# Semantic Segmentation

CP8307 - Group #3

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## Semantic Segmentation

- Process of sectioning an image into different classes (pixel-by-pixel) [1]
- Applications
  - Medical imaging
  - Self-driving cars
  - Augmented reality
- Deep learning-based models
  - o FCN[2]
  - o **U-Net** [3]
  - o RCNN [4]

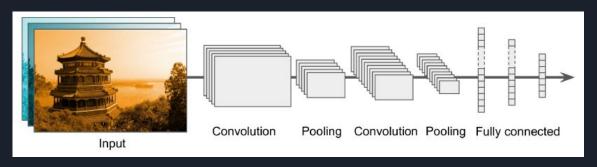


Fig 1. Semantic segmentation. [7]

- Traditional models
  - Thresholding
  - Chan-Vese [5]
  - Region Adjacency Graph (RAG) [6]

## Convolutional Neural Networks (CNNs)

- Neural network architecture for image data [8]
- Why are CNNs used for images?
  - o 2D input allows network to learn local and global image features
- Layers
  - Convolution
  - Pooling
  - Fully Connected



#### U-Net

- Published by Ronneberger et al. in 2015 with ~34000 citations
- Encoder-decoder based segmentation model for biomedical images
- Encoder-bottleneck-decoder stages with skip connections
- Outputs a segmentation map
  - Each pixel corresponds to a class

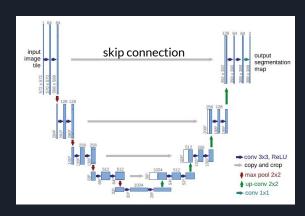


Fig 3. U-Net architecture [3]



0. Background

- l. Persor
- 2. Purse
- 3. Plants
- 4. Sidewalk
- 5. Building

## Traditional Segmentation Methods

- There are a variety of segmentation techniques that can be used for binary segmentation and classification

  Original Histogram Three
- One of the simplest approaches is thresholding
- The threshold can be automatically determined

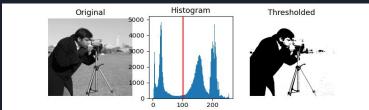


Fig 5. Thresholding [10]

- Another approach is Chan-Vese segmentation (first outlined in 1999 by Tony Chan and Luminita Vese) [5]
- Solves an energy minimization problem on intensities on the inside and outside of

contours, providing good segmentation

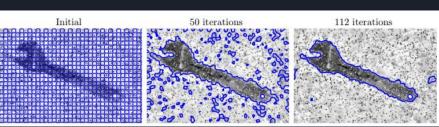


Fig 6. Chan-Vese Segmentation [11]

## Traditional Segmentation Methods Cont.

- Finally, there is segmentation using Region Adjacency Graphs (RAGs) [6]
- Key idea is to transform images into superpixel regions based on colour similarity, then merge similar regions up to some threshold
- Algorithm procedure slightly modified for our dataset



Fig 7-11. RAG Segmentation Procedure on Horse Mackerel

• There are many more classical segmentation methods, but those presented are relatively simple and have efficient implementations

## **Evaluation Metrics**

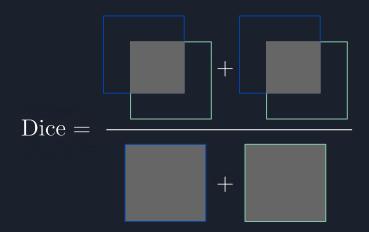
Intersection over Union (IoU) [1]

$$IoU = \frac{|A \cap B|}{|A \cup B|}$$

$$IoU = \frac{1}{1000}$$

Dice Score [1]

$$Dice = \frac{2 \mid A \cap B \mid}{\mid A \mid + \mid B \mid}$$



## Dataset

- "A Large Scale Fish Dataset" [12]
- 9000 image-mask pairs of fish

- 80%/20% training/test split
  - o 7200 samples for training
  - 1800 samples for testing





Fig 12. Sample of an image-mask pair [12]

- Includes data augmentation (rotation, flipping)
  - Method used to generate more training samples.

## Method

 Compared U-Net (TensorFlow implementation) with Region Adjacency Graph, Chan-Vese and thresholding segmentation methods

- Test set
  - 1800 (20%) image-mask pairs

• Calculated IoU and Dice score

# Results - Foreground Class

Test Set - 1800 Samples

Table 1. IoU and Dice scores on test set

	U-Net	RAG	Chan-Vese	Threshold
loU	0.89	0.72	N.C.	N.C.
Dice	0.94	0.81	N.C.	N.C.

# Results Histograms

Test Set - 1800 Samples

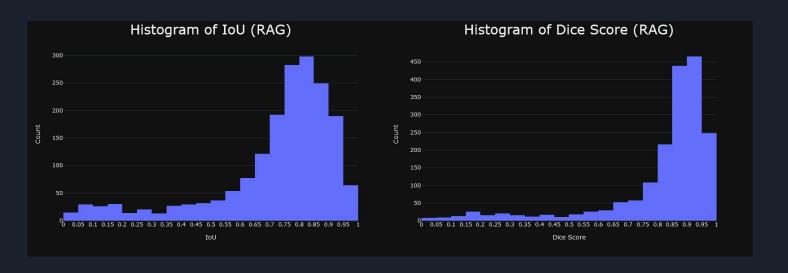


Fig 13. RAG Result Histograms

# Experimental Results - Visual



Fig 14. Experimental results

# Experimental Results - Metrics

Table 2. IoU results for four images

	U-Net	RAG	Chan-Vese	Threshold
Image 1	0.80	0.64	0.53	0.21
Image 2	0.92	0.84	0.26	0.49
Image 3	0.92	0.90	0.35	0.14
Image 4	0.94	0.87	0.26	0.32

Table 3. Dice score results for four images

	U-Net	RAG	Chan-Vese	Threshold
Image 1	0.89	0.78	0.69	0.34
lmage 2	0.96	0.91	0.42	0.66
Image 3	0.96	0.94	0.51	0.25
Image 4	0.97	0.93	0.41	0.49

## Conclusions

- U-Net offers superior performance to classical methods, but depends on large training set
- Of the classical segmentation methods, only RAG had good performance
  - Thresholding is too simple
  - Chan-Vese is not well-suited to Fish dataset
  - Colour differences between fish and background cause RAG thresholding to perform well
- Semantic segmentation is much harder than just contour detection

- Future Work
  - More segmentation techniques
  - U-Net improvements
    - Dropout layers
    - More training data
  - Adding ML to tune RAG parameters

Thank you!

#### References

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