Segmentation of the prostate using U-net

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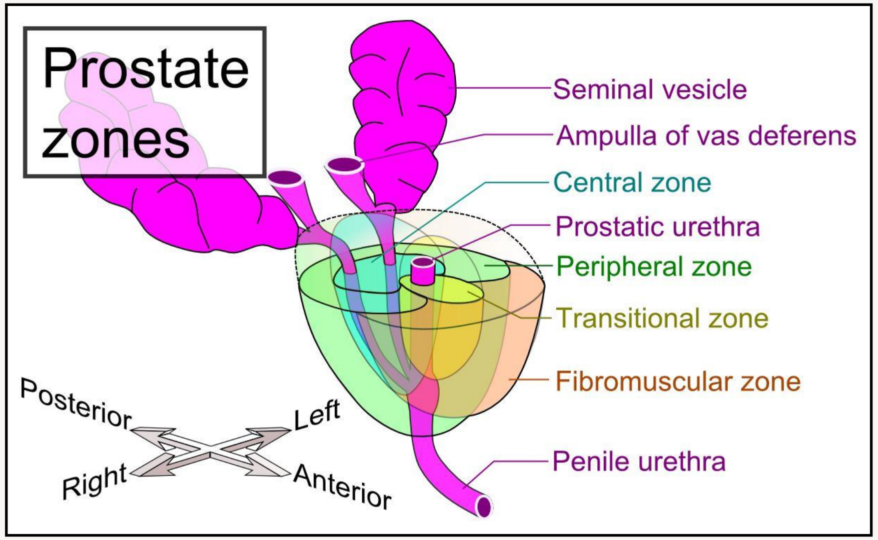
The Prostate Gland

- Small, walnut-sized gland.
- Part of the male reproductive system (produce a component of the semen fluid).
- Located below the bladder and surrounds the urethra.
- Health conditions that affect the prostate gland, such as:

1. Prostatitis: Inflammation or infection of the prostate gland.

2. BPH: Benign Prostatic Hyperplasia: Non-cancerous enlargement of the prostate gland.

3. Prostate Cancer: The most common cancer in men, characterized by the abnormal growth of cells in the prostate gland.



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Prostate Segmentation

INPUT

3D MRI scan

METHOD

3D U-net

AIM

automatically annotate the peripheral and central zones

[GitHub - jancio/3D-U-Net-Prostate-Segmentation: Implementation of the 3D U-Net model for segmentation of prostate structures]

NCI-ISBI 2013 Challenge - Automated Segmentation of Prostate Structures

The National Cancer Institute's (**NCI's**) Cancer Imaging Program in collaboration with the International Society for Biomedical Imaging (**ISBI**) launched a challenge involving prostate gland MRI

The challenge aims to improve automatically annotate the peripheral and central zones

[NCI-ISBI 2013 Challenge - Automated Segmentation of Prostate Structures - The Cancer Imaging Archive (TCIA) Public Access - Cancer Imaging Archive Wiki]

The dataset's structure

Training set

Size: 60-case prostate MRI 3D series

files: Digital Imaging and Communications in Medicine (**DICOM**) images with matched **NRRD** markups that define the tissue CG and PZ are available from the NCI via The Cancer Imaging Archive (TCIA).

Leaderboard set

Size :10 case prostate MRI 3D series

files: Digital Imaging and Communications in Medicine (**DICOM**).

Then, no NRRD segmentations were available for download for these leaderboard cases until after the conclusion of the challenge.

Test set

Size :10 case prostate MRI 3D series

files: This data (DICOMS & NNRD) was available only after the challenge.

Each case consist of 15+ (4 mm thick slices at 3T) or 28+ (3 mm thick at 1.5T) adjacent axial cross-section cuts. They were acquired as T2-weighted MR axial pulse sequences.

Preprocessing

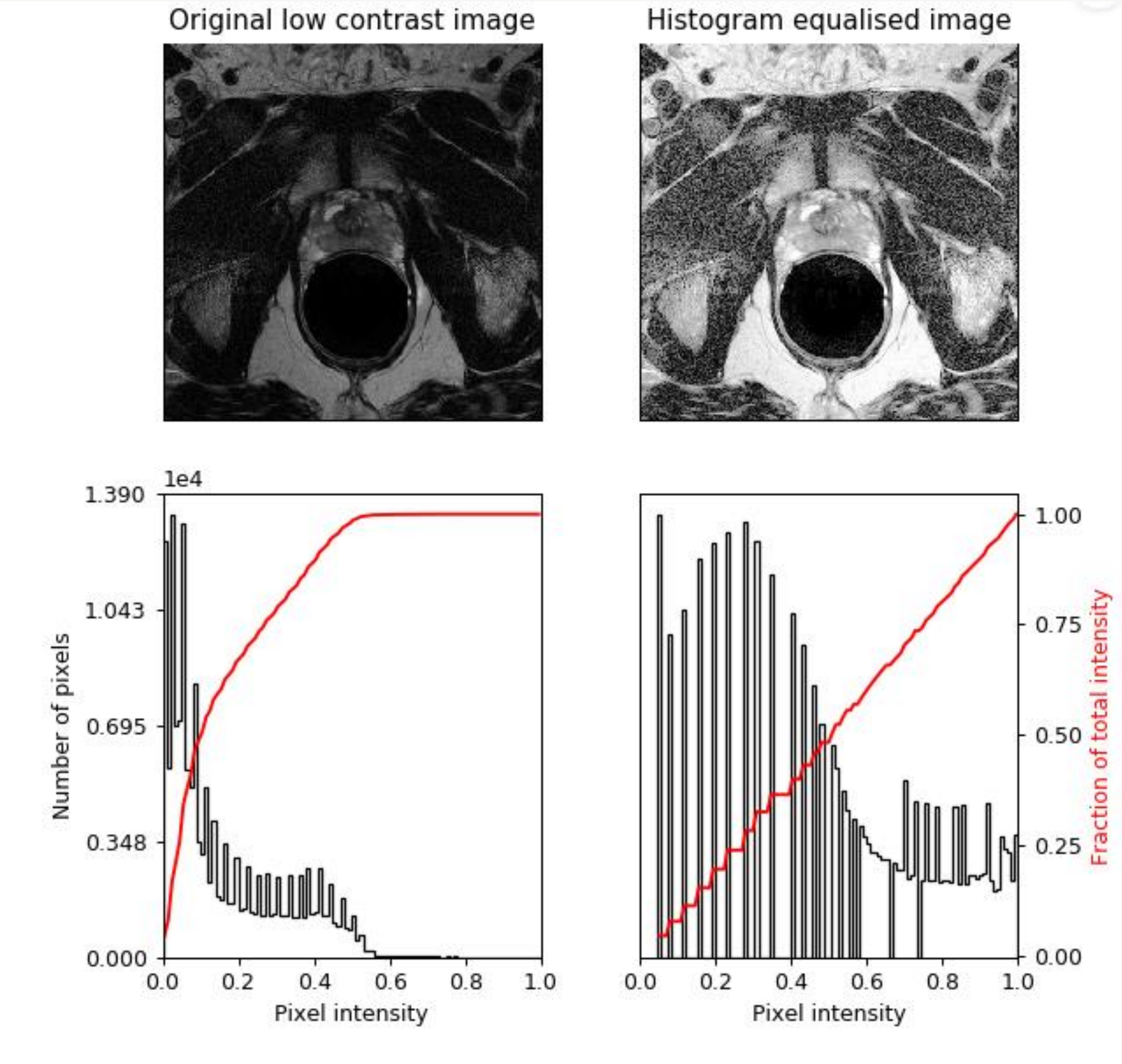
Used histogram equalisation on the input MRI, in order to increase image contrast.
This technique redistributes pixel intensity values to achieve linear cumulative distribution function.

histogram equalisation

contrast adjustment using
the image's histogram.

cumulative distribution

Histogram in which each bin equals to the count of the its value plus all bins for smaller values



Data augmentation

Using the 3D Unet paper augmentations:

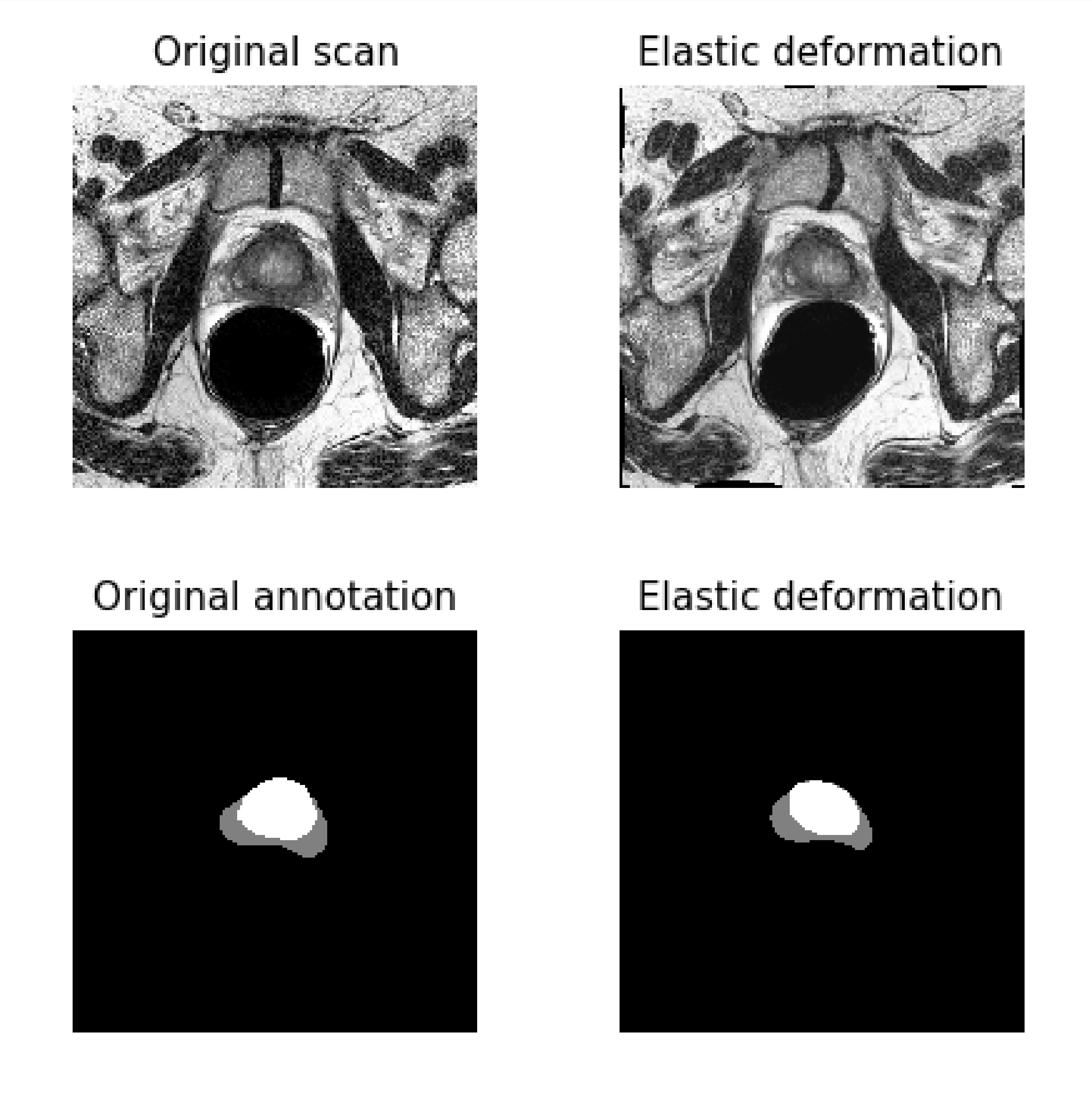
scalings

random rotations

gray value variations

elastic distortion

(same for voxel tile and its annotation)

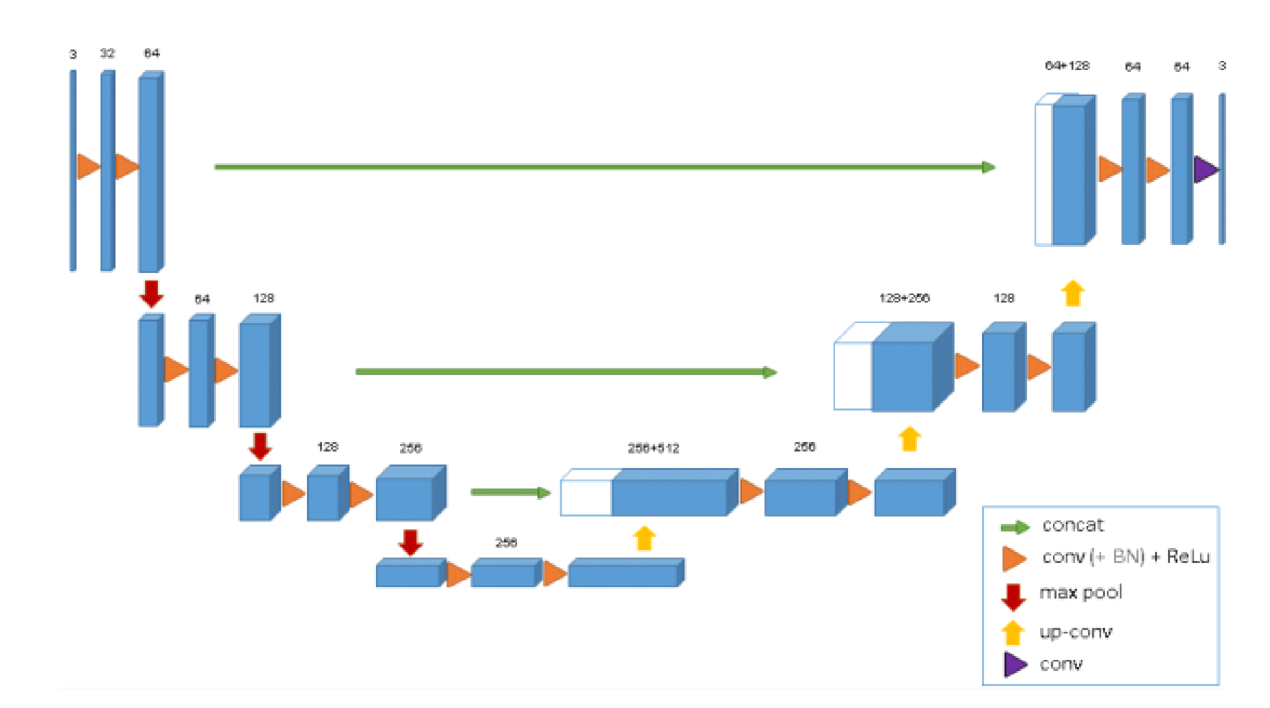


3D U-Net Architecture

Segmentation to three classes:

background, cg, pz

The structure:



Used the Unet from - [1606.06650.pdf (arxiv.org)]

Hyper parameters

Lost function: weighted cross entropy

Dropout: 0.3

Batch normalization: stride of one and kernel of three

Padding: “same”- padding chosen s.t the output

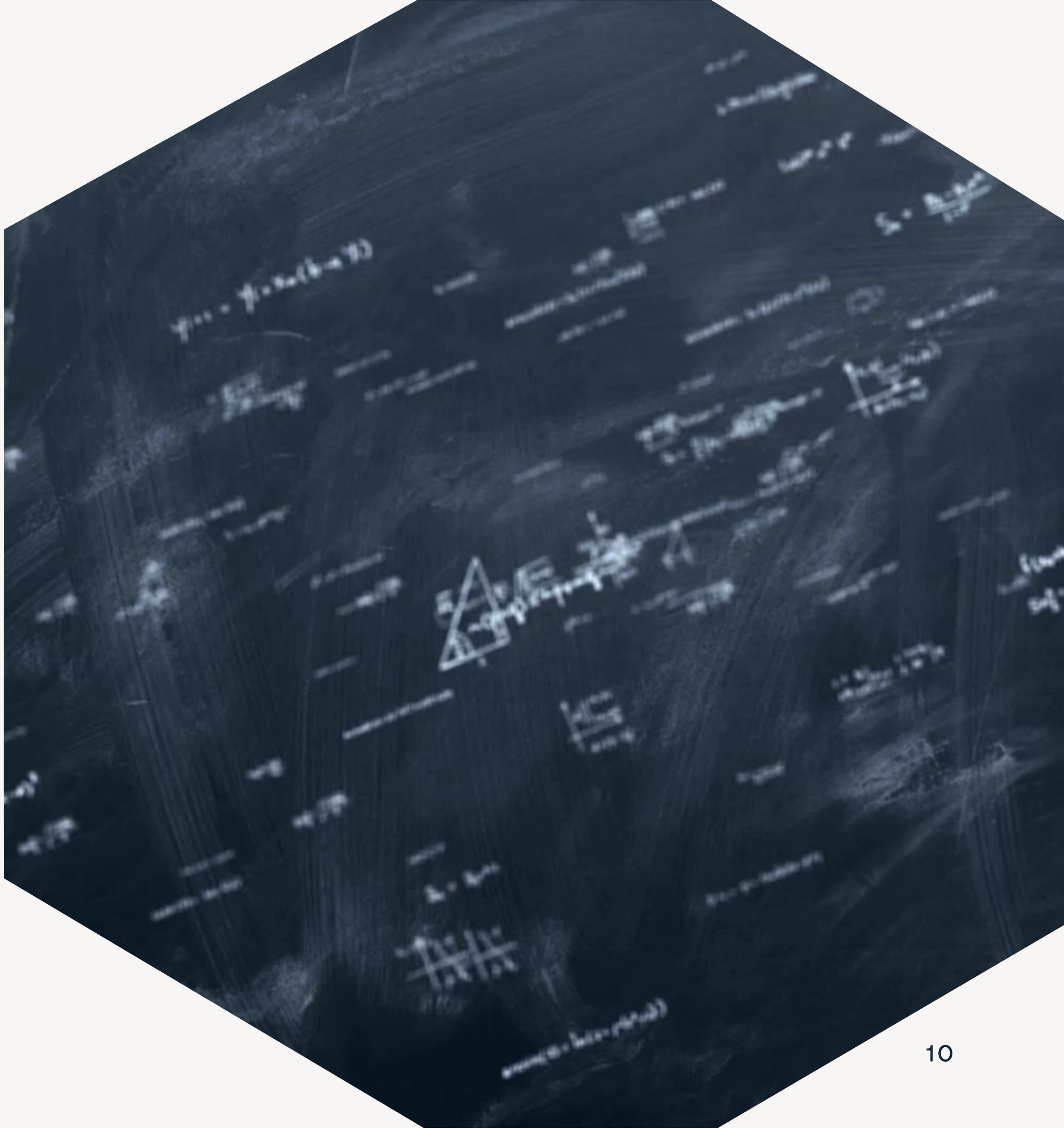
the same size as the input

Max pooling: [1,2,2], [1,2,2]

Optimizer: Adam, learning rate η = 0.001

Batch size: 32

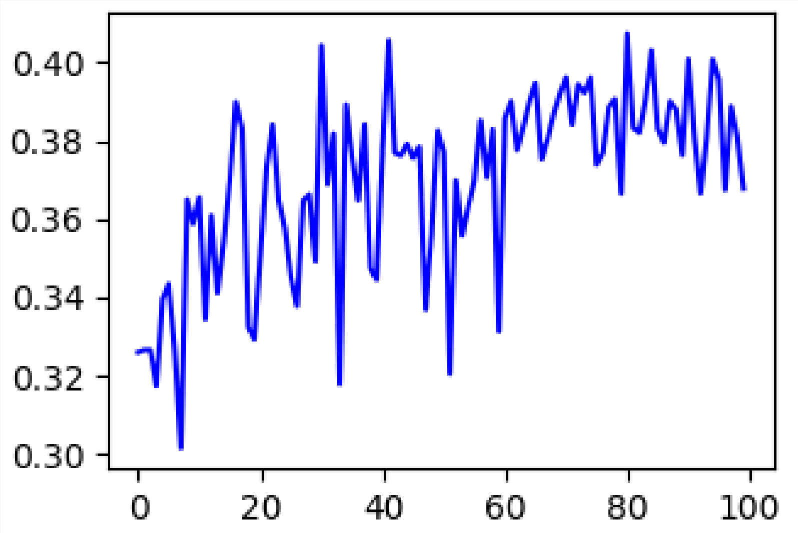
Number of epochs: 322



Evaluation & Results

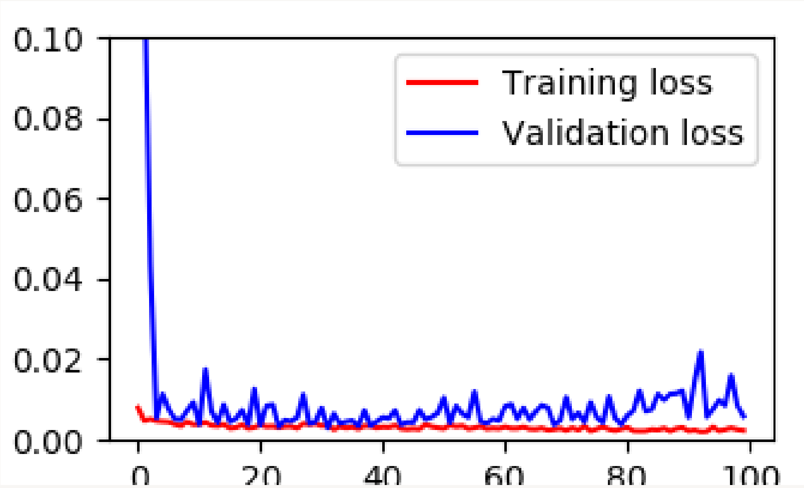
100 epochs

Validation mean IOU as a function of epochs



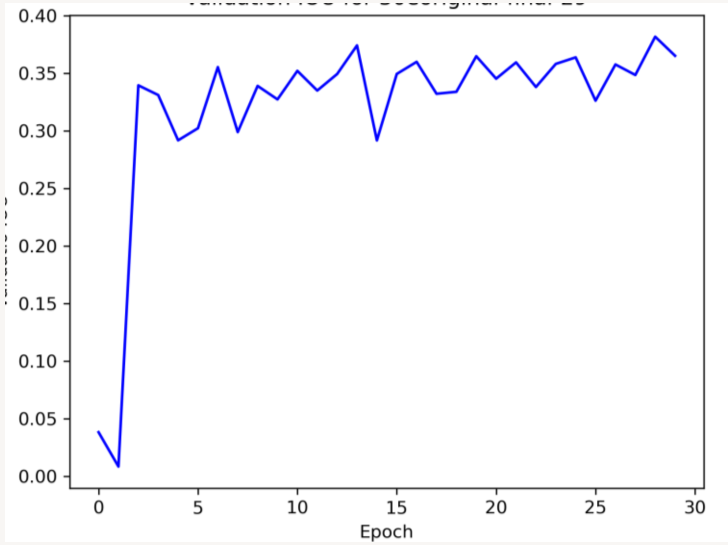
Mean test IOU 0.41029

Train and validation loss as a function of epochs



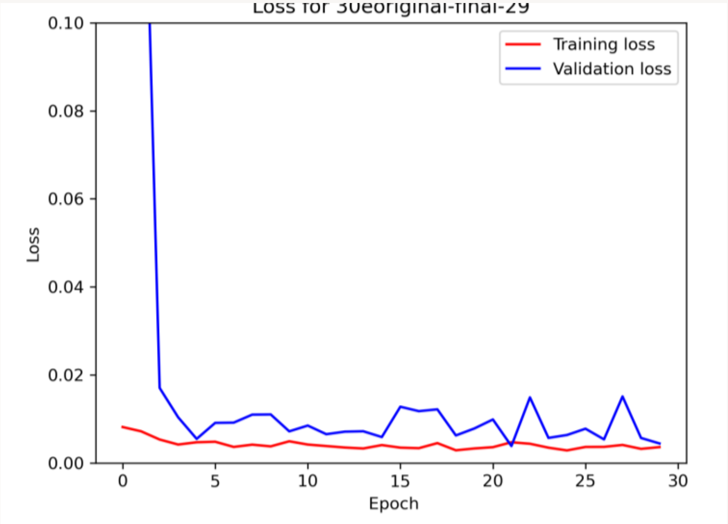
30 epochs

Validation mean IOU as a function of epochs



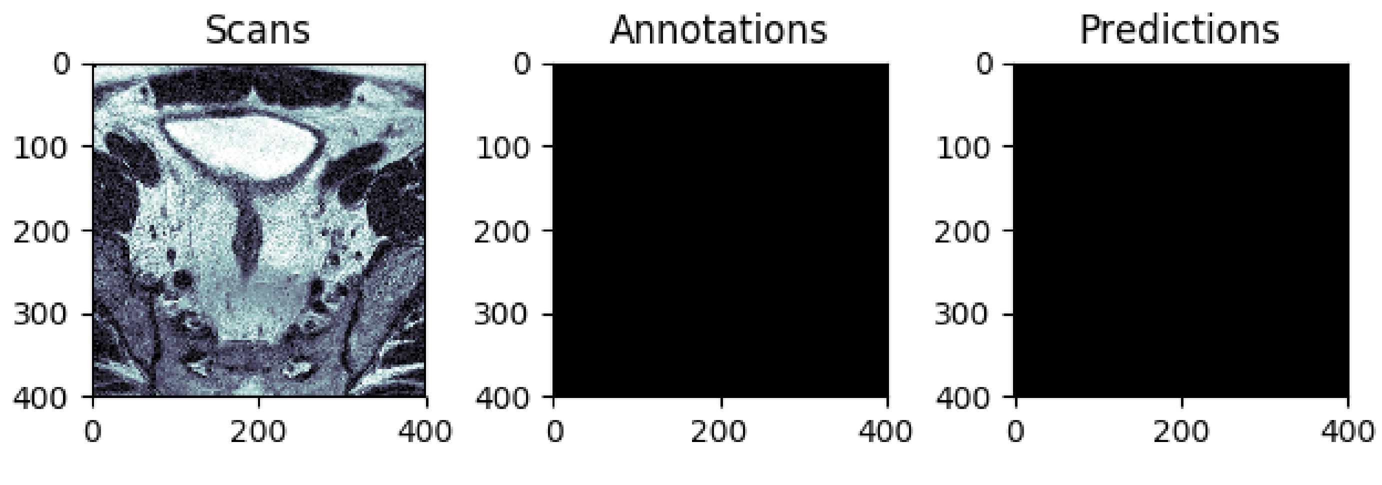
Mean test IOU 0.37005

Train and validation loss as a function of epochs

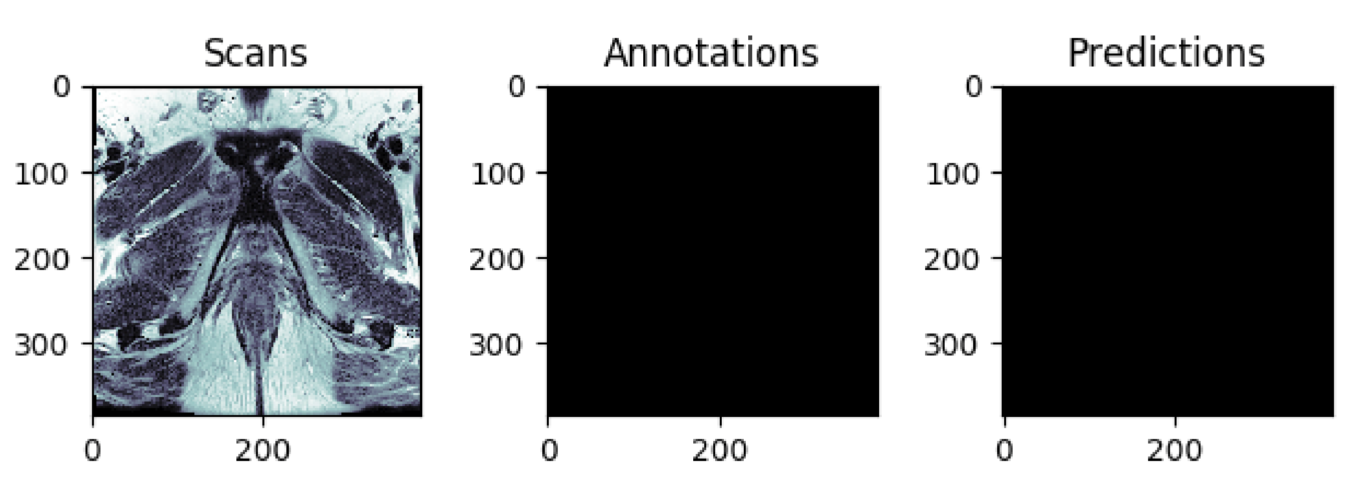


Best Result

100 epochs



v.s



Worst Result

Best Result

30 epochs

v.s

Worst Result

Our mini-trials

We had some mini-trails of 4 epochs with one of the following changes:

- Weighted Dice loss instead of weighted cross entropy
- Adding augmentation – intensity shift
- Smaller learning rate
- More augmented images and larger scale of their hyperparameters

Results of our mini-trials

Weighted Dice loss instead of weighted cross entropy

The dice loss decreased the IOU score of the validation to 0.159

Adding augmentation : intensity shift

Adding the intensity shift resulted in 0.34 IOU score on the validation set

Smaller learning rate

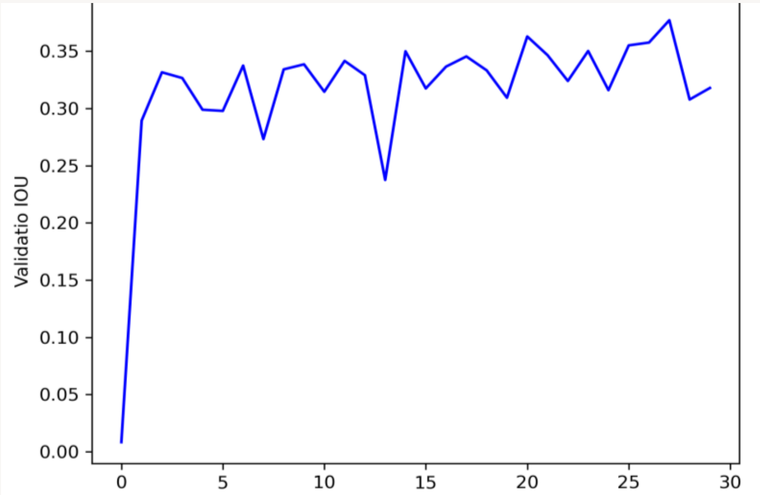
Decreasing the lr by half to 0.0005 resulted in 0.34 IOU score on the validation set

More augmented images and larger scale of their hyperparameters

Those modifications caused a decrease in the IOU score of the validation to 0.28

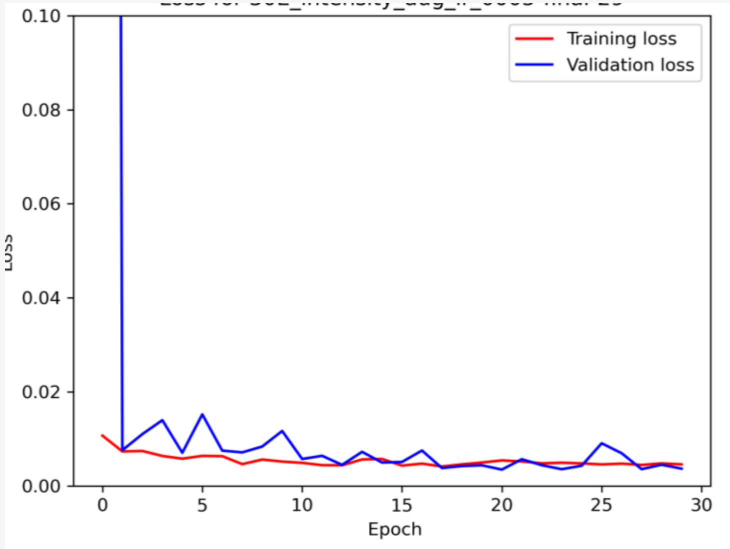
Our 30 epochs

Validation mean IOU as a function of epochs



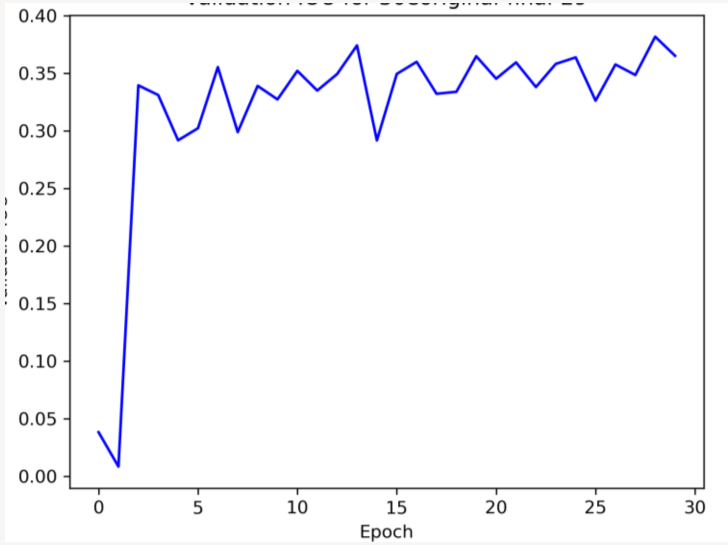
Mean test
IOU 0.32179

Train and validation loss as a function of epochs



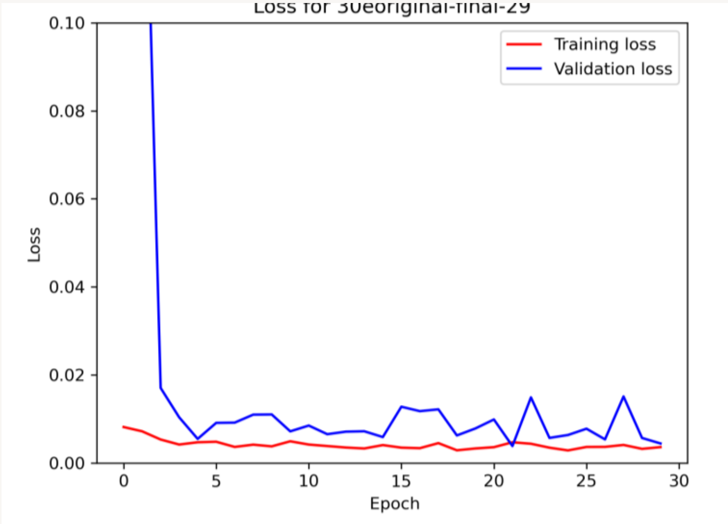
Original 30 epochs

Validation mean IOU as a function of epochs

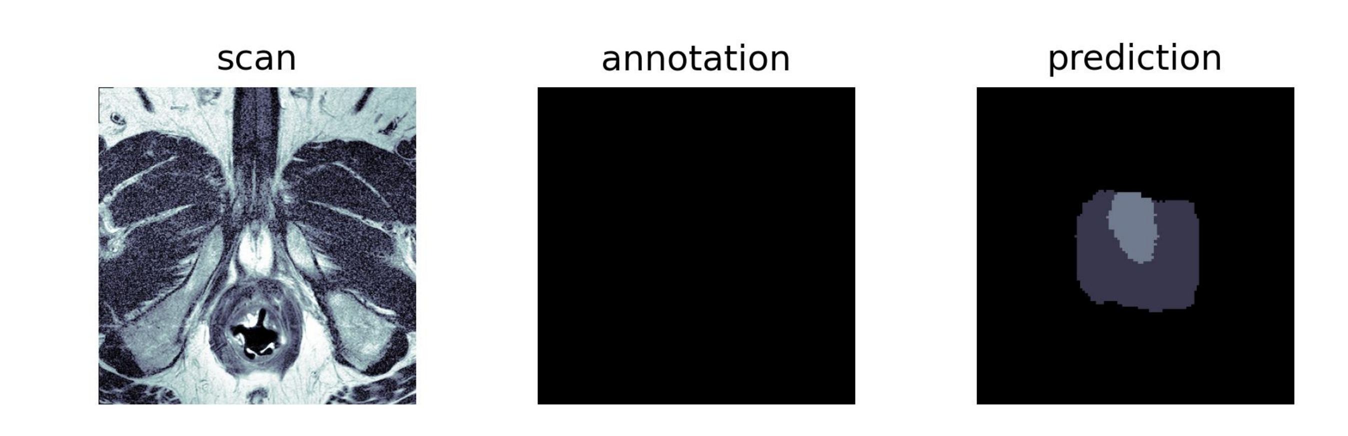


Mean test
IOU 0.37005

Train and validation loss as a function of epochs

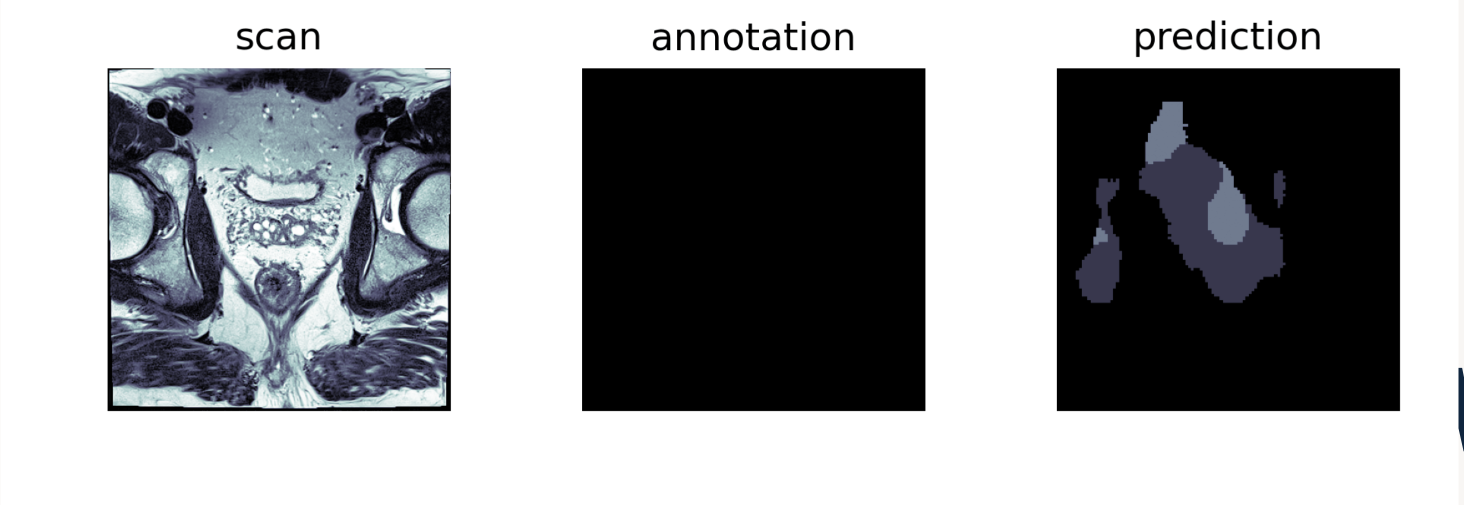


Best Result



Our 30 epochs

v.s



Worst Result

Conclusions

The original project can be reconstructed

- We were able to get similar results to the reported results.

Lower number of epochs yields sufficient results

- The IOU on the test set after 30 epochs is not significantly lower than after 100 epochs.
- In addition. we can see signs of overfitting in the loss plot of the 100 epochs in the last epochs.

Further experiments with augmentations are needed

- We did see promising initial results when adding augmentations
- The augmentation we added didn't improve the results, but there are a lot of directions to explore with this augmentation and others.




Thank you

Noam Sprei & Mor Tzadok

References

The Data:

NCI-ISBI 2013 Challenge - Automated Segmentation of Prostate Structures - The Cancer Imaging Archive (TCIA) Public Access - Cancer Imaging Archive Wiki

The Original Code (Jancio's code):

GitHub - jancio/3D-U-Net-Prostate-Segmentation: Implementation of the 3D U-Net model for segmentation of prostate structures

Our Code:

https://github.com/MorTzadok/MRI_seminar/tree/main