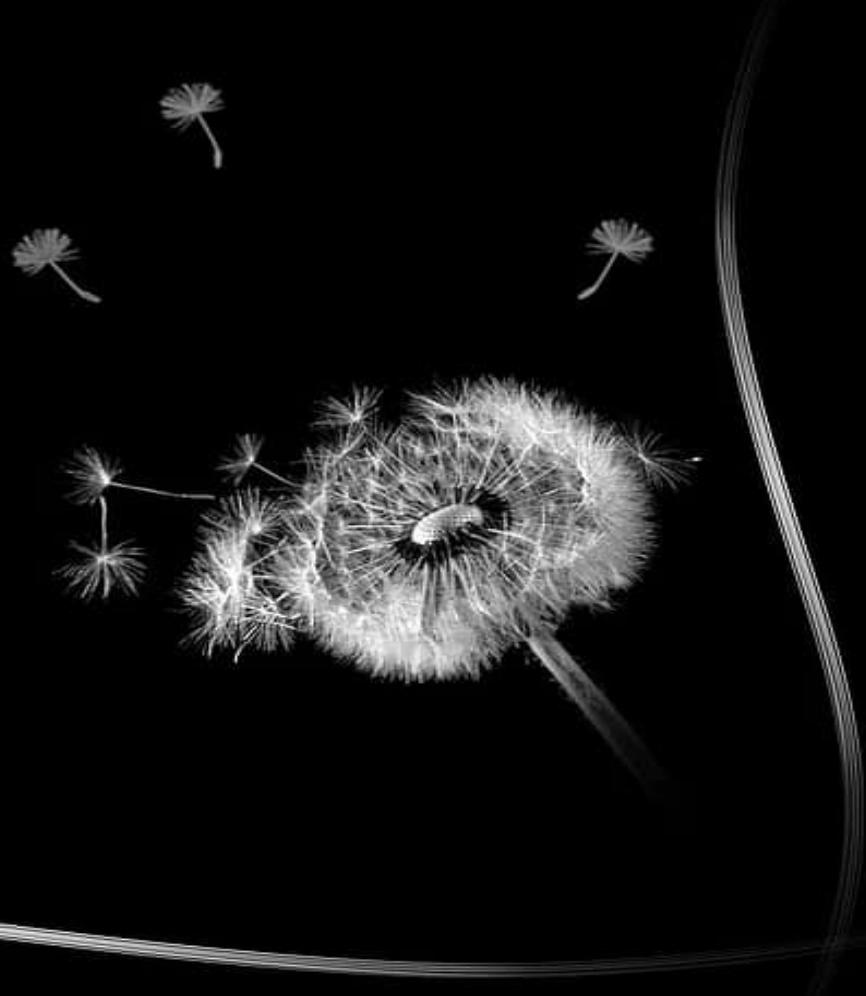


# Brain Tumor Segmentation Using U-Net (Paper Id 191)

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# Introduction

Brain tumor segmentation is an important task in medical image processing. Early diagnosis of brain tumors can increase the survival rate of the patients.

Manual segmentation of brain tumors is a difficult and time consuming task. Thus there is a need for automatic brain tumor image segmentation.

We used U-Net to segment the tumor region in the brain MR images which were obtained from TCIA dataset.

# What is Semantic Segmentation?

- ★ Image classification at a pixel level
- ★ The process of linking each pixel in an image to a class label
- ★ Applications are in autonomous vehicles, human-computer interaction, robotics, and photo editing/creativity tools

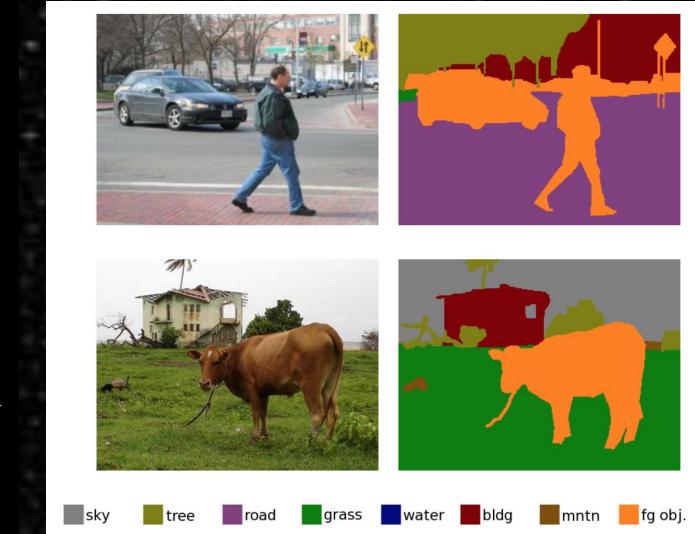


Fig 1: Semantic Segmentation

# Literature Review

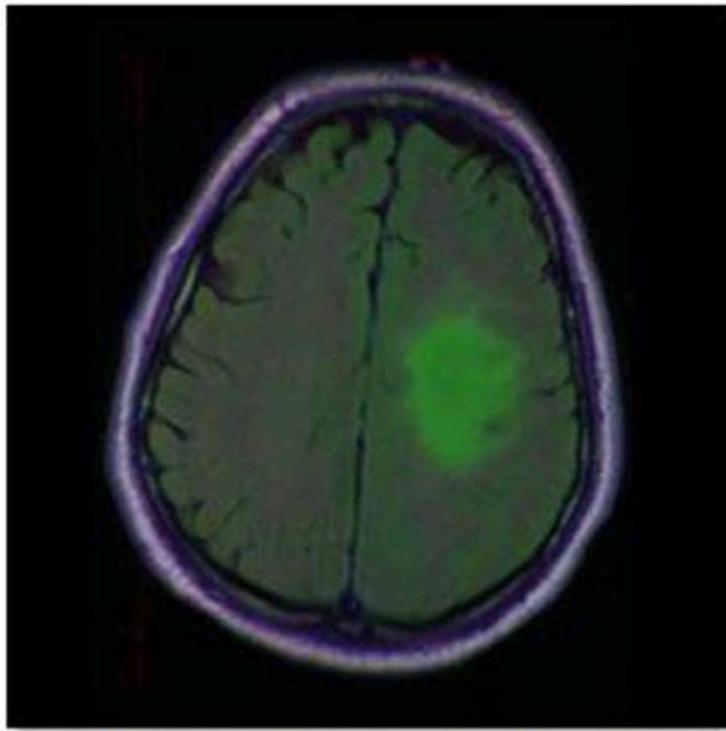
- Mateusz Buda et al.[1] proposed a fully automatic way to quantify tumor imaging characteristics using deep learning-based segmentation and test whether these characteristics are predictive of tumor genomic subtypes.
- The network used to accomplish this daunting task is U-net[2] proposed by Olaf Ronneberger et al[2].
- U-net is a fully convolutional network used for biomedical image processing.

# Dataset

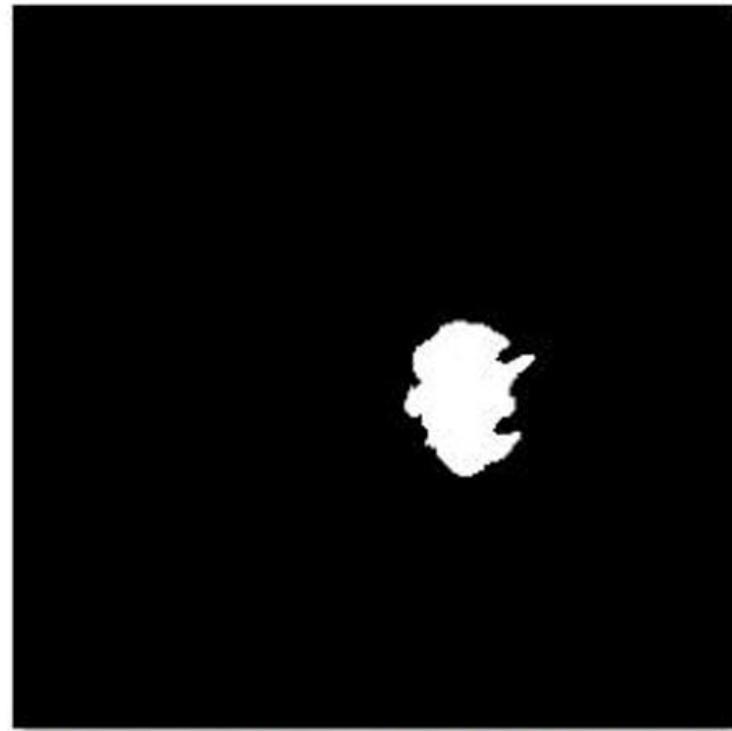
The LGG ( Lower Grade Glioma) Segmentation dataset is used to train and test the model.

The dataset contains brain MR images together with manual FLAIR abnormality segmentation masks. The images were obtained from The Cancer Imaging Archive (TCIA). They correspond to 110 patients included in The Cancer Genome Atlas (TCGA) lower grade glioma collection with at least Fluid-Attenuated Inversion Recovery (FLAIR) sequence and genomic cluster data available.

It was chosen since labelled data is in the form of binary mask images which is easy to process and use for training and testing.



TCGA\_CS\_4943\_20000902\_14



TCGA\_CS\_4943\_20000902\_14\_mask

**Figure 2: Sample image from the dataset which shows the 3 channel RGB image and mask.**

## Model Used: U-net

- U-net stems from fully convolutional network which is used for biomedical image processing.
- Biomedical image processing like many visual tasks requires localization i.e., a class label is assigned to each pixel in an image.
- The U-net architecture consists of a contracting path to capture context and a symmetric expanding path that enables precise localization.
- Since the the expansive path is more or less symmetric to the contracting path, and it yields a u-shaped architecture.
- This model relies on the strong use of data augmentation to use the available annotated samples more efficiently.

# U-Net

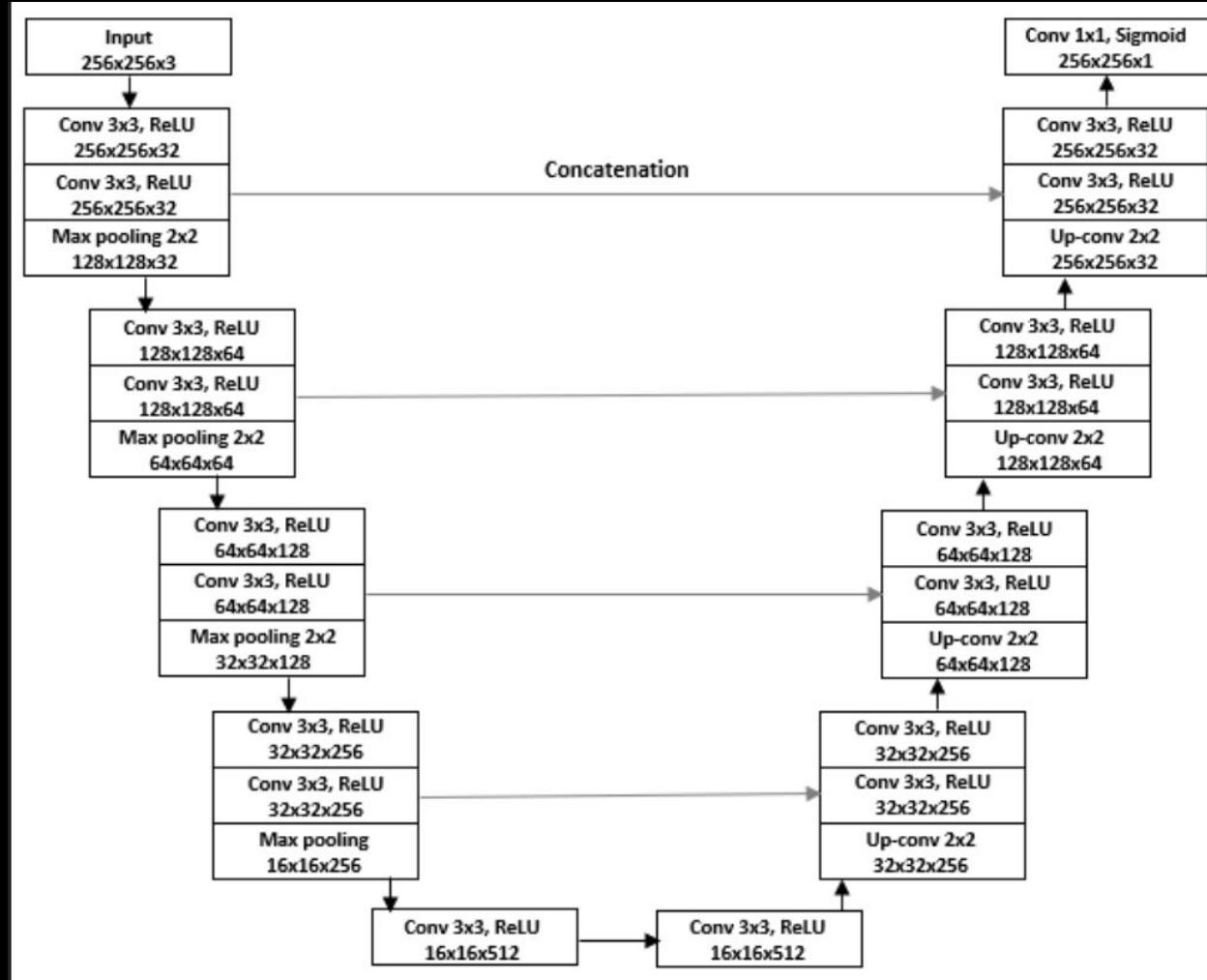


Figure 3 Unet

# Results

- The model when run at various epochs added a mask around the tumors in the test dataset and saved those images.
- For comparing the performance of our model at various epochs, we consider the value of the Dice similarity coefficient which is also known as the F1 score. DSC is a metric which lies between 0 to 1 and tells us the most comprehensive correlation between predicted pixels and real value.
- The best val\_dsc obtained was 0.8913 when the model was run at 75 epochs.

# Images from Result Folder

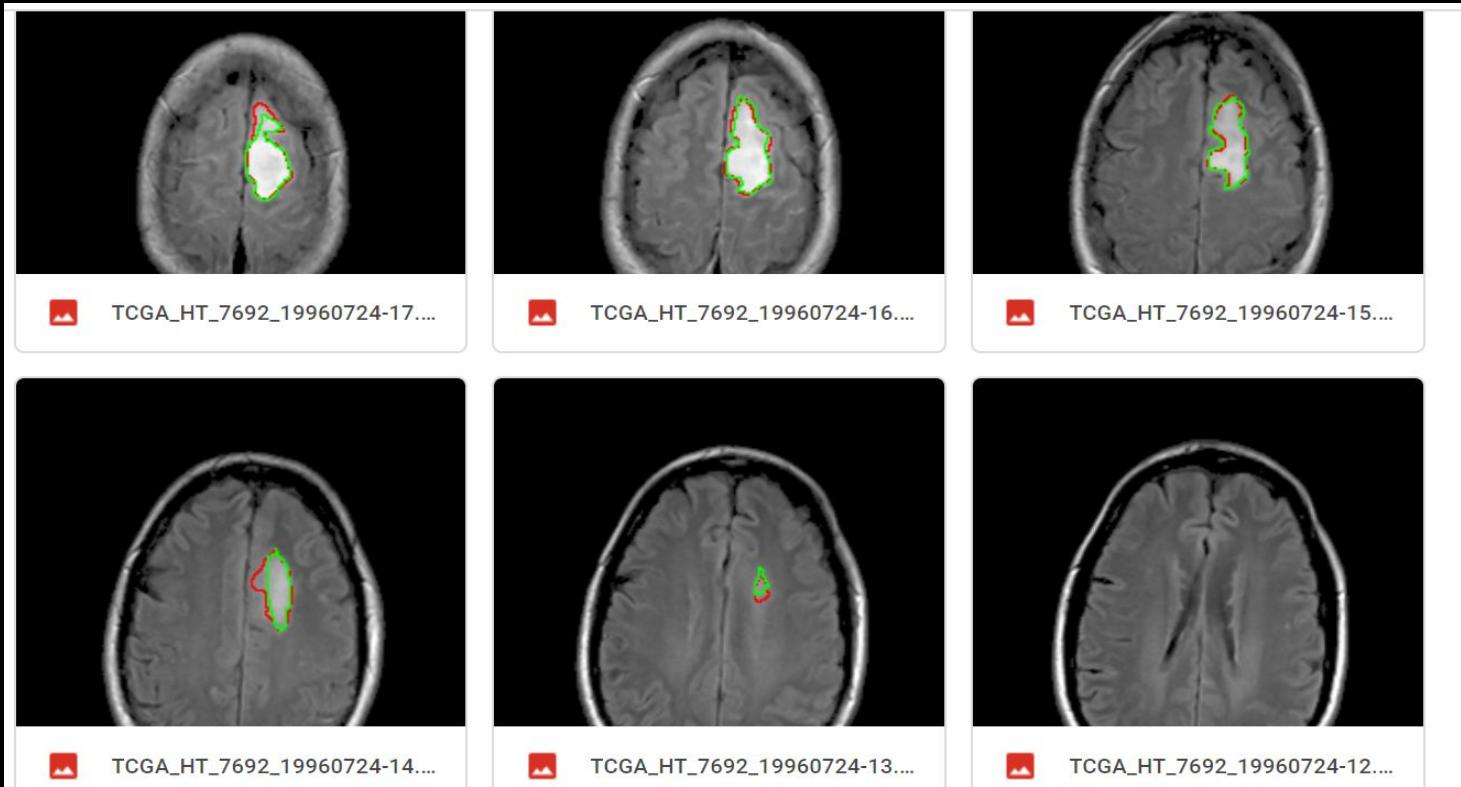


Fig 4: Results

# Result Plots for val\_dsc vs No. of epochs

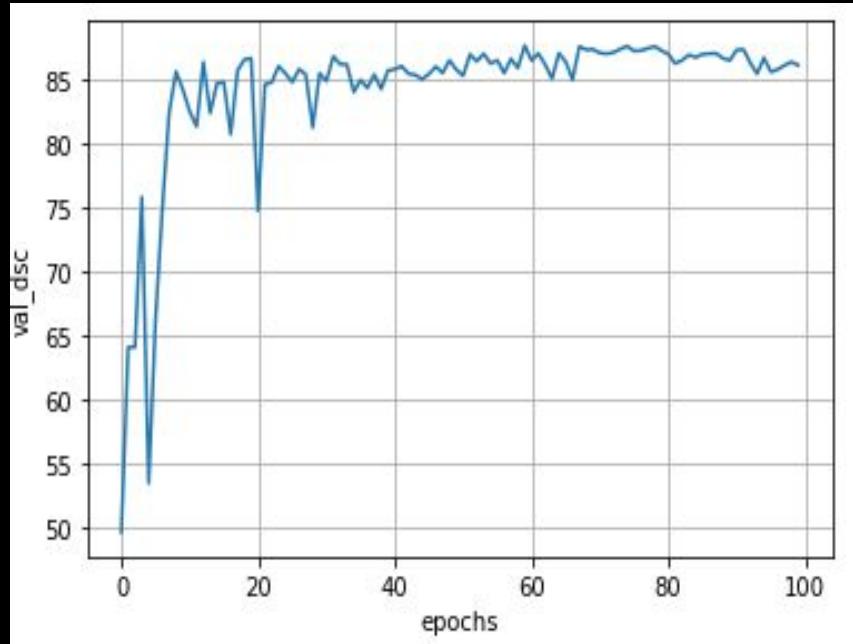


Fig 5: Plot of val\_dsc for 100 epochs

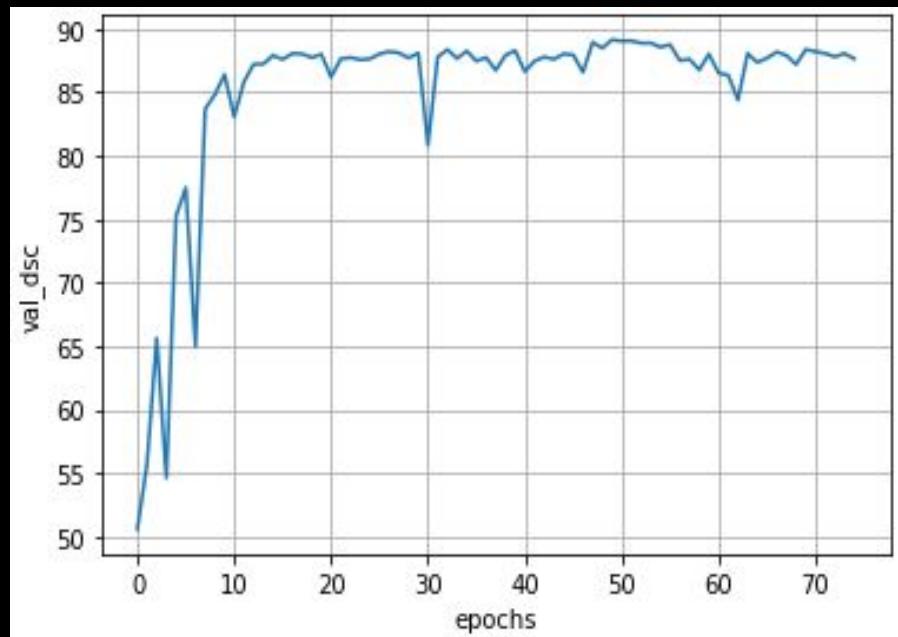


Fig 6: Plot of val\_dsc for 75 epochs

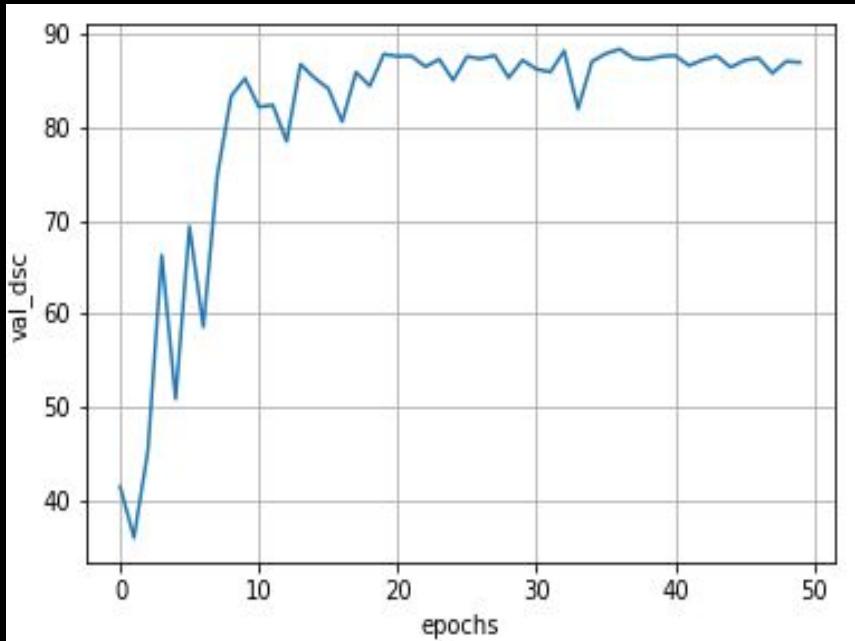


Fig 7: Plot of val\_dsc for 50 epochs

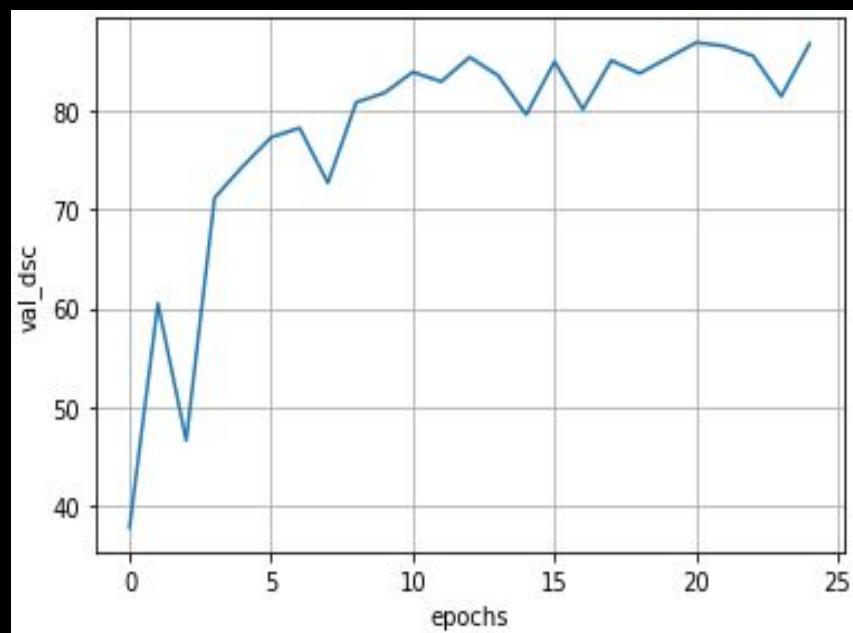


Fig 8: Plot of val\_dsc for 25 epochs

# Result

Validation mean DSC at different epochs

<b>Epochs</b>	<b>Mean DSC</b>
100	0.876262
75	0.891338
50	0.883393
25	0.869722

# Conclusion

- Biomedical imaging has a long way to go. We have managed to achieve adequate results with the technology available to us.
- The Unet model was successfully trained to predict the boundary around the tumor. We have managed to obtain a val\_dsc of **0.891338**
- We are constrained by time and resources, but if precise prototypes are created, they can be integrated in several ways into the standard treatment approach.

# Future Scope

Recently, 2D and 3D deep convolutional neural networks are increasingly being used for the segmentation task of medical images. This is due to large labeled datasets from which hierarchical features can be learned. The downside of 3D network was concluded to be the high cost of computing.

An example of such model would be RA-UNet[3] which accurately segments the section of tumors in the liver.

Many such models exist which can be experimented with to achieve better results.

# References

- [1] Mateusz Buda, Ashirbani Saha, and Maciej A. Mazurowski. “Association of genomic subtypes of lower-grade gliomas with shape features automatically extracted by a deep learning algorithm”, Computers in Biology and Medicine, Vol.109, 2019.
- [2] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. “U-net: convolutional networks for biomedical image segmentation”, Medical Image Computing and Computer-Assisted Intervention (MICCAI), Springer, LNCS, Vol.9351: 234--241, arXiv:1505.04597 [cs.CV], 2015.
- [3] Qiangguo Jin, Zhaopeng Meng, Changming Sun, Leyi Wei, Ran Su. RA-UNet: A hybrid deep attention-aware network to extract liver and tumor in CT scans. arXiv:1811.01328v1 [cs.CV], 2018.

Thank  
You

