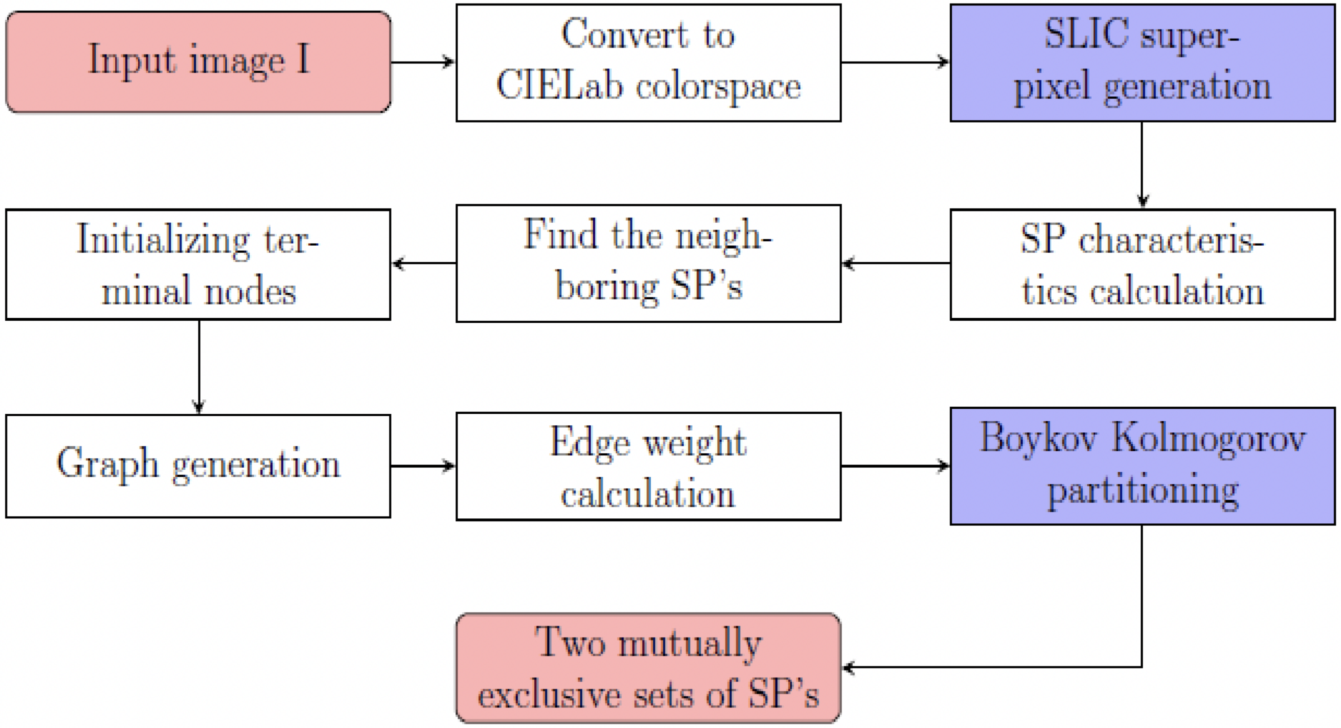
SuperPixel Image Segmentation using Graph Cuts and SLIC

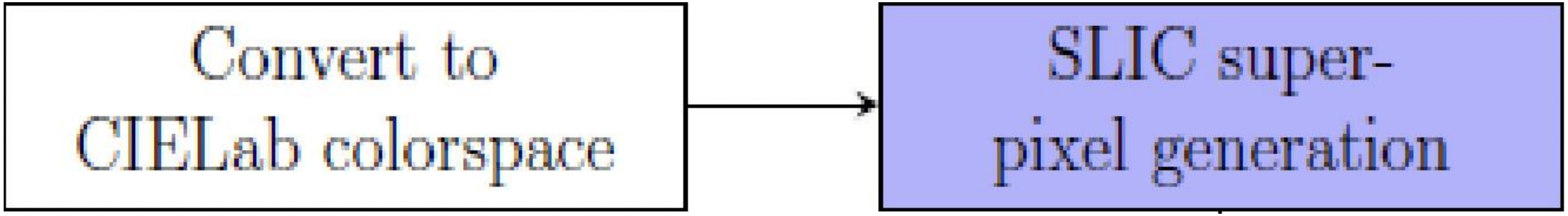
Shantanu Welling

Isha Arora

Karan Godara

Proposed Method





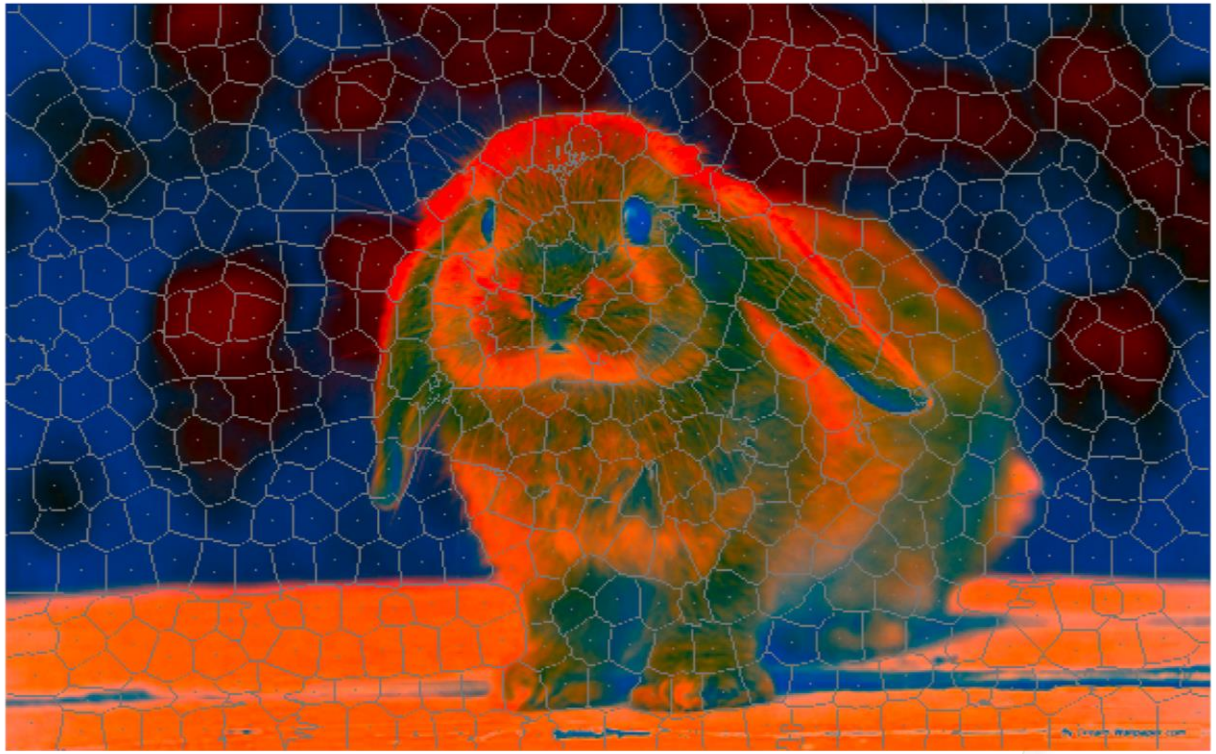
Algorithm 1: General structure of Super-pixelization algorithm.
Input : An Image with N pixels
Output: Labeled pixels

```
Initialize cluster centers C_k = [l_k, a_k, b_k, x_k, y_k]^T
Perturb C_k in an n x n neighborhood, to the
  minimal gradient position.
do
    for each cluster center do
        Assign the most similar pixels from a 2S x 2S square
        neighborhood region.
    end
    Determine new C_k and residual error E
while E > threshold;
Impose connectivity.
```

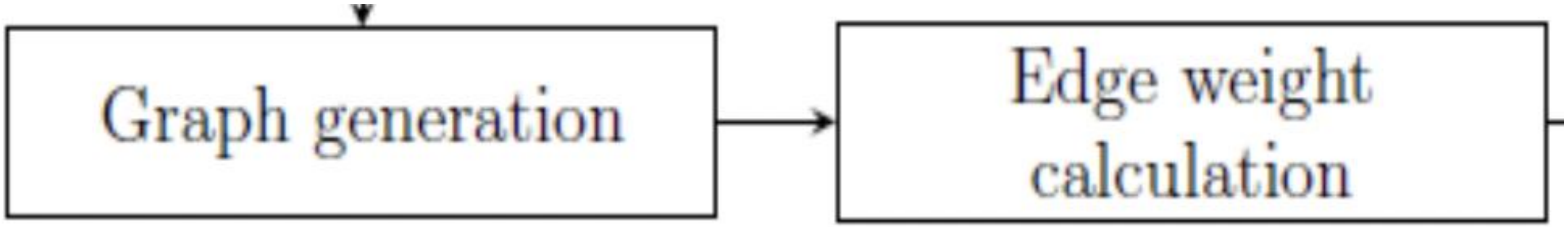
Super Pixelization has a remarkable contribution to the runtime of the partitioning algorithm

- Works on 5D image data, L, a, b color values and x, y pixel coordinates

$$d_{lab} = \sqrt{(l_k - l_i)^2 + (a_k - a_i)^2 + (b_k - b_i)^2}$$
$$d_{xy} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2}$$
$$D_s = d_{lab} + \frac{m}{S} d_{xy} \ ,$$

Original Image v/s SLIC Image in CIELab space



Edge	*Weight (cost)*	*for*
$\{p,q\}$	B_{pq}	$\{p,q\} \in N$
	$\lambda.R_p(\text{"}bkg\text{"})$	$p \in P, p \notin O \cup B$
$\{p,S\}$	K	$p \in O$
	0	$p \in B$
	$\lambda.R_p(\text{"}obj\text{"})$	$p \in P, p \notin O \cup B$
$\{p,T\}$	0	$p \in O$
	K	$p \in B$

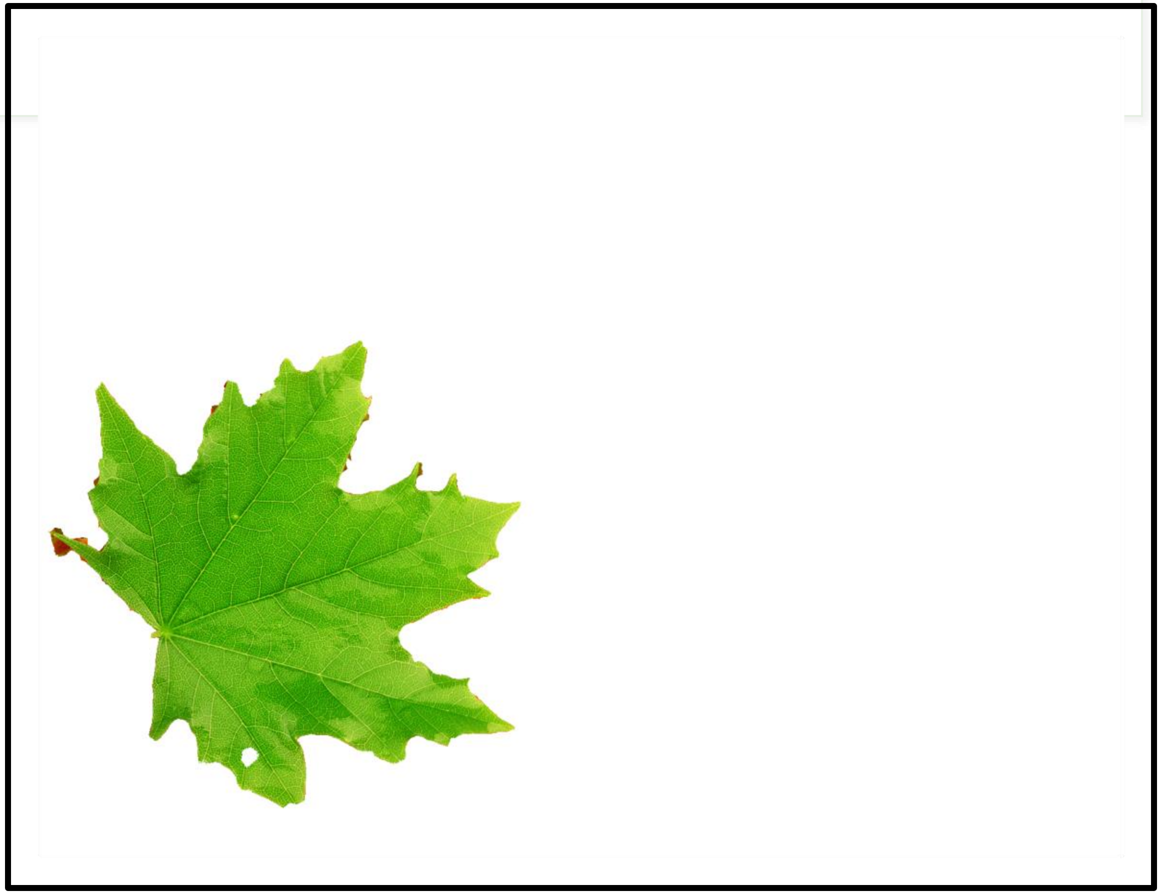
$$B_{pq} \alpha \exp\left(-\frac{(I_p - I_q)^2}{2\sigma^2}\right) \cdot \frac{1}{dist(I_p, I_q)}.$$

$$R_p(\text{"}bkg\text{"}) = -ln[P_r(C_p|H_B)]$$
$$R_p(\text{"}obj\text{"}) = -ln[P_r(C_p|H_O)]$$

Experimental Parameters

- Tested on sample images for background – foreground separation
- Tested σ among {0.1, 10, 25}
- Tunable hyperparameter λ in [0,1]. Optimal is 0.9 (visually).
- It describes the relative importance between regional and boundary terms.
- Small lambda implies less significance of regional term and relatively more weightage of boundary terms

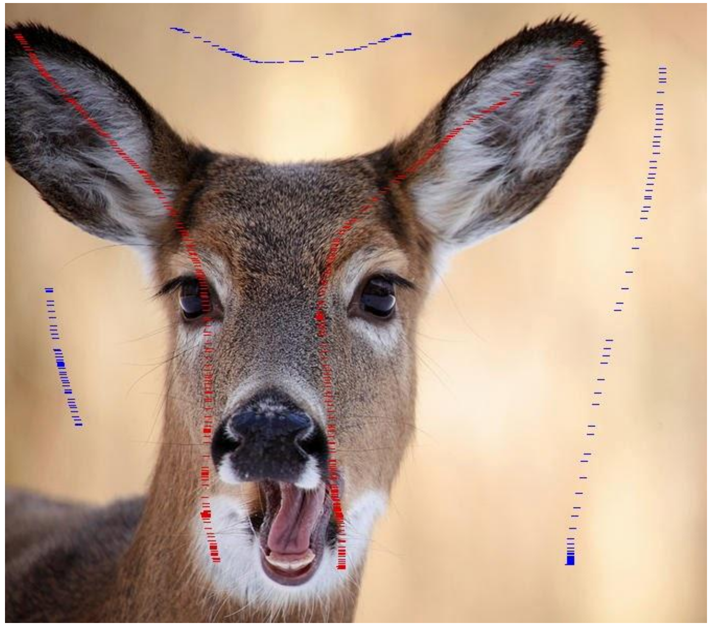
Results



Results

Classification accuracy of 99.94% on comparison with mask

Top left- Original Image
Top Right- Segmented Image
Bottom left- Ground Truth Mask
Bottom Right- User markings



Results
Colorspace Comparison

Original Image

CIELab Space

User markings

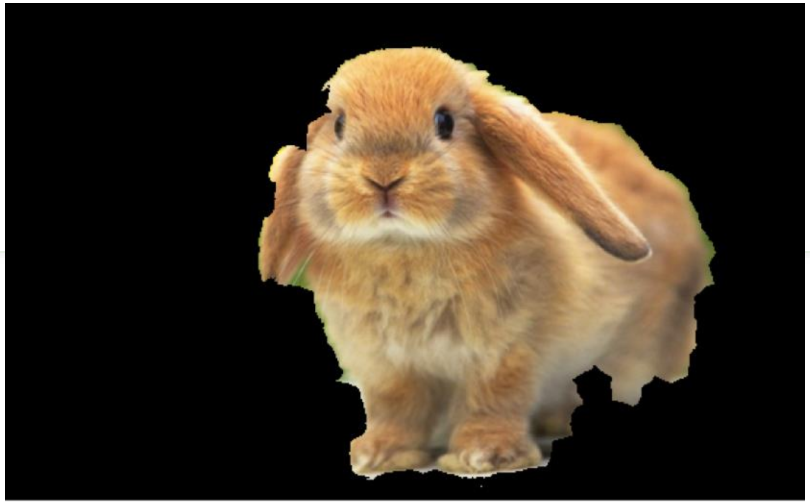
RGB Space

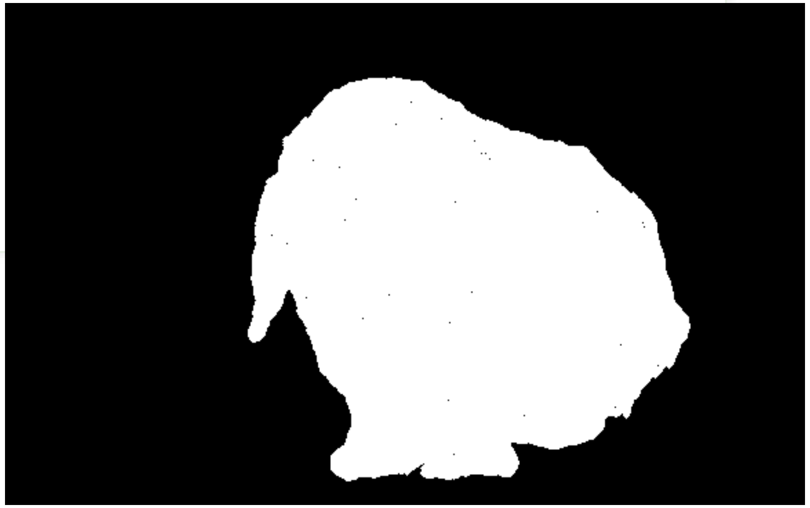
Results
σ Comparison

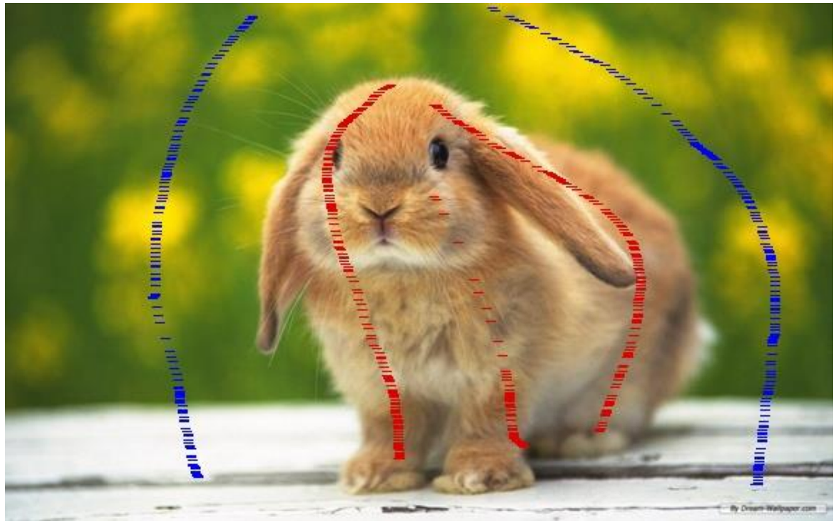
  

Sigma = 0.1, 10, 25

Results RGB vs CIELab







Original Image, Segmented Image in RGB, ground truth mask, user marking, CIElab segmentation (From top left ..)

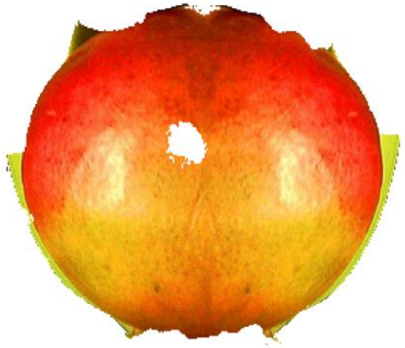
Accuracy 99.94%, 99.92% on Lab and RGB channel

Results Colorspace Comparison

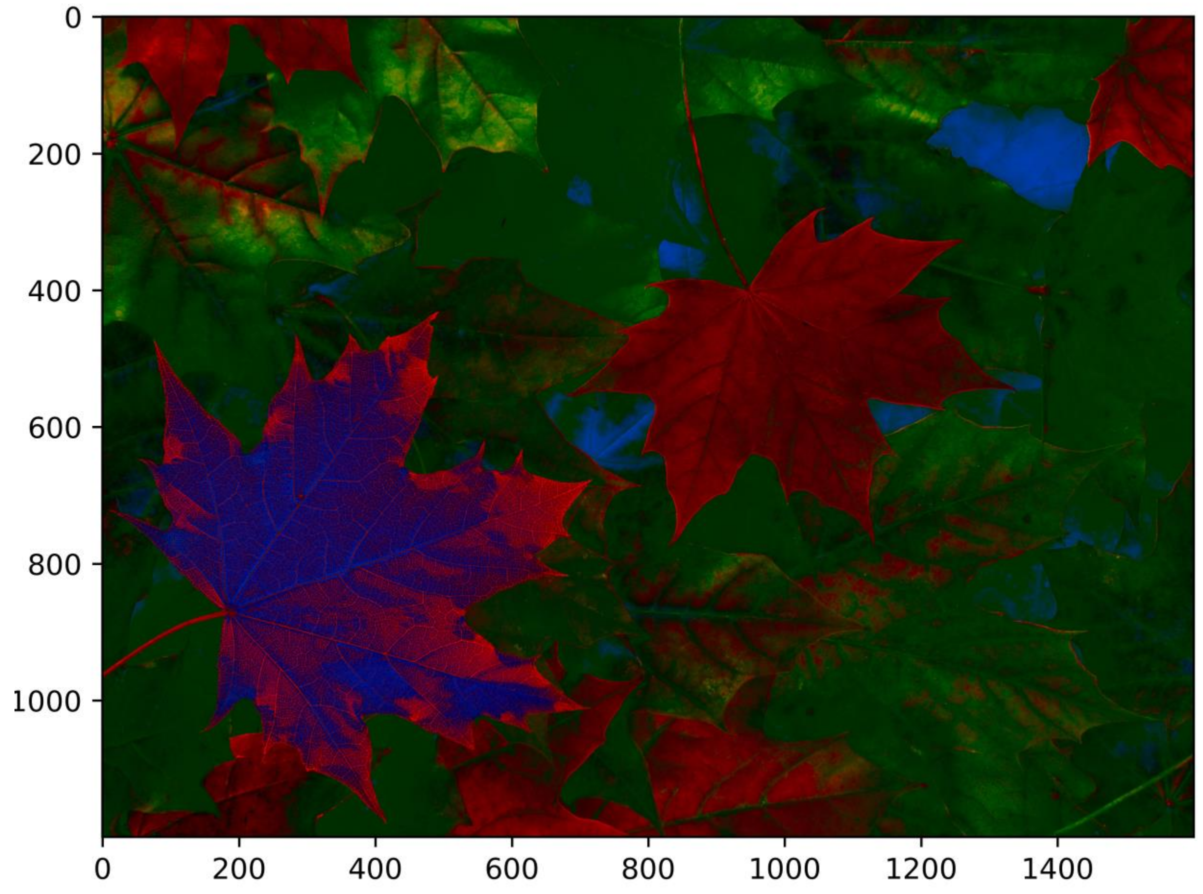
Original image,
CIELab segmentation

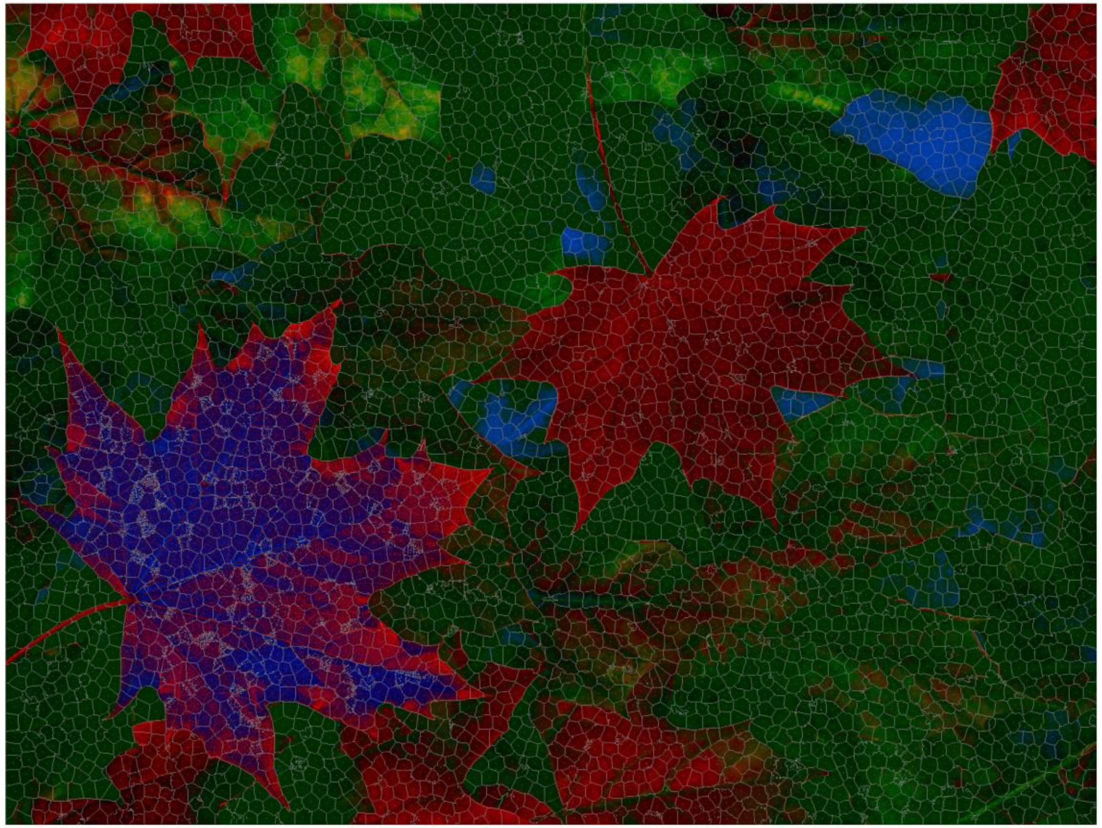
RGB Segmentation

Results



Results





Simple Linear Iterative Clustering Algorithm Over-Segmentation (SLICO) for Superpixel generation in CIELab colorspace

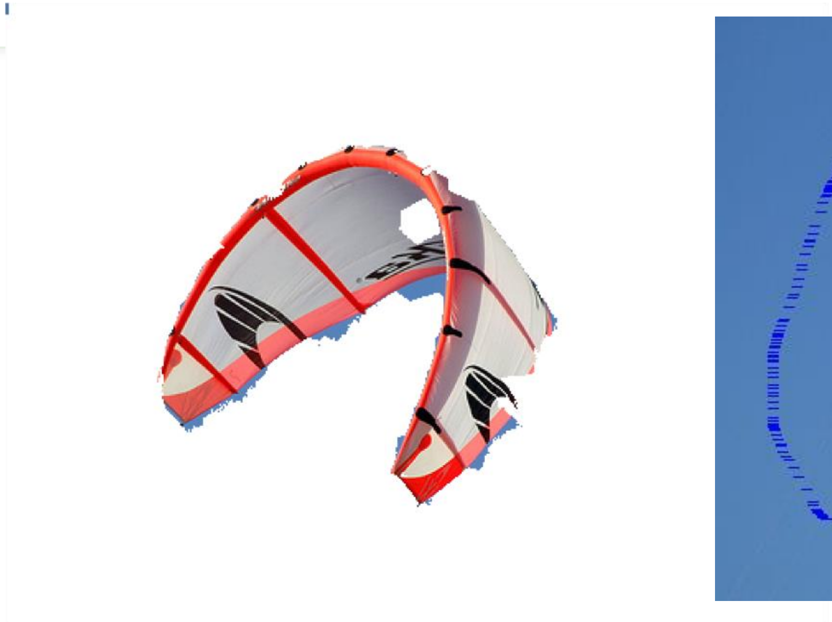
Results
Similar color assignment

Results
Constrained graph

Results: Superpixel granularity

Results

Results



Results

Results

Comparing execution time with and without using superpixels:

Since our algorithm is $O(m*n^2|C|)$, a factor of 20 (each superpixel consists of 20 pixels on average) in n will increase execution time by 20^3.

Using Super pixels : time = 1 min approx

W/O Super pixels : time = interrupted at 15 min (expected 8000 min)

Conclusion

- Usage of superpixels and CIELab colorspace reduced time complexity and increased accuracy significantly
- Performed better for smaller sigma which is intuitive
- Boykov Kolmogorov Network flow algorithm gives good segmentation
- Complex cues like texture could improve the results in scenarios where the color difference between object and background is not so distinguishable.

THANKYOU

Shantanu Welling (210010076)
Karan Godara (210050082)
Isha Arora (210050070)