Massachusetts Institute of Technology

# Computer-Aided Segmentation of Gastrointestinal Structures

## 6.8300: Advances in Computer Vision

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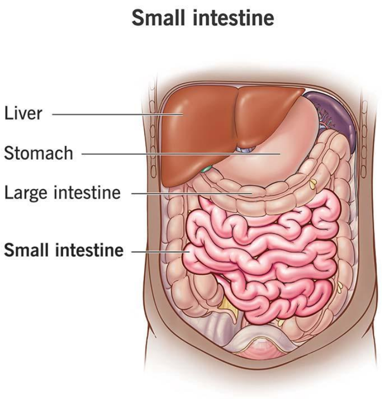
# Introduction

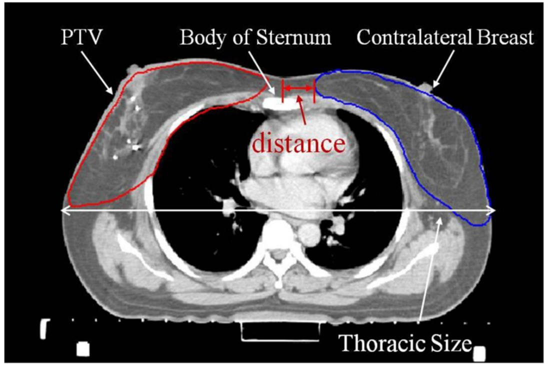
## Problem Statement

- Millions are diagnosed with GI cancer each year
- Treatment requires precise radiation therapy planning

## Current Process

- Manual segmentation of MRI scans
- Labor-intensive & Prone to errors



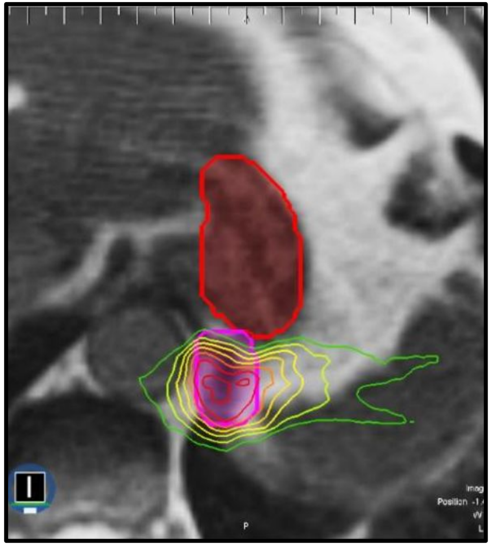

# Proposed Solution

**Objective**

- Develop a deep learning model to automate segmentation of stomach and intestines from MRI scans

**Impact**

- Expedite treatment
- Reduce errors
- Improve patient outcomes



*In figure above, the pink area is tumor, red area is stomach, and other lines are radiation dose levels*

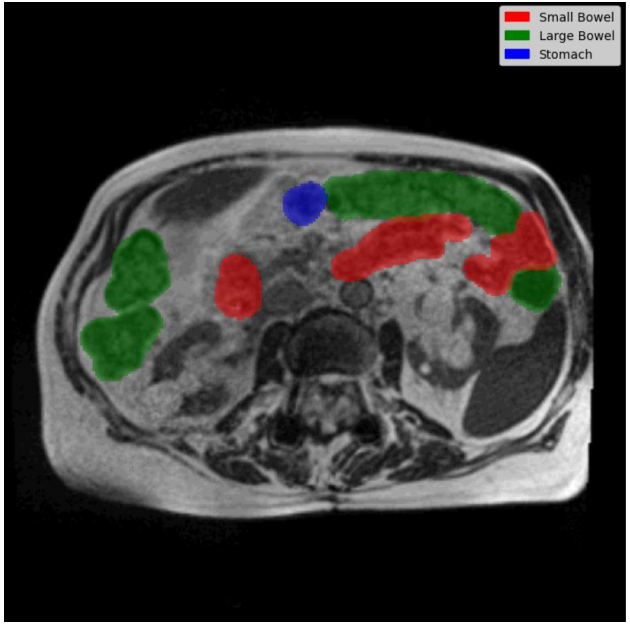
# Related work

- **U-Net Type Neural Networks**
  - Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation, 2015.
- **DeepLabv3+**
  - Liang-Chieh Chen, George Papandreou, Florian Schroff, and Hartwig Adam. Rethinking atrous convolution for semantic image segmentation, 2017.
  - Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation, 2018.
- **R-CNNs**
  - Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation, 2014.
  - Kaiming He, Georgia Gkioxari, Piotr Dollar, and Ross Girshick. Mask r-cnn, 2018.
- **Multi-Task Learning**
  - Wenjia Bai and Dinggang Shen. Self-supervised learning for cardiac mr image segmentation by anatomical position prediction. In Medical Image Computing and Computer Assisted Intervention–MICCAI 2019, Cham, 2019. Springer
  - Rich Caruana. Multitask learning. Machine Learning, 28:41–75, 1997.

# Dataset

**Dataset:**

- UW-Madison GI Tract Image Segmentation repository: Kaggle competition
    - 85 cases (patients)
    - MRI scans on different days (normally 3-5 days)
    - Different slices each day
- Segmentation and class information




*Red mask represents small bowel, green mask represents large bowel, and blue mask represents stomach*

# Data Preprocessing

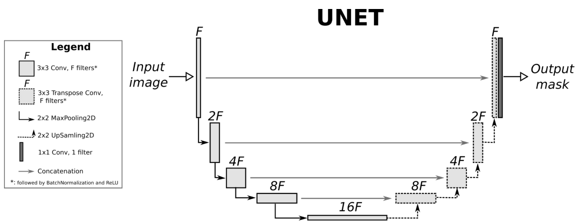
1. Extract metadata from scans (day, case, slice)
2. Converting RLE encoding to masks
3. Train (65%), Val (15%), Test (20%) split
4. Created COCO annotations
5. Developed DataLoader and DataGenerator modules

COCO
Common Objects in Context

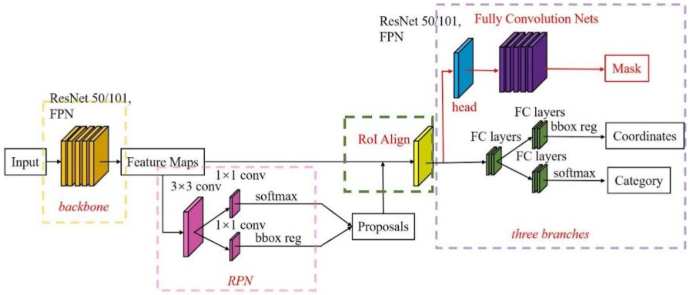

```json
{
    "categories": [
        {
            "id": 0,
            "name": "small_bowel"
        },
        {
            "id": 1,
            "name": "large_bowel"
        },
        {
            "id": 2,
            "name": "stomach"
        }
    ],
    "images": [
        {
            "id": 1,
            "file_name": "case123/case123_day20/scans/slice_0066_266_266_1.50_1.50.png",
            "width": 266,
            "height": 266
        },
        {
            "id": 2,
            "file_name": "case123/case123_day20/scans/slice_0067_266_266_1.50_1.50.png",
            "width": 266,
            "height": 266
        },
```

# Methodology

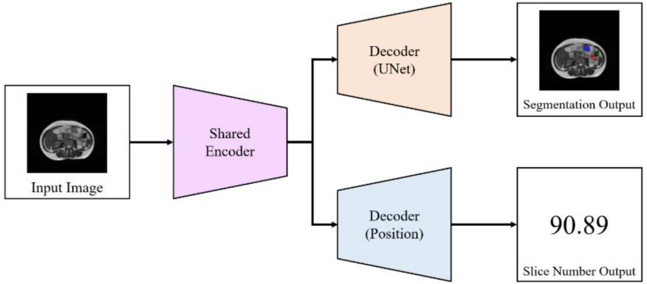
- **Simple U-Net (Baseline)**
  - This model serves as baseline, with a simple and symmetric encoder-decoder architecture
- **Efficient Net:**
  - Efficient Net is used as an encoder in the U-Net architecture. It leverages pretrained weights on imagenet dataset
- **DeepLabv3v+:**
  - Leveraging a powerful backbone ResNeXt101_32x8d for segmentation
- **Mask R-CNN:**
  - Integrate a R-CNN framework with an additional mask prediction branch
- **Multi-Task Learning U-Net:**
  - Simultaneous semantic segmentation and positional regression with shared encoder




U-Net Architecture

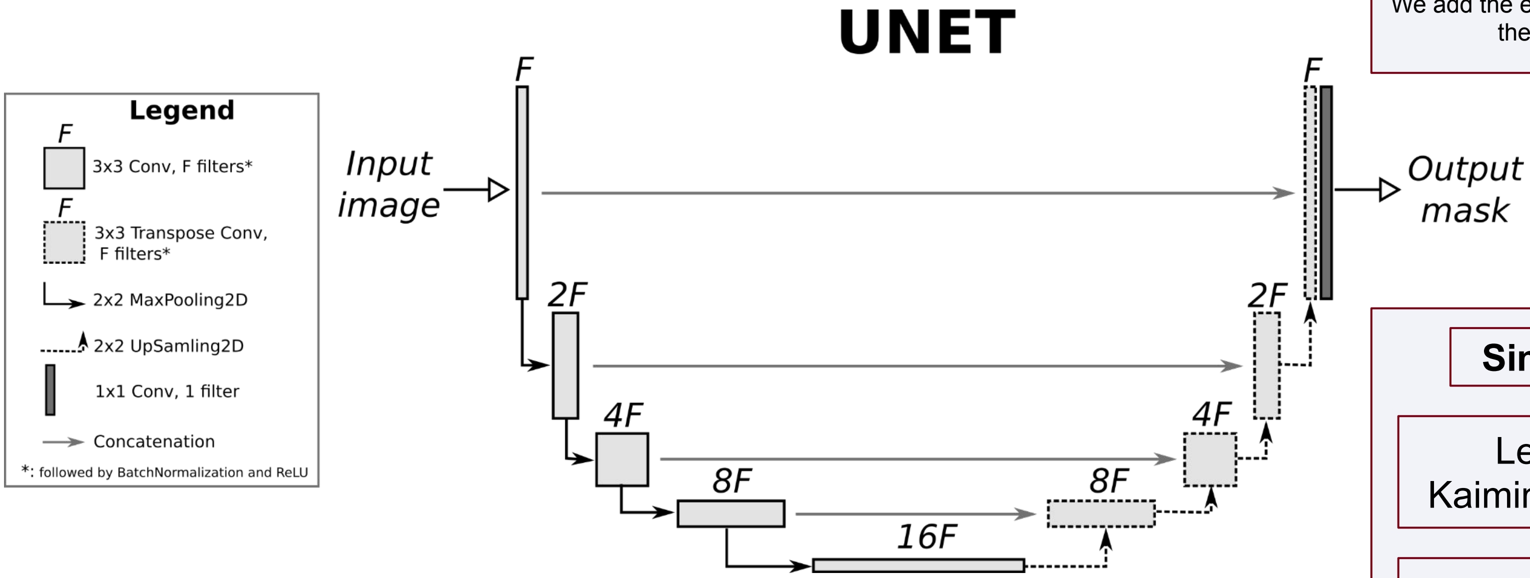



Mask R-CNN Architecture




Multi-Task Learning Architecture

# U-Net Type Models




**Efficient Net**

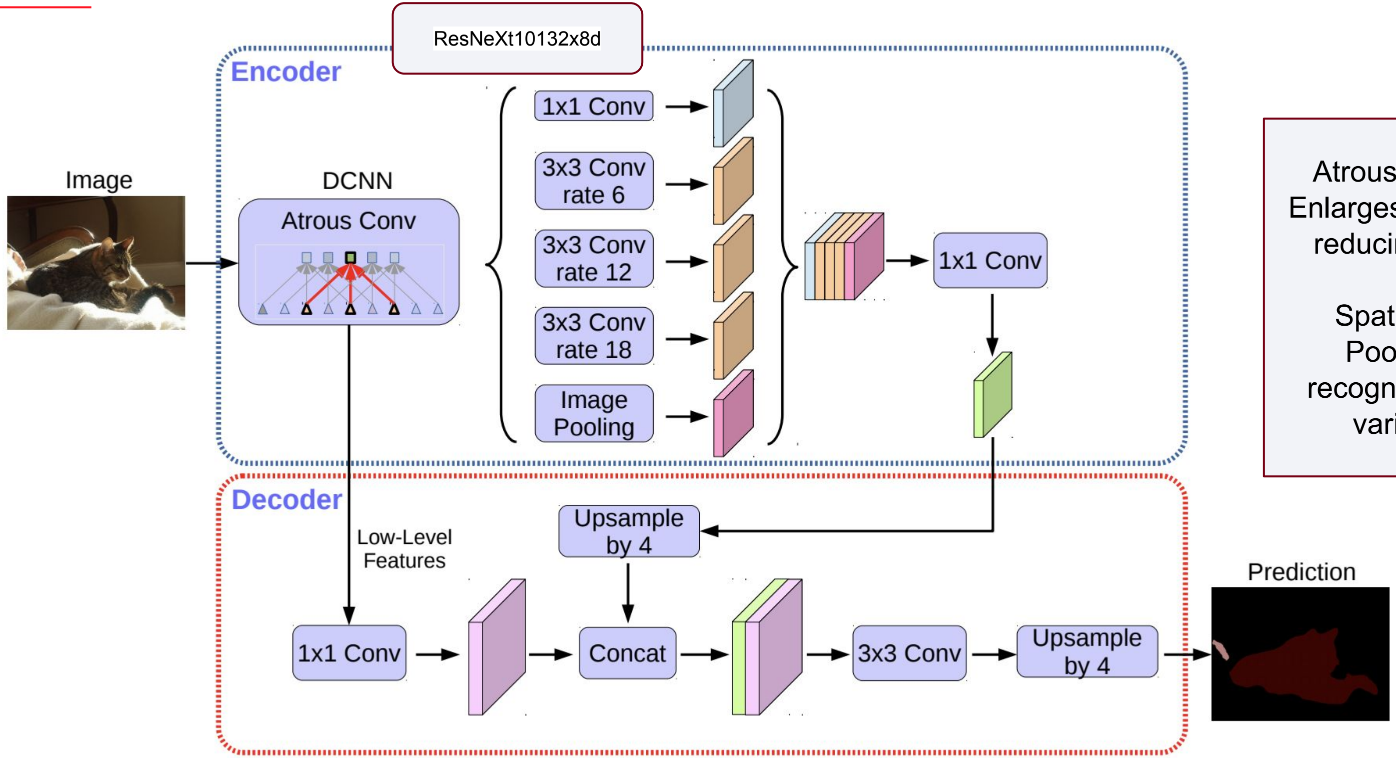
We add the efficient net architecture to the encoding layer

**Simple U-Net**

Leaky ReLU
Kaiming Initialization

Downsampling - 4 blocks
Upsampling - 4 blocks

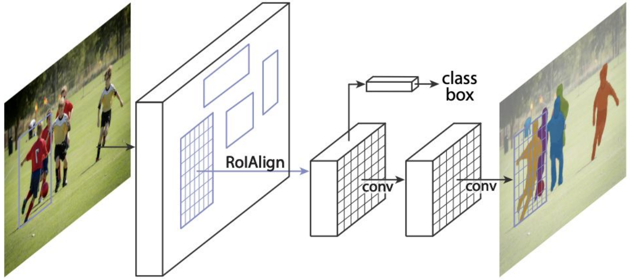
# DeepLabv3+



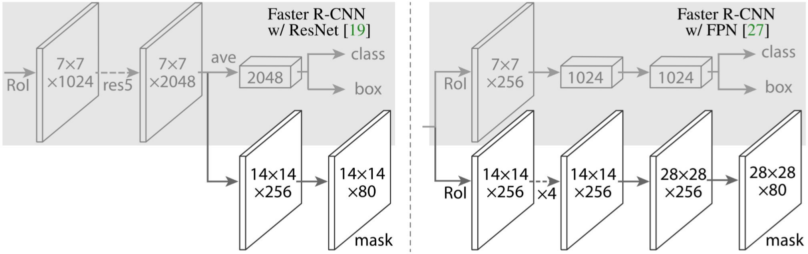

Atrous convolution: Enlarges field view w/o reducing resolution

Spatial Pyramid Pooling: helps recognize objects of various sizes

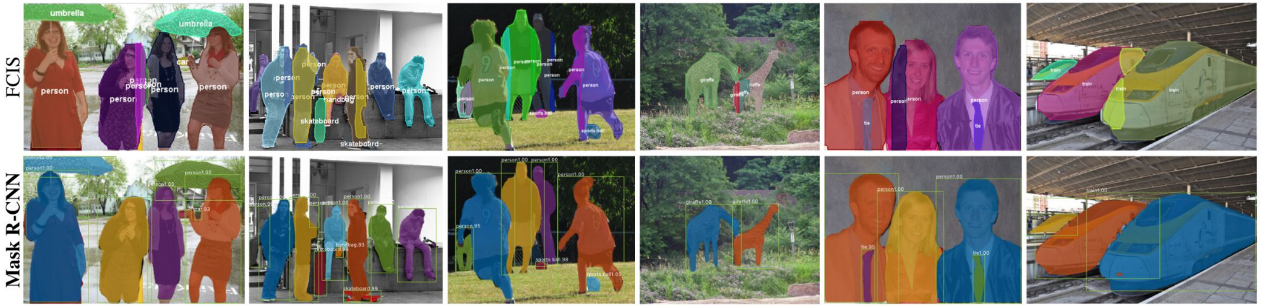
# Mask R-CNN




**Mask R-CNN framework for instance segmentation**

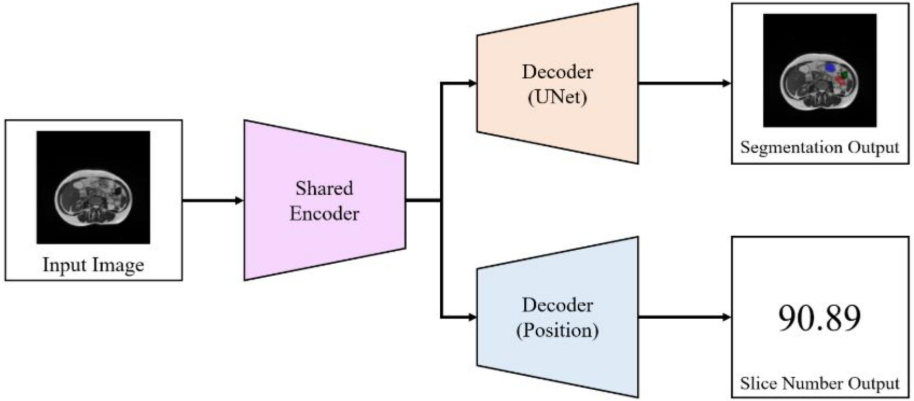


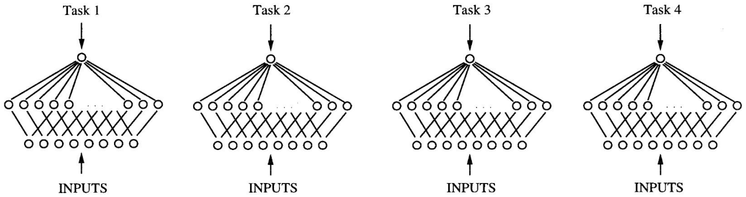

**Mask R-CNN Head Architecture**



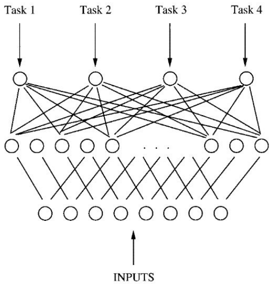

**Performance on Microsoft COCO dataset compared to FCIS model**

# Multi-Task Learning U-Net




**Single Task Backpropagation of four tasks with the same inputs**




**Multi-Task Backpropagation of four tasks with the same inputs**

# Evaluation Metrics

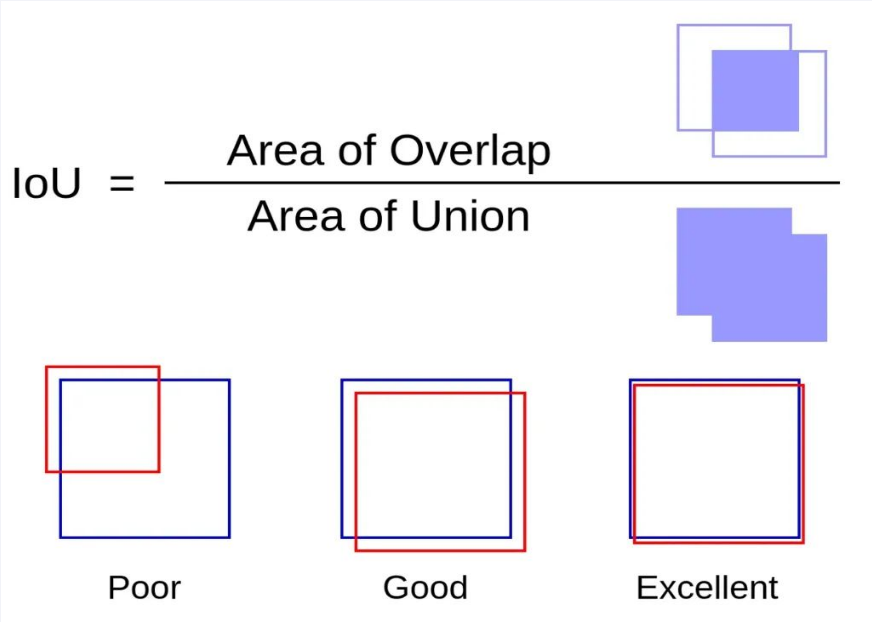
### Dice Loss

- Measures overlap between predicted and true segmentation masks
- Lower is better

$$C = \frac{2 \times |M_1 \cap M_2|}{|M_1| + |M_2|}$$

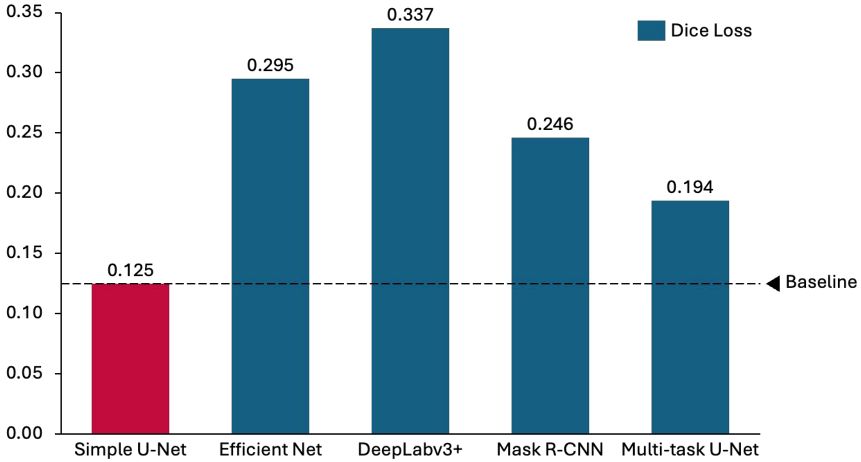
$$L_{\text{Dice}} = 1 - C$$

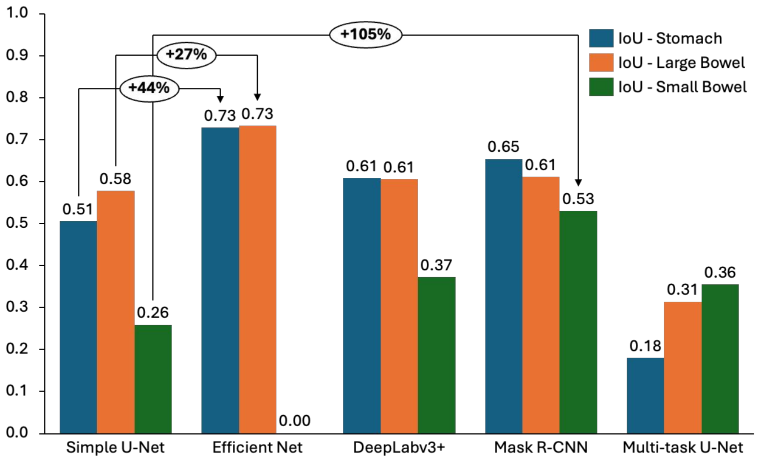
### Intersection over Union



# Model Performance

- Metrics are calculated based on test (20%) dataset
- Model training on Google Colab platform with A100 GPU




**Mask R-CNN** is overall the best model (high score and balanced in three organs)

# Result Visualization

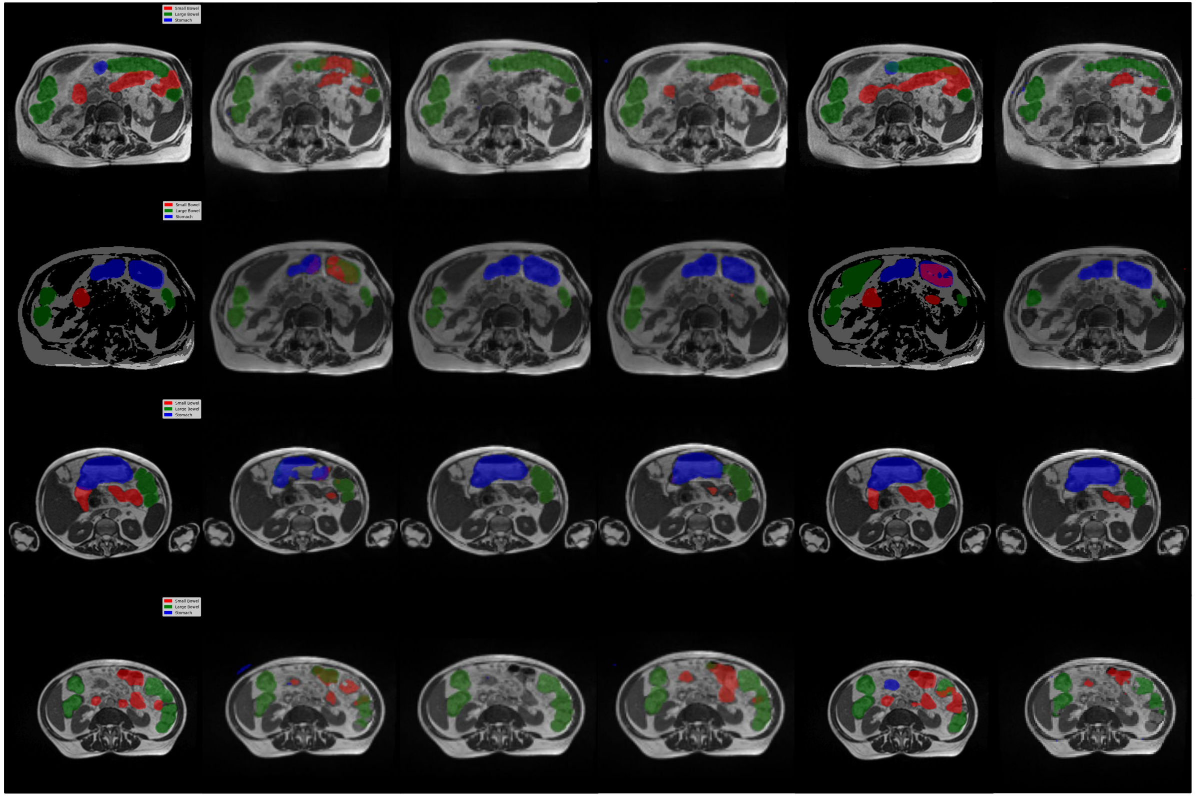
Ground Truth | Simple UNet | Efficient UNet | DeepLabv3+ | Mask R-CNN | Multi-task UNet

Train 1

Train 2

Test 1

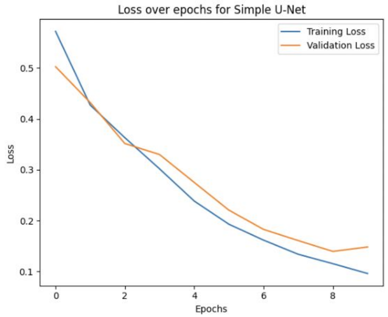
Test 2



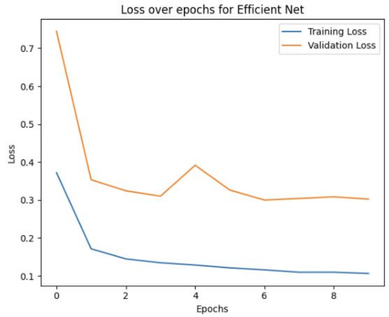
**Red: Small Bowel; Green: Large Bowel; Blue: Stomach**

# Error Analysis

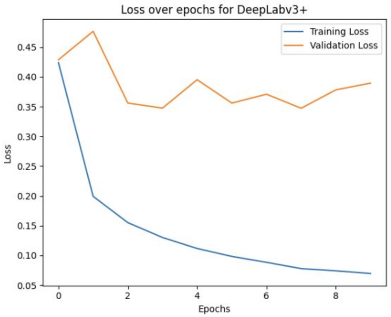
## Simple UNet



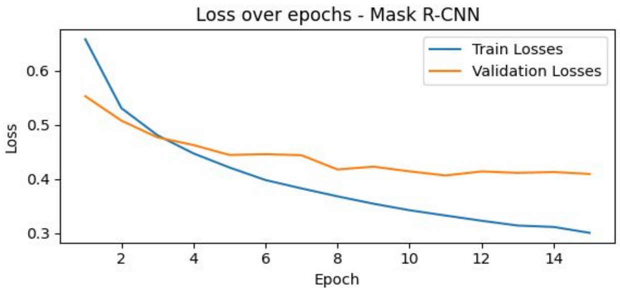

## Efficient Net



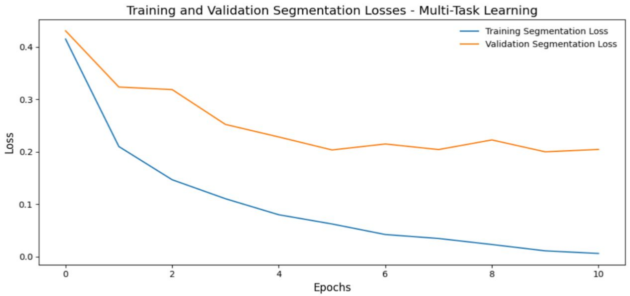

## DeepLabv3+




## Mask R-CNN



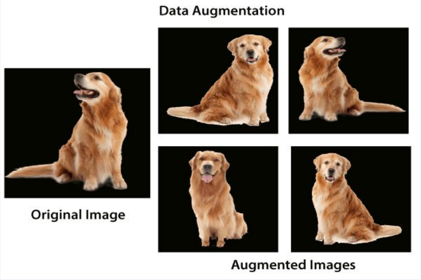

## Multi-task Learning U-Net

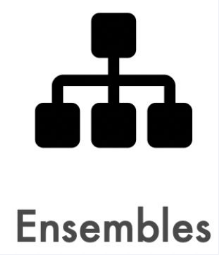


# Conclusion & Future Work

- Out of the 5 models, the simple baseline model performed well with respect to the dice loss metric
- While advanced models and multi-task learning did not consistently outperform the baseline, some showed notable improvements in specific metrics, leading to slight enhancements in test set performance for certain classes

## Future Directions




Improve the positional encoding

# References


1. Liang-Chieh Chen, George Papandreou, Florian Schroff, and Hartwig Adam. Rethinking atrous convolution for semantic image segmentation, 2017.
2. Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation, 2018.
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5. Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollar, and C. Lawrence Zitnick. Microsoft coco: Common objects in context.In David Fleet, Tomas Pajdla, Bernt Schiele, and Tinne Tuytelaars, editors,Computer Vision – ECCV 2014, pages 740–755,Cham, 2014. Springer International Publishing.
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# Any Questions? Email us!


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# Appendix

# Model Results on Metrics

Table 1. Model results

| Model | DiceLoss | IoU-S | IoU-LB | IoU-SB |
|---|---|---|---|---|
| Simple U-Net | **0.125** | 0.506 | 0.578 | 0.259 |
| Efficient Net | 0.295 | **0.728** | **0.733** | 0.000 |
| DeepLabv3+ | 0.337 | 0.609 | 0.606 | 0.372 |
| Mask R-CNN | 0.246 | 0.654 | 0.611 | **0.530** |
| Multi-task U-Net | 0.194 | 0.180 | 0.314 | 0.355 |