

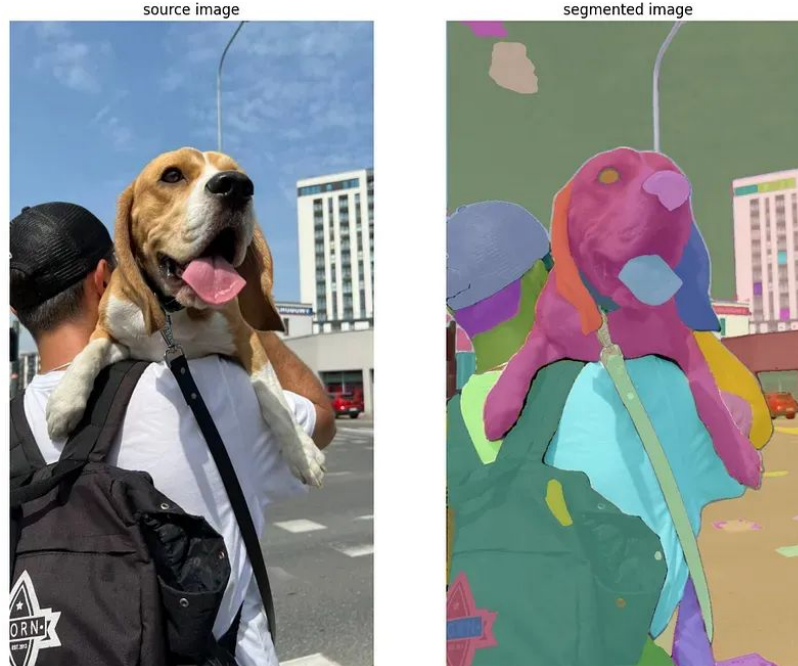
Practices in visual computing 1

Lab8: Image Segmentation 1

Simon Fraser University
Fall 2024

What is Image Segmentation?

Image segmentation divides an image into **meaningful regions** by assigning a label to each pixel based on shared characteristics.



Why is Segmentation Important?

Medical Imaging (tumor segmentation)

Autonomous Driving (road and obstacle detection)

Satellite Imagery (land-use classification)

Photo Editing (object background removal)

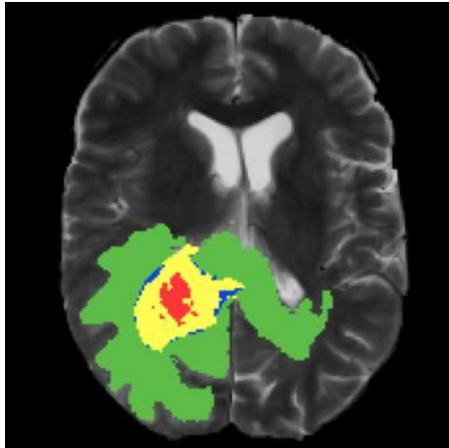
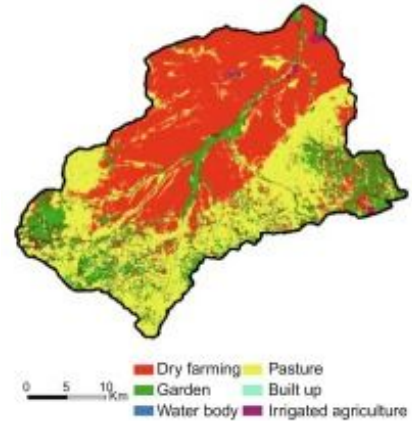
Why is Segmentation Important?

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Types of Image Segmentation

1. **Semantic Segmentation**: Assigns each pixel a class label, e.g., distinguishing car, road, and pedestrian.
2. **Instance Segmentation**: Extends semantic segmentation by labeling each object instance, e.g., three different pedestrians in one scene.
3. **Panoptic Segmentation**: Combines both, where each pixel has a class, and instances are identified.

Types of Image Segmentation



(a) Image



(b) Semantic segmentation



(c) Instance segmentation



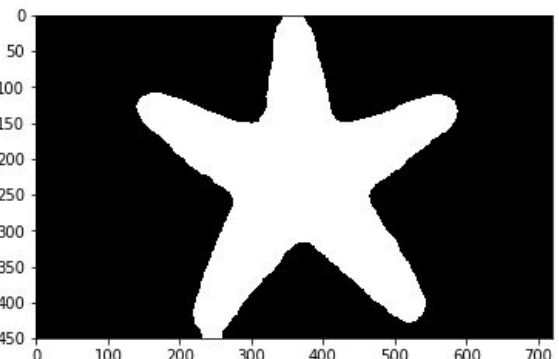
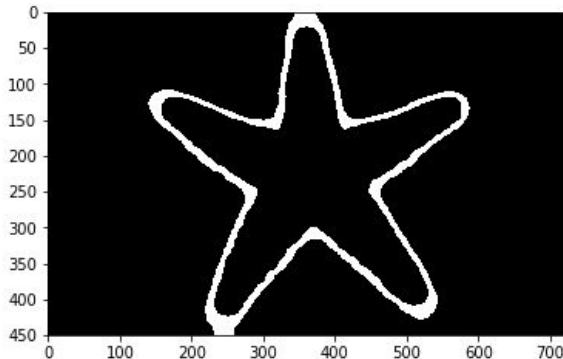
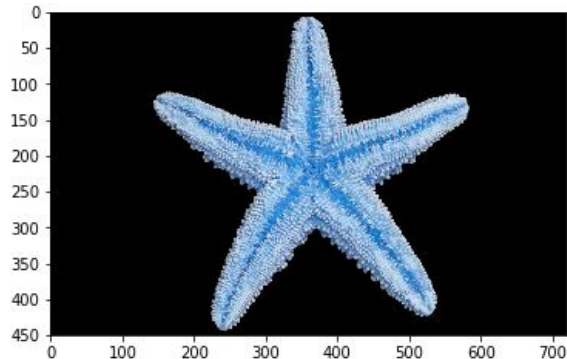
(d) Panoptic segmentation

Basic Segmentation Techniques

Thresholding: Assigns pixels to categories based on intensity thresholds.

Clustering (e.g., K-means): Groups similar pixels together in color space.

Edge Detection: Detects object boundaries using gradients (Sobel, Canny).



Deep Learning and Segmentation

Deep Learning transformed segmentation by automating feature extraction.

UNet

Mask R-CNN

DeepLab

Attention mechanisms

Other methods

Deep Learning and Segmentation

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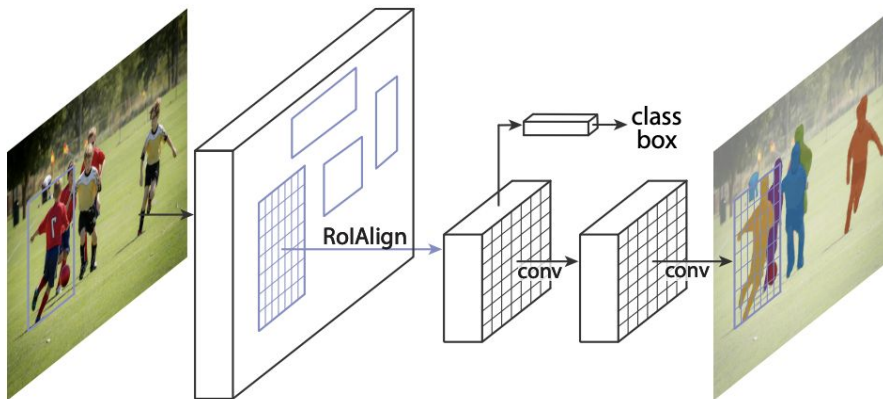
UNet

Mask R-CNN

DeepLab

Attention mechanisms

Other methods



Evaluation Metrics for Segmentation

Pixel Accuracy: Measures correctly classified pixels.

Intersection over Union (IoU): Calculates overlap between prediction and ground truth for each class.

Mean IoU: Average IoU across all classes.

Dice Coefficient: Measures similarity between predicted and actual areas, common in medical imaging.

Datasets for Segmentation

Pascal VOC: 20 classes, general-purpose segmentation.

Cityscapes: Urban street scenes, essential for autonomous driving research.

COCO: For both detection and segmentation with 80 object categories.

ADE20K: Diverse classes and environments.

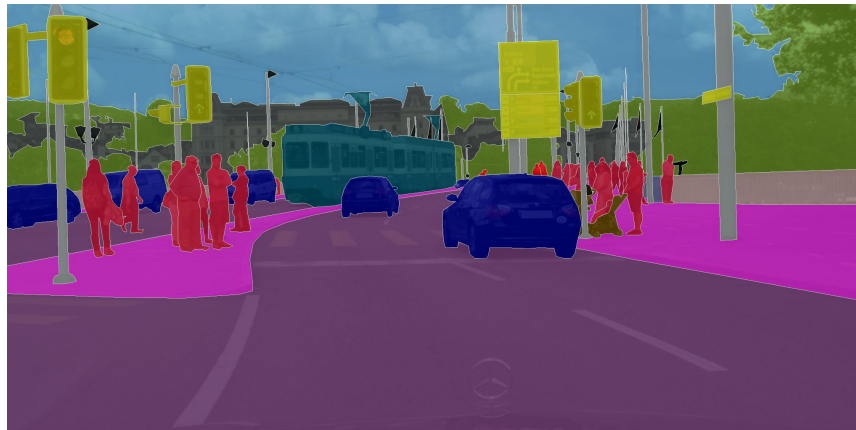
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Training a Segmentation Model (High-Level)

1. **Model Selection**: Choose appropriate architecture (e.g., UNet for medical images, Mask R-CNN for instance segmentation).
2. **Data Preparation**: Preprocess images, apply augmentations.
3. **Training**: Configure the optimizer, loss function, and learning rate.
4. **Evaluation**: Monitor metrics like IoU and adjust as needed.

Challenges in Image Segmentation

Class Imbalance: Some classes dominate (e.g., background).

Occlusion: Objects that partially overlap or are hidden.

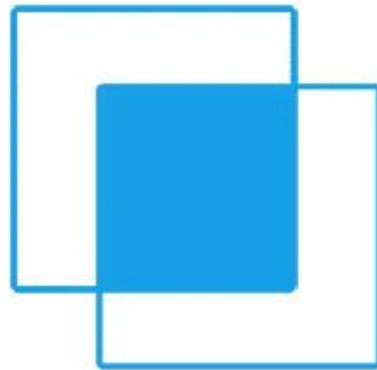
Computational Cost: Segmentation is resource-intensive.

Solution:

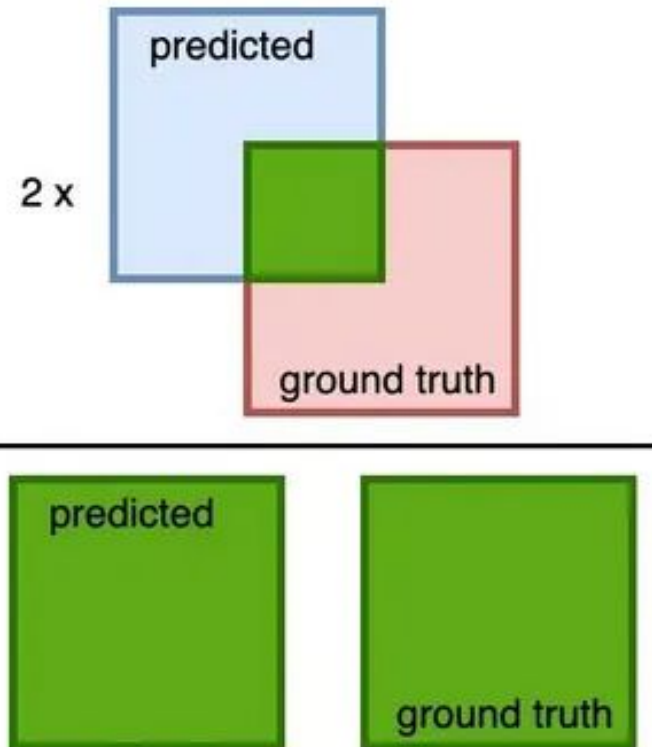
Use data augmentation, class weighting, and efficient models.

Intersection over Union

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



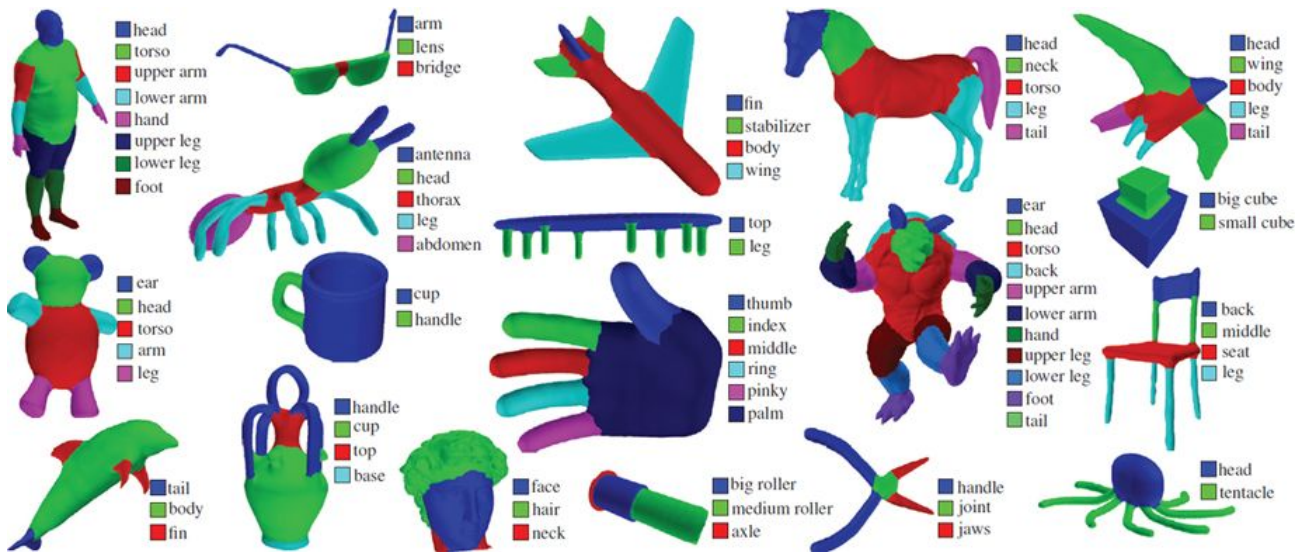
Dice Loss

$$\text{Dice coefficient} = \frac{2 \times \text{area of overlapped (green)}}{\text{total area (green)}} =$$


The diagram illustrates the Dice coefficient formula. The top part shows a blue rectangle labeled "predicted" and a red rectangle labeled "ground truth" overlapping. The overlapping area is highlighted in green and labeled "2 x". The bottom part shows two separate green rectangles, one labeled "predicted" and one labeled "ground truth", representing the total area of the green regions.

Future of Segmentation

3D and Video Segmentation: Extending 2D segmentation to video and 3D scenes.



SMITE: SEGMENT ME IN TIME

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ASIA: Adaptive 3D Segmentation using Few Image Annotations

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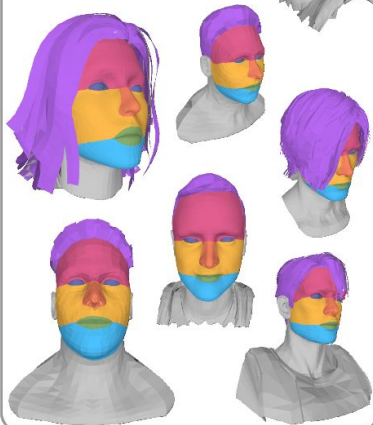
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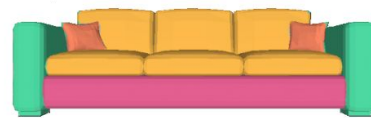
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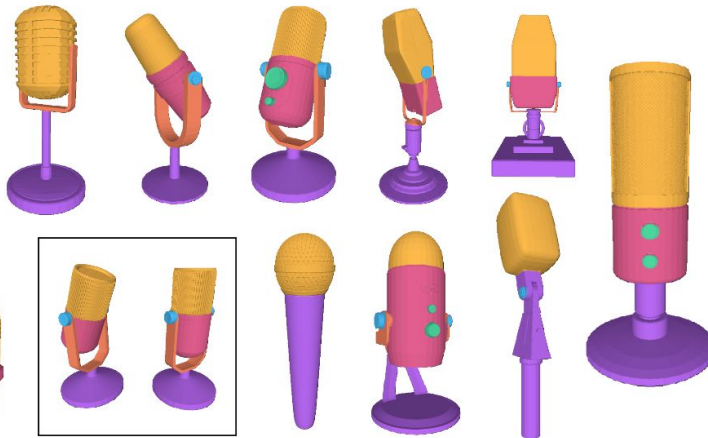
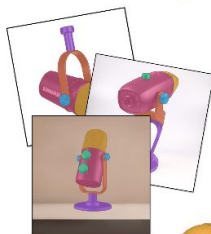
Reference
Annotations



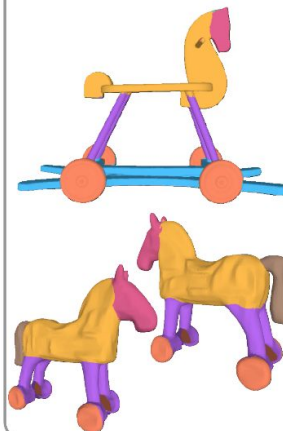
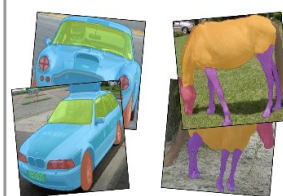
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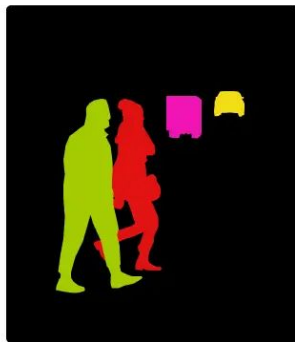
Final Thought

“Image segmentation is a vital field in computer vision, enabling intelligent systems to interpret visual data in increasingly meaningful ways.”

Types of Image Segmentation



**SEMANTIC IMAGE
SEGMENTATION**



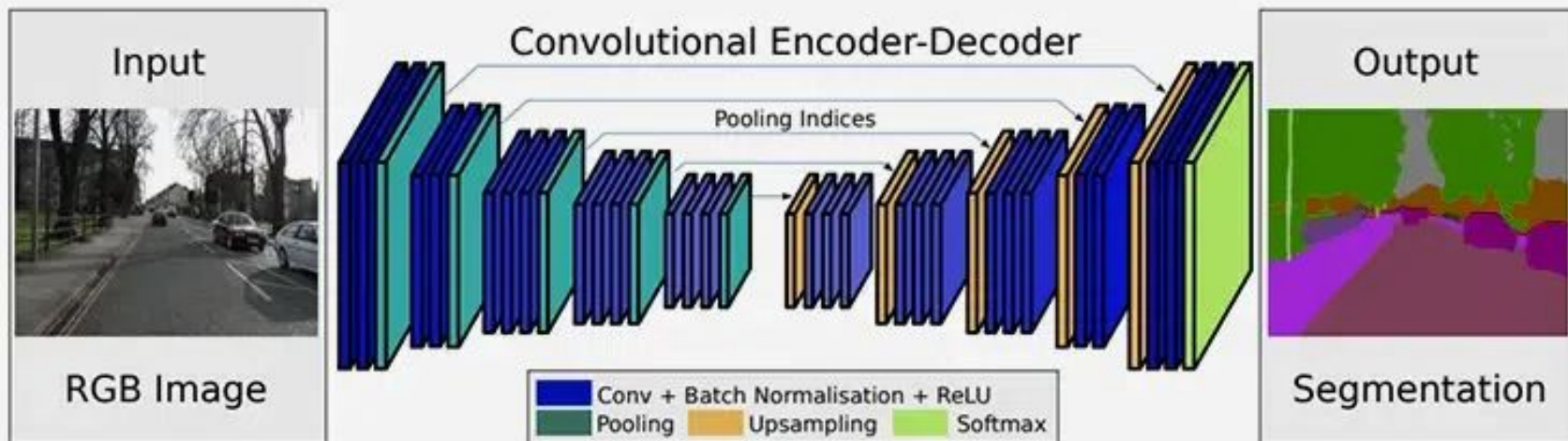
**INSTANCE
SEGMENTATION**



**PANOPTIC
SEGMENTATION**

Implementation Details

SegNet Architecture



Implementation Details

Model: Segnet

Batch Size: 32

Optimizer: SGD -> LR: 0.01, Momentum: 0.9

Loss: Cross Entropy Loss

Augmentation: RandomBrightnessContrast(p=0.3) - HorizontalFlip() -
Rotate(limit=10, p=0.5)