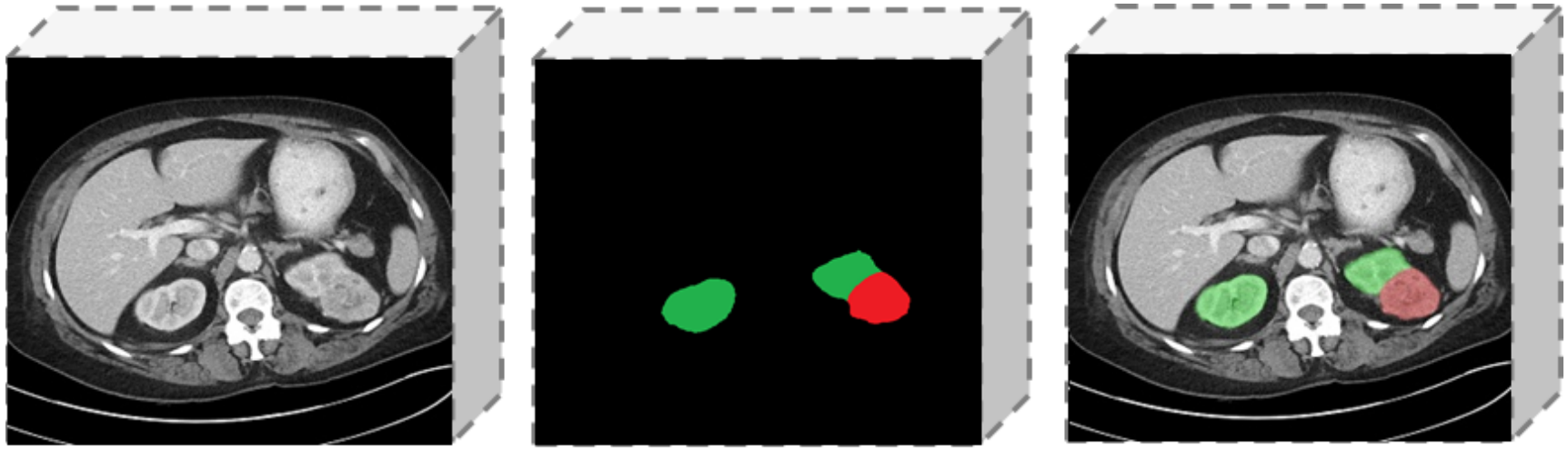
1. Overview

• (1) 대회 소개

대회 목표

- CT 데이터를 통해 신장, 신장암, 그 외 3가지를 완벽하게 분리하는 Segmentation 모델 개발

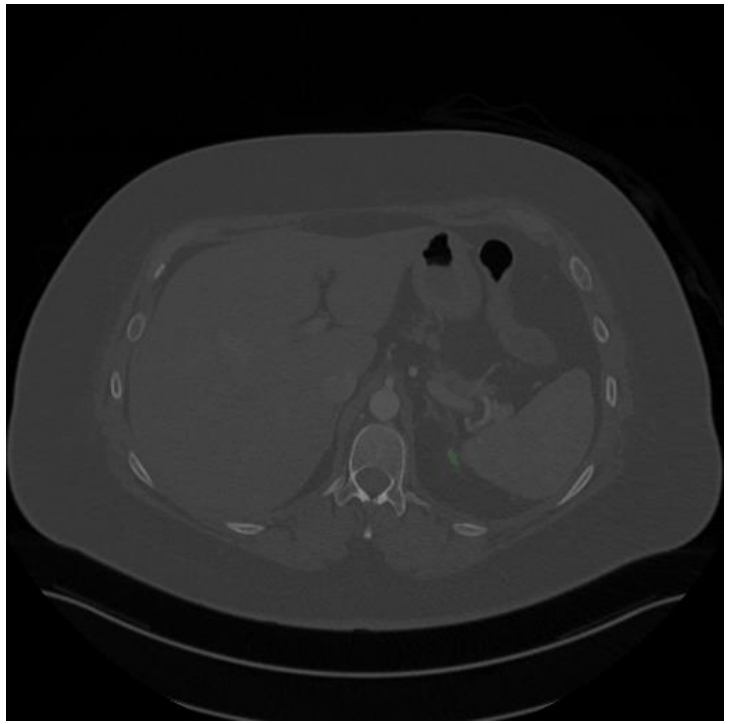


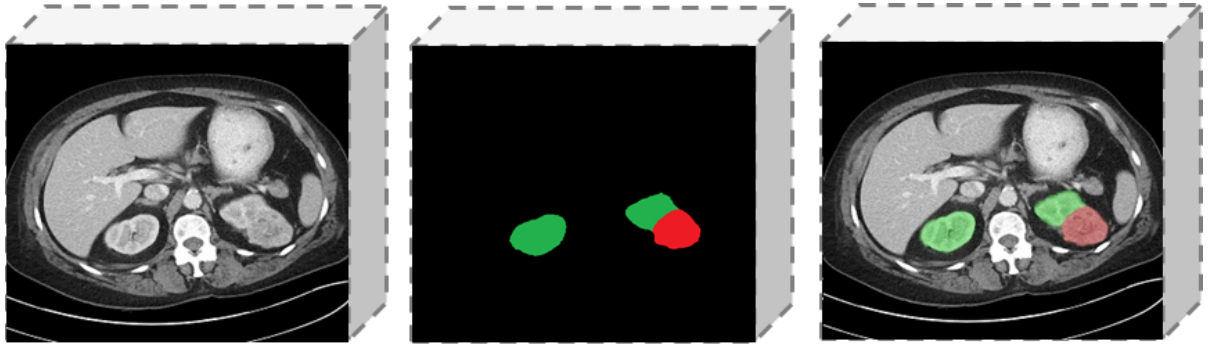
Kidney & Tumor Semantic Segmentation

- Kidney : 초록색 영역
- Tumor : 빨간색 영역
- 그 외 : 검정색 영역

1. Overview

- (2) 입력 데이터





입력값으로 제공된 데이터는 3D CT 데이터.
1 case는 총 64개의 영상 단면으로 구성되어 있음.
* shape : (64, 512, 512, 1)

INPUT

- train : 100 case (100*64 samples)
- test : 83 case (83*64 samples)

LABEL

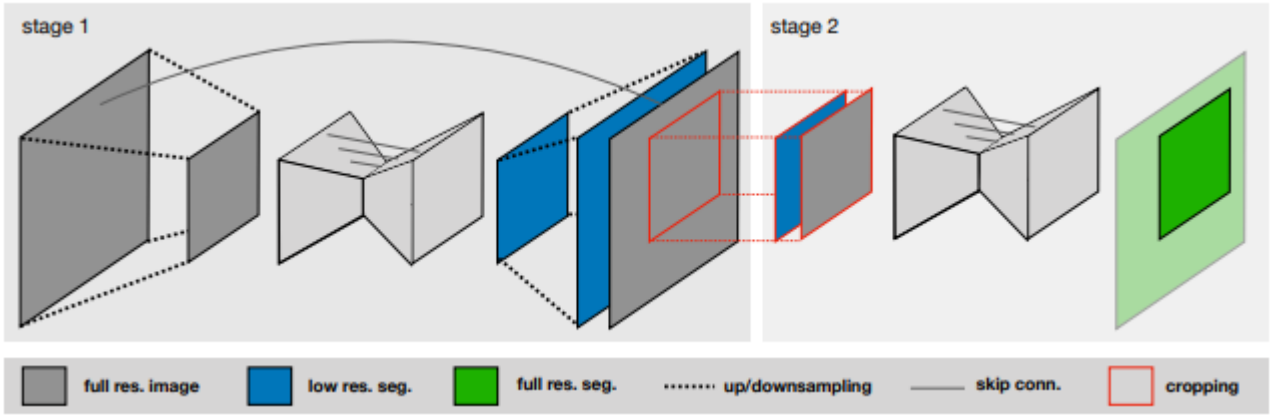
- train : 100*64 samples
- test : 83 * 64 samples

2. Solution

(1) 1st Solution

[Model]

- nnUnet
- 5 Experiments with KFold Validation
- Majority Vote Ensemble with Staple method (https://pubmed.ncbi.nlm.nih.gov/15250643/)



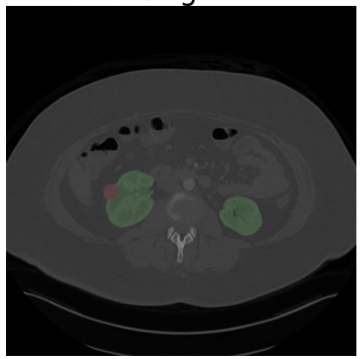
2. Solution

(1) 2nd Solution

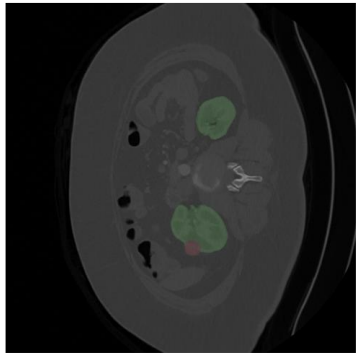
[Model]

- UnetPlusPlus + EfficientNetB8
- 5 Fold with Group KFold by UserID
- Augmentation

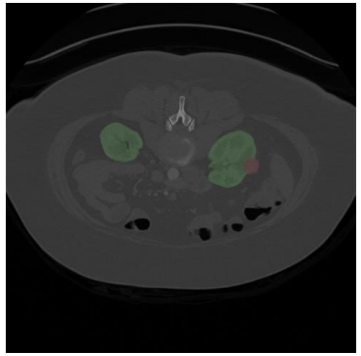
Origin



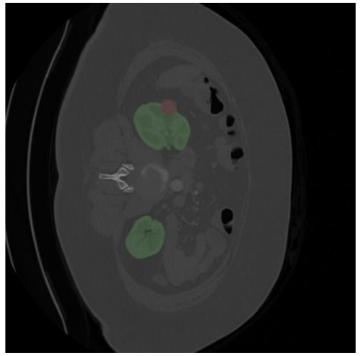
Rotation 90°



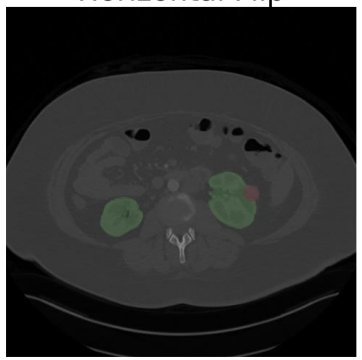
Rotation 180°



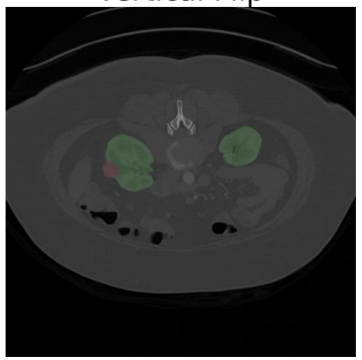
Rotation 270°



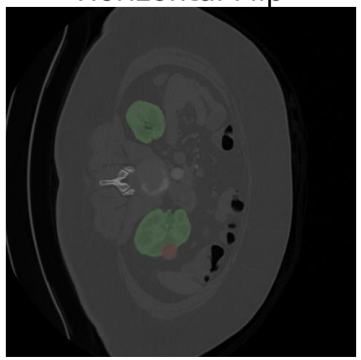
Horizontal Flip



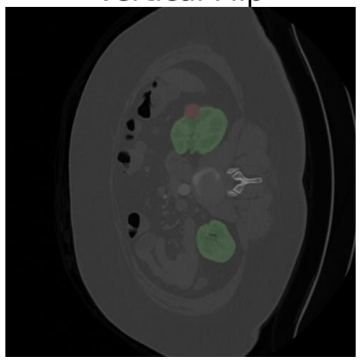
Vertical Flip



Rotation 90°
Horizontal Flip



Rotation 90°
Vertical Flip



2. Solution

(1) 2nd Solution

[Parameter]

Parameter	Best	Try
Optimizer	AdamP (learning rate : 1e-3)	Adam, AdamW, SGD
Scheduler	Polynomial Decay (1e-3 → 1e-6)	None, Cosine Annealing, Cosine Annealing with WarmUp Restart
Epochs	30	10-100
Batch Size	3-6	1-9
Loss	Cross Entropy	Binary Cross Entropy, Only 1,2 CE
Metrics	Only 1,2 Dice Similarity Coefficient	0,1,2 Dice Similarity Coefficient
Saved	validation score 1,2 DSC Average	

2. Solution

(1) 2nd Solution

[Inference]
Test 데이터를 추론 시 조금 더 유연한 예측을 할 수 있도록 probability threshold를 낮춤

Ex)

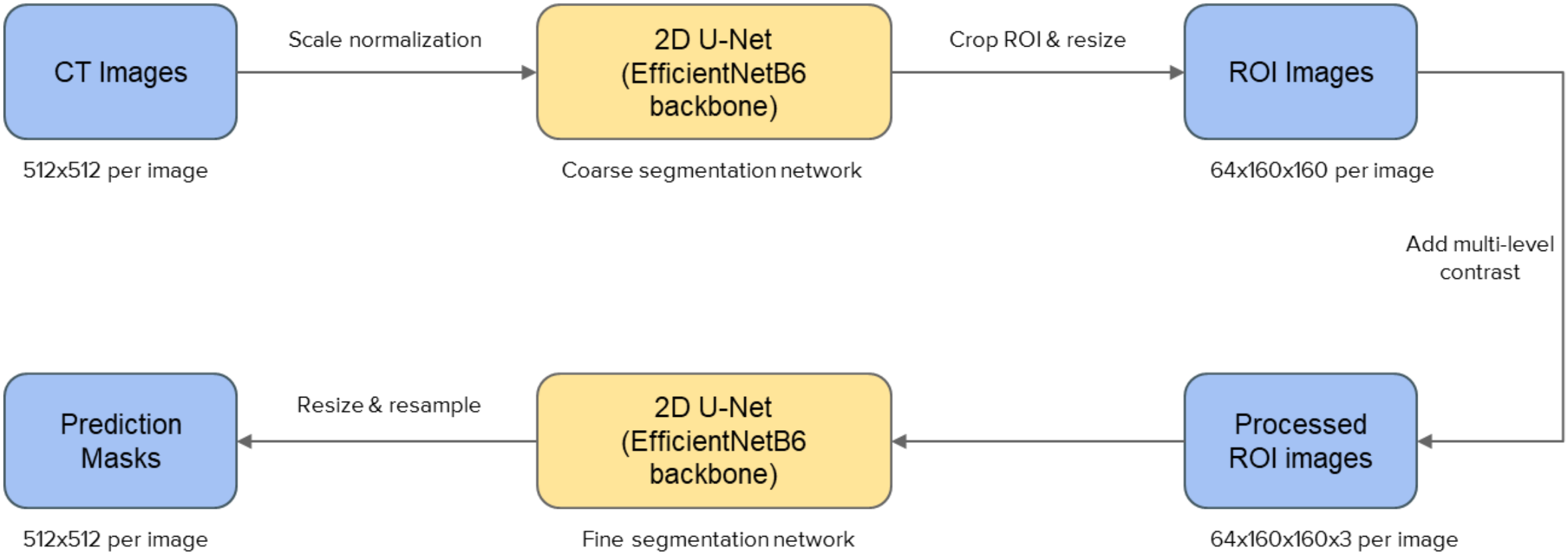
softmax output : [0.1, 0.6, 0.3]
threshold : 0.25
Prediction : 1,2

None, Kidney, Tumor 중 1개가 아닌 여러 class로 예측 할 수도 있기 때문에 Kidney와 Tumor가 겹치는 부분이 있을 수 있음. 10개 모델의 예측들을 soft ensemble하여 threshold를 적용한 결과를 최종 제출. (threshold=0.25)

2. Solution

(1) 3rd Solution

[Two-Stage Coarse to Fine Architecture]



2. Solution

(1) 3rd Solution

[Cropping 3D ROI and Resize]

- Due to the variant image scale in images taken from different CT machines,
  - we cropped 3D ROIs of left and right kidneys centered at binary segmentation results from the coarse network
  - then, we resized cropped kidney volumes to 160x160

2. Solution

(1) 3rd Solution

[Multi-level Contrast Input]

- Due to the variant contrast range in images taken from different CT machines,
  - we generated multiple-level of contrast from each image and concatenated them
  - DICOM window level and width = (0, 1024), (0, 512), (0,256)
  - e.g. 160x160 -> 160x160x3

(0, 1024)

(0, 512)

(0, 256)

2. Solution

(1) 3rd Solution

[Customized loss function]

- Our model did satisfying job for segmenting the kidney and tumor together
  - BUT, finding a right shape for tumor was challenging
  - Kidney pixels were dominant over tumor in CT images

- To address this issue, we introduced a customized loss function
  - Weighted categorical crossentropy + soft dice similarity loss
  - As applying more weight on tumor, the model acted more sensitively on the class during training
  - Weight factors:
    - Background : Kidney : Tumor = 1 : 1 : 1.5

2. Solution

(1) 3rd Solution

[Training Details]

- Image Augmentation
  - HorizontalFlip, VerticalFlip, ShiftScaleRotate, Rotate, GaussNoise, RandomBrightnessContrast
- Epoch : 100
- Optimizer : Adam
- Learning Rate : 1e-3
- Activation Function : Softmax
- classes : 3
- All Training Image (No Validation)