CISC/CMPE 472 – Assignment 3

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1. Data exploration

Graphical user interface

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Text

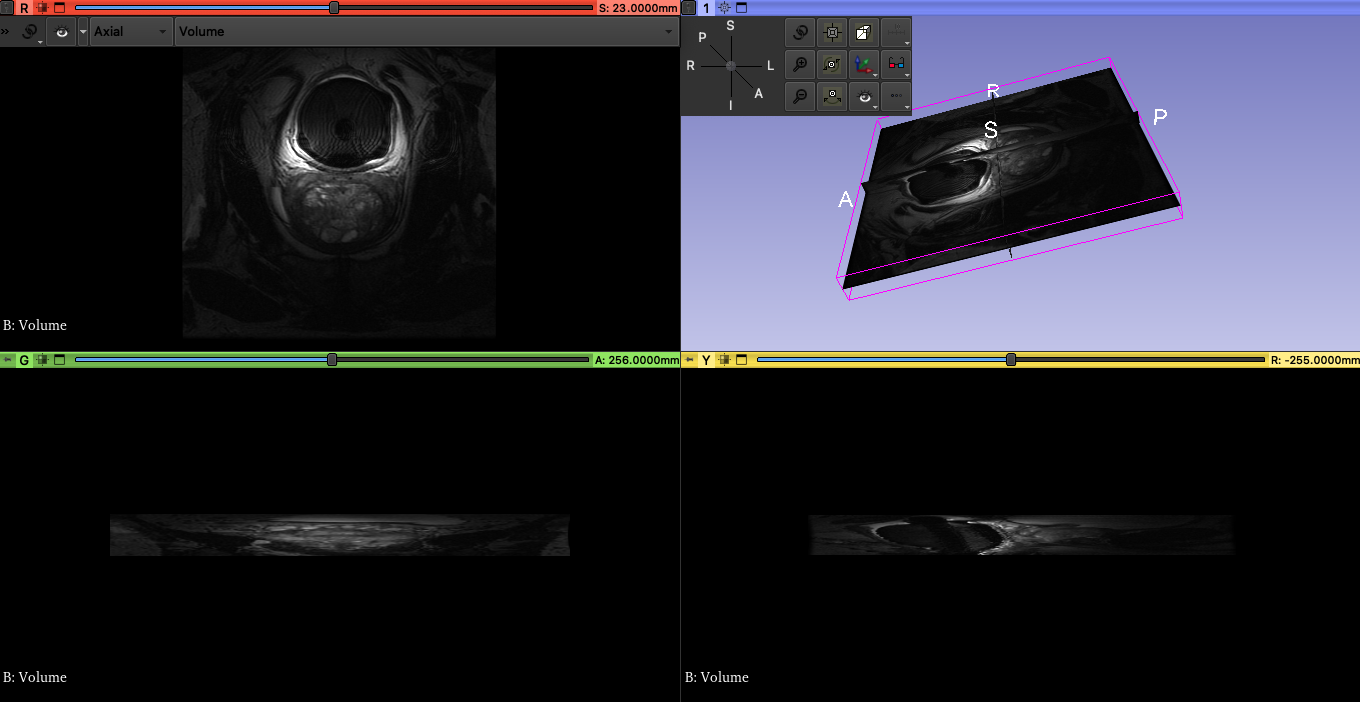
Description automatically generated with medium confidence A picture containing text

Description automatically generated Graphical user interface, text

Description automatically generated with medium confidence A picture containing text

Description automatically generated

Upon segmenting the center slice from the axial, sagittal, and coronal view from Case00, I can observe and get a better understanding of where the prostate is in the original image. A visualization of these 2 volumes in Slicer is shown below:



An immediate observation from viewing Case00 is that the Axial slice is wider and looks square compared to the Sagittal and Coronal views. I print out the dimension of the volume and I got (47, 512, 512).

I printed out a set of all different volume dimensions from the folder. This is the result of the set:

{(39, 512, 512), (15, 320, 320), (46, 512, 512), (34, 512, 512), (28, 384, 384), (28, 320, 320), (26, 512, 512), (18, 256, 256), (24, 320, 320), (20, 320, 320), (45, 512, 512), (29, 512, 512), (23, 512, 512), (47, 512, 512), (54, 512, 512), (17, 320, 320), (23, 256, 256), (42, 512, 512), (40, 512, 512)}

There is a good variation of:

* Axial depth: [15, 54]
* Sagittal depth: [256, 512]
* Coronal depth: [256, 512]

All volumes seem to have all 3 slice views.

1. Dataset creation

N/A

1. Data splitting

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Train data | | Validate data | | Test data | |
| Images | Segmentations | Images | Segmentations | Images | Segmentations |
| image\_74.png  image\_1.png  image\_22.png  image\_70.png  image\_16.png  image\_42.png  image\_58.png  image\_98.png  image\_69.png  image\_9.png  image\_77.png  image\_55.png  image\_96.png  image\_80.png  image\_52.png  image\_23.png  image\_28.png  image\_26.png  image\_54.png  image\_34.png  image\_73.png  image\_47.png  image\_68.png  image\_41.png  image\_17.png  image\_56.png  image\_45.png  image\_14.png  image\_87.png  image\_94.png  image\_50.png  image\_92.png  image\_13.png  image\_31.png  image\_99.png  image\_82.png  image\_64.png  image\_33.png  image\_48.png  image\_21.png  image\_38.png  image\_51.png  image\_24.png  image\_63.png  image\_62.png  image\_35.png  image\_88.png  image\_67.png  image\_20.png  image\_89.png  image\_61.png  image\_4.png  image\_32.png  image\_95.png  image\_27.png  image\_53.png  image\_66.png  image\_76.png  image\_93.png  image\_46.png | segmentation\_74.png  segmentation\_1.png  segmentation\_22.png  segmentation\_70.png  segmentation\_16.png  segmentation\_42.png  segmentation\_58.png  segmentation\_98.png  segmentation\_69.png  segmenttation\_9.png  segmentation\_77.png  segmentation\_55.png  segmentation\_96.png  segmentation\_80.png  segmentation\_52.png  segmentation\_23.png  segmentation\_28.png  segmentation\_26.png  segmentation\_54.png  segmentation\_34.png  segmentation\_73.png  segmentation\_47.png  segmentation\_68.png  segmentation\_41.png  segmentation\_17.png  segmentation\_56.png  segmentation\_45.png  segmentation\_14.png  segmentation\_87.png  segmentation\_94.png  segmentation\_50.png  segmentation\_92.png  segmentation\_13.png  segmentation\_31.png  segmentation\_99.png  segmentation\_82.png  segmentation\_64.png  segmentation\_33.png  segmentation\_48.png  segmentation\_21.png  segmentation\_38.png  segmentation\_51.png  segmentation\_24.png  segmentation\_63.png  segmentation\_62.png  segmentation\_35.png  segmentation\_88.png  segmentation\_67.png  segmentation\_20.png  segmentation\_89.png  segmentation\_61.png  segmentation\_4.png  segmentation\_32.png  segmentation\_95.png  segmentation\_27.png  segmentation\_53.png  segmentation\_66.png  segmentation\_76.png  segmentation\_93.png  ation\_46.png | image\_30.png  image\_59.png  image\_15.png  image\_11.png  image\_40.png  image\_65.png  image\_19.png  image\_91.png  image\_71.png  image\_86.png  image\_97.png  image\_43.png  image\_10.png  image\_8.png  image\_3.png  image\_7.png  image\_83.png  image\_85.png  image\_60.png  image\_6.png | segmentation\_30.png  segmentation\_59.png  segmentation\_15.png  segmentation\_11.png  segmentation\_40.png  segmentation\_65.png  segmentation\_19.png  segmentation\_91.png  segmentation\_71.png  segmentation\_86.png  segmentation\_97.png  segmentation\_43.png  segmentation\_10.png  segmentation\_8.png  segmentation\_3.png  segmentation\_7.png  segmentation\_83.png  segmentation\_85.png  segmentation\_60.png  segmentation\_6.png | image\_84.png  image\_57.png  image\_72.png  image\_5.png  image\_49.png  image\_44.png  image\_29.png  image\_81.png  image\_18.png  image\_0.png  image\_25.png  image\_36.png  image\_75.png  image\_39.png  image\_90.png  image\_12.png  image\_78.png  image\_79.png  image\_2.png  image\_37.png | segmentation\_84.png  segmentation\_57.png  segmentation\_72.png  segmentation\_5.png  segmentation\_49.png  segmentation\_44.png  segmentation\_29.png  segmentation\_81.png  segmentation\_18.png  segmentation\_0.png  segmentation\_25.png  segmentation\_36.png  segmentation\_75.png  segmentation\_39.png  segmentation\_90.png  segmentation\_12.png  segmentation\_78.png  segmentation\_79.png  segmentation\_2.png  segmentation\_37.png |

1. Initial preprocessing

Read image: Since I’m getting image shape as (128, 128, 3) back from the image I produce, the first thing that I have to do is to cast it back into (128, 128, 1) shape. Thus, I use numpy.mean to get the average of all three RGB channels and keep only one channel for the result image. I also threshold the circle value between (230, 255) so that it is not to noisy and hard for the model to detect the edge. That makes the image a bit cleaner and easier to define the circle edge. I didn’t use any edge filter or sharpening filter as I figure those make the circle looks distorted.

1. Cross-entropy loss
2. Experiment 1: 20 epochs + Early stopping

I set my model up to train for 20 epochs. I also coupled early stopping with model checkpoint. Wtih this approach, I’m able to help stop the training once no metric improvement is seen for several epochs. The early stopping will halt the training once it does not see the validation accuracy improve for 3 consecutive epochs (patience = 3).

Chart, line chart

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1. Experiment 2: Trying other optimizers (SGD, Adagard, RMSprop)

Adam optimizer provides fast convergence rate and being robust to noise in the gradients, in this 2nd experiment, I tried to test out other popular optimizer as well!

* 1. SGD optimizer is a simple optimization algorithm that updates the parameters of the network based on the gradient of the loss function with respect to the parameters. It is computationally efficient and easy to implement, but can be slow to converge, as seen in the slow decrease in loss value over epochs, but with a simple task that we have. It achieves high accuracy still.

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* 1. Adagard optimizer is an adaptive learning rate method that adapts the learning rate for each parameter based on the history of its gradients. It works well on sparse data. Thus, loss value decreases quickly through epochs and accuracy is well as good as Adam optimizer.

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* 1. RMSprop optimizer is another adaptive learning rate method that uses a moving average of the squared gradients to adjust the learning rate for each parameter. It is designed to handle moving objects, but we will try it anyway for our task as it is a popular and well researched optimizer!

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Optimizer experiment conclusion: In the context of our task, the choice of optimizer can have significant impact on the convergence rate and accuracy of the model. Adam optimizer will remain the optimizer we are moving forward with due to its ability to its performance on accuracy and loss convergence. However, it was interesting to experiment with other optimizers and hyperparameters.

1. IOU Loss

For IOU loss

Chart

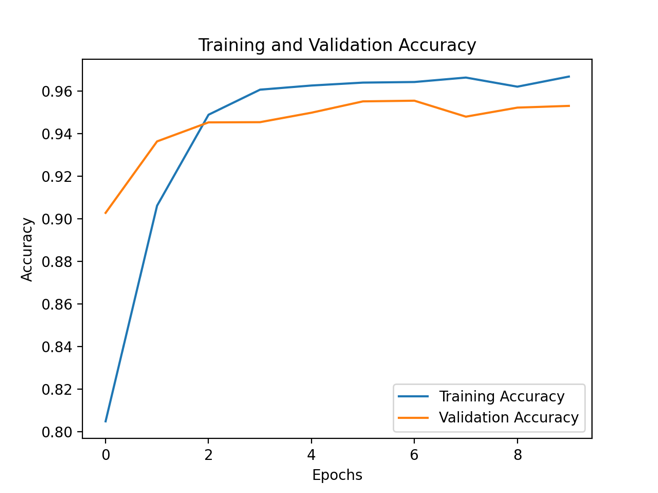
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Description automatically generated

The loss values drastically reduces within the first few epochs, showing quick adaptation to training process and the entire training takes 14 epochs to converge. While the accuracy bumps up and down for a good ~10 epochs, it also converges by the 14 and shows promisingly high numbers!

1. Additional metrics
2. For IOU loss (best weights prioritize loss, not accuracy)
3. For DICE loss (best weights prioritize loss, not accuracy)

Chart, line chart

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1. For Hausdoff

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1. Qualitative evaluation

|  |  |  |  |
| --- | --- | --- | --- |
| Original image | Cross\_entropy loss predictions | IOU loss predictions | DICE loss predictions |
| image\_84.png  A picture containing blur  Description automatically generated | A picture containing logo  Description automatically generated | A picture containing logo  Description automatically generated | A picture containing logo  Description automatically generated |
| image\_57.png | A picture containing chart  Description automatically generated | Chart  Description automatically generated with medium confidence | A picture containing chart  Description automatically generated |
| image\_72.png  A picture containing blur  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing graphical user interface  Description automatically generated | A picture containing graphical user interface  Description automatically generated |
| image\_5.png  A close up of the moon  Description automatically generated with medium confidence | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated |
| image\_49.png  A close up of the moon  Description automatically generated with medium confidence | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing logo  Description automatically generated |
| image\_44.png  A white circle with a black background  Description automatically generated with low confidence | Chart  Description automatically generated with medium confidence | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated |
| image\_29.png  A close up of the moon  Description automatically generated with medium confidence | A picture containing logo  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing logo  Description automatically generated |
| image\_81.png  A close up of the moon  Description automatically generated with medium confidence | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated |
| image\_18.png  A picture containing blur, light  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated |
| image\_0.png  A bright light in the dark  Description automatically generated with low confidence | Chart  Description automatically generated | Chart  Description automatically generated with low confidence | Chart  Description automatically generated with medium confidence |
| image\_25.png  A white circle with a black background  Description automatically generated with low confidence | A picture containing chart  Description automatically generated | A picture containing graphical user interface  Description automatically generated | A picture containing chart  Description automatically generated |
| image\_36.png  A bright light in the dark  Description automatically generated with low confidence | A picture containing logo  Description automatically generated | Logo  Description automatically generated with medium confidence | A picture containing logo  Description automatically generated |
| image\_75.png  A picture containing blur  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated |
| image\_39.png  A white circle with a black background  Description automatically generated with low confidence | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated | Chart  Description automatically generated |
| image\_90.png  A close up of the moon  Description automatically generated with medium confidence | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated |
| image\_12.png  A close up of the moon  Description automatically generated with medium confidence | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated | Chart  Description automatically generated with medium confidence |
| image\_78.png  A picture containing blur  Description automatically generated | Chart  Description automatically generated with low confidence | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated |
| image\_79.png  A close up of the moon  Description automatically generated with medium confidence | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated |
| image\_2.png  A bright light in the dark  Description automatically generated with low confidence | A picture containing chart  Description automatically generated | A picture containing graphical user interface  Description automatically generated | A picture containing graphical user interface  Description automatically generated |
| image\_37.pngA bright light in the dark  Description automatically generated with low confidence | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated | A picture containing chart  Description automatically generated |

Speculation:

1. Cross Entropy loss: This loss function is sentitive to class imbalance, thus the circles produced are smaller than the other two loss function. The images also have a bit more of a fuzzy edge since the model may assign some pixels to the wrong class.
2. IOU loss: This loss function produces a slightly better result with clearer boundaries than cross entropy. It is more robust to class imbalance.
3. Dice loss: Dice loss is often preferred for imbalanced datasets, and it is more sensitive to small differences in overlap than IOU loss. The result circles can be slightly bigger than IOU loss, but in generally these two produces quiet similar segmentations.
4. Quantitative evaluation

|  |  |  |  |
| --- | --- | --- | --- |
| Metrics/ Loss function | Cross entropy loss function | IOU loss function | DICE loss function |
| F1 score | 0.9670 | 0.6337 | 0.9698 |
| Precision score | 0.9534 | 0.6290 | 0.9657 |
| Recall score | 0.8790 | 0.6313 | 0.9639 |

Speculations

1. Cross Entropy Loss function:

Inference: This loss function is commonly used in image segmentation tasks and works by penalizing the model for misclassifying pixels. High F1 score and precision score suggest that the model was able to accurately identify the white pixels that belong to the white circle. However, the lower recall score suggests that the black background may have made it harder for the model to distinguish between the circle and the background, leading to some false negatives.

1. IOU Loss functions:

Inference: IOU loss function works by computing the intersection over the union between the predicted segmentation mask and the ground truth mast. It aims to maximize the overlap between the predicted and true masks. The lower F1, precision, and recall score suggest that the model may have struggled to accurately segment the white circle. A possible explanation is that the IOU loss function may not take into the account the shape or size of the circle?

1. DICE Loss function:

Inference: This loss function is similar to IOU function, but it computers the harmonic mean between the precision and recall scores. The high F1 score, precision, and recall score obtained with the DICE loss function suggest that the model was able to accurately segment the white circle. One possible explanation for this is that the DICE loss function is more sensitive to small differences in overlap between the predicted and true masks.