot_image(image_sample, 'image')
plot_image(seg_sample, 'seg')

#  run SLIC on the sample image and plot the corresponding SLIC segments
from skimage.segmentation import slic

segments_sample = slic(image_sample, n_segments=100, compactness=10)
superpixel_plot(image_sample, segments_sample, title = "SLIC Segmentation")
```

seg



SLIC Segmentation

```
from IPython import embed
import os
current_directory = os.getcwd()
msrc_directory = current_directory + '/MSRC_ObjCategImageDatabase_v1'
```

```
#Superpixel dataset preparation

# from Dataset_v1
SEG_LABELS_LIST_v1 = [
    {"id": -1, "name": "void",        "rgb_values": [0,   0,    0]},
    {"id": 0,  "name": "building",    "rgb_values": [128, 0,    0]},
    {"id": 1,  "name": "grass",       "rgb_values": [0,   128,  0]},
    {"id": 2,  "name": "tree",        "rgb_values": [128, 128,  0]},
    {"id": 3,  "name": "cow",         "rgb_values": [0,   0,    128]},
    {"id": 4,  "name": "sky",         "rgb_values": [128, 128,  128]},
    {"id": 5,  "name": "airplane",    "rgb_values": [192, 0,    0]},
    {"id": 6, "name": "face",        "rgb_values": [192, 128,  0]},
    {"id": 7, "name": "car",         "rgb_values": [64,  0,    128]},
    {"id": 8, "name": "bicycle",     "rgb_values": [192, 0,    128]},
    {"id": -1, "name": "horse",       "rgb_values": [128,   0,
128]},
    {"id": -1, "name": "water",       "rgb_values": [64,   128,
0]},
    {"id": -1, "name": "mountain",       "rgb_values": [64,   0,
0]},
    {"id": -1, "name": "sheep",       "rgb_values": [0,   128,
128]}]

# from Dataset_v2
SEG_LABELS_LIST_v2 = [
    {"id": -1, "name": "void",        "rgb_values": [0,   0,    0]},
    {"id": 0,  "name": "building",    "rgb_values": [128, 0,    0]},
    {"id": 1,  "name": "grass",       "rgb_values": [0,   128,  0]},
    {"id": 2,  "name": "tree",        "rgb_values": [128, 128,  0]},
    {"id": 3,  "name": "cow",         "rgb_values": [0,   0,    128]},
    {"id": 4,  "name": "horse",       "rgb_values": [128, 0,    128]},
    {"id": 5,  "name": "sheep",       "rgb_values": [0,   128,  128]},
    {"id": 6,  "name": "sky",         "rgb_values": [128, 128,  128]},
    {"id": 7,  "name": "mountain",    "rgb_values": [64,  0,    0]},
    {"id": 8,  "name": "airplane",    "rgb_values": [192, 0,    0]},
    {"id": 9,  "name": "water",       "rgb_values": [64,  128,  0]},
    {"id": 10, "name": "face",        "rgb_values": [192, 128,  0]},
    {"id": 11, "name": "car",         "rgb_values": [64,  0,    128]},
    {"id": 12, "name": "bicycle",     "rgb_values": [192, 0,    128]},
    {"id": 13, "name": "flower",      "rgb_values": [64,  128,  128]},
    {"id": 14, "name": "sign",        "rgb_values": [192, 128,  128]},
    {"id": 15, "name": "bird",        "rgb_values": [0,   64,   0]},
    {"id": 16, "name": "book",        "rgb_values": [128, 64,   0]},
    {"id": 17, "name": "chair",       "rgb_values": [0,   192,  0]},
    {"id": 18, "name": "road",        "rgb_values": [128, 64,   128]},
    {"id": 19, "name": "cat",         "rgb_values": [0,   192,  128]},
    {"id": 20, "name": "dog",         "rgb_values": [128, 192,  128]},
    {"id": 21, "name": "body",        "rgb_values": [64,  64,   0]},
    {"id": 22, "name": "boat",        "rgb_values": [192, 64,   0]}]
```

```
# create a map rgb_2_label, where mapping the ground truth 3-d array segmentation into a single ID label.
rgb_2_label = {}
labels_2_rgb = {}
for i in SEG_LABELS_LIST_v1:
    rgb_2_label[tuple(i['rgb_values'])] = i['id']
    labels_2_rgb[i['id']] = i['rgb_values']
```

Question 5: Superpixel Dataset (30 points)

First, we dilate each superpixel and save the output superpixel patch from SLIC into 224X224 size image (after rescaling), alongwith the ground truth segments label.

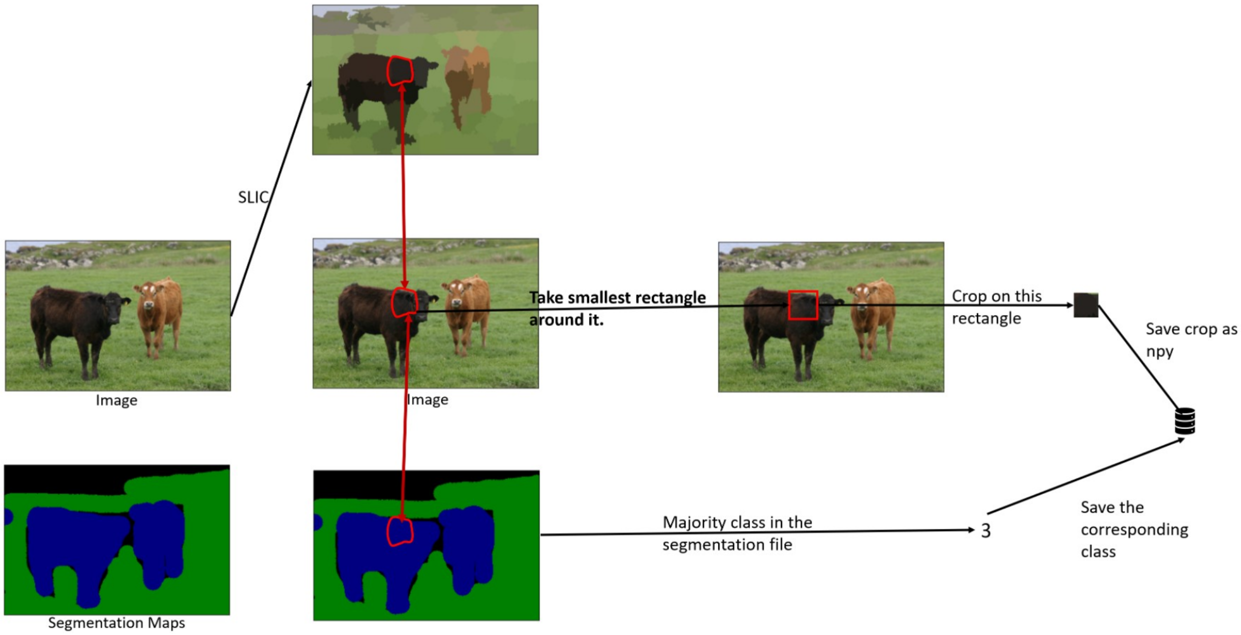
For the purpose of consistency, we adopt the existing SLIC implementation from the scikit-learn machine learning package.

Suggested algorithm: Save the superpixels along with their segmentation class. You could implement this as follows:

For each image

1. Get superpixels sp_i for image x. We adopt 100 segments in this assignment, 'segments = slic(image, n_segments=100, compactness=10)'.
2. For every superpixel sp_i in the image, \ 2.1. find the smallest rectangle which can enclose sp_i 2.2. Dilate the rectangle by 3 pixels. 2.3. Get the same region from the segmentation image (from the file with similar name with *_GT). The class for this sp_i is mode of segmentation classes in that same region. Save the dilated region as npy (jpg is lossy for such small patches).

Alternatively, you could create a single csv with columns segment patch location, class label for each sp_i of each image.italicized text



In addition to your code, **the primary graded deliverables** for this question are the 12 demo images we request after you have written code for the dataset.

```
import cv2
from skimage.segmentation import slic
from IPython import embed
import os

from tqdm import tqdm
import pandas as pd

def make_dir(directory):
  dir_path = os.path.join(msrc_directory, directory)
  if not os.path.exists(dir_path):
    os.mkdir(dir_path)
  return dir_path


datasets_dir = 'datasets'
train_dir = 'datasets/train'
test_dir = 'datasets/test'
datasets_path = os.path.join(msrc_directory, datasets_dir)
if not os.path.exists(datasets_path):
  os.mkdir(datasets_path)


datasets_path = make_dir(datasets_dir)
training_path = make_dir(train_dir)
testing_path = make_dir(test_dir)
```

```
# run SLIC on each original images and save the (segment patch, ID
label) pair
# segments = slic(image, n_segments=100, compactness=10)
# it may take up to half an hour to process, depending on the hardware
resources
# save the output file names to train.txt
# Alternatively, you don't save the segment patch and ID label
offline, instead,
# you process them on the fly later.

# if os.path.exists('./datasets/train.txt'):
#     os.remove('./datasets/train.txt')

files = os.listdir(msrc_directory)
total_images = len(files)
#80-20 SPLIT
training_size = int(len(files) * 0.8)
testing_size = total_images - training_size

train_files = files[:training_size]
test_files = files[training_size:]


# for filename in os.listdir(msrc_directory):
#     # Your code
#     pass


def give_rectangular_patch(list_of_indices):
  y_list = list_of_indices[0]
  x_list = list_of_indices[1]
  x_min, x_max = min(x_list), max(x_list)
  y_min, y_max = min(y_list), max(y_list)
  return x_min, x_max, y_min, y_max


def dilate(rectangle_patch_location, Height, Width):
  x_min, x_max, y_min, y_max = rectangle_patch_location
  pixels_dilate=3# pixel to dilate the patch with
  x_min = max(0, x_min -   pixels_dilate)
  y_min = max(0, y_min -   pixels_dilate)

  x_max = min(Width, x_max + pixels_dilate)
  y_max = max(Height, y_max + pixels_dilate)

  return x_min, x_max, y_min, y_max


def rectangle_patch_location(segmap, segmented_labels):
  Height, Width = segmap.shape
  seg_label_index = np.where(segmap == segmented_labels)
```

```
  if len(seg_label_index[0]) == 0:
    return None
  rectangle_patch_location = give_rectangular_patch(seg_label_index)
  # dilate the rectangular superpixel patch
  rectangle_patch_location = dilate(rectangle_patch_location, Height,
Width)
  return rectangle_patch_location


def crop_img(image, rect_patch_location):
  x_min, x_max, y_min, y_max = rect_patch_location
  cropped_image = image[y_min:y_max, x_min:x_max, :]
  return cropped_image

def Groundtruth_seg_class(Groundtruth_image_patch):
  # Due to negative labels having errors with pytorch so I added +1 to
the labels.
  #initialize labels as zeros
  map = np.zeros(10)
  height, width = Groundtruth_image_patch.shape[:-1]
  for i in range(height):
    for j in range(width):
      Colour = tuple(Groundtruth_image_patch[i,j])
      labels = rgb_2_label.get(Colour, -1)
      map[labels+1] += 1

  segmented_class = np.argmax(map)


  return (segmented_class)


number_of_segments = 100 #given to do 100 segments in superpixels
image
def crop_segments_save(segmented_map, source_image, groundtruth_image,
image_filename, data_path, csv_files, text_file):
  for label in range(number_of_segments):
    rectangle_patch_loc = rectangle_patch_location(segmented_map,
label)
    if rectangle_patch_loc is not None:
      sample_im_cropped = crop_img(source_image, rectangle_patch_loc)
      gt_im_cropped = crop_img(groundtruth_image, rectangle_patch_loc)
      segmented_class_label = Groundtruth_seg_class(gt_im_cropped)
      data_filename = image_filename.replace(".bmp",
(f'_{label}_{".npy"}'))
      data_filename_path = f'{data_path}/{data_filename}'

      np.save(data_filename_path, sample_im_cropped)

      csv_files.append([data_filename, segmented_class_label])
```

```
      with open(f'{datasets_path}/{text_file}', 'a+') as textfile:
        textfile.write(data_filename + '\n')


files = os.listdir(msrc_directory)
total_images = len(files)
training_size = int(len(files) * 0.8)
testing_size = total_images - training_size

train_files = files[:training_size]
test_files = files[training_size:]
# Your code
def create_dataset(list_file, data_path, csv_file, text_save):
  items = []
  for filename in tqdm(list_file, leave=False):
    if ".bmp" in filename and "_GT" not in filename:
      print(filename)
      source_filename = filename
      groundtruth_filename = filename.replace(".bmp", ("_GT"+".bmp"))

      source_filename = os.path.join(msrc_directory, source_filename)
      groundtruth_filename = os.path.join(msrc_directory,
groundtruth_filename)

      source_image = cv2.imread(source_filename)
      groundtruth_image = cv2.imread(groundtruth_filename)
      #BGR to RGB for ground truth and sample image
      source_image = source_image[:,:,::-1]
      groundtruth_image = groundtruth_image[:,:,::-1]

      seg_map = slic(source_image, n_segments=number_of_segments,
compactness=10)
      crop_segments_save(seg_map, source_image, groundtruth_image,
filename, data_path, items, text_save)


  # create csv file:
  imagepath_label = pd.DataFrame(items, columns=['image_path',
'label'])
  imagepath_label.to_csv(f'{data_path}/{csv_file}')



create_dataset(train_files, training_path, 'train.csv', 'train.txt')
print('Finished generating training data')

create_dataset(test_files, testing_path, 'test.csv', 'test.txt')
print('Finished generating testing data')
```

```
  0%|          | 0/386 [00:00<?, ?it/s]
```

```
7_24_s.bmp
  1%|          | 3/386 [00:02<06:02,  1.06it/s]
2_25_s.bmp
  1%|          | 4/386 [00:05<09:28,  1.49s/it]
6_30_s.bmp
  2%|▏         | 9/386 [00:08<05:09,  1.22it/s]
4_9_s.bmp
  3%|▎         | 10/386 [00:11<07:20,  1.17s/it]
7_19_s.bmp
  3%|▎         | 13/386 [00:13<06:27,  1.04s/it]
8_9_s.bmp
  4%|▍         | 16/386 [00:16<05:55,  1.04it/s]
7_23_s.bmp
  4%|▍         | 17/386 [00:18<07:20,  1.19s/it]
2_2_s.bmp
  5%|▌         | 20/386 [00:21<06:28,  1.06s/it]
2_22_s.bmp
  5%|▌         | 21/386 [00:23<07:50,  1.29s/it]
4_24_s.bmp
  6%|▌         | 22/386 [00:26<09:39,  1.59s/it]
2_17_s.bmp
  7%|▋         | 26/386 [00:28<06:26,  1.07s/it]
3_9_s.bmp
  8%|▊         | 29/386 [00:31<05:53,  1.01it/s]
5_22_s.bmp
  8%|▊         | 30/386 [00:34<07:20,  1.24s/it]
5_28_s.bmp
  8%|▊         | 32/386 [00:36<07:27,  1.26s/it]
```

```
6_17_s.bmp
  9%|▉         | 35/386 [00:39<06:32,  1.12s/it]
3_29_s.bmp
 10%|▉         | 37/386 [00:41<06:38,  1.14s/it]
6_18_s.bmp
 10%|▉         | 38/386 [00:44<08:04,  1.39s/it]
3_23_s.bmp
 10%|█         | 39/386 [00:46<09:06,  1.57s/it]
3_1_s.bmp
 11%|█         | 41/386 [00:49<08:04,  1.41s/it]
4_22_s.bmp
 11%|█         | 42/386 [00:51<09:39,  1.68s/it]
6_2_s.bmp
 11%|█         | 43/386 [00:54<10:20,  1.81s/it]
1_18_s.bmp
 12%|█▏        | 45/386 [00:56<09:11,  1.62s/it]
2_23_s.bmp
 13%|█▎        | 49/386 [00:58<05:47,  1.03s/it]
3_28_s.bmp
 13%|█▎        | 51/386 [01:01<06:00,  1.08s/it]
7_6_s.bmp
 13%|█▎        | 52/386 [01:03<06:57,  1.25s/it]
6_10_s.bmp
 14%|█▎        | 53/386 [01:05<08:18,  1.50s/it]
3_16_s.bmp
 14%|█▍        | 54/386 [01:08<09:24,  1.70s/it]
5_2_s.bmp
 14%|█▍        | 55/386 [01:10<10:25,  1.89s/it]
```

```
6_15_s.bmp
 15%|█▍        | 56/386 [01:13<10:54,  1.98s/it]
8_30_s.bmp
 15%|█▌        | 59/386 [01:15<07:03,  1.29s/it]
5_6_s.bmp
 16%|█▌        | 61/386 [01:17<07:08,  1.32s/it]
4_1_s.bmp
 16%|█▌        | 62/386 [01:20<08:37,  1.60s/it]
4_5_s.bmp
 17%|█▋        | 65/386 [01:23<07:12,  1.35s/it]
3_2_s.bmp
 17%|█▋        | 67/386 [01:26<07:27,  1.40s/it]
7_22_s.bmp
 18%|█▊        | 68/386 [01:29<08:52,  1.67s/it]
2_11_s.bmp
 18%|█▊        | 69/386 [01:31<08:57,  1.70s/it]
1_20_s.bmp
 18%|█▊        | 70/386 [01:34<10:05,  1.92s/it]
4_11_s.bmp
 19%|█▊        | 72/386 [01:36<08:50,  1.69s/it]
7_29_s.bmp
 19%|█▉        | 74/386 [01:39<07:58,  1.53s/it]
5_12_s.bmp
 19%|█▉        | 75/386 [01:41<08:57,  1.73s/it]
5_19_s.bmp
 20%|██        | 78/386 [01:44<06:51,  1.34s/it]
4_2_s.bmp
 20%|██        | 79/386 [01:47<07:58,  1.56s/it]
```

```
4_19_s.bmp
 21%|██        | 80/386 [01:49<09:09,  1.80s/it]
6_8_s.bmp
 21%|██        | 81/386 [01:52<10:06,  1.99s/it]
1_30_s.bmp
 22%|██▏       | 83/386 [01:54<08:31,  1.69s/it]
1_26_s.bmp
 22%|██▏       | 85/386 [01:57<07:42,  1.54s/it]
4_15_s.bmp
 23%|██▎       | 90/386 [02:00<04:49,  1.02it/s]
7_14_s.bmp
 24%|██▍       | 93/386 [02:03<04:55,  1.01s/it]
2_10_s.bmp
 25%|██▍       | 95/386 [02:05<04:47,  1.01it/s]
5_8_s.bmp
 25%|██▌       | 97/386 [02:07<05:09,  1.07s/it]
2_8_s.bmp
 25%|██▌       | 98/386 [02:10<06:25,  1.34s/it]
7_17_s.bmp
 26%|██▌       | 99/386 [02:13<07:35,  1.59s/it]
5_3_s.bmp
 26%|██▌       | 100/386 [02:16<08:45,  1.84s/it]
8_22_s.bmp
 26%|██▋       | 102/386 [02:18<07:41,  1.62s/it]
7_25_s.bmp
 27%|██▋       | 103/386 [02:21<08:51,  1.88s/it]
5_9_s.bmp
 27%|██▋       | 105/386 [02:23<07:20,  1.57s/it]
```

```
8_23_s.bmp
 28%|██▊       | 107/386 [02:25<06:32,  1.41s/it]
7_20_s.bmp
 29%|██▉       | 111/386 [02:28<04:42,  1.03s/it]
8_6_s.bmp
 29%|██▉       | 112/386 [02:30<05:38,  1.24s/it]
1_16_s.bmp
 30%|██▉       | 114/386 [02:34<06:07,  1.35s/it]
1_29_s.bmp
 31%|███       | 118/386 [02:36<04:31,  1.01s/it]
8_28_s.bmp
 31%|███       | 119/386 [02:38<04:53,  1.10s/it]
7_8_s.bmp
 32%|███▏      | 122/386 [02:41<04:36,  1.05s/it]
4_23_s.bmp
 33%|███▎      | 126/386 [02:44<04:05,  1.06it/s]
3_10_s.bmp
 33%|███▎      | 127/386 [02:46<04:52,  1.13s/it]
4_27_s.bmp
 33%|███▎      | 128/386 [02:49<06:06,  1.42s/it]
3_24_s.bmp
 34%|███▎      | 130/386 [02:52<06:07,  1.44s/it]
6_29_s.bmp
 34%|███▍      | 133/386 [02:55<05:17,  1.26s/it]
2_5_s.bmp
 35%|███▍      | 134/386 [02:58<06:41,  1.59s/it]
6_5_s.bmp
 35%|███▌      | 136/386 [03:01<06:21,  1.53s/it]
```

```
8_24_s.bmp
 35%|███▌      | 137/386 [03:03<06:57,  1.68s/it]
8_11_s.bmp
 36%|███▌      | 138/386 [03:06<07:24,  1.79s/it]
7_7_s.bmp
 37%|███▋      | 141/386 [03:08<05:25,  1.33s/it]
1_22_s.bmp
 38%|███▊      | 145/386 [03:11<04:02,  1.00s/it]
8_21_s.bmp
 38%|███▊      | 147/386 [03:12<03:49,  1.04it/s]
1_10_s.bmp
 38%|███▊      | 148/386 [03:15<05:05,  1.28s/it]
6_25_s.bmp
 39%|███▉      | 150/386 [03:18<05:17,  1.34s/it]
4_8_s.bmp
 40%|███▉      | 154/386 [03:22<04:10,  1.08s/it]
3_22_s.bmp
 40%|████      | 156/386 [03:24<04:21,  1.14s/it]
5_11_s.bmp
 41%|████▏     | 160/386 [03:27<03:36,  1.04it/s]
7_5_s.bmp
 42%|████▏     | 164/386 [03:30<03:10,  1.17it/s]
8_1_s.bmp
 43%|████▎     | 166/386 [03:32<03:22,  1.09it/s]
4_14_s.bmp
 44%|████▎     | 168/386 [03:35<03:41,  1.02s/it]
6_12_s.bmp
 44%|████▍     | 169/386 [03:37<04:27,  1.23s/it]
```

```
3_14_s.bmp
 44%|████▍     | 170/386 [03:40<05:24,  1.50s/it]
4_25_s.bmp
 45%|████▍     | 173/386 [03:43<04:32,  1.28s/it]
7_26_s.bmp
 45%|████▌     | 174/386 [03:46<05:20,  1.51s/it]
3_26_s.bmp
 46%|████▌     | 177/386 [03:48<04:05,  1.18s/it]
6_1_s.bmp
 47%|████▋     | 181/386 [03:50<03:06,  1.10it/s]
7_18_s.bmp
 47%|████▋     | 182/386 [03:52<03:47,  1.11s/it]
5_30_s.bmp
 48%|████▊     | 187/386 [03:55<02:46,  1.19it/s]
4_13_s.bmp
 50%|████▉     | 192/386 [03:58<02:19,  1.39it/s]
7_16_s.bmp
 50%|█████     | 193/386 [04:01<02:55,  1.10it/s]
1_19_s.bmp
 50%|█████     | 194/386 [04:03<03:42,  1.16s/it]
4_3_s.bmp
 51%|█████     | 195/386 [04:06<04:27,  1.40s/it]
6_4_s.bmp
 52%|█████▏    | 201/386 [04:09<02:43,  1.13it/s]
1_23_s.bmp
 53%|█████▎    | 204/386 [04:12<02:39,  1.14it/s]
6_24_s.bmp
 53%|█████▎    | 206/386 [04:14<02:53,  1.04it/s]
```

```
5_20_s.bmp
 54%|█████▍    | 208/386 [04:17<03:12,  1.08s/it]
2_15_s.bmp
 54%|█████▍    | 210/386 [04:19<02:59,  1.02s/it]
4_4_s.bmp
 55%|█████▍    | 211/386 [04:22<03:46,  1.29s/it]
6_9_s.bmp
 55%|█████▍    | 212/386 [04:24<04:28,  1.54s/it]
3_8_s.bmp
 55%|█████▌    | 213/386 [04:26<04:32,  1.57s/it]
7_1_s.bmp
 56%|█████▋    | 218/386 [04:29<02:57,  1.05s/it]
4_17_s.bmp
 57%|█████▋    | 219/386 [04:33<03:49,  1.38s/it]
4_28_s.bmp
 57%|█████▋    | 220/386 [04:35<04:25,  1.60s/it]
8_16_s.bmp
 57%|█████▋    | 221/386 [04:37<04:35,  1.67s/it]
2_26_s.bmp
 58%|█████▊    | 222/386 [04:39<04:42,  1.72s/it]
8_12_s.bmp
 59%|█████▊    | 226/386 [04:42<03:08,  1.18s/it]
5_27_s.bmp
 59%|█████▉    | 228/386 [04:44<03:03,  1.16s/it]
2_21_s.bmp
 62%|██████▏   | 241/386 [04:47<01:07,  2.16it/s]
1_7_s.bmp
 63%|██████▎   | 242/386 [04:50<01:32,  1.56it/s]
```

```
1_5_s.bmp
 63%|██████▎   | 243/386 [04:53<02:00,  1.18it/s]
3_6_s.bmp
 63%|██████▎   | 244/386 [04:55<02:30,  1.06s/it]
7_4_s.bmp
 64%|██████▍   | 247/386 [04:58<02:16,  1.01it/s]
3_20_s.bmp
 65%|██████▍   | 249/386 [05:00<02:22,  1.04s/it]
5_26_s.bmp
 65%|██████▌   | 251/386 [05:03<02:36,  1.16s/it]
7_15_s.bmp
 65%|██████▌   | 252/386 [05:06<03:11,  1.43s/it]
3_7_s.bmp
 66%|██████▌   | 255/386 [05:09<02:33,  1.17s/it]
2_29_s.bmp
 66%|██████▋   | 256/386 [05:11<02:51,  1.32s/it]
8_14_s.bmp
 67%|██████▋   | 258/386 [05:13<02:33,  1.20s/it]
1_15_s.bmp
 68%|██████▊   | 261/386 [05:15<02:15,  1.09s/it]
3_4_s.bmp
 68%|██████▊   | 264/386 [05:18<02:01,  1.00it/s]
2_24_s.bmp
 70%|██████▉   | 270/386 [05:20<01:14,  1.56it/s]
7_10_s.bmp
 70%|███████   | 272/386 [05:23<01:33,  1.22it/s]
6_28_s.bmp
 72%|███████▏  | 278/386 [05:25<01:11,  1.52it/s]
```

```
3_11_s.bmp
 72%|███████▏  | 279/386 [05:28<01:31,  1.16it/s]
4_6_s.bmp
 73%|███████▎  | 281/386 [05:31<01:40,  1.05it/s]
2_20_s.bmp
 73%|███████▎  | 282/386 [05:34<02:09,  1.25s/it]
6_22_s.bmp
 73%|███████▎  | 283/386 [05:36<02:26,  1.43s/it]
5_21_s.bmp
 74%|███████▎  | 284/386 [05:39<02:55,  1.72s/it]
5_10_s.bmp
 74%|███████▍  | 286/386 [05:42<02:35,  1.56s/it]
6_16_s.bmp
 74%|███████▍  | 287/386 [05:44<02:53,  1.75s/it]
8_4_s.bmp
 75%|███████▌  | 290/386 [05:45<01:48,  1.13s/it]
2_13_s.bmp
 76%|███████▋  | 295/386 [05:49<01:19,  1.15it/s]
4_18_s.bmp
 77%|███████▋  | 296/386 [05:51<01:41,  1.12s/it]
1_2_s.bmp
 77%|███████▋  | 297/386 [05:52<01:37,  1.10s/it]
8_25_s.bmp
 77%|███████▋  | 299/386 [05:54<01:33,  1.07s/it]
3_13_s.bmp
 78%|███████▊  | 301/386 [05:57<01:33,  1.10s/it]
4_16_s.bmp
 78%|███████▊  | 302/386 [05:59<01:56,  1.39s/it]
```

```
6_19_s.bmp
 79%|███████▉  | 305/386 [06:01<01:25,  1.06s/it]
5_25_s.bmp
 79%|███████▉  | 306/386 [06:04<01:47,  1.35s/it]
3_5_s.bmp
 80%|███████▉  | 307/386 [06:07<02:02,  1.55s/it]
5_15_s.bmp
 80%|███████▉  | 308/386 [06:09<02:22,  1.83s/it]
1_4_s.bmp
 80%|████████  | 310/386 [06:11<01:53,  1.50s/it]
8_20_s.bmp
 81%|████████  | 311/386 [06:13<01:55,  1.54s/it]
8_29_s.bmp
 81%|████████  | 312/386 [06:15<01:55,  1.57s/it]
1_13_s.bmp
 81%|████████  | 313/386 [06:17<02:17,  1.89s/it]
7_11_s.bmp
 82%|████████▏ | 316/386 [06:20<01:39,  1.42s/it]
8_17_s.bmp
 82%|████████▏ | 318/386 [06:22<01:24,  1.24s/it]
1_25_s.bmp
 83%|████████▎ | 319/386 [06:25<01:41,  1.51s/it]
1_8_s.bmp
 83%|████████▎ | 320/386 [06:28<01:56,  1.77s/it]
8_10_s.bmp
 83%|████████▎ | 321/386 [06:29<01:56,  1.80s/it]
5_13_s.bmp
 83%|████████▎ | 322/386 [06:32<02:06,  1.97s/it]
```

```
4_10_s.bmp
 84%|████████▎ | 323/386 [06:35<02:18,  2.20s/it]
8_19_s.bmp
 84%|████████▍ | 324/386 [06:37<02:11,  2.12s/it]
1_6_s.bmp
 84%|████████▍ | 326/386 [06:39<01:39,  1.67s/it]
3_25_s.bmp
 85%|████████▍ | 328/386 [06:42<01:30,  1.56s/it]
8_5_s.bmp
 85%|████████▌ | 329/386 [06:44<01:39,  1.75s/it]
1_12_s.bmp
 86%|████████▋ | 333/386 [06:46<00:55,  1.05s/it]
6_21_s.bmp
 87%|████████▋ | 334/386 [06:49<01:10,  1.36s/it]
1_11_s.bmp
 87%|████████▋ | 335/386 [06:52<01:22,  1.62s/it]
4_26_s.bmp
 87%|████████▋ | 336/386 [06:55<01:34,  1.89s/it]
3_18_s.bmp
 87%|████████▋ | 337/386 [06:57<01:39,  2.04s/it]
1_1_s.bmp
 88%|████████▊ | 339/386 [06:59<01:18,  1.67s/it]
4_12_s.bmp
 89%|████████▉ | 343/386 [07:02<00:49,  1.15s/it]
1_27_s.bmp
 89%|████████▉ | 344/386 [07:05<00:59,  1.41s/it]
7_13_s.bmp
 90%|█████████ | 349/386 [07:08<00:37,  1.00s/it]
```

```
2_28_s.bmp
 91%|█████████ | 351/386 [07:10<00:36,  1.05s/it]
2_3_s.bmp
 92%|█████████▏| 356/386 [07:13<00:23,  1.28it/s]
8_8_s.bmp
 92%|█████████▏| 357/386 [07:15<00:28,  1.03it/s]
4_30_s.bmp
 93%|█████████▎| 359/386 [07:18<00:30,  1.12s/it]
5_24_s.bmp
 94%|█████████▎| 361/386 [07:21<00:29,  1.16s/it]
3_17_s.bmp
 94%|█████████▍| 363/386 [07:23<00:27,  1.18s/it]
3_21_s.bmp
 94%|█████████▍| 364/386 [07:26<00:31,  1.43s/it]
5_14_s.bmp
 95%|█████████▍| 365/386 [07:29<00:35,  1.69s/it]
7_12_s.bmp
 95%|█████████▌| 367/386 [07:32<00:31,  1.65s/it]
2_19_s.bmp
 95%|█████████▌| 368/386 [07:35<00:32,  1.83s/it]
8_2_s.bmp
 96%|█████████▌| 369/386 [07:37<00:32,  1.91s/it]
3_15_s.bmp
 96%|█████████▌| 371/386 [07:39<00:24,  1.66s/it]
7_2_s.bmp
 97%|█████████▋| 374/386 [07:42<00:15,  1.30s/it]
6_11_s.bmp
 97%|█████████▋| 375/386 [07:45<00:17,  1.58s/it]
```

```
7_3_s.bmp
 97%|█████████▋| 376/386 [07:48<00:18,  1.87s/it]
6_3_s.bmp
 98%|█████████▊| 377/386 [07:51<00:19,  2.16s/it]
5_17_s.bmp
 98%|█████████▊| 378/386 [07:54<00:18,  2.33s/it]
2_12_s.bmp
 99%|█████████▉| 382/386 [07:56<00:04,  1.22s/it]
3_3_s.bmp
 99%|█████████▉| 383/386 [07:59<00:04,  1.57s/it]
6_7_s.bmp
100%|█████████▉| 385/386 [08:02<00:01,  1.51s/it]
4_20_s.bmp


Finished generating training data
  0%|          | 0/97 [00:00<?, ?it/s]
2_7_s.bmp
  1%|          | 1/97 [00:02<03:32,  2.22s/it]
1_28_s.bmp
  2%|▏         | 2/97 [00:04<03:47,  2.39s/it]
8_3_s.bmp
  3%|▎         | 3/97 [00:06<03:03,  1.95s/it]
4_7_s.bmp
  5%|▌         | 5/97 [00:09<02:33,  1.67s/it]
5_18_s.bmp
  6%|▌         | 6/97 [00:11<02:56,  1.94s/it]
2_6_s.bmp
  7%|▋         | 7/97 [00:14<03:16,  2.19s/it]
```

```
1_24_s.bmp
 10%|█         | 10/97 [00:17<02:08,  1.48s/it]
7_30_s.bmp
 12%|█▏        | 12/97 [00:20<02:08,  1.51s/it]
5_1_s.bmp
 13%|█▎        | 13/97 [00:22<02:14,  1.60s/it]
7_9_s.bmp
 18%|█▊        | 17/97 [00:24<01:28,  1.11s/it]
3_12_s.bmp
 22%|██▏       | 21/97 [00:27<01:10,  1.07it/s]
3_30_s.bmp
 24%|██▎       | 23/97 [00:29<01:09,  1.06it/s]
2_1_s.bmp
 27%|██▋       | 26/97 [00:32<01:08,  1.03it/s]
2_9_s.bmp
 28%|██▊       | 27/97 [00:35<01:23,  1.19s/it]
6_13_s.bmp
 30%|██▉       | 29/97 [00:38<01:25,  1.26s/it]
5_4_s.bmp
 31%|███       | 30/97 [00:40<01:38,  1.47s/it]
5_29_s.bmp
 33%|███▎      | 32/97 [00:43<01:34,  1.46s/it]
6_6_s.bmp
 36%|███▌      | 35/97 [00:46<01:18,  1.26s/it]
1_17_s.bmp
 38%|███▊      | 37/97 [00:49<01:21,  1.35s/it]
6_27_s.bmp
 40%|████      | 39/97 [00:52<01:19,  1.37s/it]
```

```
6_26_s.bmp
 41%|████      | 40/97 [00:55<01:31,  1.61s/it]
5_16_s.bmp
 43%|████▎     | 42/97 [00:57<01:22,  1.50s/it]
2_18_s.bmp
 45%|████▌     | 44/97 [01:00<01:17,  1.45s/it]
5_23_s.bmp
 46%|████▋     | 45/97 [01:03<01:27,  1.68s/it]
7_21_s.bmp
 49%|████▉     | 48/97 [01:06<01:06,  1.36s/it]
6_14_s.bmp
 51%|█████     | 49/97 [01:09<01:19,  1.65s/it]
8_18_s.bmp
 52%|█████▏    | 50/97 [01:11<01:26,  1.85s/it]
5_7_s.bmp
 55%|█████▍    | 53/97 [01:14<01:04,  1.48s/it]
3_27_s.bmp
 57%|█████▋    | 55/97 [01:17<00:56,  1.35s/it]
8_13_s.bmp
 58%|█████▊    | 56/97 [01:19<01:00,  1.48s/it]
8_7_s.bmp
 59%|█████▉    | 57/97 [01:21<01:03,  1.59s/it]
7_28_s.bmp
 62%|██████▏   | 60/97 [01:23<00:45,  1.22s/it]
6_20_s.bmp
 64%|██████▍   | 62/97 [01:26<00:45,  1.30s/it]
1_3_s.bmp
 65%|██████▍   | 63/97 [01:28<00:47,  1.39s/it]
```

```
2_30_s.bmp
 67%|██████▋   | 65/97 [01:30<00:43,  1.37s/it]
4_29_s.bmp
 68%|██████▊   | 66/97 [01:34<00:52,  1.69s/it]
2_14_s.bmp
 69%|██████▉   | 67/97 [01:37<01:01,  2.04s/it]
1_9_s.bmp
 70%|███████   | 68/97 [01:40<01:04,  2.22s/it]
5_5_s.bmp
 72%|███████▏  | 70/97 [01:42<00:48,  1.79s/it]
1_21_s.bmp
 78%|███████▊  | 76/97 [01:45<00:19,  1.06it/s]
4_21_s.bmp
 82%|████████▏ | 80/97 [01:47<00:14,  1.18it/s]
2_4_s.bmp
 84%|████████▎ | 81/97 [01:50<00:16,  1.06s/it]
1_14_s.bmp
 85%|████████▍ | 82/97 [01:53<00:19,  1.32s/it]
7_27_s.bmp
 87%|████████▋ | 84/97 [01:56<00:17,  1.35s/it]
8_27_s.bmp
 89%|████████▊ | 86/97 [01:58<00:14,  1.29s/it]
8_15_s.bmp
 94%|█████████▍| 91/97 [02:00<00:05,  1.16it/s]
2_16_s.bmp
 96%|█████████▌| 93/97 [02:02<00:03,  1.17it/s]
2_27_s.bmp
 97%|█████████▋| 94/97 [02:04<00:03,  1.05s/it]
```

```
8_26_s.bmp

 98%|█████████▊| 95/97 [02:06<00:02,  1.18s/it]

6_23_s.bmp

 99%|█████████▉| 96/97 [02:09<00:01,  1.43s/it]

3_19_s.bmp



Finished generating testing data
```

```
import os
import numpy as np
import torch
import torch.utils.data as data
from PIL import Image
from torchvision import transforms
import _pickle as pickle
import torch.nn as nn
import torchvision.models as models
import torch.nn.functional as F
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.optim.lr_scheduler import ReduceLROnPlateau
import time
import copy
# -------------
# Dataset class
# -------------
#
# ``torch.utils.data.Dataset`` is an abstract class representing a
# dataset.
# Your custom dataset should inherit ``Dataset`` and override the
following
# methods:
#
# -  ``__len__`` so that ``len(dataset)`` returns the size of the
dataset.
# -  ``__getitem__`` to support the indexing such that ``dataset[i]``
can
#    be used to get sp_i sample
#
# Let's create a dataset class for our superpixel dataset. We will
# read the csv in ``__init__`` but leave the reading of images to
# ``__getitem__``. This is memory efficient because all the images are
not
```

```
# stored in the memory at once but read as required.
#
# Sample of our dataset will be a dict
# ``{'superpixel image': image, 'superpixel class': class}``. Our
dataset will take an
# optional argument ``transform`` so that any required processing can
be
# applied on the sample. Remember to resize the image using
``transform``.

class SegmentationData(data.Dataset):
    def __init__(self, data_path, csv_file, transform=None):
      # Your code
      self.data = pd.read_csv(f'{data_path}/{csv_file}', skiprows=1,
header=None)
      self.data_size = len(self.data)
      self.data_path = data_path
      self.transform = transform


    def __len__(self):
      # Your code
      return self.data_size


    def __getitem__(self, index):
      # Your code
      filename = self.data.iloc[index, 1]
      image_path = f'{self.data_path}/{filename}'
      image = np.load(image_path, allow_pickle=True)
      label_y = int(self.data.iloc[index, 2])

      data_y = torch.tensor(label_y)
      if self.transform:
        image = self.transform(image)

      return (image, label_y)
```

Show some outputs! Choose 1 image. For that image, plot the image, along with the superpixel map for the image, as you did for Assignment 1. Then, show the first 10 superpixel patches for the image, retrieved from your dataset.

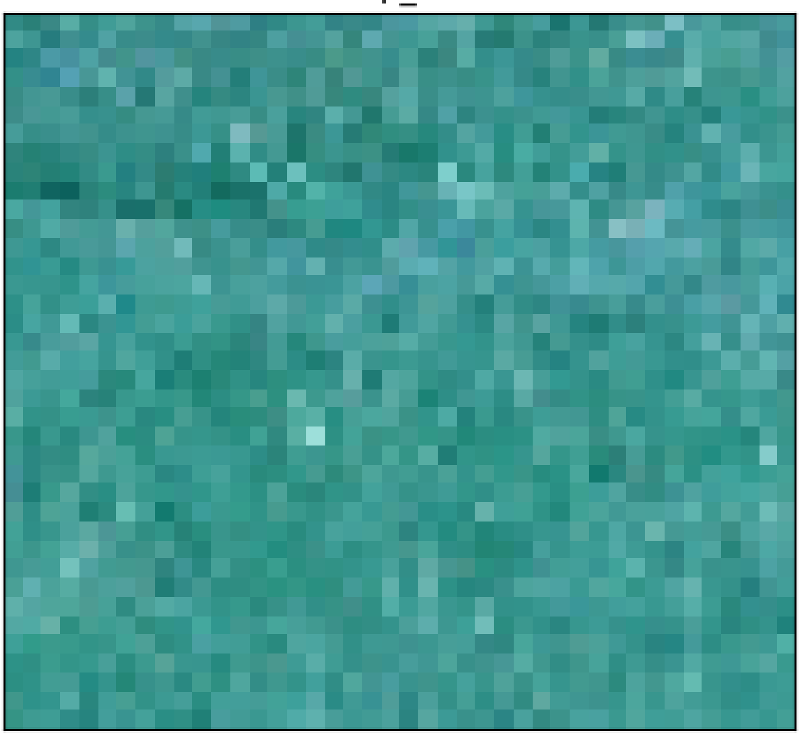
The output for this portion will be 12 images, displayed below your code below.

```
### YOUR CODE TO PLOT 12 images (original RGB + superpixel map + first
10 superpixels) ###
import glob
import cv2
test_image_name = "1_11_s.bmp"
test_image = cv2.imread(os.path.join(msrc_directory,"1_11_s.bmp"))
```

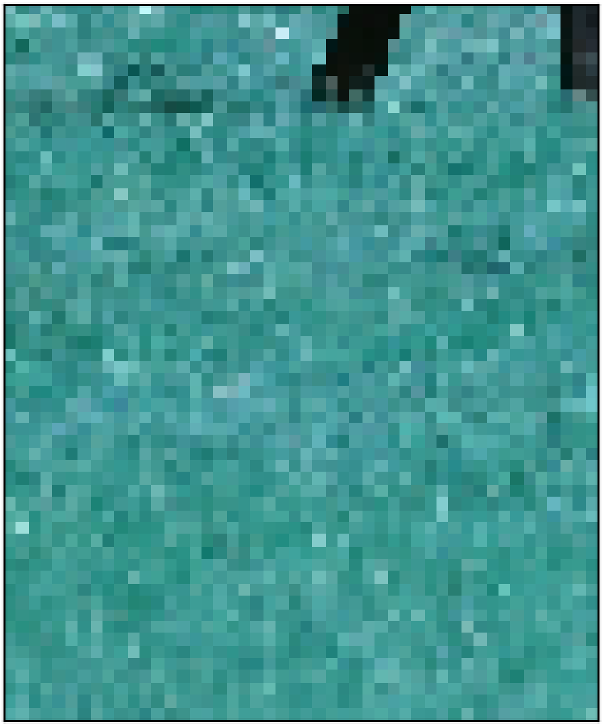
```
segments= slic(test_image, n_segments=100, compactness=10)
plot_image(test_image, 'image')

superpixel_plot(test_image, segments, title = "SLIC Segmentation
Superpixel plot")
i=0
print()
for file_name in glob.glob(msrc_directory+"/**/*.npy", recursive =
True):

  test_image_name=test_image_name.replace(".bmp","")

  if test_image_name in file_name:
    i=i+1
    plot_image(np.load(file_name),"sp_"+str(i))
    if i == 10:
      break
```

SLIC Segmentation Superpixel plot

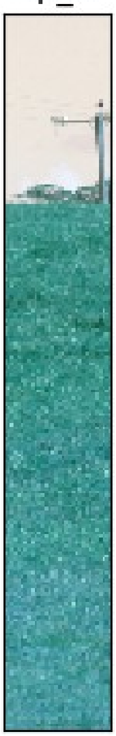
sp_1



sp_2



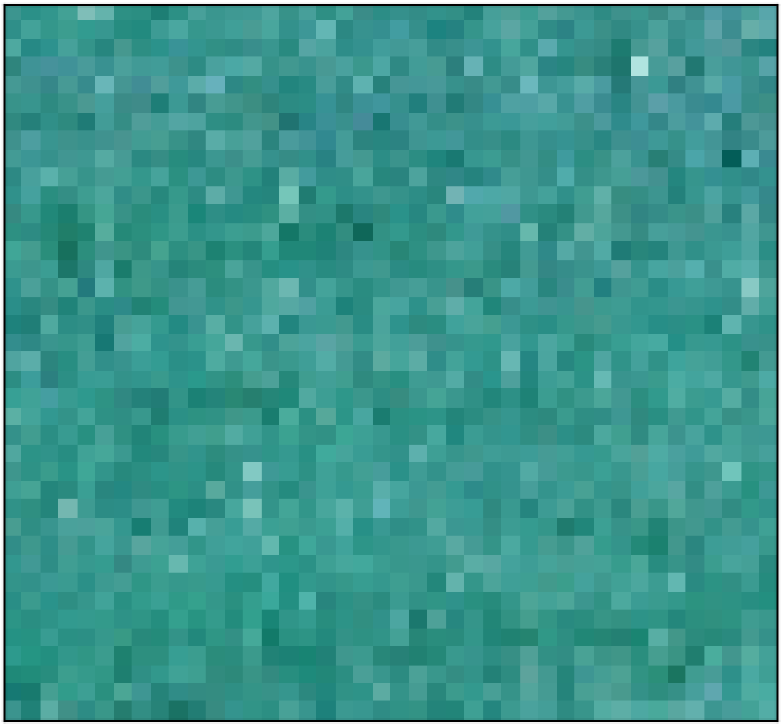
sp_3



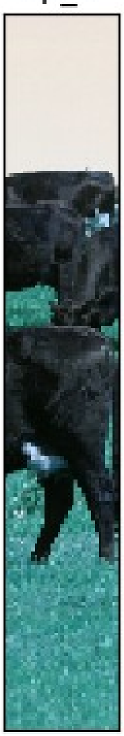
sp_4

sp_5

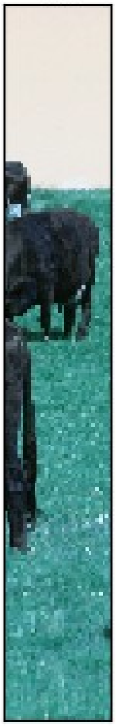
sp_6



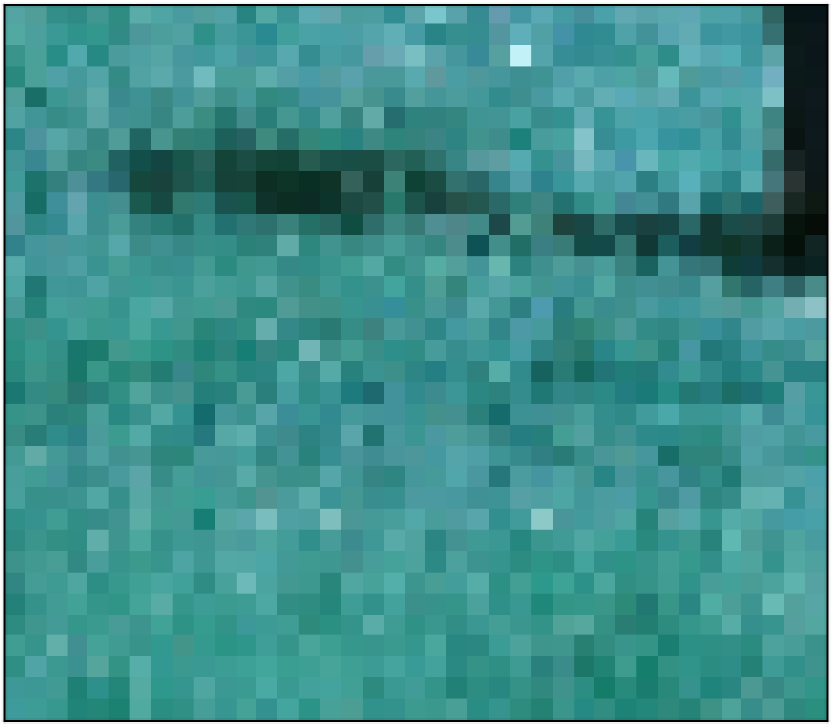
sp_7



sp_8



sp_9




```
is_cuda_available = torch.cuda.is_available()
if is_cuda_available:
    print("Using CUDA")
device = torch.device("cuda:0" if is_cuda_available else "cpu")
print(device)

Using CUDA
cuda:0
```

Question 6: Deep Network (10 points)

You could use a pre-trained network (like VGG) and replace the last few layers with a fully connected layer.

```
# Model definition
#Using RESNET18 pretrained model and replacing last layers with fully
connected layer
class SegmentationNN(nn.Module):
    def __init__(self):
        super(SegmentationNN, self).__init__()

        self.super_res_net =
models.resnet18(weights=models.ResNet18_Weights.DEFAULT)
        self.super_res_net.fc=nn.Linear(512,10)
```

```
        for param in self.super_res_net.parameters():
            param.requires_grad = False

        for param in self.super_res_net.fc.parameters():
            param.requires_grad=True
        self.softmax_layer=nn.Softmax(dim=-1)
        print(self.super_res_net)
        self.super_res_net.to(device)

    def forward(self, x):
        y = self.super_res_net(x)

        return y
```

Question 7: Optimizer (10 points)

Finally, we define the classification loss and optimizer such that we can learn a superpixel classifier from the backproporgation algorithm.

```


# hyperparameters
number_of_epochs = 15
learning_rate = 1e-3
# Optimizer
import time
class Solver(object):
    def __init__(self, super_res_net, learning_rate=learning_rate):
      self.super_res_net = super_res_net
      self.criterion = nn.CrossEntropyLoss()
      self.optimizer = optim.Adam(super_res_net.parameters(),
lr=learning_rate)
      self.scheduler = ReduceLROnPlateau(self.optimizer, factor=0.1,
patience=5, verbose=True
      )
      #Create list for accuracy and losses
      self.epoch_accuracy = []
      self.epoch_loss = []
      self.running_loss = []
      self.running_acc = []

    def train(self, data_loader):
        # Your code
        self.best_accuracy=0.0
        self.super_res_net.train()
        starting_time = time.time()
        for epoch in range(number_of_epochs):
          list_losses = []
          running_corrects = 0
```

```
          n_sample = 0
          best_accuracy=0.0
          best_model_wts =
copy.deepcopy(self.super_res_net.state_dict())
          data= tqdm(enumerate(data_loader), total=len(data_loader),
leave=True)

          for idx, (inputs, labels) in data:

            inputs = inputs.to(device=device)
            labels = labels.to(device=device)
            # forward
            pred_labels = self.super_res_net(inputs)
            _, preds = torch.max(pred_labels, 1)

            loss = self.criterion(pred_labels, labels)

            list_losses.append(loss.item())

            running_corrects += torch.sum(preds == labels)
            n_sample += pred_labels.size(0)


            self.optimizer.zero_grad()
            loss.backward()

            self.optimizer.step()

            data.set_description(f'Epoch
[{epoch}/{number_of_epochs}]')
            data.set_postfix(loss=loss.item(),
acc=(running_corrects/n_sample).item())


self.running_loss.append(sum(list_losses)/len(list_losses))

          average_loss = sum(list_losses)/len(list_losses)
          average_accuracy = running_corrects/n_sample
          self.scheduler.step(average_loss)

          self.epoch_accuracy.append(average_accuracy)
          self.epoch_loss.append(average_loss)

          time_diff = time.time() - starting_time
          print('Epoch: [{}/{}] Time: {}min:{}sec Training Loss:
{:.4f} Acc: {:.4f}'.format(epoch, number_of_epochs, time_diff//60,
time_diff%60, average_loss, average_accuracy))

    def testing(self, data_loader):
        self.super_res_net.eval()
        self.epoch_acc = []
```

```
        start = time.time()
        for epoch in range(number_of_epochs):
          running_corrects = 0
          n_sample = 0
          data = tqdm(enumerate(data_loader), total=len(data_loader),
leave=True)
          with torch.no_grad():
            for _, (input, labels) in data:
              input = input.to(device=device)
              labels = labels.to(device=device)

              # forward
              pred_labels = self.super_res_net(input)
              _, preds = torch.max(pred_labels, 1)

              running_corrects += torch.sum(preds == labels)
              n_sample += pred_labels.size(0)

              data.set_description(f'Epoch
[{epoch}/{number_of_epochs}]')
              data.set_postfix(acc=(running_corrects/n_sample).item())

          average_accuracy = running_corrects/n_sample

          self.epoch_acc.append(average_accuracy)

          time_diff = time.time() - start
          print('Epoch: [{}/{}] Time: {}min:{}sec Acc:
{:.4f}'.format(epoch, number_of_epochs, time_diff//60, time_diff%60,
average_accuracy))
```

Question 8: Putting it together (50 points)

Train your network and observe the loss in time. During the inference stage, combine the SLIC Superpixels' predicted labels to form the whole input image's superpixel segmentation results. The following 4 items are the primary graded components:

1. You must randomly split the whole dataset into train and test subset (80:20 split is fine).
2. You must show the training loss of the classifier after every epoch
3. You must show the training accuracy and test accuracy of the classifier after training.
4. You must plot as least one visualization showing the test segmentation map vs. ground truth segmentation map.

```
transform_train = transforms.Compose([
        transforms.ToPILImage(),
        transforms.Resize((224,224)),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
```

```
        transforms.Normalize((0.485, 0.456, 0.406), (0.229, 0.224,
0.225))
    ])
transform_test = transforms.Compose([
    transforms.ToPILImage(),
    transforms.Resize((224,224)),
    transforms.ToTensor(),
    transforms.Normalize((0.485, 0.456, 0.406), (0.229, 0.224, 0.225))
])



# load the data
train_dataset = SegmentationData(training_path, 'train.csv',
transform_train)
test_dataset = SegmentationData(testing_path, 'test.csv',
transform_test)


# data loader
train_data_loader = data.DataLoader(dataset=train_dataset,
batch_size=128 ,shuffle=True, num_workers=2)
test_data_loader = data.DataLoader(dataset=test_dataset,
batch_size=128, shuffle=True, num_workers=2)

dataiter = iter(train_data_loader)
data_samp = next(dataiter)
print(data_samp[0][0].shape)
#model
super_res_net = SegmentationNN()
# train the model

solver = Solver(super_res_net, learning_rate)
# start training
solver.train(train_data_loader)
print('Training Done!')
```

```
torch.Size([3, 224, 224])
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2),
padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1,
ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
```

```
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2),
bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
```

```
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2),
bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2),
bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
```

```
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=512, out_features=10, bias=True)
)

Epoch [0/15]: 100%|██████████| 90/90 [00:28<00:00,  3.21it/s,
acc=0.651, loss=0.738]

Epoch: [0/15] Time: 0.0min:28.171237230300903sec Training Loss: 1.0808
Acc: 0.6509


Epoch [1/15]: 100%|██████████| 90/90 [00:22<00:00,  4.07it/s,
acc=0.793, loss=0.474]

Epoch: [1/15] Time: 0.0min:50.441810131073sec Training Loss: 0.6116
Acc: 0.7927


Epoch [2/15]: 100%|██████████| 90/90 [00:22<00:00,  4.06it/s,
acc=0.818, loss=0.454]

Epoch: [2/15] Time: 1.0min:12.766627550125122sec Training Loss: 0.5188
Acc: 0.8181


Epoch [3/15]: 100%|██████████| 90/90 [00:25<00:00,  3.58it/s,
acc=0.834, loss=0.629]

Epoch: [3/15] Time: 1.0min:38.01956534385681sec Training Loss: 0.4746
Acc: 0.8343


Epoch [4/15]: 100%|██████████| 90/90 [00:22<00:00,  4.04it/s,
acc=0.838, loss=0.352]

Epoch: [4/15] Time: 2.0min:0.5265746116638184sec Training Loss: 0.4447
Acc: 0.8384
```

```
Epoch [5/15]: 100%|██████████| 90/90 [00:22<00:00,  4.08it/s,
acc=0.846, loss=0.46]

Epoch: [5/15] Time: 2.0min:22.734110593795776sec Training Loss: 0.4278
Acc: 0.8456


Epoch [6/15]: 100%|██████████| 90/90 [00:21<00:00,  4.12it/s,
acc=0.854, loss=0.386]

Epoch: [6/15] Time: 2.0min:44.70318675041199sec Training Loss: 0.4100
Acc: 0.8536


Epoch [7/15]: 100%|██████████| 90/90 [00:21<00:00,  4.13it/s,
acc=0.858, loss=0.384]

Epoch: [7/15] Time: 3.0min:6.651939392089844sec Training Loss: 0.3963
Acc: 0.8582


Epoch [8/15]: 100%|██████████| 90/90 [00:21<00:00,  4.12it/s,
acc=0.864, loss=0.425]

Epoch: [8/15] Time: 3.0min:28.624839544296265sec Training Loss: 0.3784
Acc: 0.8643


Epoch [9/15]: 100%|██████████| 90/90 [00:22<00:00,  4.09it/s,
acc=0.865, loss=0.389]

Epoch: [9/15] Time: 3.0min:50.770721673965454sec Training Loss: 0.3720
Acc: 0.8646


Epoch [10/15]: 100%|██████████| 90/90 [00:22<00:00,  4.06it/s,
acc=0.87, loss=0.358]

Epoch: [10/15] Time: 4.0min:13.086344480514526sec Training Loss:
0.3617 Acc: 0.8696


Epoch [11/15]: 100%|██████████| 90/90 [00:22<00:00,  4.07it/s,
acc=0.866, loss=0.236]

Epoch: [11/15] Time: 4.0min:35.34725832939148sec Training Loss: 0.3612
Acc: 0.8663


Epoch [12/15]: 100%|██████████| 90/90 [00:22<00:00,  4.06it/s,
acc=0.874, loss=0.453]
```

```
Epoch: [12/15] Time: 4.0min:57.67282724380493sec Training Loss: 0.3471
Acc: 0.8740


Epoch [13/15]: 100%|██████████| 90/90 [00:22<00:00,  4.06it/s,
acc=0.876, loss=0.454]

Epoch: [13/15] Time: 5.0min:19.95331072807312sec Training Loss: 0.3474
Acc: 0.8757


Epoch [14/15]: 100%|██████████| 90/90 [00:21<00:00,  4.10it/s,
acc=0.874, loss=0.288]

Epoch: [14/15] Time: 5.0min:42.05187749862671sec Training Loss: 0.3421
Acc: 0.8739
Training Done!
```

```
# del super_res_net
#   I am doing 80-20 split on data i.e, 20 is testing
solver.testing(test_data_loader)
print('testing finished. Lets go!')
```

```
Epoch [0/15]: 100%|██████████| 24/24 [00:05<00:00,  4.15it/s,
acc=0.805]

Epoch: [0/15] Time: 0.0min:5.938882350921631sec Acc: 0.8050


Epoch [1/15]: 100%|██████████| 24/24 [00:05<00:00,  4.24it/s,
acc=0.805]

Epoch: [1/15] Time: 0.0min:11.72918963432312sec Acc: 0.8050


Epoch [2/15]: 100%|██████████| 24/24 [00:05<00:00,  4.25it/s,
acc=0.805]

Epoch: [2/15] Time: 0.0min:17.49733304977417sec Acc: 0.8050


Epoch [3/15]: 100%|██████████| 24/24 [00:05<00:00,  4.20it/s,
acc=0.805]

Epoch: [3/15] Time: 0.0min:23.337915182113647sec Acc: 0.8050


Epoch [4/15]: 100%|██████████| 24/24 [00:05<00:00,  4.22it/s,
acc=0.805]
```

```
Epoch: [4/15] Time: 0.0min:29.15439224243164sec Acc: 0.8050

Epoch [5/15]: 100%|██████████| 24/24 [00:05<00:00,  4.20it/s,
acc=0.805]

Epoch: [5/15] Time: 0.0min:34.997843742370605sec Acc: 0.8050

Epoch [6/15]: 100%|██████████| 24/24 [00:05<00:00,  4.24it/s,
acc=0.805]

Epoch: [6/15] Time: 0.0min:40.78106117248535sec Acc: 0.8050

Epoch [7/15]: 100%|██████████| 24/24 [00:05<00:00,  4.22it/s,
acc=0.805]

Epoch: [7/15] Time: 0.0min:46.59689784049988sec Acc: 0.8050

Epoch [8/15]: 100%|██████████| 24/24 [00:05<00:00,  4.25it/s,
acc=0.805]

Epoch: [8/15] Time: 0.0min:52.37264657020569sec Acc: 0.8050

Epoch [9/15]: 100%|██████████| 24/24 [00:05<00:00,  4.23it/s,
acc=0.805]

Epoch: [9/15] Time: 0.0min:58.17456531524658sec Acc: 0.8050

Epoch [10/15]: 100%|██████████| 24/24 [00:05<00:00,  4.21it/s,
acc=0.805]

Epoch: [10/15] Time: 1.0min:3.9951138496398926sec Acc: 0.8050

Epoch [11/15]: 100%|██████████| 24/24 [00:05<00:00,  4.24it/s,
acc=0.805]

Epoch: [11/15] Time: 1.0min:9.786503314971924sec Acc: 0.8050

Epoch [12/15]: 100%|██████████| 24/24 [00:05<00:00,  4.21it/s,
acc=0.805]

Epoch: [12/15] Time: 1.0min:15.63439655303955sec Acc: 0.8050

Epoch [13/15]: 100%|██████████| 24/24 [00:05<00:00,  4.22it/s,
acc=0.805]
```

```
Epoch: [13/15] Time: 1.0min:21.456085443496704sec Acc: 0.8050


Epoch [14/15]: 100%|██████████| 24/24 [00:05<00:00,  4.20it/s,
acc=0.805]

Epoch: [14/15] Time: 1.0min:27.30000591278076sec Acc: 0.8050
testing finished. Lets go!
```

```
files = os.listdir(msrc_directory)
total_images = len(files)
training_size = int(len(files) * 0.8)
testing_size = total_images - training_size
train_files = files[:training_size]
test_files = files[training_size:]
random_image=test_files[11]# took random image from test images our
segmentation model

test_image_file=random_image
test_image_gt_filelocation = random_image.replace(".bmp",
("_GT"+".bmp"))

test_image_file = os.path.join(msrc_directory, test_image_file)
test_image_gt_filelocation = os.path.join(msrc_directory,
test_image_gt_filelocation)

test_image = cv2.imread(test_image_file)
test_image_groundtruth = cv2.imread(test_image_gt_filelocation)
#convert bgr to rgb since cv2 gives bgr
test_image = test_image[:,:,::-1]
test_image_groundtruth = test_image_groundtruth[:,:,::-1]


segmented_map = slic(test_image, n_segments=100, compactness=10)
map_labels = {}
predicted_seg = np.zeros(test_image.shape)
super_res_net.eval()
for i in range(100):
  rect_loc = rectangle_patch_location(segmented_map, i)
  if rect_loc is not None:
    image_patch=crop_img(test_image,rect_loc)
    image_patch = transform_test(image_patch).to(device)
    cut_image = image_patch.unsqueeze(0)

    pred_labels = super_res_net(cut_image)
    _, preds = torch.max(pred_labels, 1)
    #-1 now since I did +1 in the model
    map_labels[i] = preds.item() - 1
    ind = (segmented_map == i)
```

```
    predicted_seg[ind] = labels_2_rgb[preds.item()-1]

plot_image(test_image, 'image')
plot_image(predicted_seg, 'predicted_segement')
plot_image(test_image_groundtruth, 'segmented_ground truth')
```

```
Clipping input data to the valid range for imshow with RGB data
([0..1] for floats or [0..255] for integers).
```

image

predicted_segement

segmented_ground truth

Question 9: Bonus Question (20 points, OPTIONAL):

IMPORTANT: No matter which option you choose, you can earn a maximum of 20 points for this section.

We always want to increase the classifier accuracy and achieve a better performance by building a complicated deep learning model. There are a lot of tricks which are very popular and work in practice. Try to implement either of following two,

1. Could you effictively fuse different deep features from multiple layers in your network? You are welcome to use the pretrained network. Does your network achieve a better accuracy? There are a lot of exploration in the literature, including ION (Inside-Outside Net) [1], Hypercolumns [2], and PixelNet [3]. The following figure illustrates ION architecture combining features from different layers. Can you do similar thing for our Superpixel classifier?

2. Could you build a Multi-resolution network to explore the effectiveness of the multi-scale on the task of Superpixels segmentation? By multi-scale, we mean multiple resolutions of superpixels. See [4] for an example.

[1] Inside-Outside Net: Detecting Objects in Context with Skip Pooling and Recurrent Neural Networks

[2] Hypercolumns for Object Segmentation and Fine-grained Localization

[3] PixelNet: Representationofthe pixels, by the pixels, and for the pixels

[4] Feedforward semantic segmentation with zoom-out features

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# Bonus
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