Multiple Sclerosis Lesion Segmentation using 3D Unet

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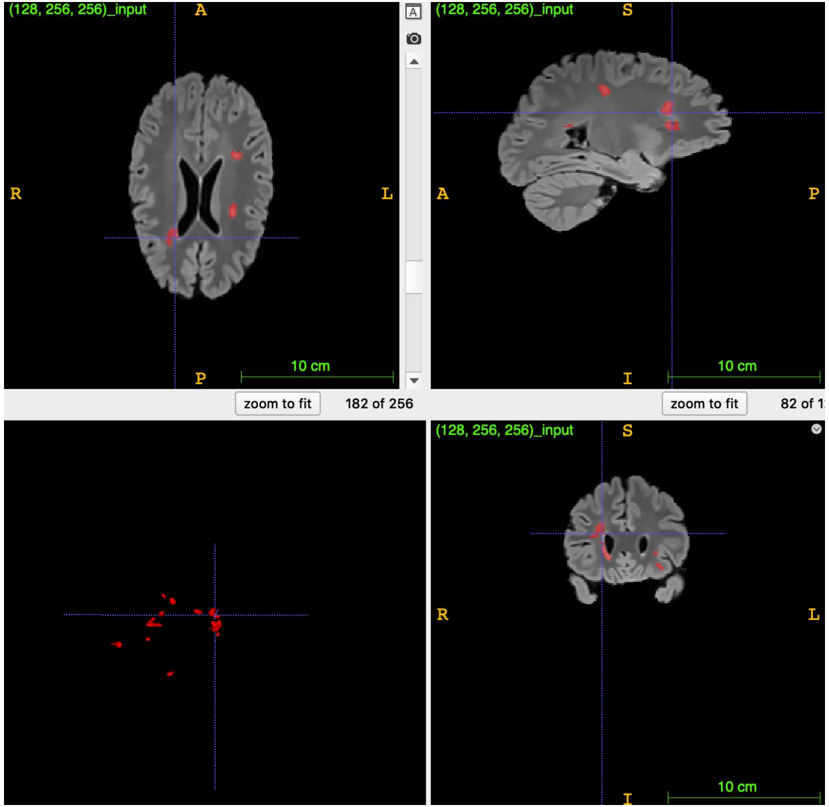
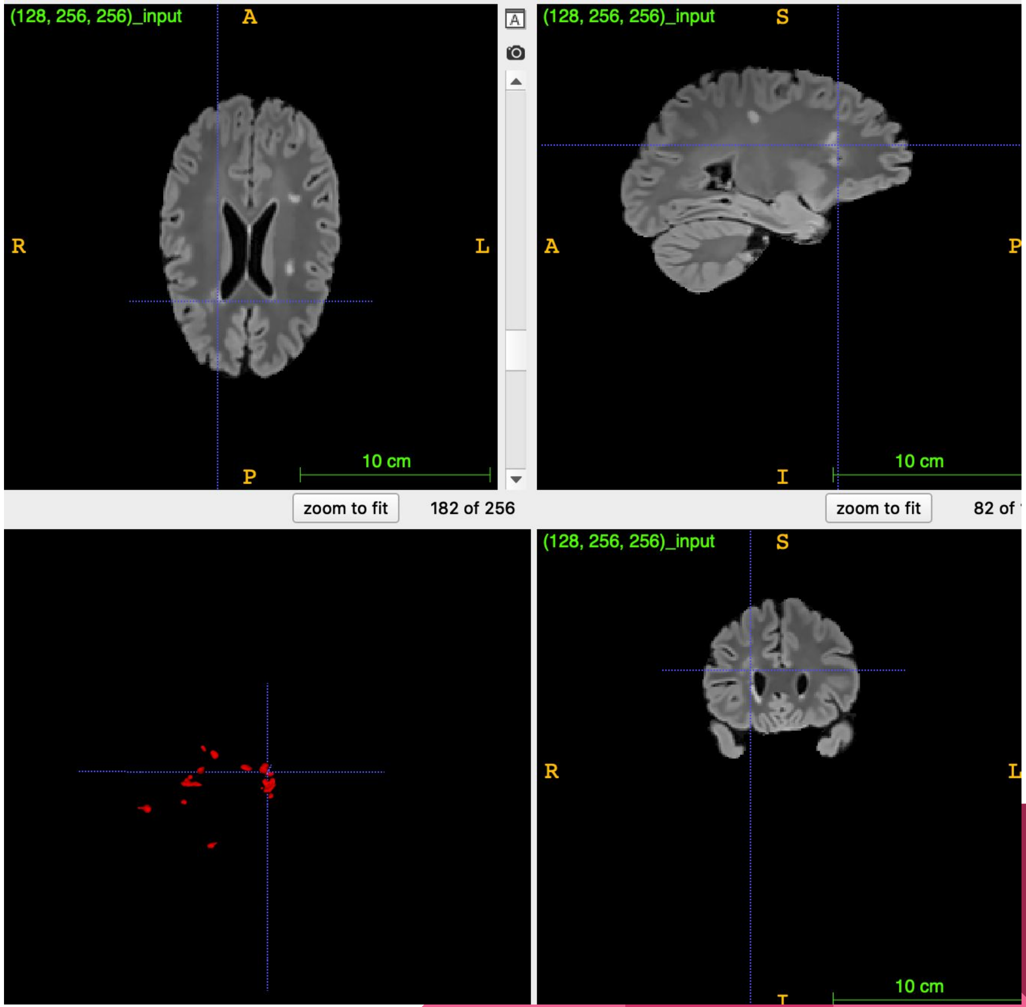
May 21, 2019

Introduction

- Manual segmentation requires expert knowledge and a bunch of time
- MRI has different modalities and qualities
- Experts have their own discretion
- Very small amount of data are available

Introduction





MICCAI 2016 challenge

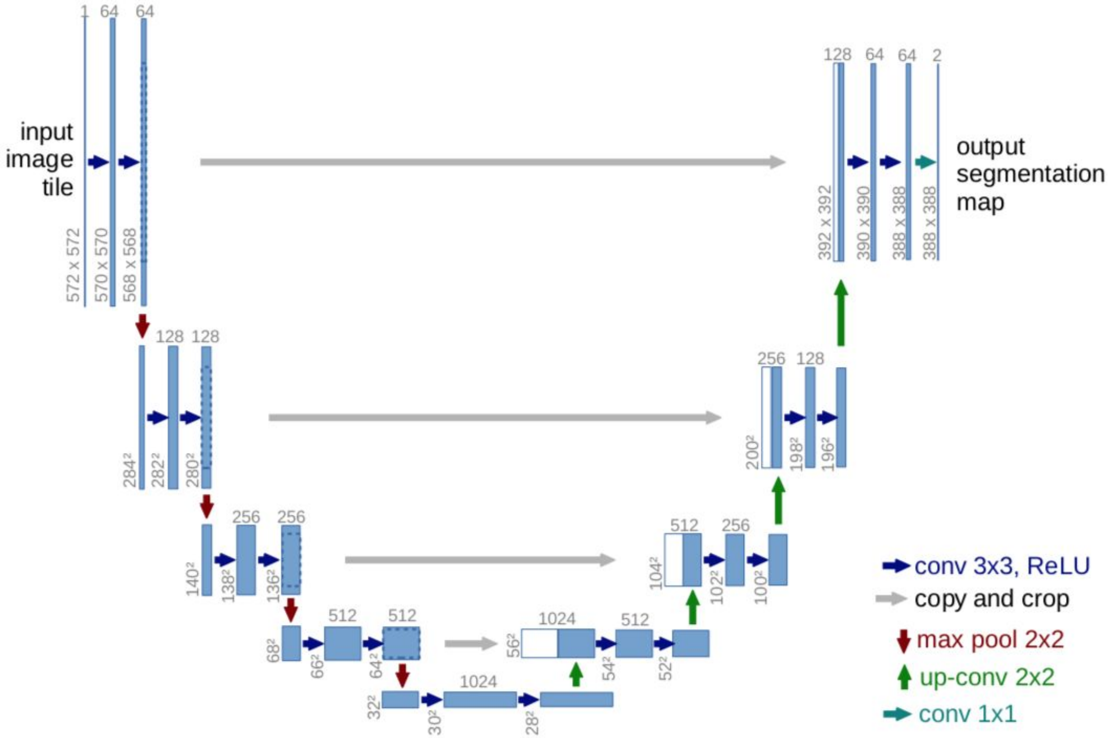
- Provide in total 15 images from 3 centers
- Ground truth segmentation is processed by 7 expert segmentations
- Best dice score from the challenge: 0.59

Scanner	Matrix	Training cases
GE Discovery 3T	512 * 512 * 224	5
Siemens Aera 1.5T	256 * 224 * 128	5
Philips Ingenia 3T	336 * 336 * 261	5

Approach

- 3D Unet model structure
- Train on patches
- Test different loss functions (Dice Loss and Binary Cross Entropy)
- Refine output and dice score with thresholding

3D Unet

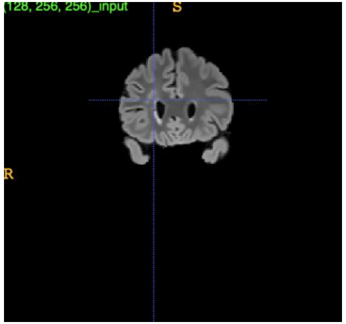


- Modify original Unet so that it could take 3D images as input
- Customize loss function

Patches

- If feeding entire image for training: require too much memory
- Slice each image into (64, 64, 64) patches for training

Training with Dice Loss with all patches

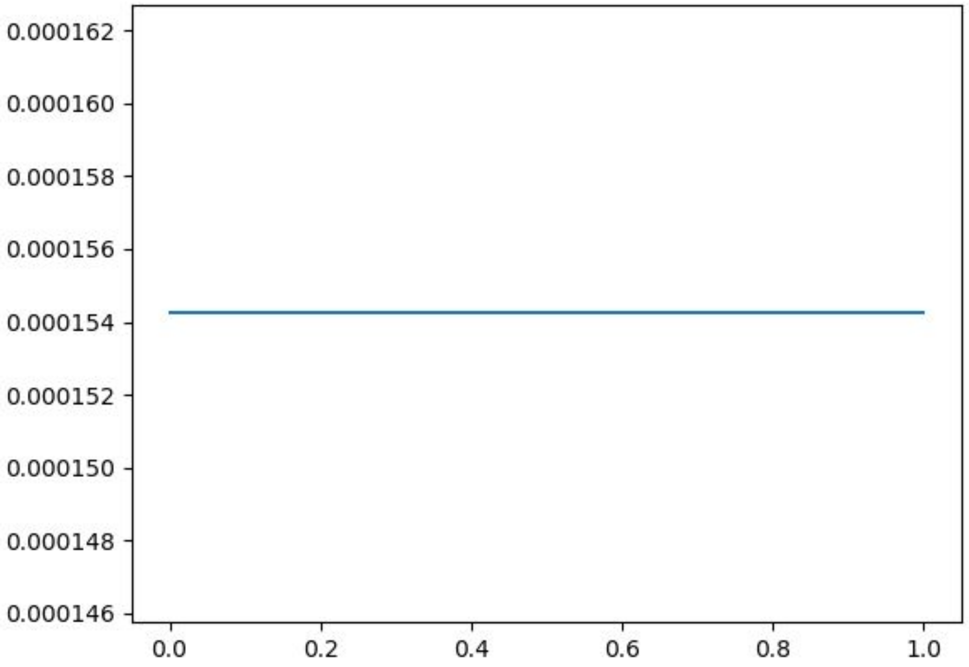


- Most of them do not contain useful information
- Lesions are relatively small:
  - Most ground truth patches do not contain any lesion voxels
- Some input patches do not have any information (empty region)

Training with Dice Loss with all patches

Epoch	Training Dice Score	Training Loss	Validation Dice Score	Validation Loss
1	0.6220	0.3780	0.6039	0.3961
2	0.6385	0.3615	0.6039	0.3961
3	0.6385	0.3615	0.6039	0.3961
4	0.6385	0.3615	0.6039	0.3961
5	0.6385	0.3615	0.6039	0.3961

Training with Dice Loss with all patches



- The resulting patches are almost all black
- The model does not learn anything useful for segmentation

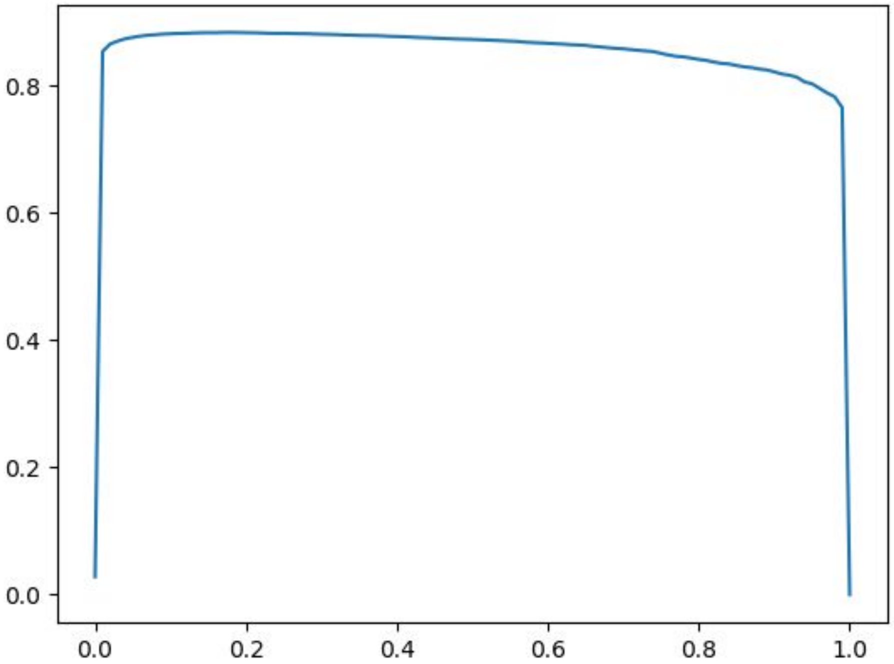
Training with Dice Loss with selected patches

- Instead: only train on patches with at least 0.01% lesions in them
- Inspired by A Multiscale Patch Based Convolutional Network for Brain Tumor Segmentation.

Training with Dice Loss with selected patches

Epoch	Training Dice Score	Training Loss	Validation Dice Score	Validation Loss
1	0.6566	0.3434	0.6013	0.3987
2	0.8843	0.1157	0.5048	0.4952
3	0.9240	0.0760	0.6145	0.3855
4	0.9425	0.0575	0.5981	0.4019
5	0.9544	0.0456	0.6021	0.3979

Training with Dice Loss with selected patches

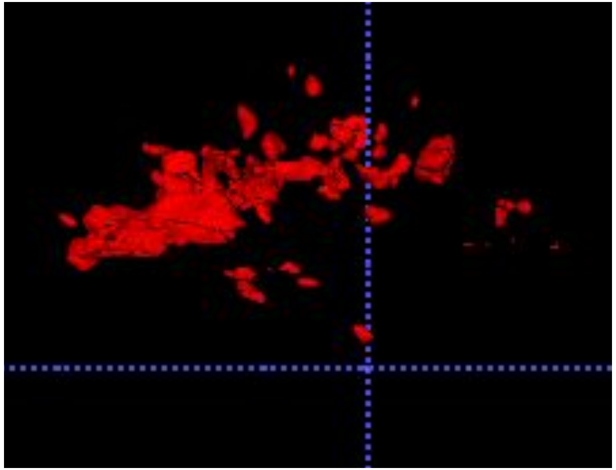


- Optimal dice score:
- 0.88

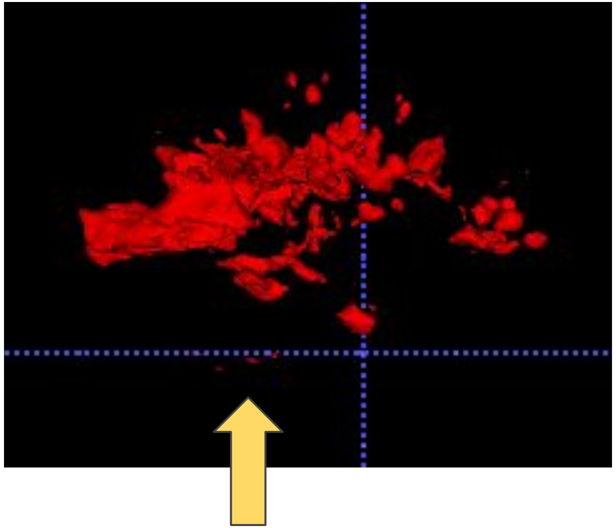
- Optimal threshold:
- 0.18

Training with Dice Loss with selected patches

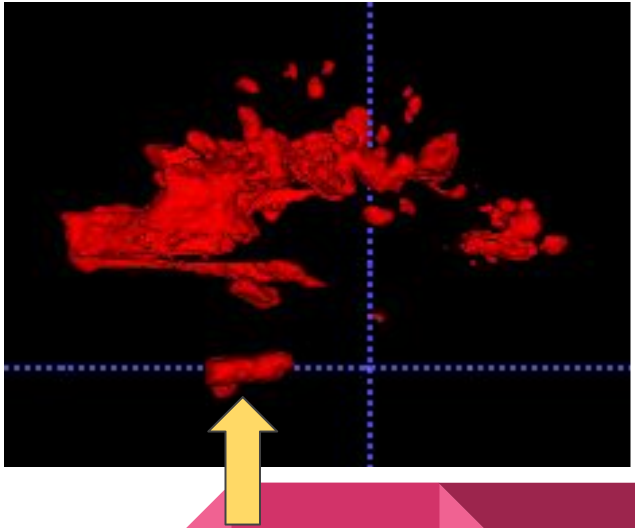
Merged Output



Thresholded Output



Ground Truth



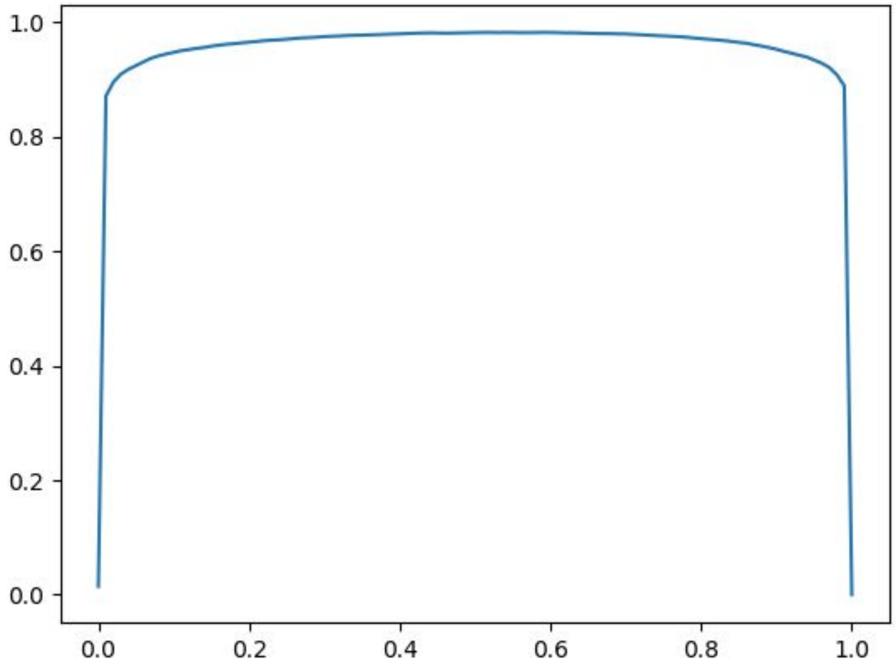
Training with Binary Cross Entropy with selected patches

- Check whether Dice Loss is good in practice

Training with Binary Cross Entropy with selected patches

Epoch	Training Dice score	Training Loss	Validation Dice score	Validation Loss
1	0.5122	0.0245	0.5665	0.0353
2	0.8538	0.0041	0.5879	0.0518
3	0.9160	0.0025	0.5985	0.0580
4	0.9450	0.0017	0.6130	0.0550
5	0.9634	0.0012	0.6266	0.0626

Training with Binary Cross Entropy with selected patches

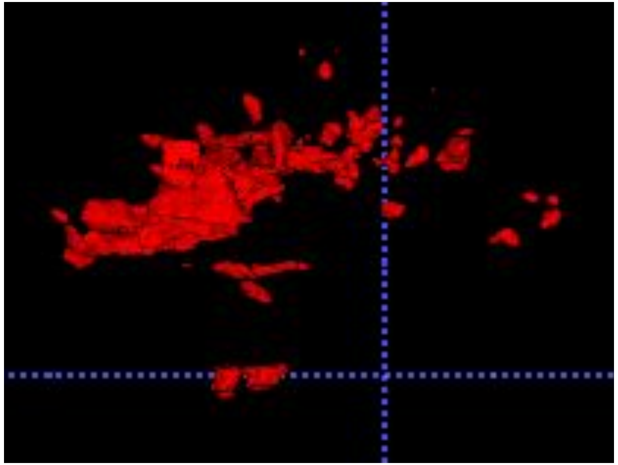


- Optimal dice score:
- 0.98

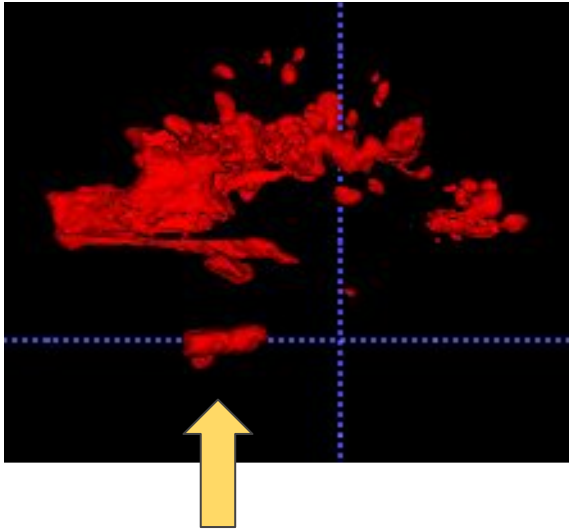
- Optimal threshold:
- 0.59

Training with Binary Cross Entropy with selected patches

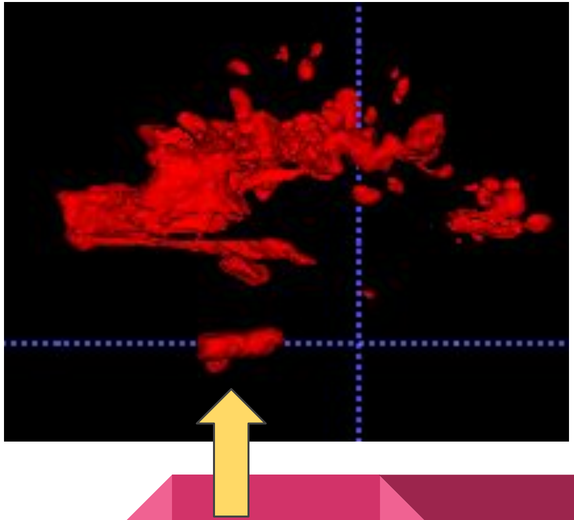
Merged Output



Thresholded Output



Ground Truth



Conclusion

- 3D Unet as model structure
- Train with selected patches (> 0.01% lesion voxels)
- Dice Loss model: 0.88 final dice, 0.18 threshold value
- Binary Cross Entropy model: 0.98 final dice, 0.59 threshold value

Future work

- Dataset from 2015 Longitudinal MS Lesion Segmentation Challenge
- Use more modalities than only FLAIR
- K-fold cross validation to determine optimal values for hyper parameters