Image Segmentation

Sree Tushar
Anirudh Gajjala

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Questions

1. What is image segmentation? (you can explain it in your own words as per your understanding)
2. Fill in the Blanks:

   OTSU Thresholding Algorithm _________ within-class variance and ________ between-class variance.

3. Which Image Segmentation Algorithm did you like the most?

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- ➔ PhD Student, Computer Engineering
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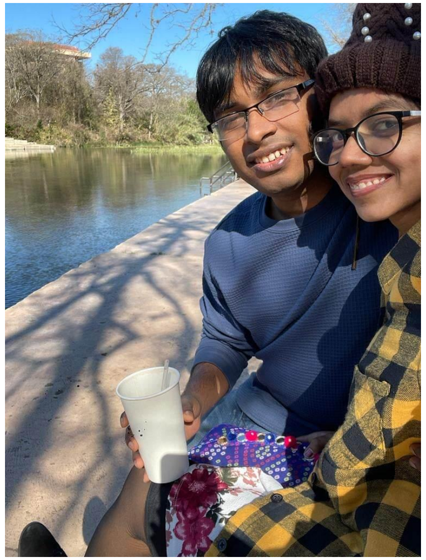
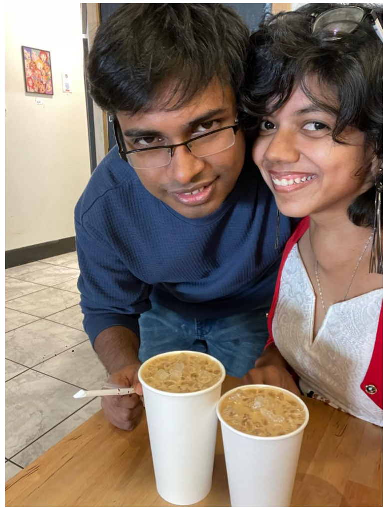
- ➔ MS from TXST (EE)
- ➔ Hindu, Vegetarian
- ➔ Language (Bangla, English)

Tourist Attractions

Hobbies and Family

- Story Writing
- Photography
- Listening Music
- Traveling
- Favourite Sport: Soccer, Cricket
- Gitanjoli by Rabindranath Thakur
- Sherlock Holmes





Traveling

Food

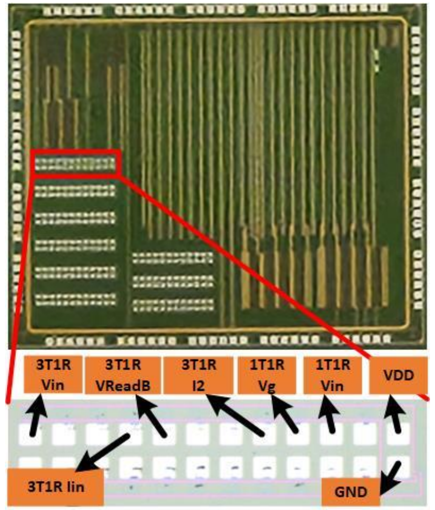
Research (SENECA Lab)

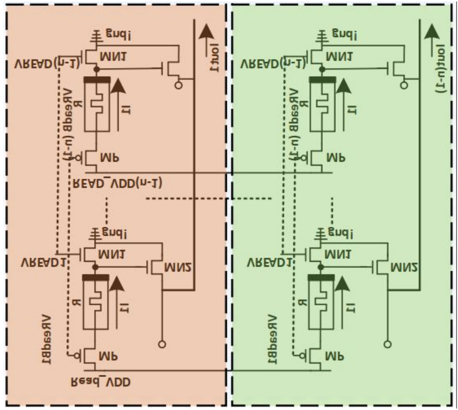
Nonvolatile Multiple Bit Emerging Memory

In Memory Computing

Biologically inspired Algorithm

Low power Machine Learning, Control System





Dr. Garret Rose

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MAHE
Skyscape_Photography
India - States and Capitals

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Charminar | Ramoji Film City | Buddha Statue, Hussain Sagar Lake

Salar Jung Museum | Golconda Fort | Birla Mandir

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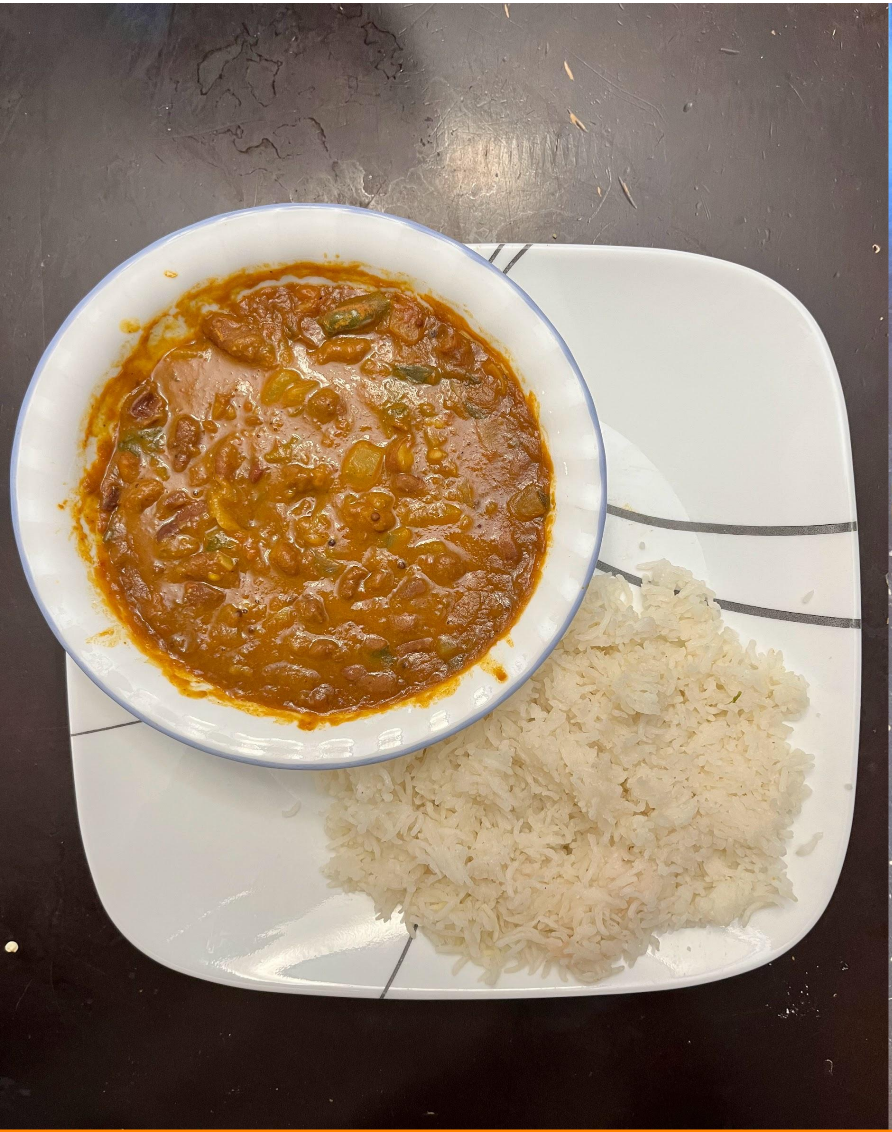
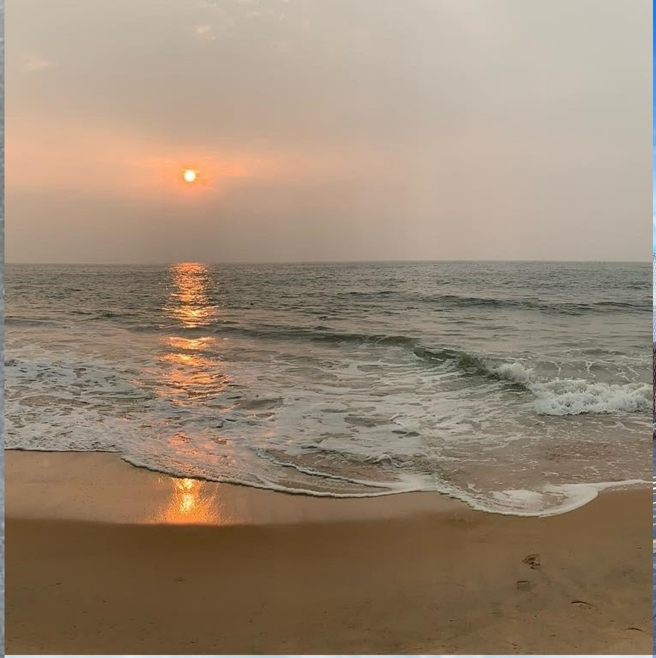
Irani Chai Hyderabadi Biriyani Osmania Biscuits
Stuffed Brinjal Curry Haleem Butter Masala Dosa

My Culinary Chronicles





Outline

- History of Image Segmentation
- Algorithms
  - Global Thresholding
  - Otsu Thresholding
  - K-Means Clustering
  - CNN
  - U-Net Architecture
- Applications
- Open Issues
- References and Discussions
- Test Questions Revisited

Overview

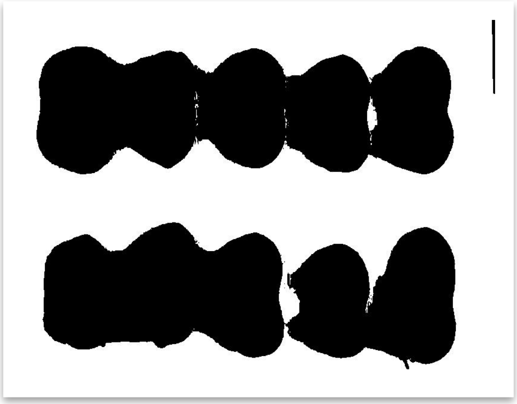
- ➢ Image Segmentation: Image Segmentation is the process of partitioning a digital image into multiple image segments, also known as image regions or image objects (sets of pixels).
- ➢ Pixel: The smallest unit of an image that can be represented or processed.
- ➢ Clustering: It is a technique in unsupervised machine learning that groups similar data points or objects together based on their attributes. Can be used for image segmentation.
- ➢ Image Segmentation Applications:
  - Medical Imaging
  - Object Detection and Tracking
  - Agriculture
  - Environmental Monitoring
  - Entertainment and Gaming
  - Astronomy

History

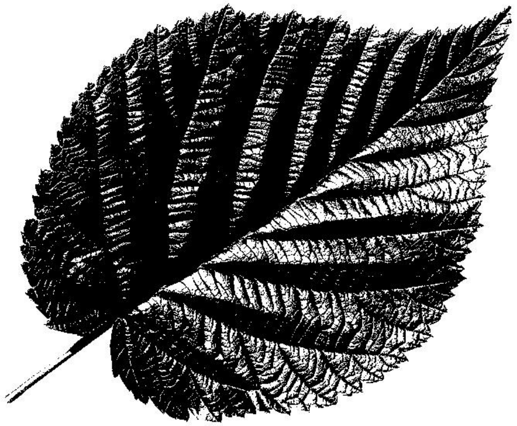
- Early Developments: Image segmentation has a long history, dating back to the early days of computer vision research in the 1960s and 1970s.
- Thresholding Techniques: In the 1980s, researchers began to develop more sophisticated techniques for image segmentation, such as thresholding-based methods.
- Edge-Based Segmentation: Another approach to image segmentation that emerged in the 1980s was edge-based segmentation.
- Region-Based Segmentation: In the 1990s, region-based segmentation became popular, which involved grouping pixels or regions of the image together based on their similarity in terms of color, texture, or other features.
- Hybrid Techniques: In recent years, researchers have been exploring hybrid techniques that combine multiple segmentation methods or algorithms to improve accuracy and robustness.

Global Thresholding

1. del_T=0, min_T, max_iter
2. while (del_T>min_T) and (i<max_iter):
    1. Select an initial estimate for the global threshold. T (e.g. mean of intensity)
    2. Segment the image using T into regions c1 (above T) and c2 (below T)
    3. Compute the average intensity of pixels at c1 as m1 and c2 as m2.
    4. Set new threshold $T = \frac{1}{2}(m1+m2)$
    5. Update del_T



Implementation



Run Time Complexity: O(n*k)

Otsu Thresholding

- ▪Find the histogram of the image
- ▪For all Threshold T:

  Divide the image into c1 and c2 based on T

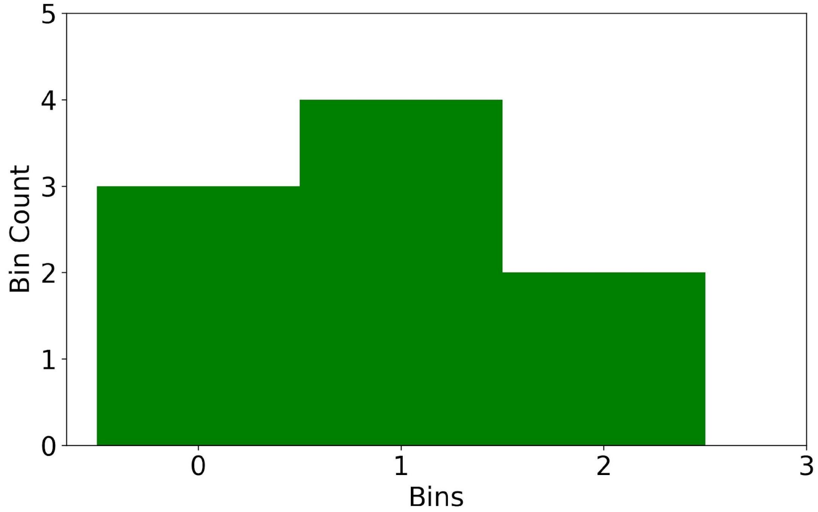
  Find the within-class variance or between-class variance using a histogram

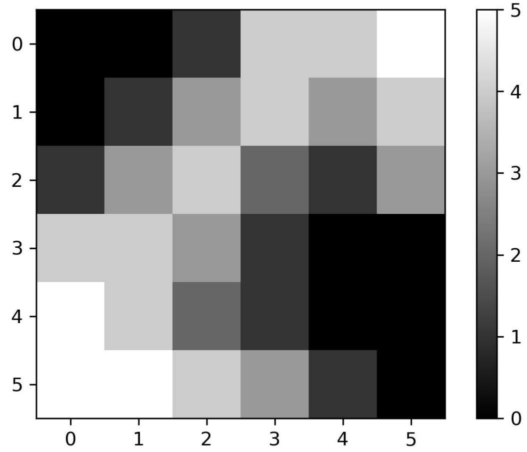
- ▪Find the threshold that minimizes within-class variance or maximizes between-class variance
- ▪Run Time Complexity O(n*L)

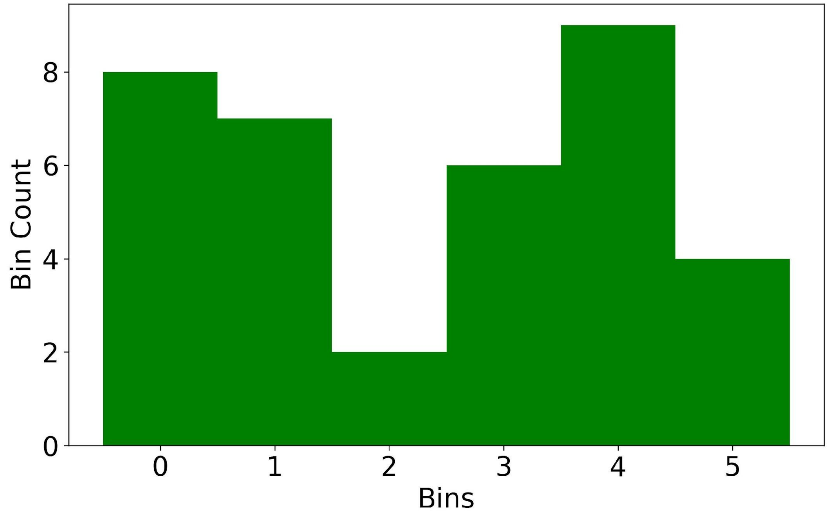
Histogram

1	0	1
2	1	0
0	1	2

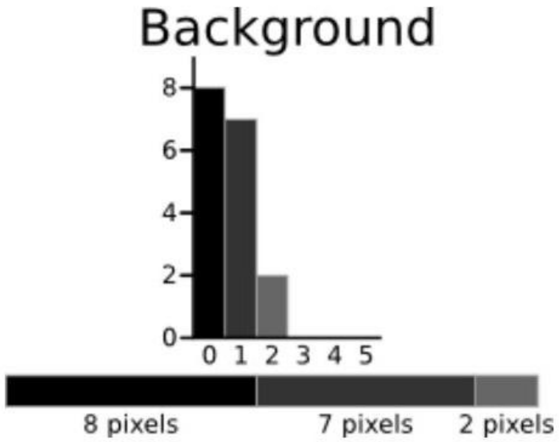
Bin	Bin Count
0	3
1	4
2	2







Within Class Variance



$$\text{Weight} \quad W_b = \frac{8+7+2}{36} = 0.4722$$

$$\text{Mean} \quad \mu_b = \frac{(0\times 8)+(1\times 7)+(2\times 2)}{17} = 0.6471$$

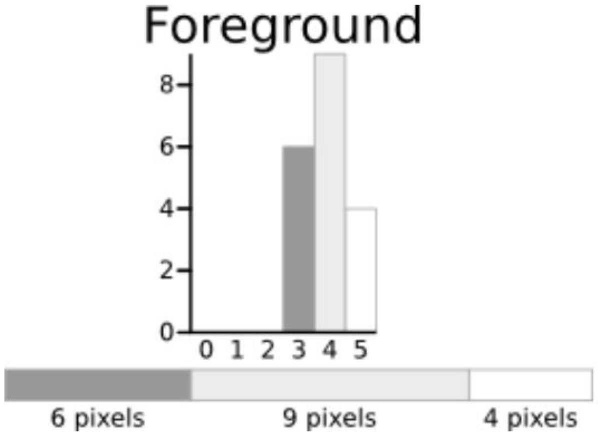
$$\text{Variance} \quad \sigma_b^2 = \frac{((0-0.6471)^2\times 8)+((1-0.6471)^2\times 7)+((2-0.6471)^2\times 2)}{17}$$

$$= \frac{(0.4187\times 8)+(0.1246\times 7)+(1.8304\times 2)}{17}$$

$$= 0.4637$$

Mean,μ:$\sum i n_i / \sum n_i$

Variance,σ:$\sum (i-\mu)^2 \times n_i / \sum n_i$



$$\text{Weight} \quad W_f = \frac{6+9+4}{36} = 0.5278$$

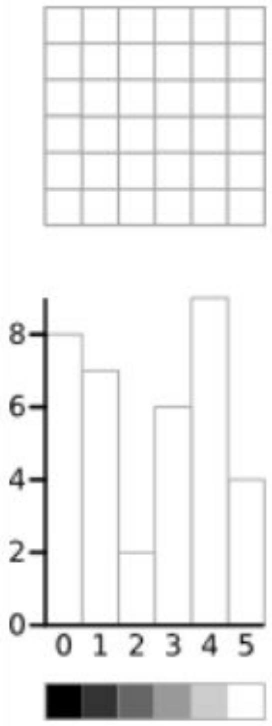
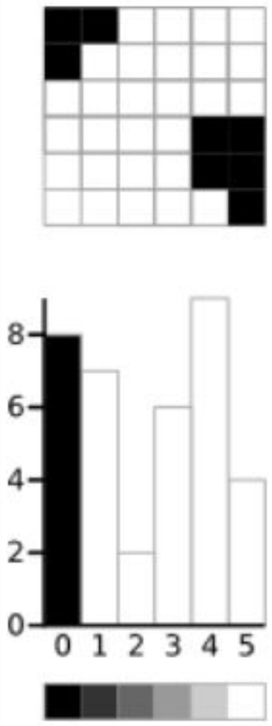
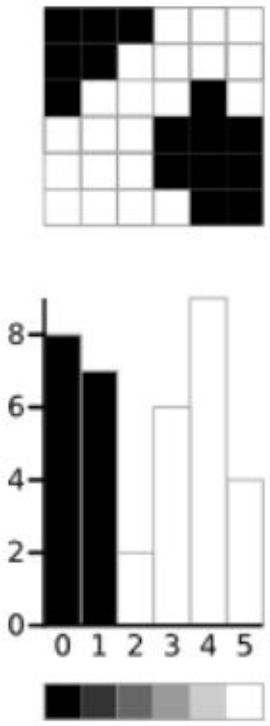
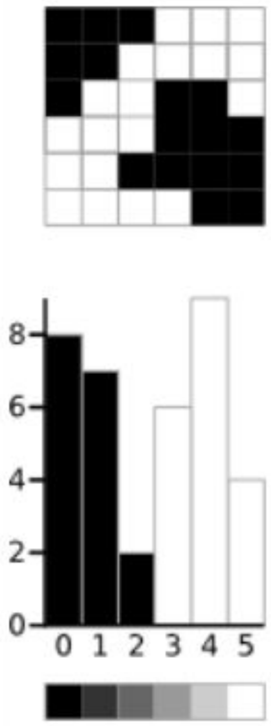
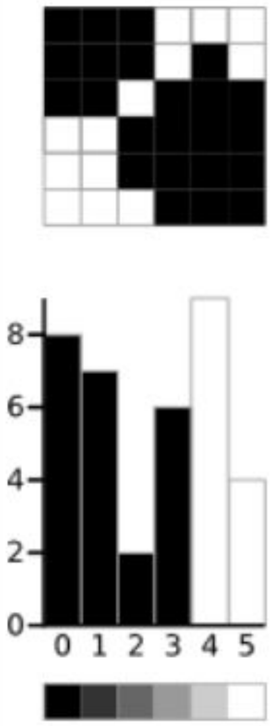
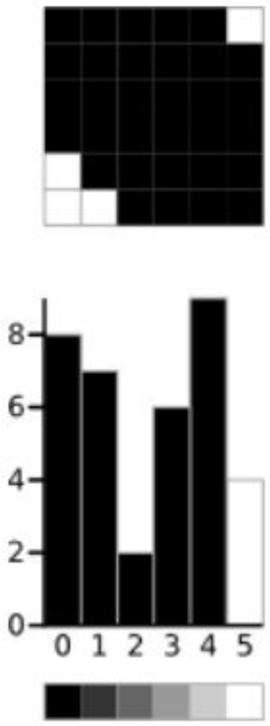
$$\text{Mean} \quad \mu_f = \frac{(3\times 6)+(4\times 9)+(5\times 4)}{19} = 3.8947$$

$$\text{Variance} \quad \sigma_f^2 = \frac{((3-3.8947)^2\times 6)+((4-3.8947)^2\times 9)+((5-3.8947)^2\times 4)}{19}$$

$$= \frac{(4.8033\times 6)+(0.0997\times 9)+(4.8864\times 4)}{19}$$

$$= 0.5152$$

$$\text{Within Class Variance} \quad \sigma_W^2 = W_b\,\sigma_b^2 + W_f\,\sigma_f^2$$

Threshold	T=0	T=1	T=2	T=3	T=4	T=5
						
Weight, Background	$W_b = 0$	$W_b = 0.222$	$W_b = 0.4167$	$W_b = 0.4722$	$W_b = 0.6389$	$W_b = 0.8889$
Mean, Background	$M_b = 0$	$M_b = 0$	$M_b = 0.4667$	$M_b = 0.6471$	$M_b = 1.2609$	$M_b = 2.0313$
Variance, Background	$\sigma^2_b = 0$	$\sigma^2_b = 0$	$\sigma^2_b = 0.2489$	$\sigma^2_b = 0.4637$	$\sigma^2_b = 1.4102$	$\sigma^2_b = 2.5303$
Weight, Foreground	$W_f = 1$	$W_f = 0.7778$	$W_f = 0.5833$	$W_f = 0.5278$	$W_f = 0.3611$	$W_f = 0.1111$
Mean, Foreground	$M_f = 2.3611$	$M_f = 3.0357$	$M_f = 3.7143$	$M_f = 3.8947$	$M_f = 4.3077$	$M_f = 5.000$
Variance, Foreground	$\sigma^2_f = 3.1196$	$\sigma^2_f = 1.9639$	$\sigma^2_f = 0.7755$	$\sigma^2_f = 0.5152$	$\sigma^2_f = 0.2130$	$\sigma^2_f = 0$
Within Class Variance	$\sigma^2_W = 3.1196$	$\sigma^2_W = 1.5268$	$\sigma^2_W = 0.5561$	$\boldsymbol{\sigma^2_W = 0.4909}$	$\sigma^2_W = 0.9779$	$\sigma^2_W = 2.2491$

Between Class Variance

$$\text{Within Class Variance} \quad \sigma_W^2 = W_b\,\sigma_b^2 + W_f\,\sigma_f^2 \quad \text{(as seen above)}$$

$$\begin{aligned} \text{Between Class Variance} \quad \sigma_B^2 &= \sigma^2 - \sigma_W^2 \\ &= W_b(\mu_b - \mu)^2 + W_f(\mu_f - \mu)^2 \quad (\text{where } \mu = W_b\,\mu_b + W_f\,\mu_f) \\ &= W_b\,W_f\,(\mu_b - \mu_f)^2 \end{aligned}$$

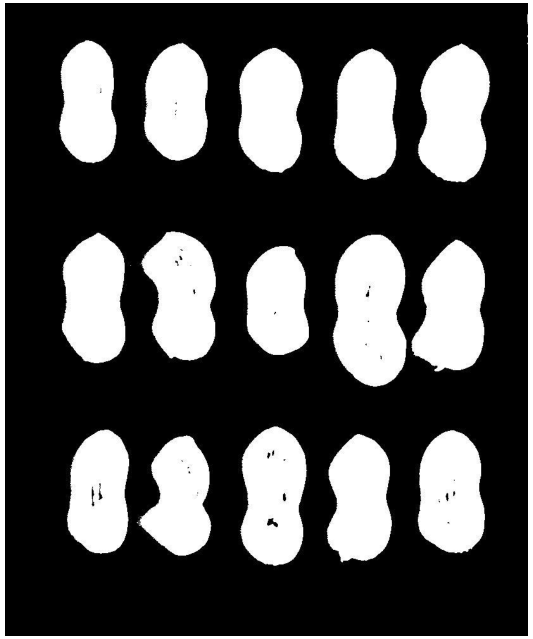
Tl

The table below shows the different variances for each threshold value.

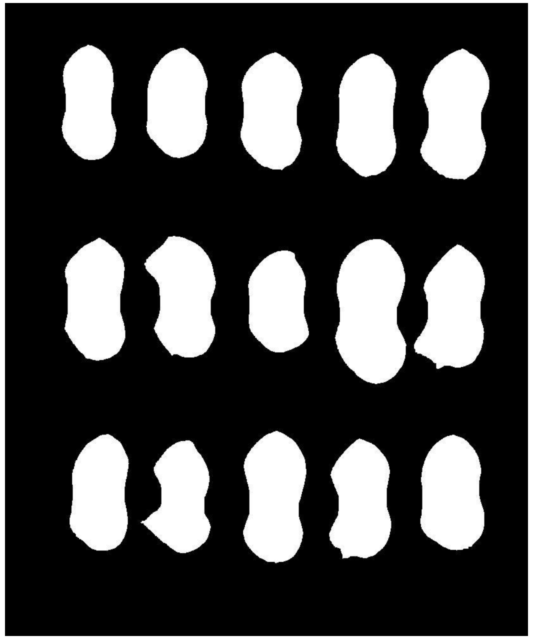
Threshold	T=0	T=1	T=2	T=3	T=4	T=5
Within Class Variance	$\sigma^2_W = 3.1196$	$\sigma^2_W = 1.5268$	$\sigma^2_W = 0.5561$	$\boldsymbol{\sigma^2_W = 0.4909}$	$\sigma^2_W = 0.9779$	$\sigma^2_W = 2.2491$
Between Class Variance	$\sigma^2_B = 0$	$\sigma^2_B = 1.5928$	$\sigma^2_B = 2.5635$	$\boldsymbol{\sigma^2_B = 2.6287}$	$\sigma^2_B = 2.1417$	$\sigma^2_B = 0.8705$

Implementation

RGB Image



Otsu Thresholding



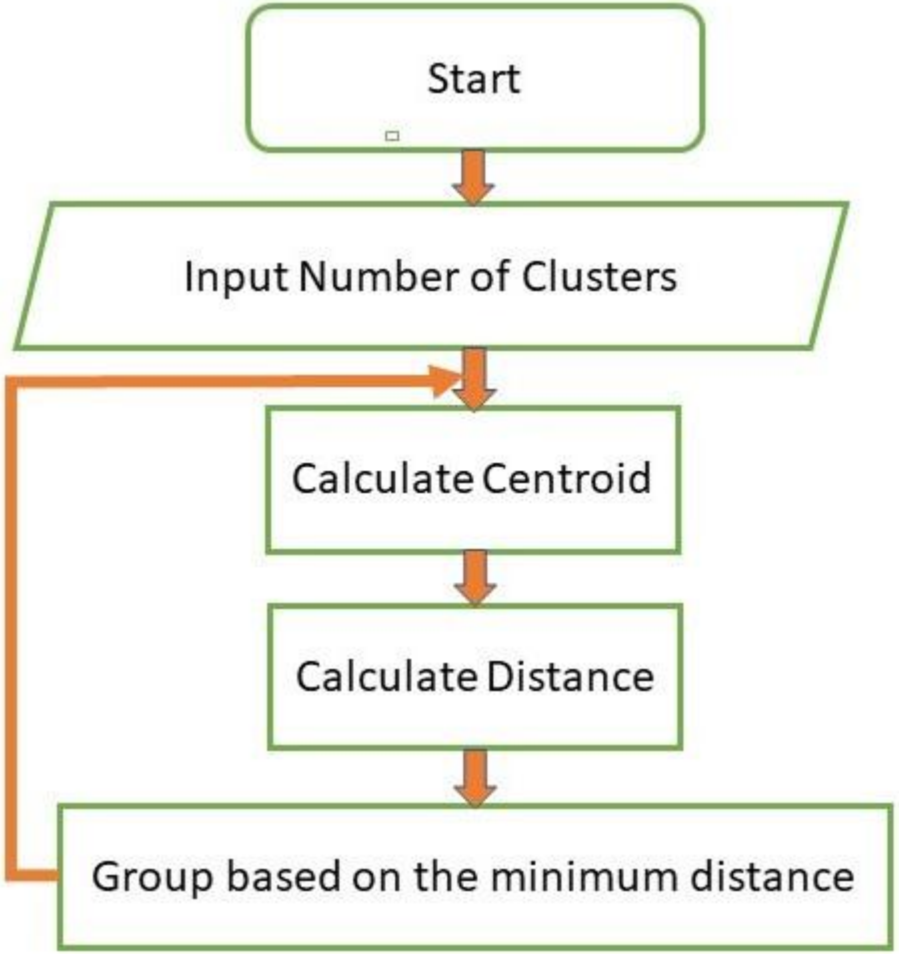
Otsu Thresholding +
Morphological operation

Sree Nirmillo Biswash Tushar, Soma Sarker, William Stapleton, and Damian Valles, "Peanut maturity classification by features extracted from selected hyperspectral components", 2022 IEEE Global Humanitarian Technology Conference (GHTC), pp. 176-183. IEEE, 2022

K means Clustering (k=2)

Features: (number of pixels,color_levels)

Pixel No	R	G
1	185	72
2	170	56
3	168	60
4	179	68
5	182	72
6	188	77



Step 3-5

Cluster	R	G
K1	185	72
K2	170	56

Cluster	K1	K2	Assignment
3 (168, 60)	20.808	4.472	2

Cluster	R	G
K1	185	72
K2	(170+168)/2=169	(60+56)/2=58

$$\text{Distance from Cluster 1} = \sqrt{(168-185)^2+(60-72)^2}$$

(185,72)

$$= \sqrt{(-17)^2+(-12)^2}$$
$$= \sqrt{283+144}$$
$$= \sqrt{433}$$
$$= 20.808$$

$$\text{Distance from Cluster 2} = \sqrt{(168-170)^2+(60-56)^2}$$

(170,56)

$$= \sqrt{(-2)^2+(-4)^2}$$
$$= \sqrt{4+16}$$
$$= \sqrt{20}$$
$$= 4.472$$

Final Assignment

Pixel No	R	G	Assignment
1	185	72	1
2	170	56	2
3	168	60	2
4	179	68	1
5	182	72	1
6	188	77	1

Implementation

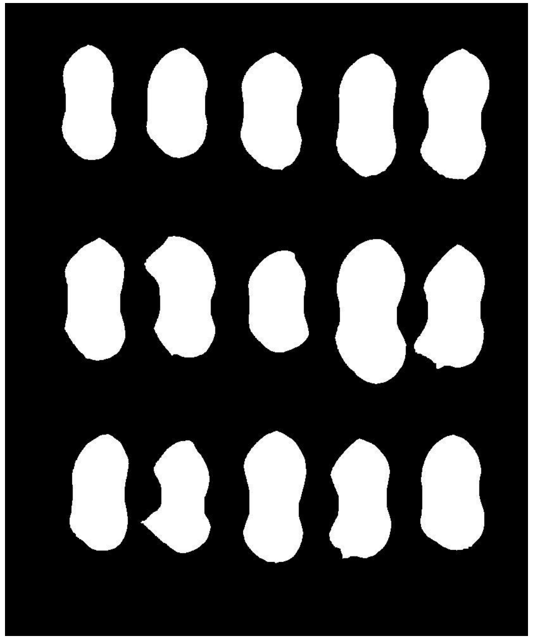
Image of size (H,W,c) to Image of size (H*W,c) and then apply 2 means clustering

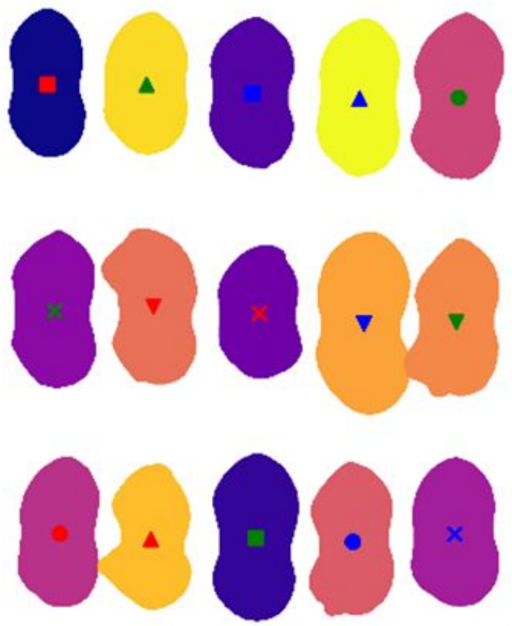
(a) RGB image

S. Zou, Y.-C. Tseng, A. Zare, D. L. Rowland, B. L. Tillman, and S.C. Yoon, “Peanut maturity classification using hyperspectral imagery,”biosystems engineering, vol. 188, pp. 165–177, 2019.

Implementation

15 means clustering, Spatial position was the features





Sree Nirmillo Biswash Tushar, Soma Sarker, William Stapleton, and Damian Valles, “Peanut maturity classification by features extracted from selected hyperspectral components”, 2022 IEEE Global Humanitarian Technology Conference (GHTC), pp. 176-183. IEEE, 2022

Deep-Learning Based Segmentation Techniques - CNN (Background)

- CNNs were developed in the 1980s and could recognize handwritten digits.
- They were primarily used in the postal sector to read zip codes, pin codes, etc.
- CNNs require a large amount of data to train and a lot of computing resources.
- Limited computing resources were a major drawback for CNNs in the 1980s.
- Due to these limitations, CNNs failed to enter the world of machine learning at that time.
- In 2012, Alex Krizhevsky revived the use of multi-layered neural networks in deep learning, as the availability of large labeled datasets such as ImageNet and ample computing resources enabled researchers to bring back CNNs.

Convolutional Neural Networks, Explained
Image-Segmentation-Using-Convolutional-Neural-Network.pdf

Deep-Learning Based Segmentation Techniques - CNN

- ➢ Modeled after the structure of the human brain's visual cortex
- ➢ Let’s try to understand it with a simple example - basket of fruits

Convolutional Neural Networks, Explained
Image-Segmentation-Using-Convolutional-Neural-Network.pdf

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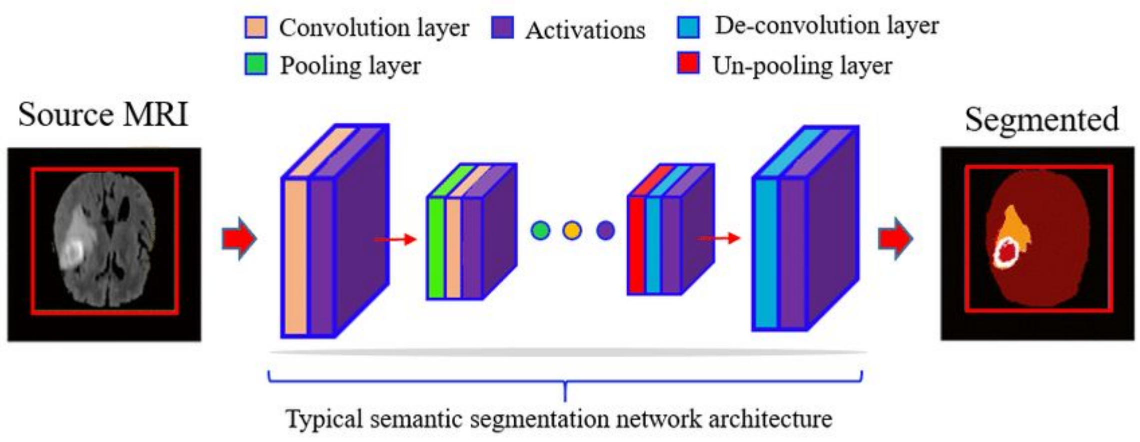
Deep-Learning Based Segmentation Techniques - CNN



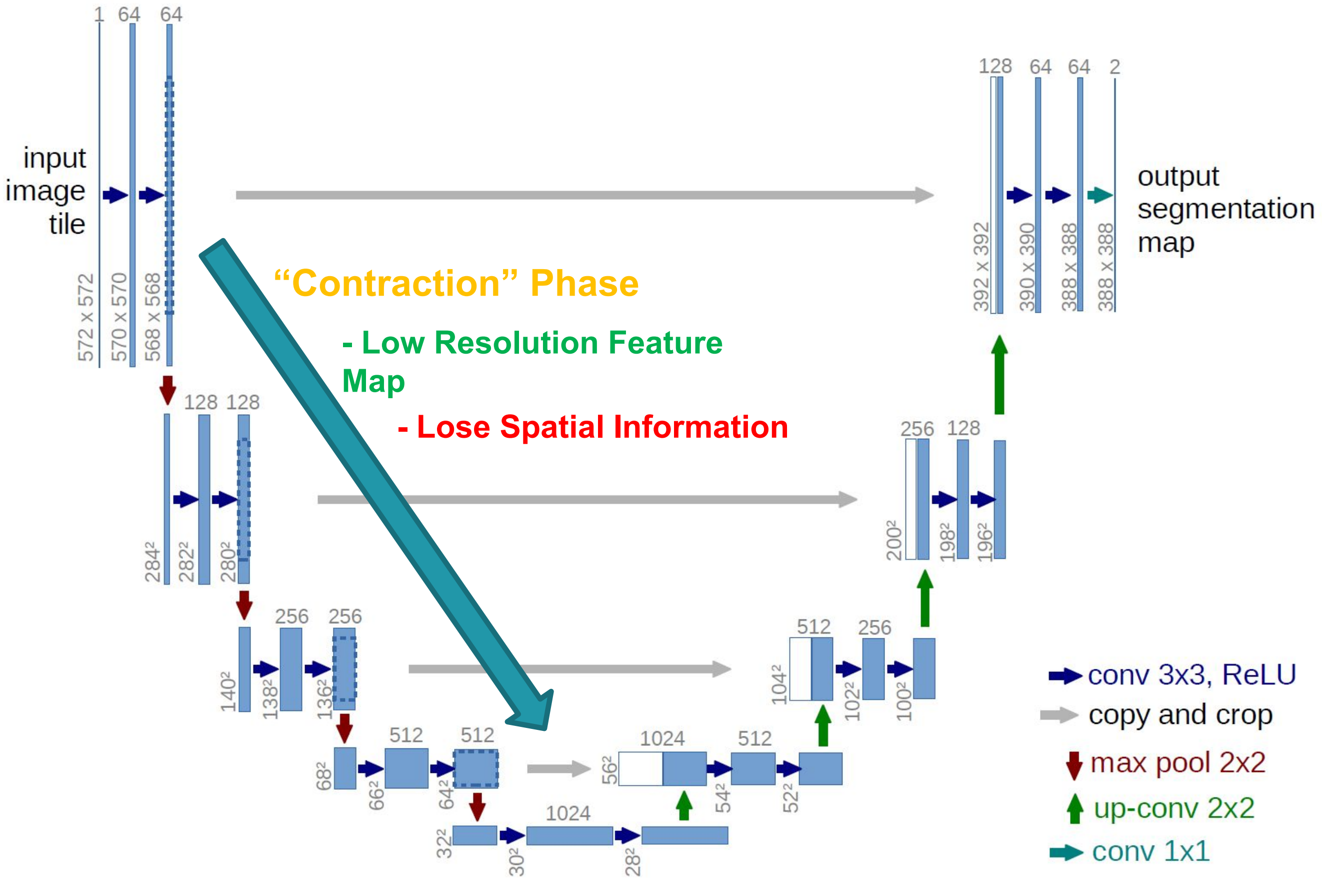
- Input image: A medical image is presented to the CNN.
- Convolutional layers: The CNN extracts features, such as edges and textures, using convolutional filters.
- Pooling layers: The CNN reduces the spatial resolution of the image while preserving important features using pooling operations.
- Fully connected layers: The CNN generates a segmentation map of the image, identifying the tumor and its location within the image.
- Output: The segmented tumor is analyzed by doctors to diagnose and treat diseases more accurately.

Mathematics behind CNN

- Gentle Dive into Math Behind Convolutional Neural Networks
- Demystifying the Mathematics Behind Convolutional Neural Networks (CNNs)

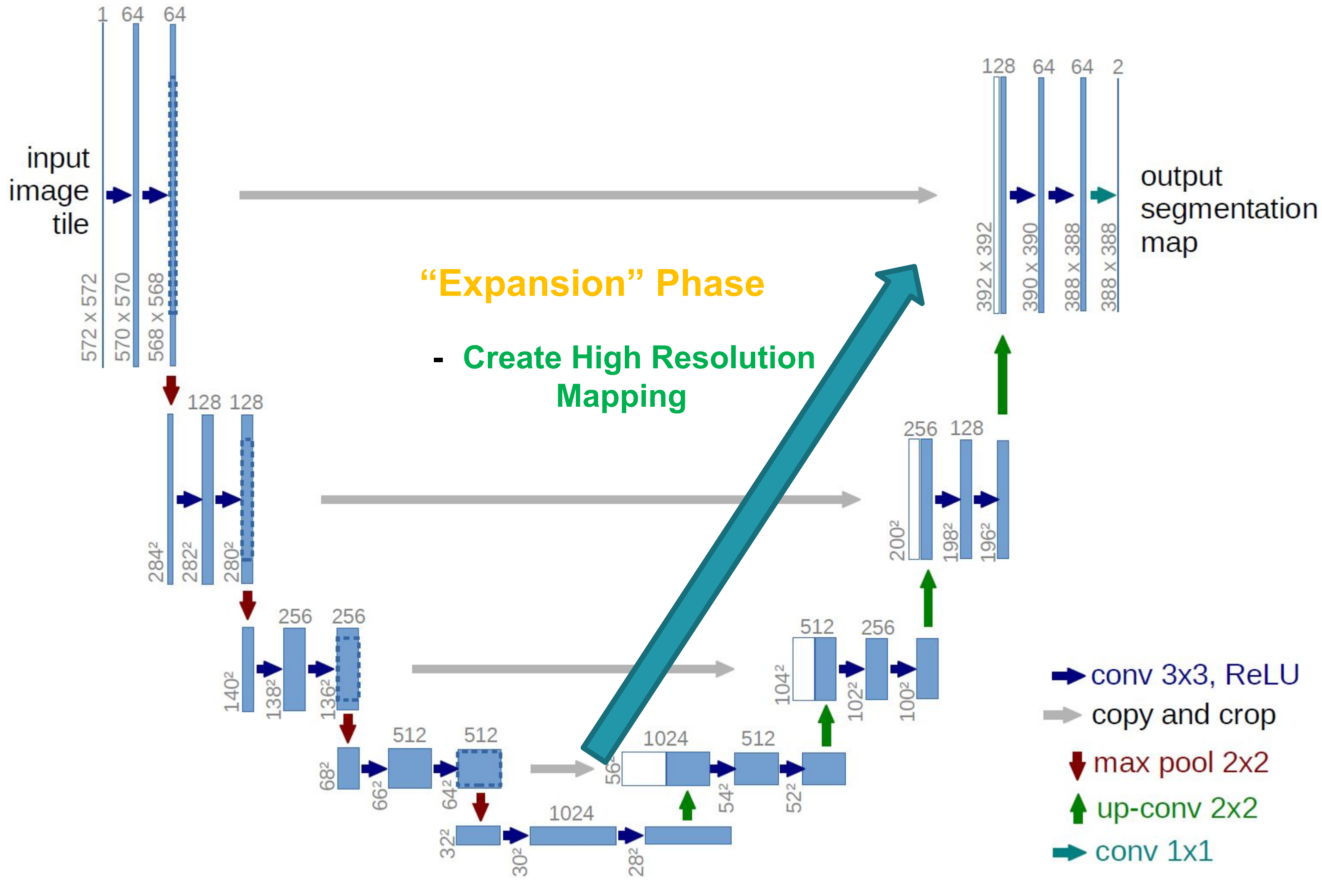
U-Net Architecture

- The encoder extracting the features
- Reduce its spatial resolution.
- capture the global context of the input image and identify key features that can be used
  to segment the image.

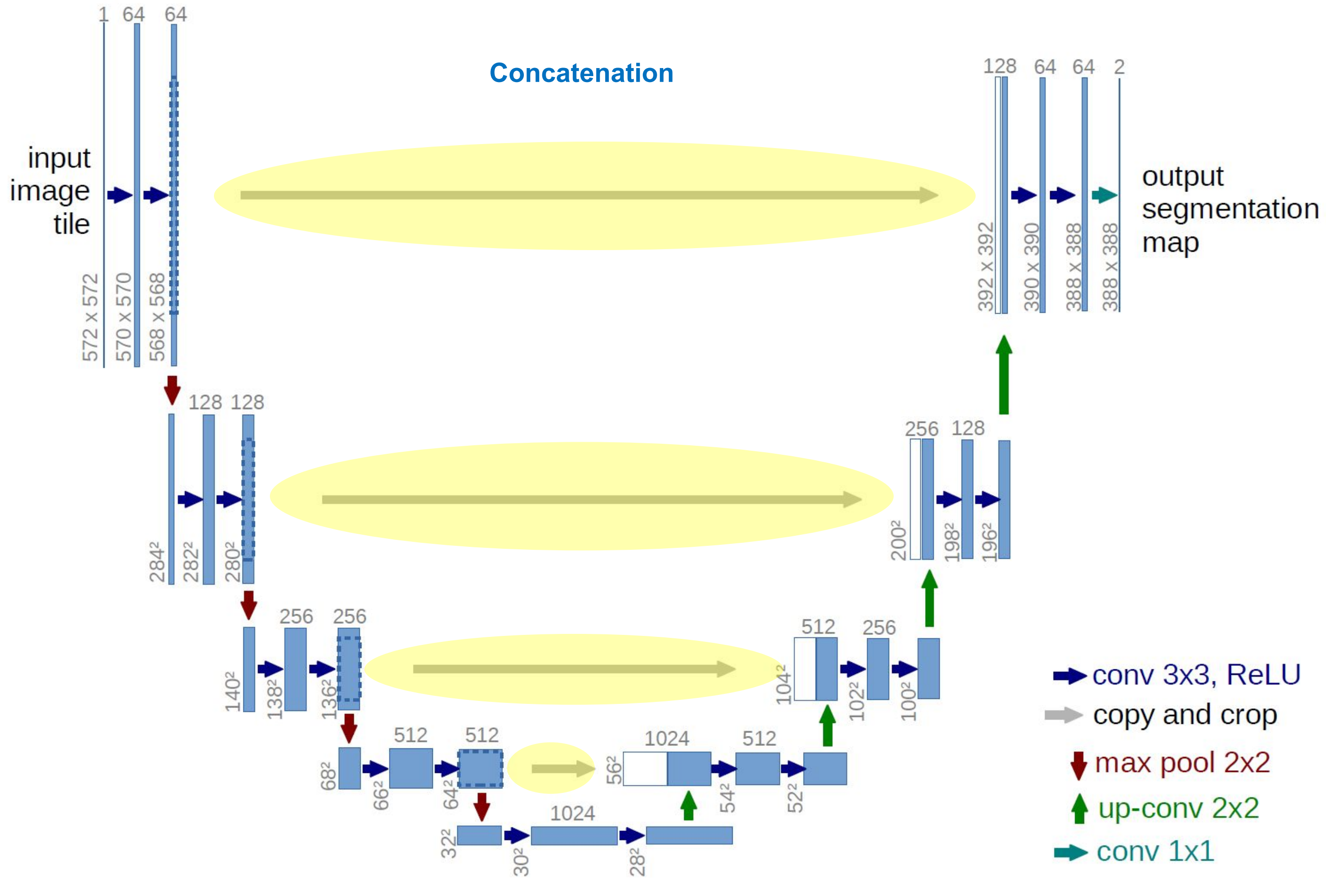


U-Net Architecture

- The decoder generates the segmented image.
- Increase the spatial resolution of the feature.
- The upsampling operation helps to recover the details lost during the downsampling process and provide finer details to the decoder.

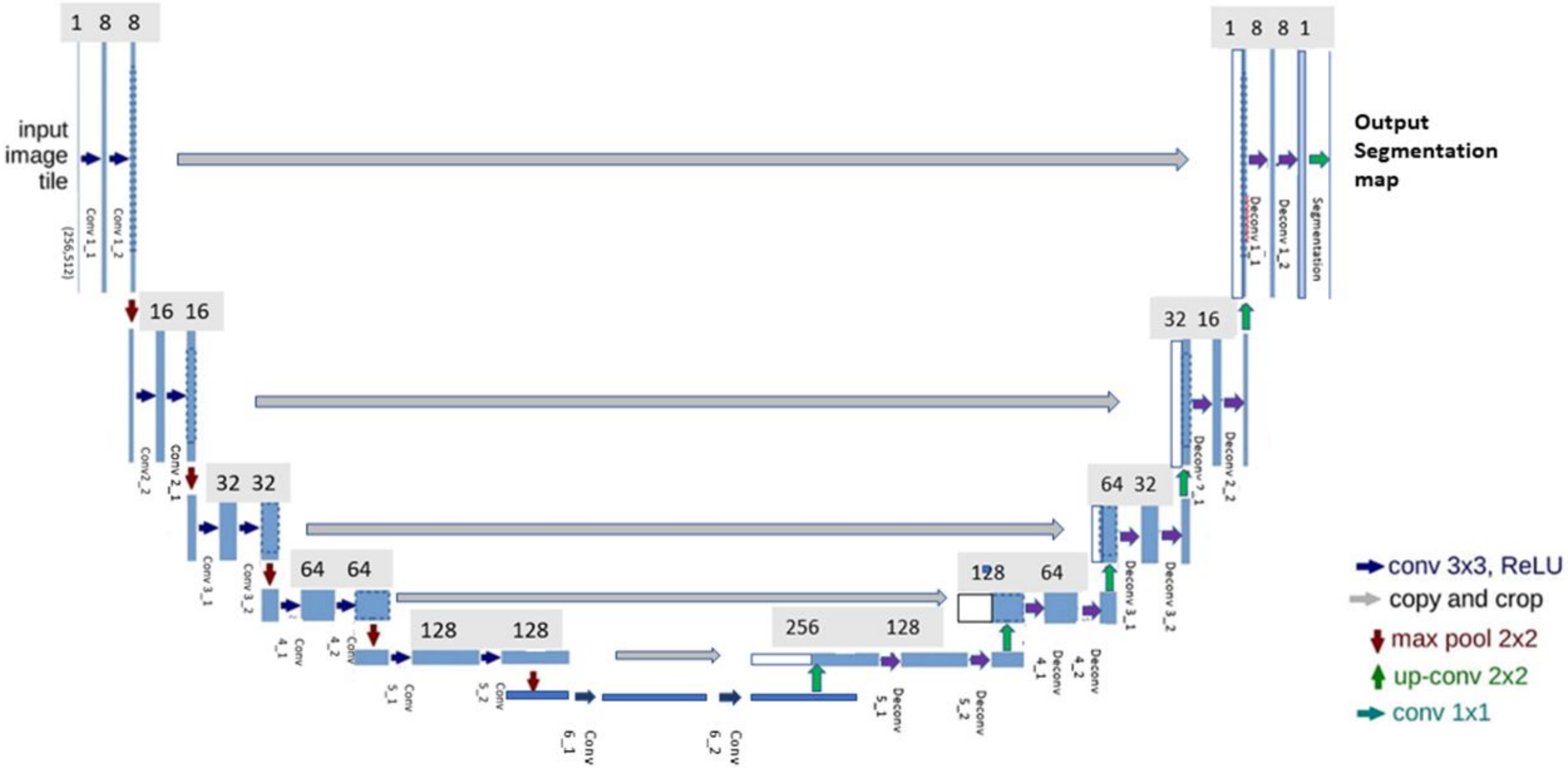


U-Net Architecture



Ronneberger et al. (2015) U-net Architecture

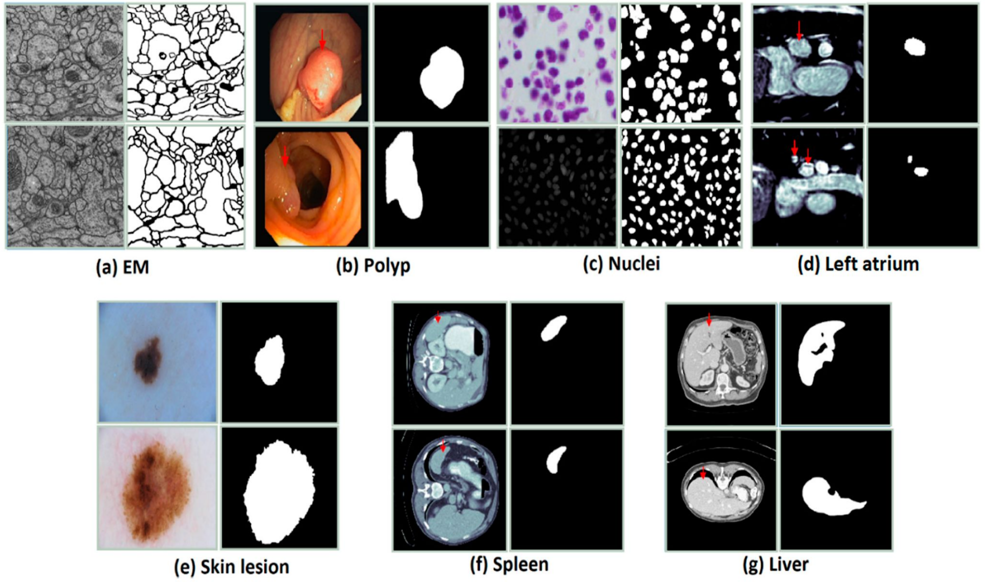
U-Net Architecture

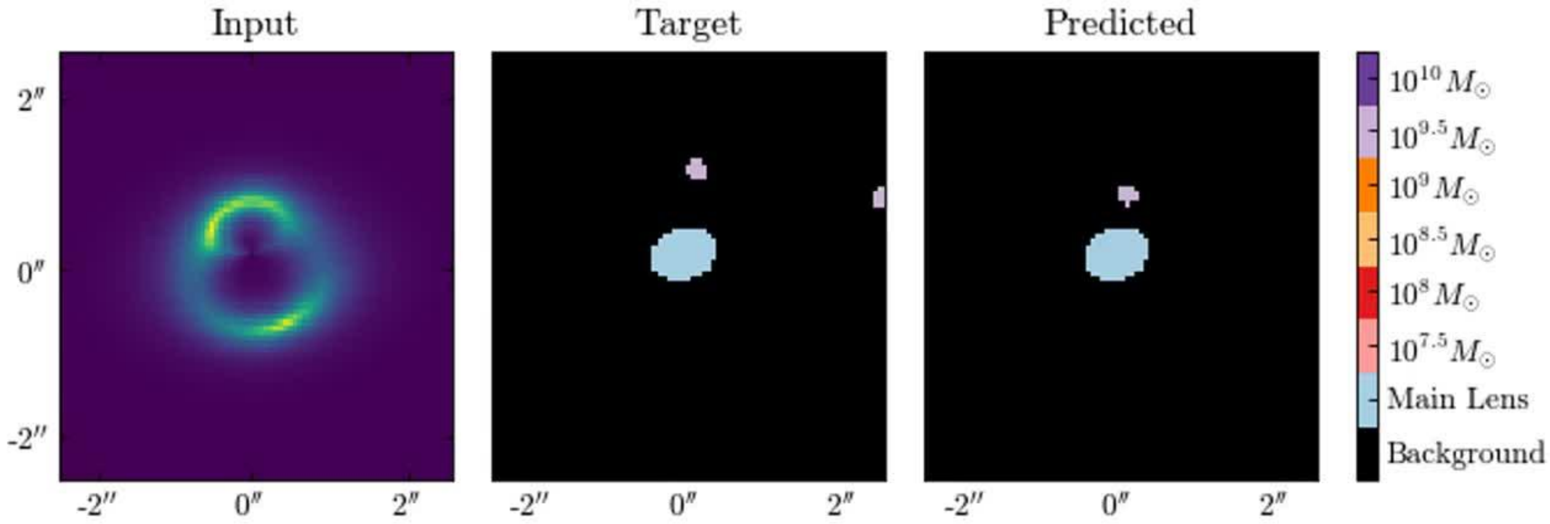


Implementation

Applications

- ➢ Medical Imaging
- ➢ Object Detection and Tracking
- ➢ Agriculture
- ➢ Environmental Monitoring
- ➢ Entertainment and Gaming
- ➢ Astronomy





Open Issues

- Ambiguity: Challenges arise when objects in the image have similar shapes, textures or colors.
- Noise: The presence of noise in images can make it difficult to accurately segment objects.
- Variability: Objects in images can exhibit significant variability in terms of shape, size, and appearance.
- Computational complexity: Segmentation algorithms can be computationally complex and time-consuming, especially for large or high-resolution images.
- Training data: Deep learning-based techniques require large amounts of training data, which can be expensive and time-consuming to obtain and label.
- Interpretability: Some segmentation techniques, especially deep learning-based methods, can be difficult to interpret or explain.
- Integration with other algorithms: Integrating segmentation algorithms with other image processing techniques and algorithms can be challenging.

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Discussion

Ostu Thresholding

Let {0,1,2,..., L — 1} denote the set of L distinct integer intensity levels in a digital image with n=MxN pixels.

The normalized histogram has components p_i =n_i/n, $\sum_0^n p_i$ and p_i >0

The average Intensity of the image, m_G = $\sum_0^{L-1} ip_i$

For each possible threshold k (0 < k < L — 1):

Make two classes c_1 (the intensity range [0, k]) and c_2 (intensity range [k + 1,L — 1])

Probability of a pixel in class c_1 or c_2 : P_1(k) = $\sum_0^k p_i$ and P_2(k) = $\sum_{k+1}^{L-1} p_i$

Mean Intensity of class c_1 and c_2: m_1(k) = $\sum_0^k ip_i$ / $\sum_0^k p_i$, m_2(k) = $\sum_{k+1}^{L-1} ip_i$ /$\sum_{k+1}^{L-1} p_i$

Between class c1 and c2 variance: P_1(k) *(m_1(k) - m_G)**2 + and P_2(k) *(m_2(k) - m_G)**2