

# **Detecting stomach and** Bowels (intestines) in MRI scans of cancer patients



Vikram (B19CSE098)

## **Under:**

#### Dr. Binod Kumar

Assistant Professor, Electrical Engineering, IIT Jodhpur

#### **Motivation**

■ 5 million people were diagnosed with a cancer of the Gastro-intestinal tract worldwide

- 50% are eligible for radiation therapy,
  - High X-ray delivered 10-15 minutes/day for 1-6 weeks.

- Manually outline the position of the stomach and intestines
  - prolong treatments from 15 minutes a day to an hour a day
  - difficult for patients to tolerate for patient

Unless there is some technique to automatically detect stomach and intestines.

### **Solution and Future Use**

 Solution to this problem is to create a deep learning model to automate segmentation process.

- It will make cancer patient treatment faster
- get more effective treatment with less side effects
- better long-term cancer control

#### **Dataset**

**UW-Madison GI Tract Image Segmentation (Kaggle)** -





CSV

contain rows with id, class and predicted columns

Total no. of unique images: 101739

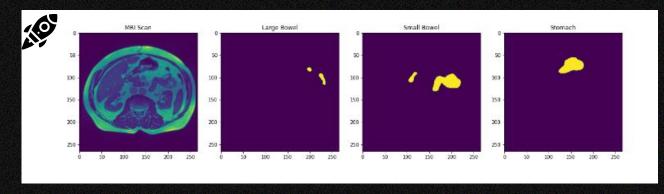
	id	class	segmentation
194	case123_day20_slice_0065	stomach	28094 3 28358 7 28623 9 28889 9 29155 9 29421
197	case123_day20_slice_0066	stomach	27561 8 27825 11 28090 13 28355 14 28620 15 28
200	case123_day20_slice_0067	stomach	15323 4 15587 8 15852 10 16117 11 16383 12 166
203	case123_day20_slice_0068	stomach	14792 5 15056 9 15321 11 15587 11 15852 13 161
206	case123_day20_slice_0069	stomach	14526 6 14789 12 15054 14 15319 16 15584 17 15

### **Dataset**

Image Data IMG

Along with CSV MRI scans with respective masks are provided for each scan

MRI scan and mask corresponding to different parts



## Preprocessing:

#### Strategy 1

Tried to generate all three masks for all of the images

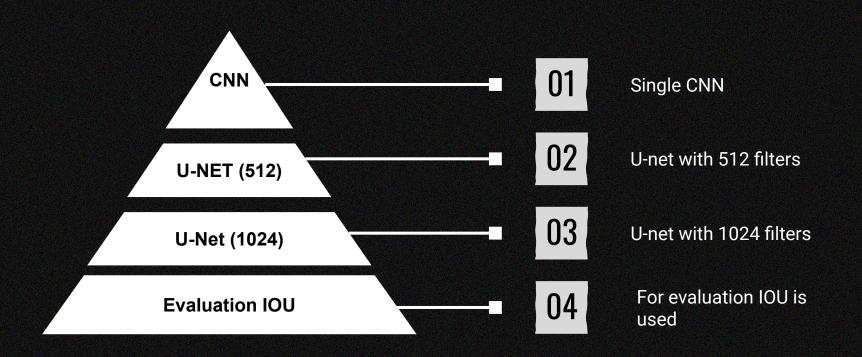
GPU memory was getting exceeded

#### Strategy 2

Generated masks during training for a batch of 32 images at the time

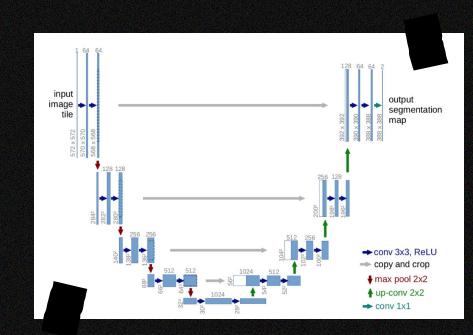
Created a csv file containing all the RLE encoded values of the masks and generated masks while training.

## Model



#### **U-net**

- Contraction Phase: Reduce spatial dimension, but increases the "what."
- Expansion Phase :Recovers object details and the dimensions, which is the "where."
- Concatenating feature maps from the
   Contraction phase helps the Expansion phase
   with recovering the "where" information.



## Training:

- Due to low available GPU memory I generated mask images for every batch (32 images) during training
- Due to very long training time, I saved checkpoints after every 5 epochs during training

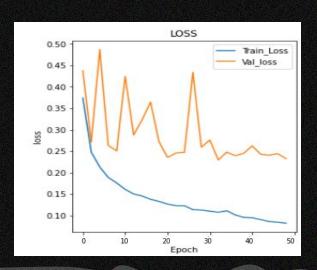
Total params: 31,042,369
Trainable params: 31,042,369
Non-trainable params: 0
Input size (MB): 0.25
Forward/backward pass size (MB): 808.00
Params size (MB): 118.42
Estimated Total Size (MB): 926.67

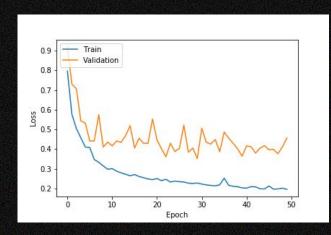
# **Training Loss:**

Epoches	Small Bowel	Large Bowel	Stomach
Epoch 5	0.1012	0.0732	0.4400
Epoch 20	0.0301	0.0131	0.2003
Epoch 30	0.0072	0.0062	0.1031
Epoch 40	0.0063	0.0045	0.0329
Epoch 50	0.0055	0.0037	0.0146

# Training Loss vs Epochs

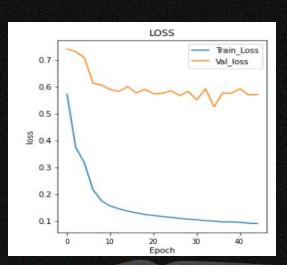
#### **Small Bowel**





Stomach

#### Large Bowel



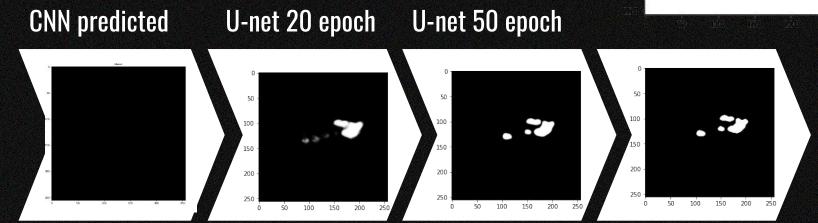
# **Predictions**

Class	MRI SCAN	Mask	Predicted mask	
Stomach		2		
Large Bowel		*		
Small Bowel				

## Improvement in Results



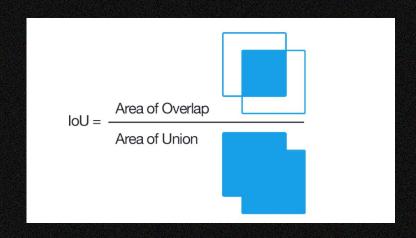
Small Bowel



Real

## **Evaluation: IOU Intersection over union**

Intersection over Union is an evaluation metric used to measure the accuracy of an object detector on a particular dataset.

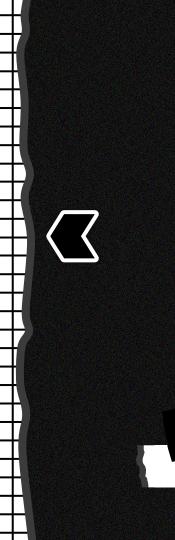


# **Testing Results**

Rank	Class	IOU	Loss (after 50 epochs)
1.	Stomach	0.480353	0.0046
2.	Large Bowel	0.578355	0.0037
3.	Small Bowel	0.613420	0.0055

#### Conclusion

- Learned and implemented UNet architecture in pytorch
- Performed image segmentation
- Results obtained after 50 epochs were decent
- With more computational resources we can converge the models even better



# Thanks

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