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Multi-Organ Image Segmentation

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Introduction

- A specific application of image segmentation techniques in the field of medical imagings.
- Identify and isolate multiple organs within medical scans such as CT, MRI, or ultrasound images.
- **Data Source**: UW-Madison Carbone Cancer Center. MRI scans from actual cancer patients on separate days during radiation treatment.

Dataset

id: unique identifier for object

class: the predicted class for the object(large_bowel, small_bowel, stomach

	id	class
0	case123_day20_slice_0001	large_bowel
1	case123_day20_slice_0001	small_bowel
2	case123_day20_slice_0001	stomach

segmentation: Run-Length Encoding(RLE)-encoded pixels for the identified object(28094 3 28358 7...). Run-length encoding is a basic form of data compression where sequences of the **same data value (runs)** are stored as **a single data value and count**. This method is particularly efficient for images with large areas of **uniform pixels**。

Data processing

- Create new columns: width, height, path... "slice_0105_266_266_1.50_1.50.png" (115488, 3)
- Create separate column for class: large bowel, small bowel, stomach. The values are corresponding segmentation(RLE-encoded pixels) (38496, 11).
- Remove images with no masks (16590, 11)

Exploratory Data Analysis (EDA)

Figure 1： Sample Image

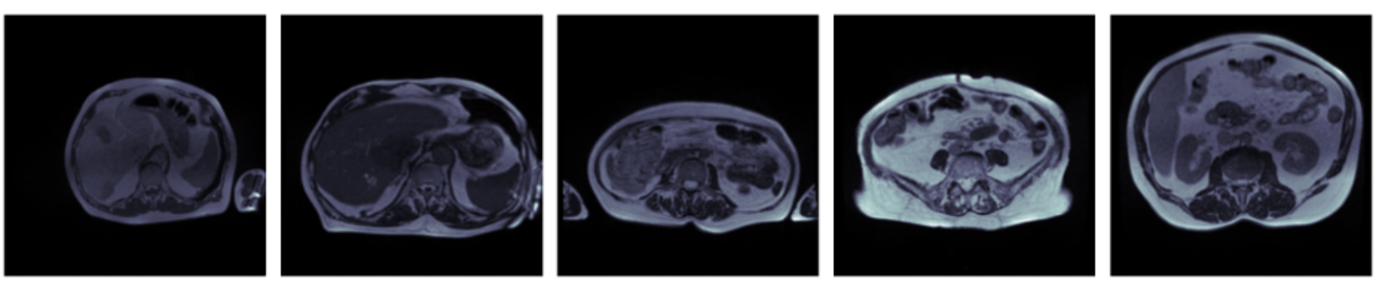


Figure 2： Image with Masks

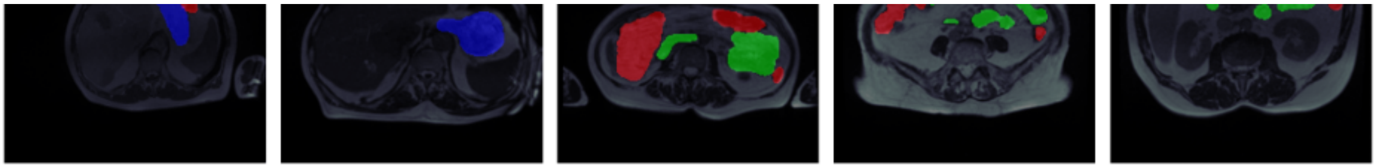
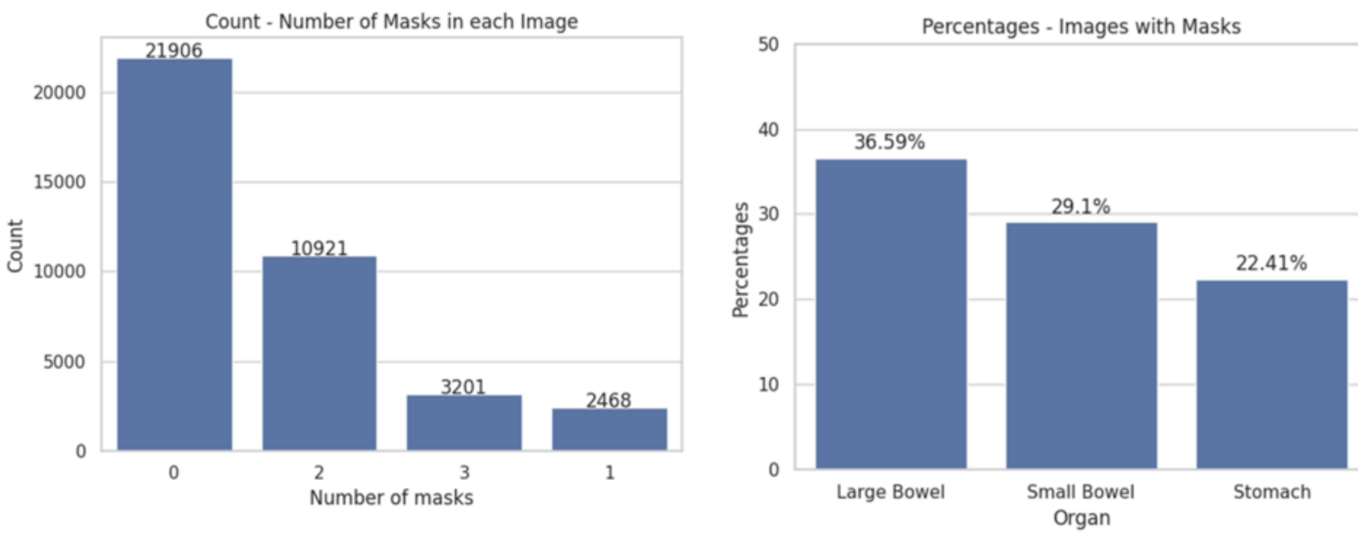


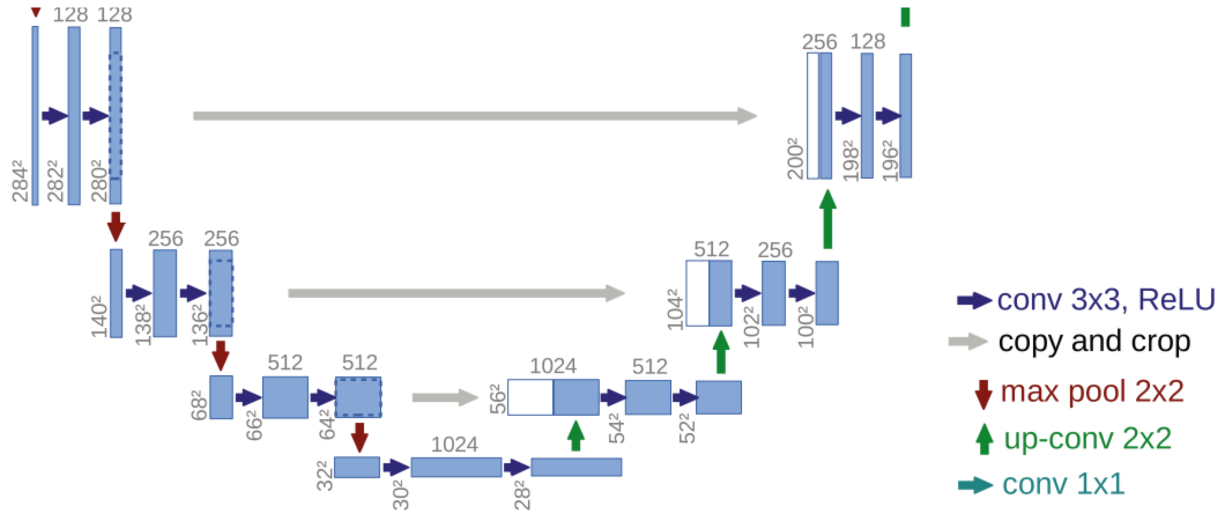
Figure 3： Statistics



Model 1: U-Net

Brief Intro

- A convolutional neural network (CNN) architecture which was originally developed for biomedical image segmentation tasks.
- U-shaped' structure - Contracting Path & Expansive Path.
- The feature maps from the contracting path and expansive path was concatenated.



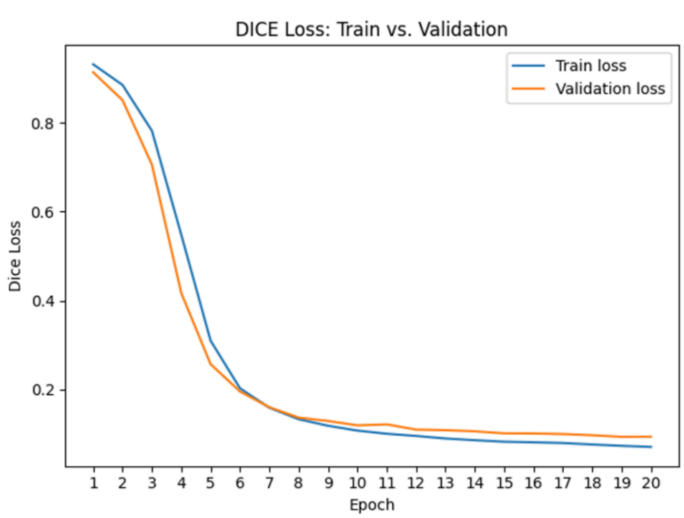
Experiment & Results

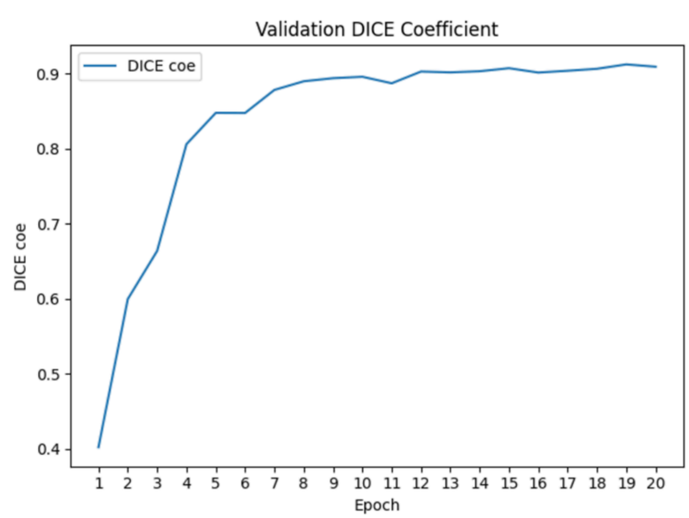
DICE coefficient: A statistical tool used to measure the similarity between two sets of data. Compare the **pixel-wise agreement** between a **ground truth** segmentation and a **predicted** segmentation.

$$\text{Dice} = \frac{2 \times |X \cap Y|}{|X| + |Y|}$$

DICE Loss: Directly considers the overlap between the predicted and true segmentation masks

$$\text{Dice} = 1 \text{ - Dice Coefficient}$$

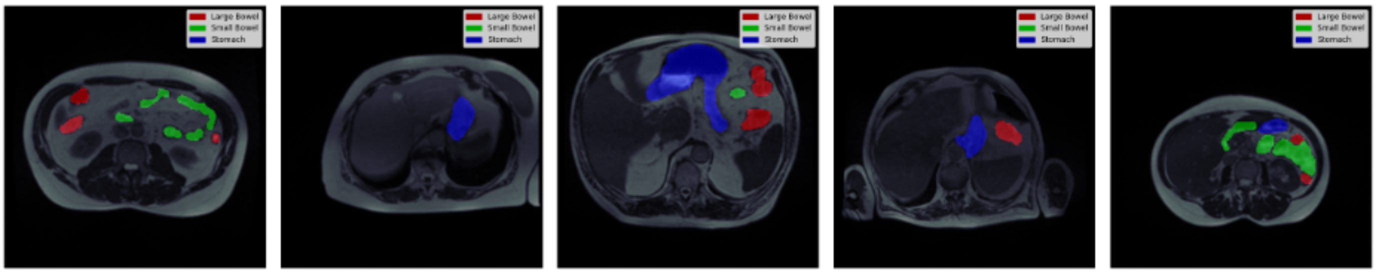




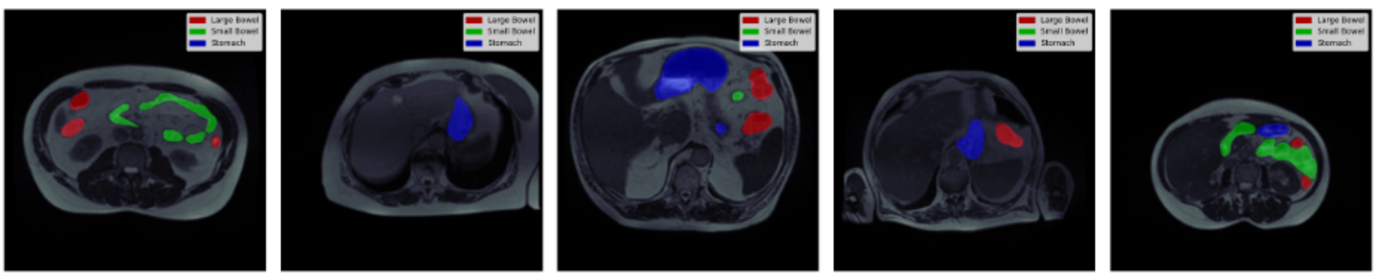
Test - DICE coefficient by Classes

Large Bowel	Small Bowel	Stomach
0.90	0.88	0.93

Test - Ground Truth



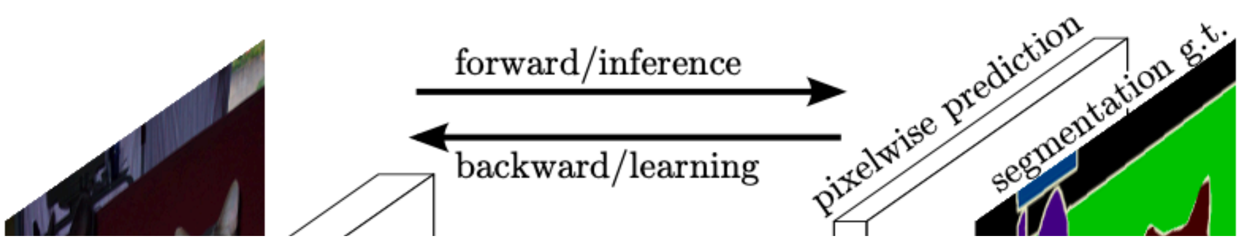
Test - Prediction

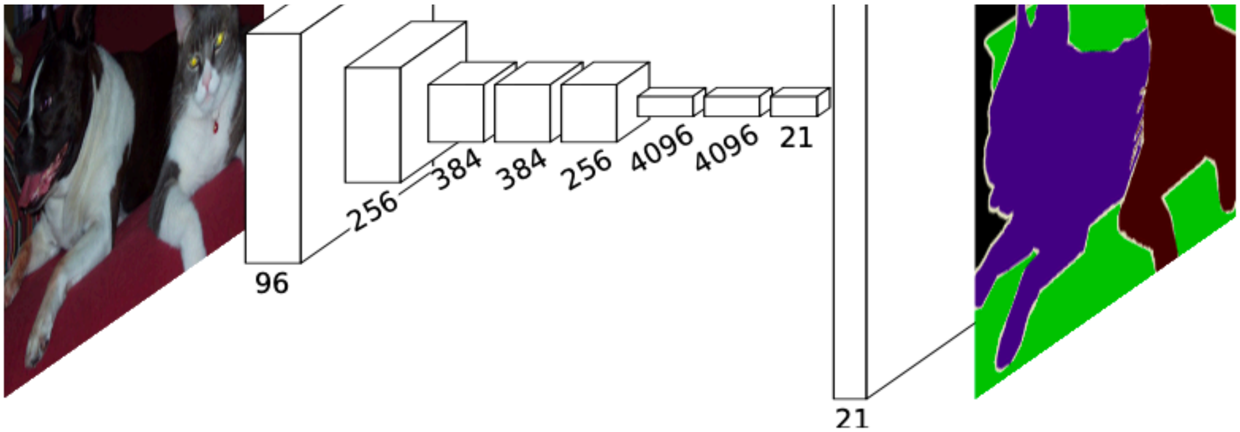


Model 2: F-CNN

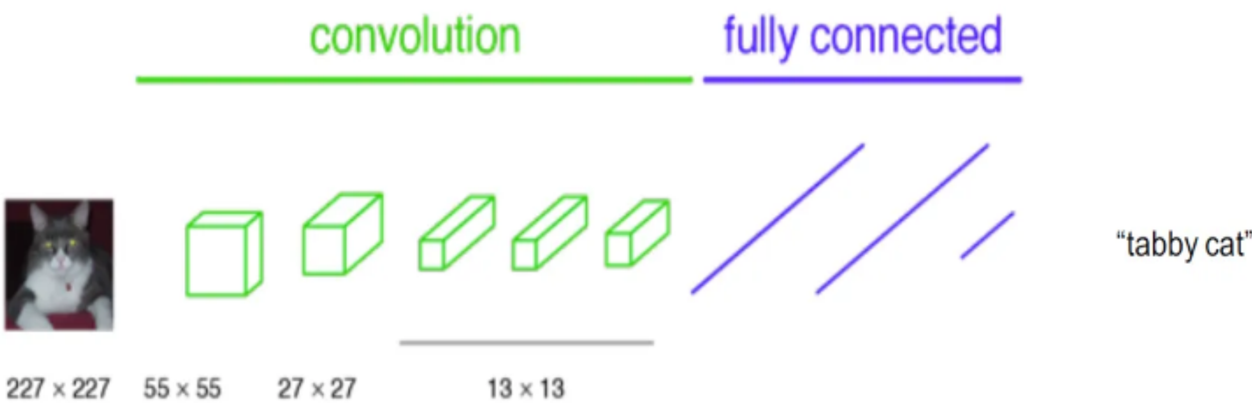
Brief Intro

- Though UNET is quite popular for Bio-medical image segmentation.
- FCN has also been used for image segmentation previously. UNET is an extension.
- Take input of arbitrary size and produce correspondingly-sized output with efficient inference and learning.
- The model architecture consists of an encoder network and a decoder network.

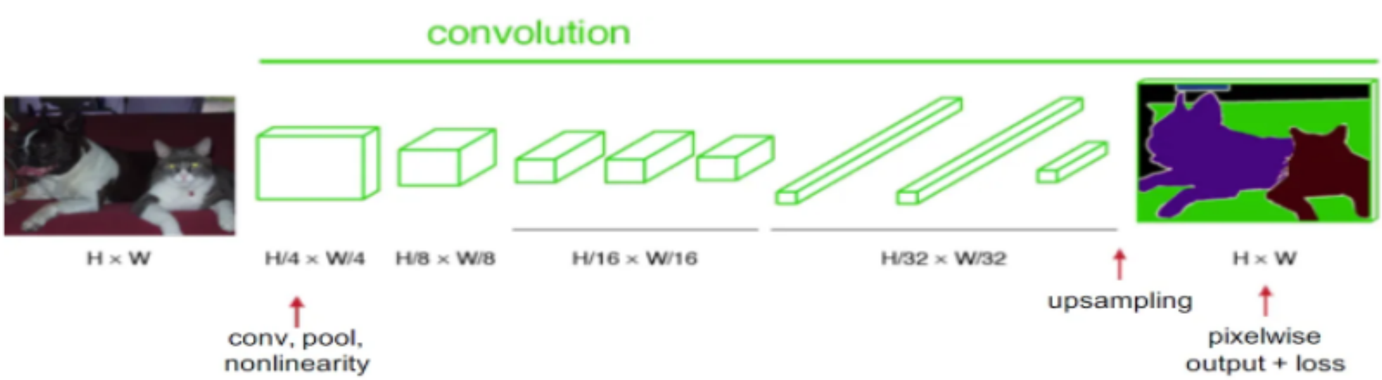




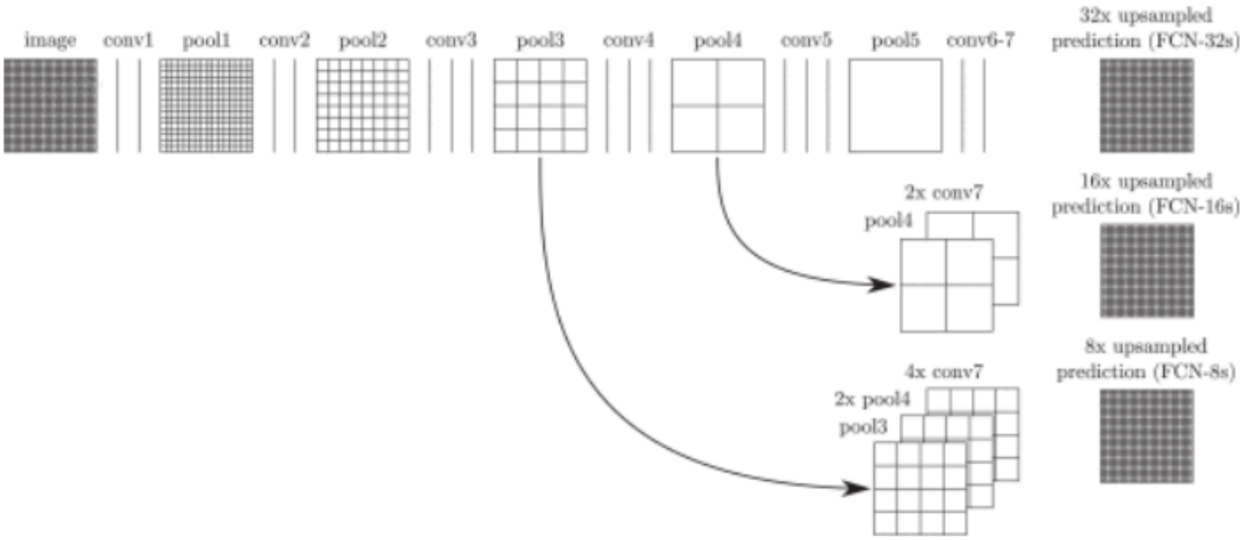
- For image classification, we downsize image to output one predicted label.



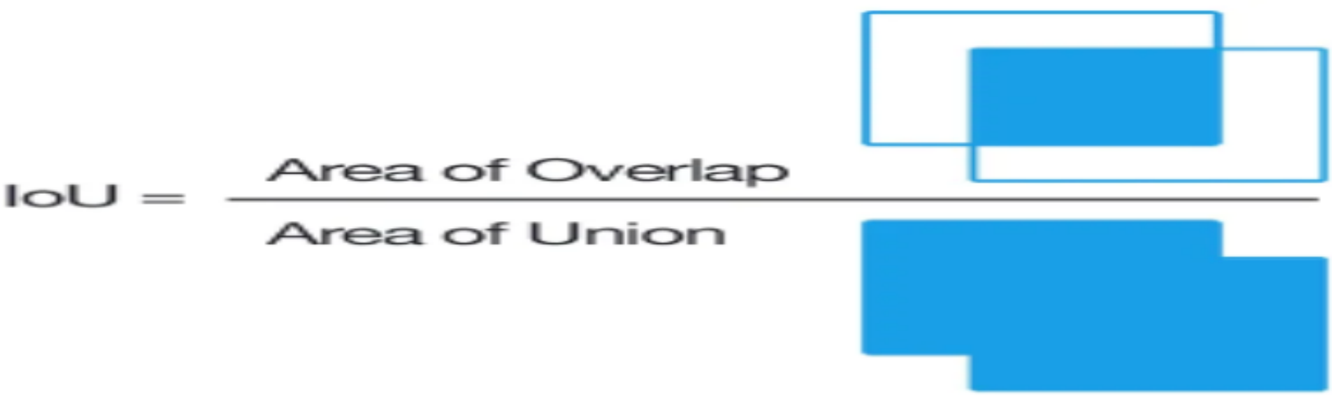
- Rather we can upsample to calculate the pixel wise output.



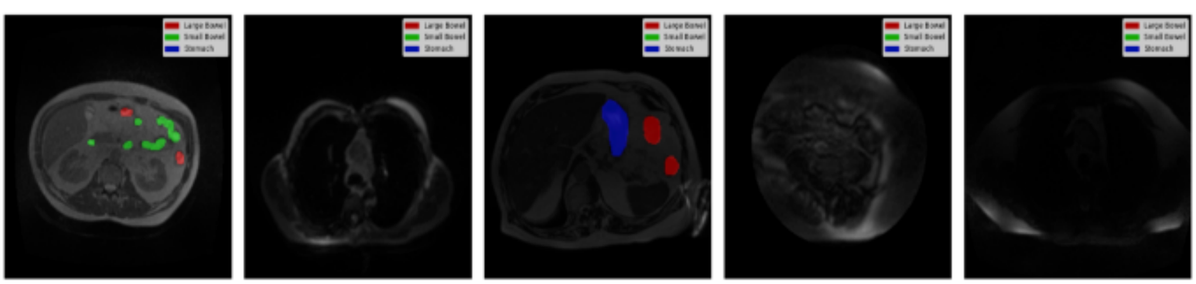
- This fusing operation actually is just like the boosting / ensemble technique used in VGGNet, where they add the results by multiple model to make the prediction more accurate.



Experiment results



- *Train score = 0.5(dice coeff) + 0.5*(IoU coeff) = 0.69**



Conclusion

- UNet is able to do image localisation by predicting the image pixel by pixel
- U-Net combines the strengths of traditional FCNs with additional features that make it more effective for image segmentation tasks.
- The two models differ in symmetricity of the encoder and decoder portions of the network and the skip connections between them.