Brain Structure Segmentation Using Adversarial Learning

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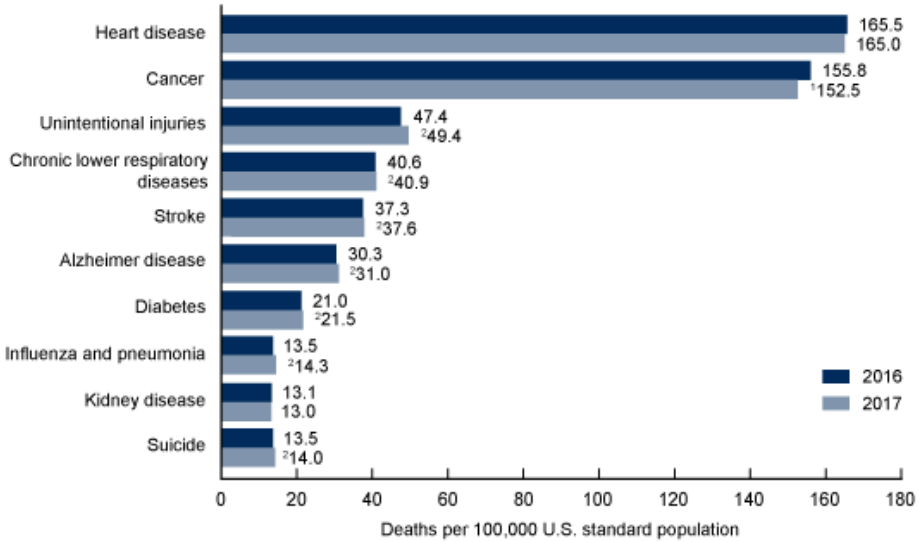
Clinical Motivation



Brain structure segmentation is important to detect brain disorders:

- Alzheimer‘s disease
- Epilepsy
- Schizophrenia
- multiple sclerosis (MS)

Alzheimer’s disease is sixth highest cause of death in US in 2017.

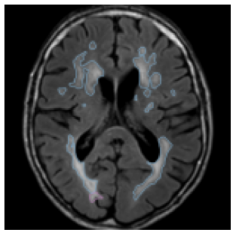
Manual segmentation is very tedious.

Need for automatic segmentation with highest possible accuracy.

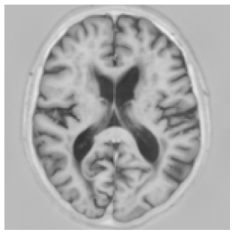
[1] Image Source: https://www.cdc.gov/nchs/products/databriefs/db328.htm

Dataset

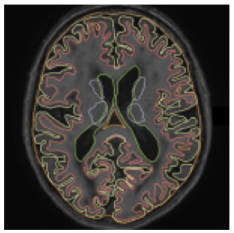
Brain MRI scans by MRBrains18 [1] and MICCAI-WMH[2].
Each scan is of size 240 X 240 X 48.
[1] 7 annotated subjects of 3 modalities : T1, T1-IR, FLAIR.
[2] 4 unannotated subjects of 2 modalities : FLAIR, T1
Scans are bias corrected using N4ITK algorithm.
We used FLAIR and T1 for training.



FLAIR



T1-IR



T1

Mode	No. Of Subjects	Subject List
Training (Annotated)	4 subjects	[4, 5, 7, 70]
Training(Unannotated)	4 subjects	[0, 2, 4, 6]
Validation	1 subject	[148]
Testing	2 subjects	[1, 14]

Dataset Splitting

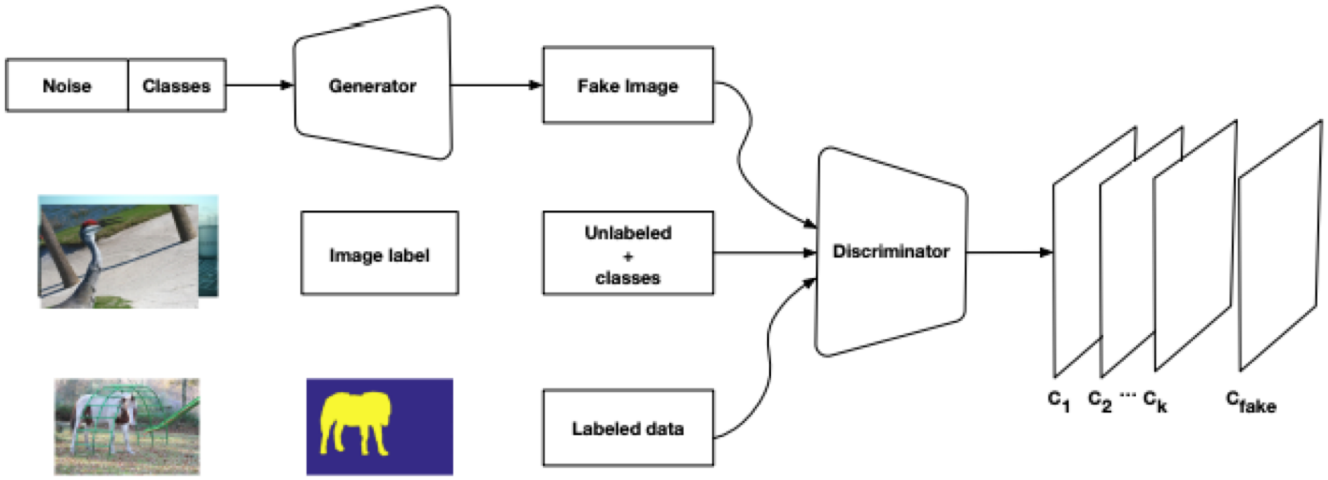
Label	Description
0	Background
1	Cortical Gray Matter
2	Basal Ganglia
3	White Matter
4	White Matter Lesions
5	Cerebrospinal fluid in the extracerebral space
6	Ventricles
7	Cerebellum
8	Brain Stem

Segmentation Classes

[1] https://mrbrains18.isi.uu.nl/
[2] https://wmh.isi.uu.nl/

Motivation

Expensive manual segmentation of scans by medical experts.
Have a lot of unannotated data
GANs improve semantic segmentation in semi-supervised setting [1],[2].



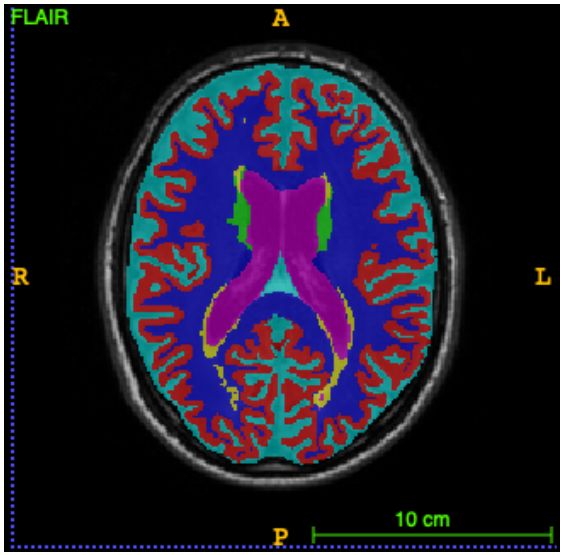
[1] M. S. Nasim Souly Concetto Spampinato. “Semi and Weakly Supervised SemanticSegmentation Using Generative Adversarial Network”. In: (2017).
[2] C. D. Arnab Kumar Mondal Jose Dolz. “Few-shot 3D Multi-modal Medical ImageSegmentation using Generative Adversarial Learning”. In: (2018).

Pre-processing

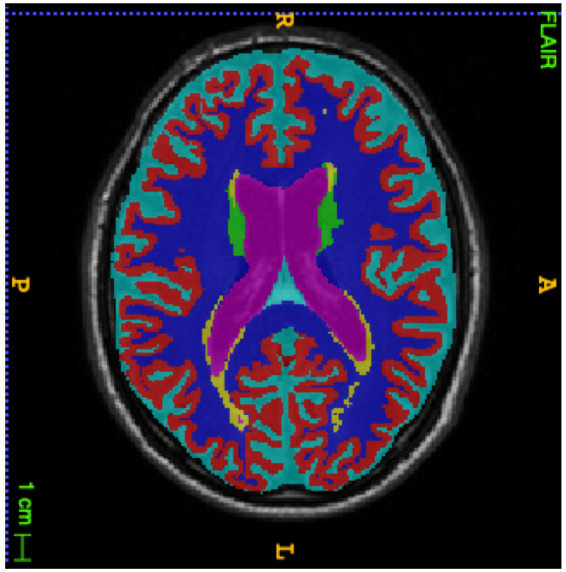
MRI scans are noisy and contain a lot variance in pixel values.

Two step normalization process:

1. All the axial slices are cropped to remove black background borders.
2. Gaussian Normalization to rescale the voxel intensities within each brain scan.



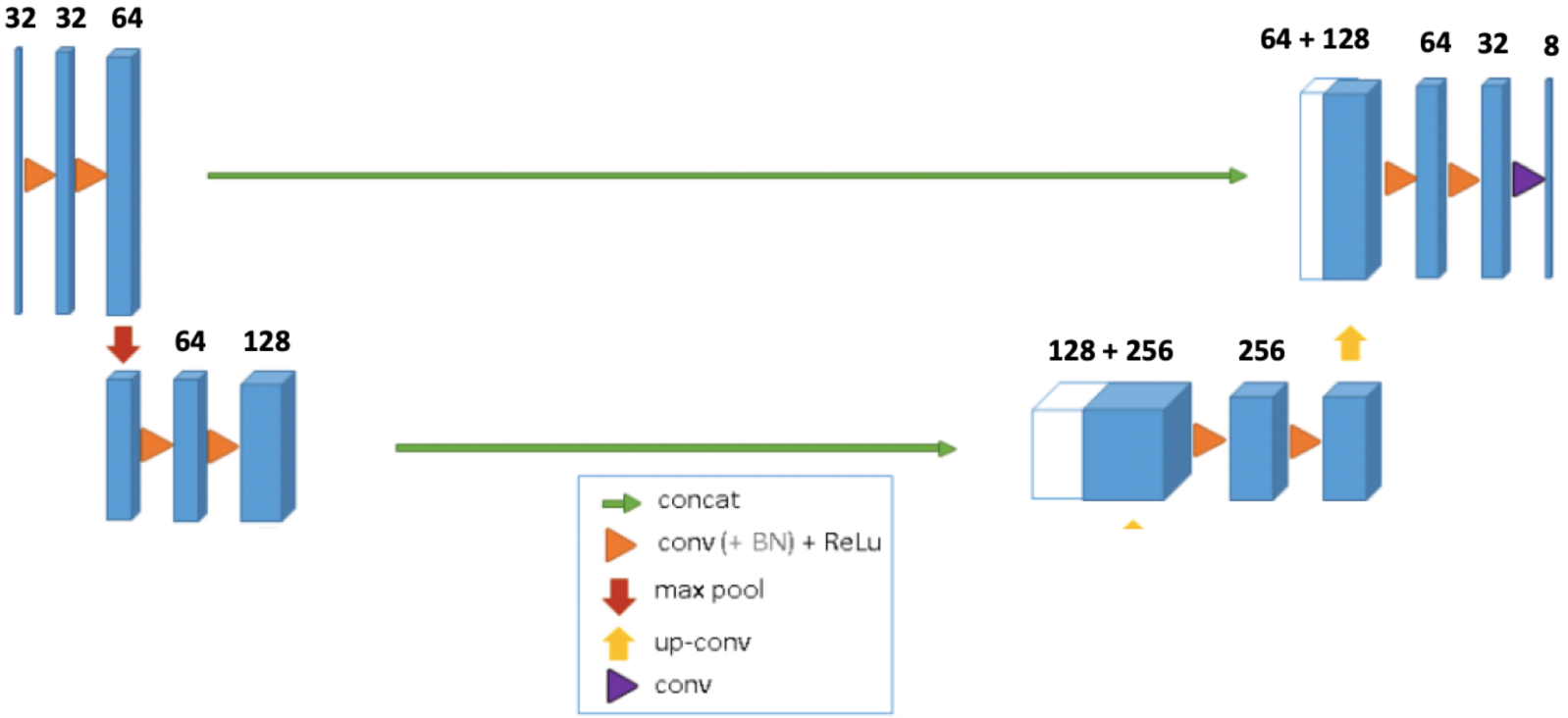
Original



Pre-processed

Network Architecture

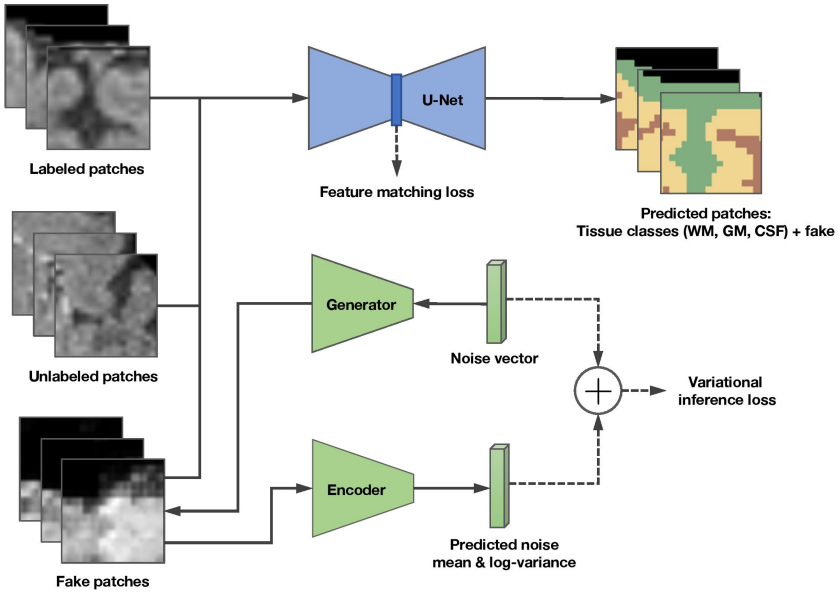
Baseline : 3D UNET



Only annotated images are used.
Trained with Multi-class Cross Entropy Loss.

Network Architecture

Our Network : 3D GAN



Feature Matching loss is to match features in an intermediate layer of discriminator

- Unlabeled patches are also included for training
- Fake patches generated by generator
- Discriminator determines real (annotated + unannotated) or fake (by generator)
- Predicts (K + 1) classes, additional class for fake generated patch

Metrics

G is the ground-truth segmentation mask, and P is the predicted segmentation mask

Dice Score

$$Dice = \frac{|G| \cap |P|}{|G| + |P|}$$

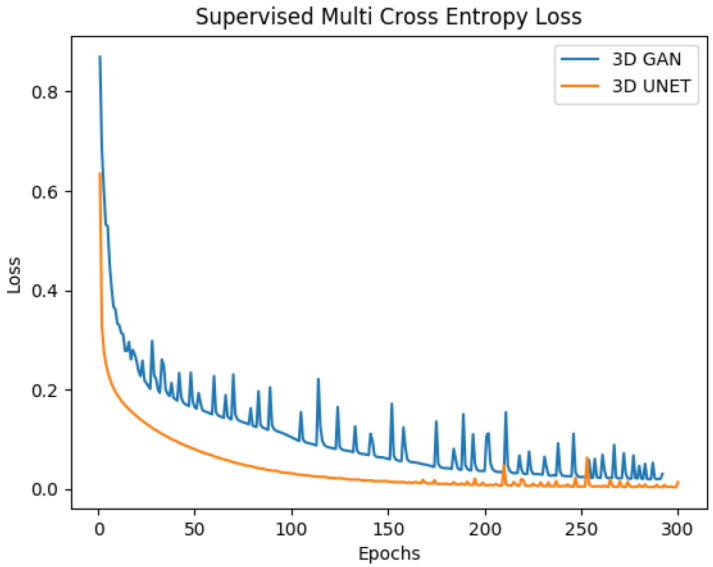
95-percentile Hausdorff Distance

$$H(G,P) = max\{\sup_{x \in G} \inf_{y \in P} d(x,y), \sup_{y \in P} \inf_{x \in G} d(x,y)\}$$

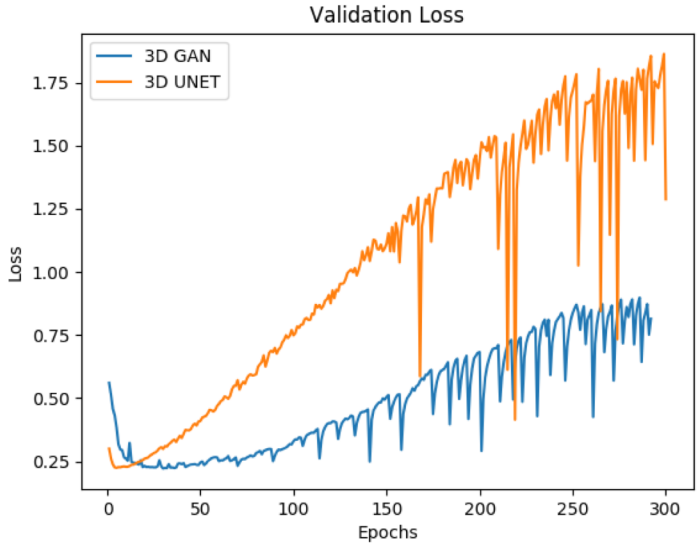
Volumetric Similaritv

$$V_S = \frac{|V_G - V_P|}{V_G}$$

Results : Loss Curves

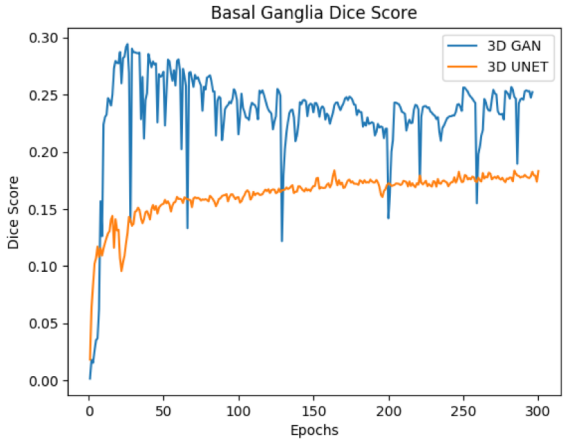


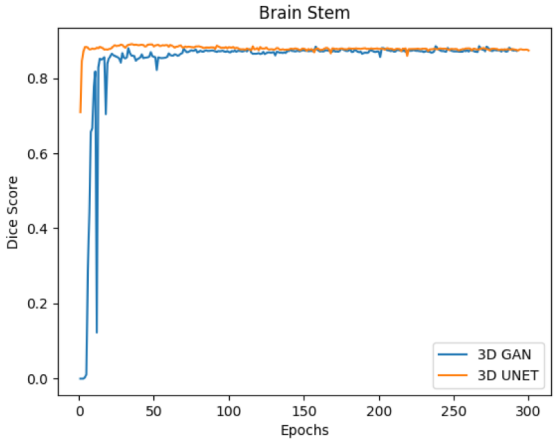
Training Loss

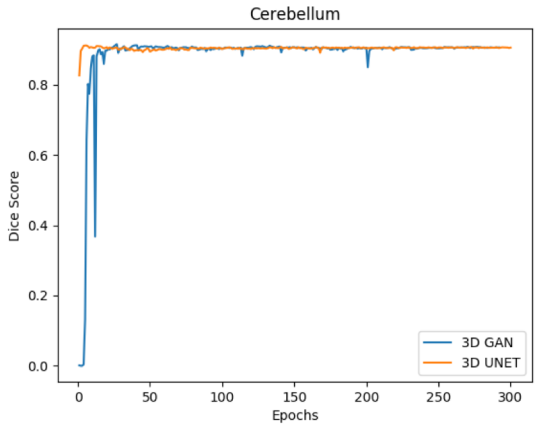


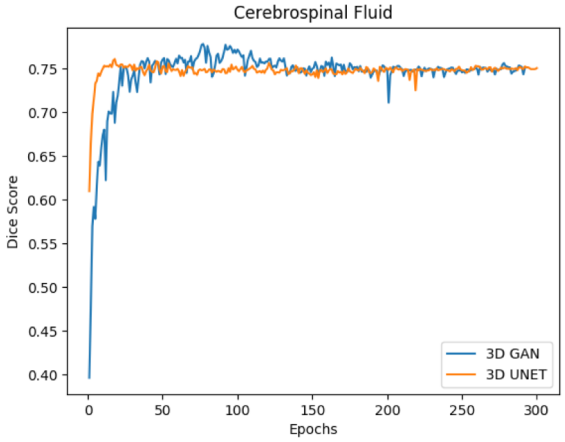
Validation Loss

Results : Dice Score on Validation Set

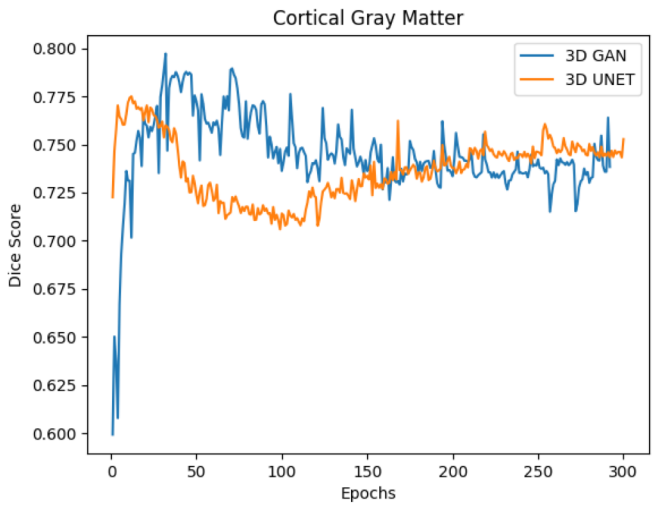


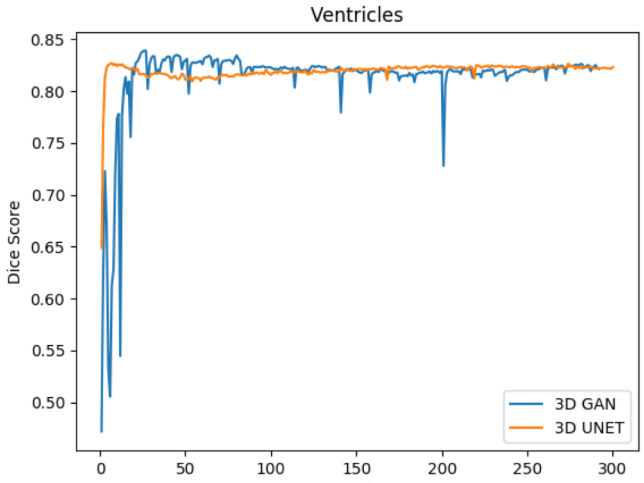


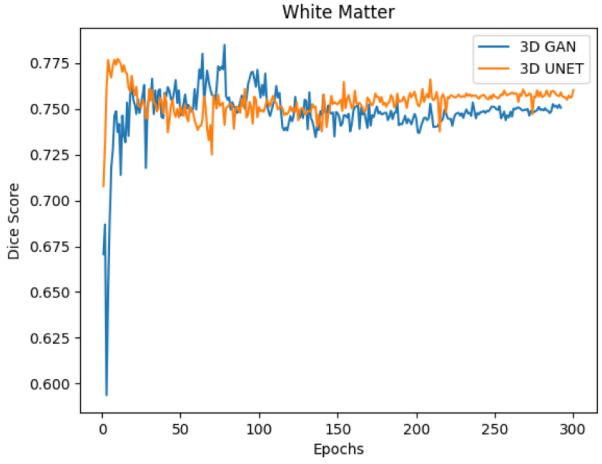


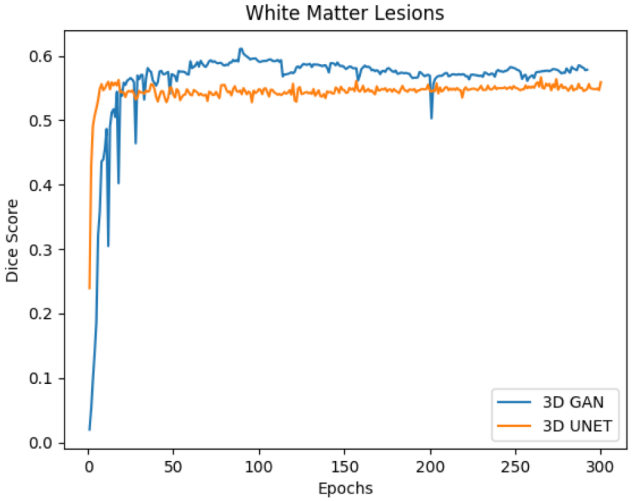


Results : Dice Score on Validation Set





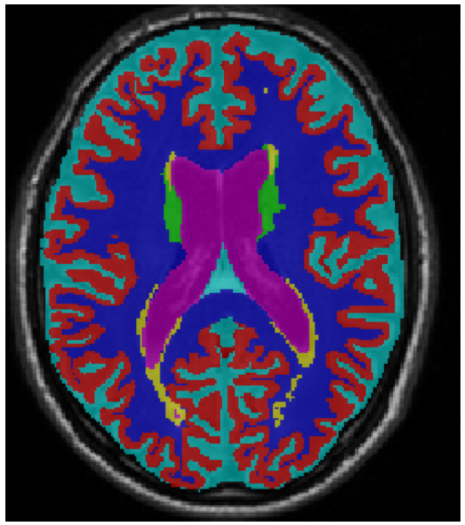




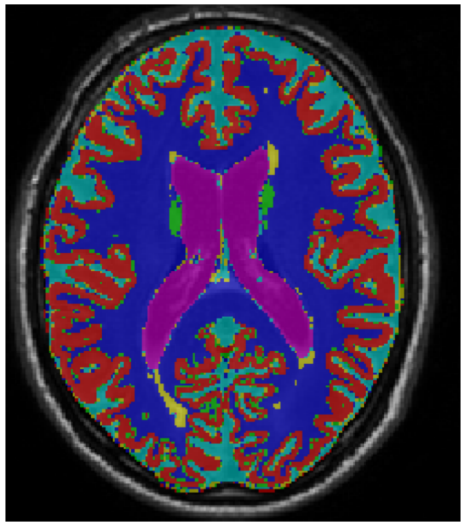
Results on Test Set : Subject 1

Class	Model	Dice Similarity	Hausdorff Distance	Volume Similarity
Cortical Gray Matter	3D UNET	0.78	3.46	**0.98**
	3D GAN	**0.82**	**2.0**	0.95
Basal Ganglia	3D UNET	0.32	**53.61**	0.44
	3D GAN	**0.39**	54.19	**0.51**
White Matter	3D UNET	0.83	4.12	0.95
	3D GAN	**0.85**	4.12	**0.97**
White Matter Lesions	3D UNET	0.10	**25.96**	0.16
	3D GAN	**0.11**	26.55	**0.18**
Cerebrospinal Fluid	3D UNET	0.73	2.0	0.80
	3D GAN	**0.74**	2.0	0.80
Ventricles	3D UNET	0.82	22.29	0.91
	3D GAN	**0.84**	**22.02**	0.91
Cerebellum	3D UNET	0.90	2.23	0.97
	3D GAN	0.90	2.23	0.97
Brain Stem	3D UNET	0.97	**3.16**	0.90
	3D GAN	0.97	3.74	0.90

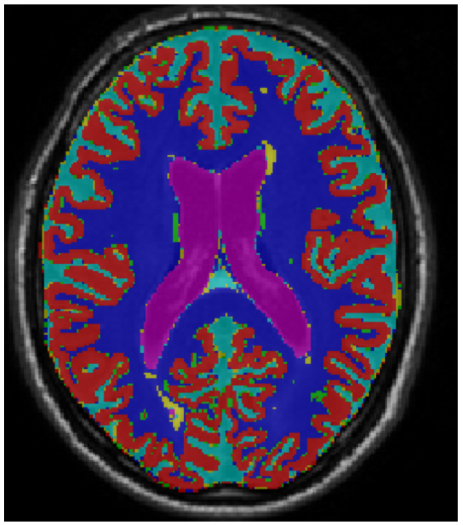
Results on Test Set : Subject 1



Ground Truth



3D UNET

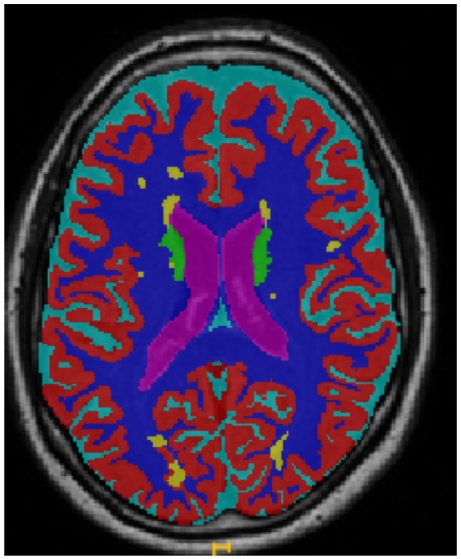


3D GAN

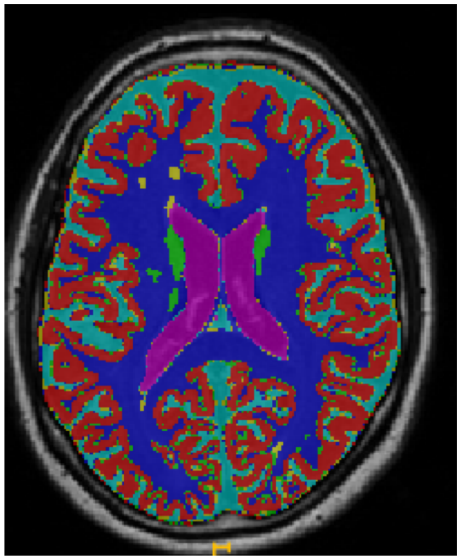
Results on Test Set : Subject 14

Class	Model	Dice Similarity	Hausdorff Distance	Volume Similarity
Cortical Gray Matter	3D UNET	0.81	2.0	0.93
	3D GAN	**0.86**	**1.41**	**0.97**
Basal Ganglia	3D UNET	0.32	53.25	0.37
	3D GAN	**0.38**	53.30	**0.44**
White Matter	3D UNET	0.83	4.123	0.98
	3D GAN	**0.84**	4.123	0.98
White Matter Lesions	3D UNET	0.05	**27.94**	0.14
	3D GAN	**0.06**	29.68	**0.17**
Cerebrospinal Fluid	3D UNET	0.76	**1.73**	**0.93**
	3D GAN	**0.78**	2.0	0.92
Ventricles	3D UNET	0.75	28.57	0.83
	3D GAN	**0.77**	**27.92**	**0.85**
Cerebellum	3D UNET	0.90	3.31	0.94
	3D GAN	**0.92**	**3.0**	**0.95**
Brain Stem	3D UNET	0.85	3.31	0.88
	3D GAN	**0.88**	**2.82**	**0.93**

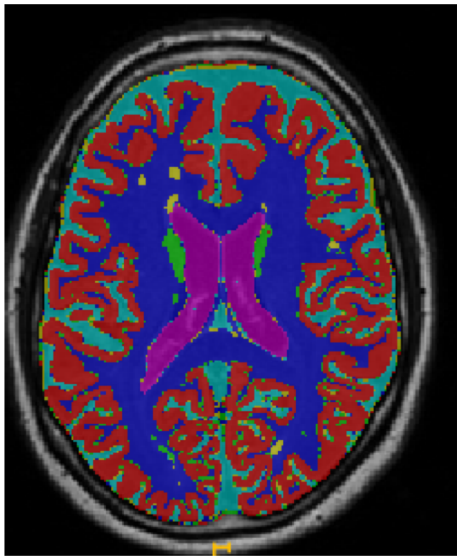
Results on Test Set : Subject 14



Ground Truth

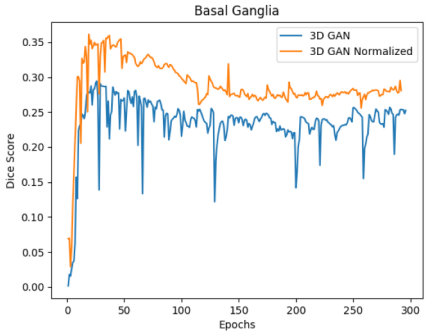


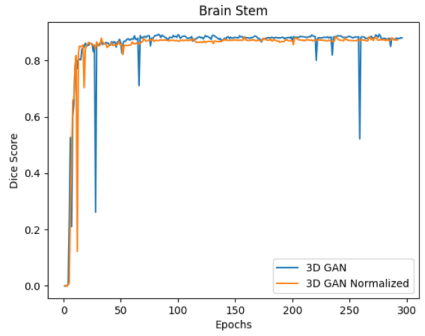
3D UNET

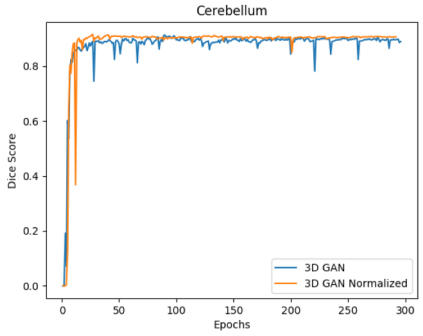


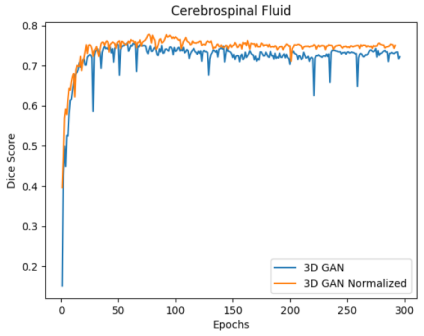
3D GAN

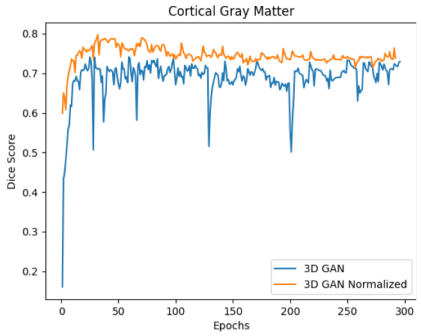
Preprocessed vs Non-preprocessed Scans On Validation Set

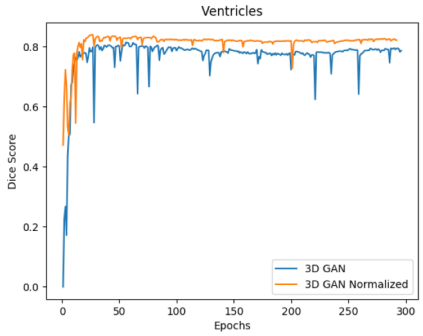


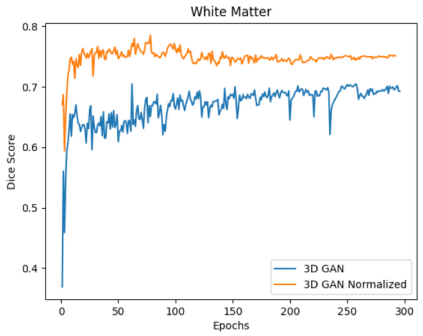


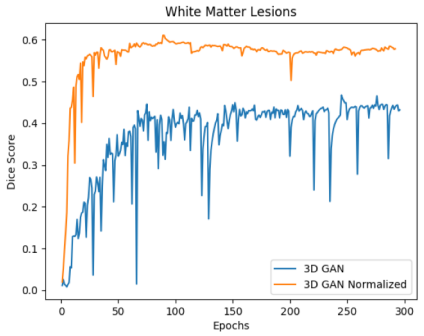












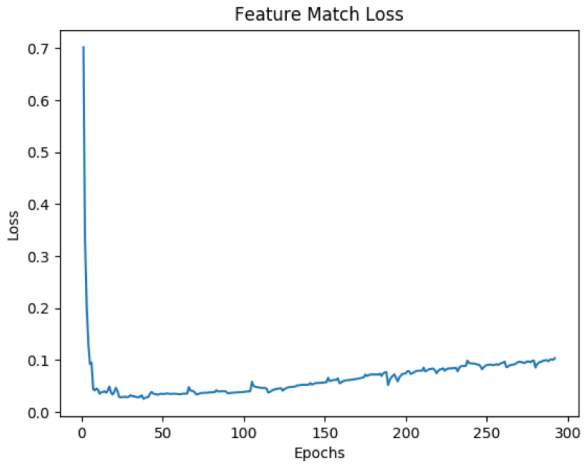
Conclusion

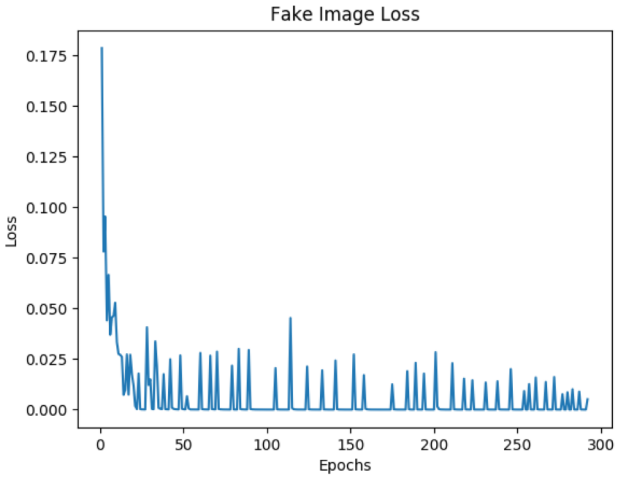
- 3D UNET with adversarial learning using unannotated data performs slightly better that simple 3D UNET.

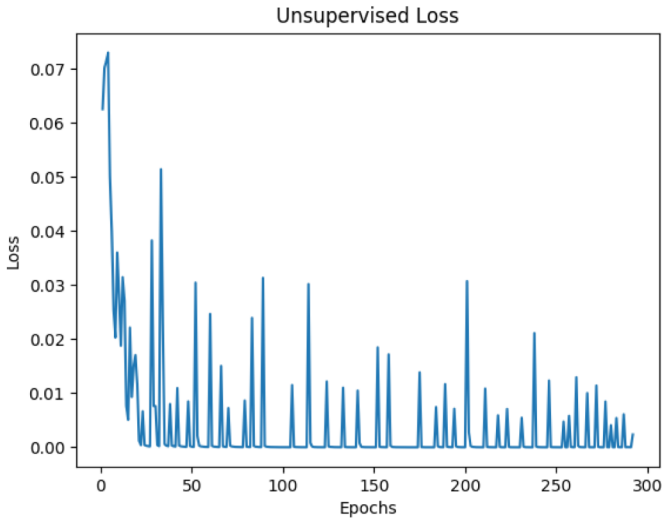
- Preprocessing improves the results by a significant margin.

THANK YOU

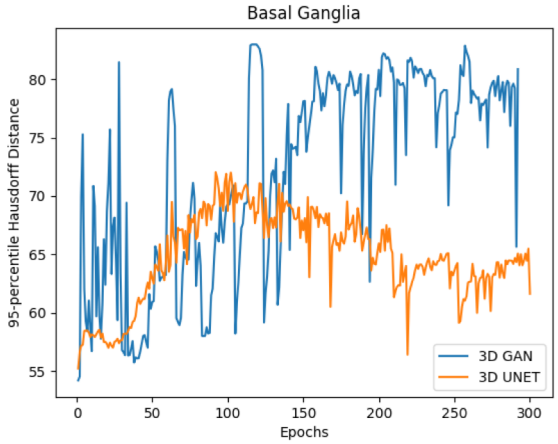
3D GAN Loss Curves

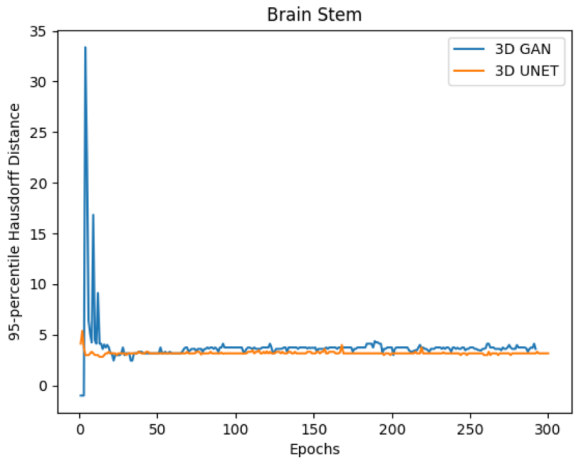


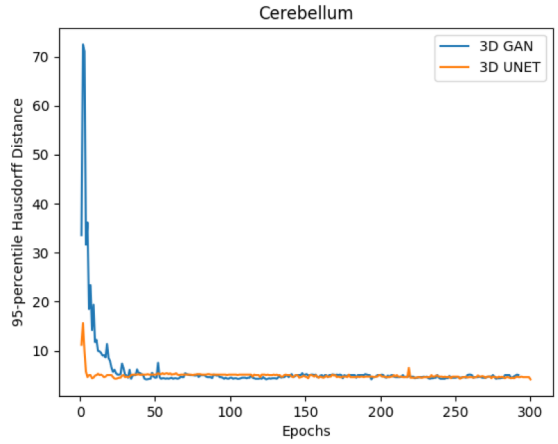


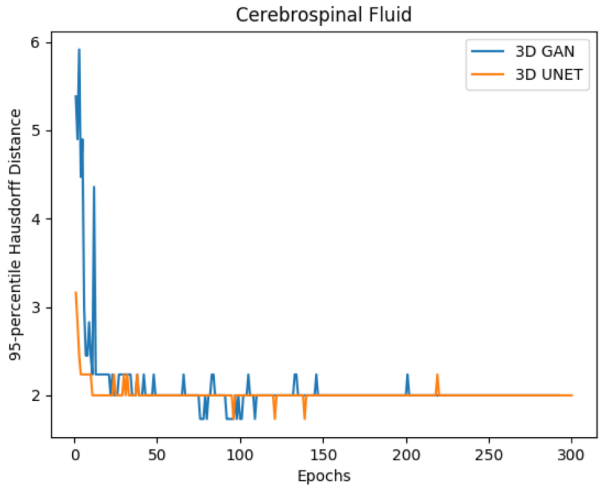


95-percentile Hausdorff Distance

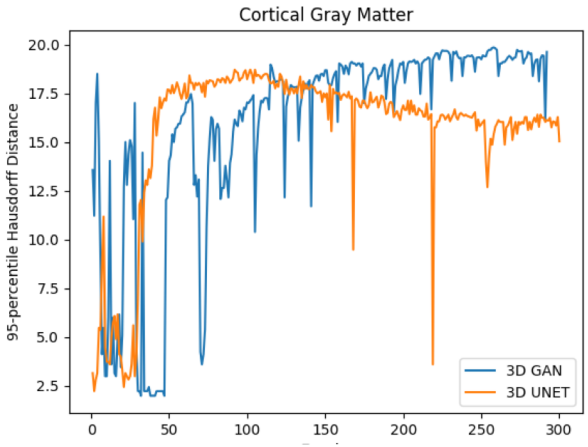


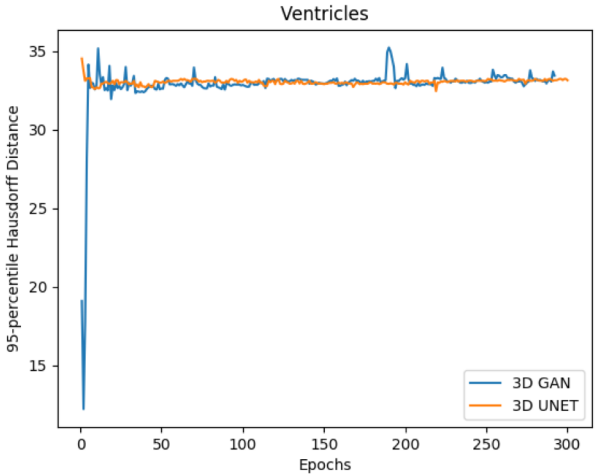


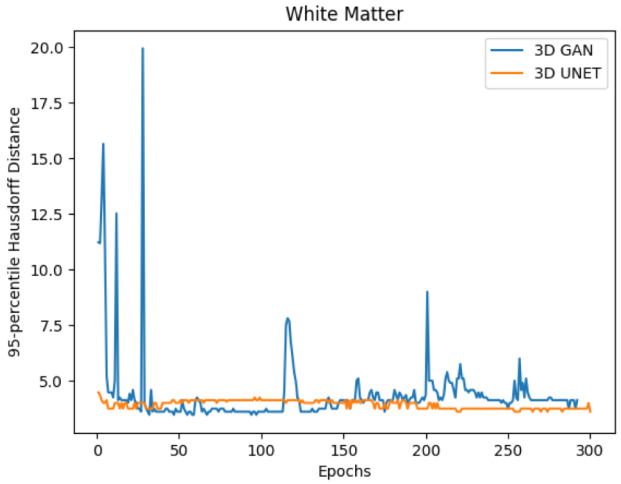


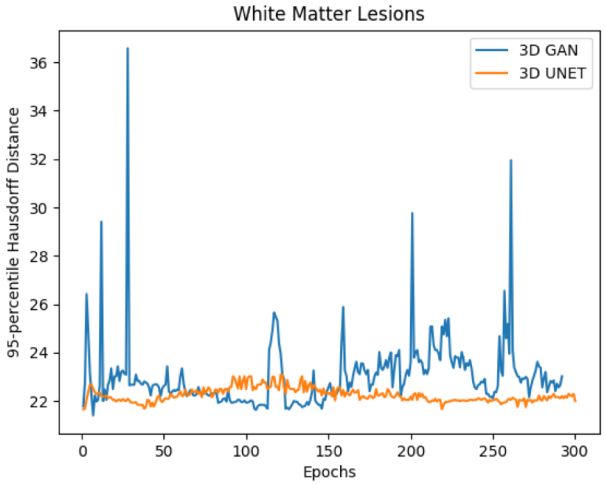


95-percentile Hausdorff Distance

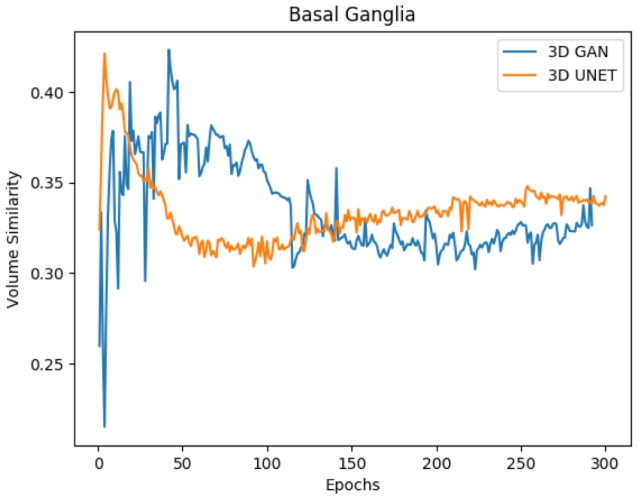


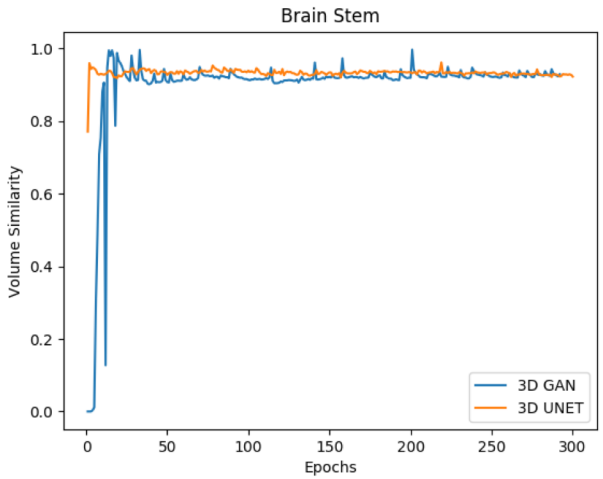


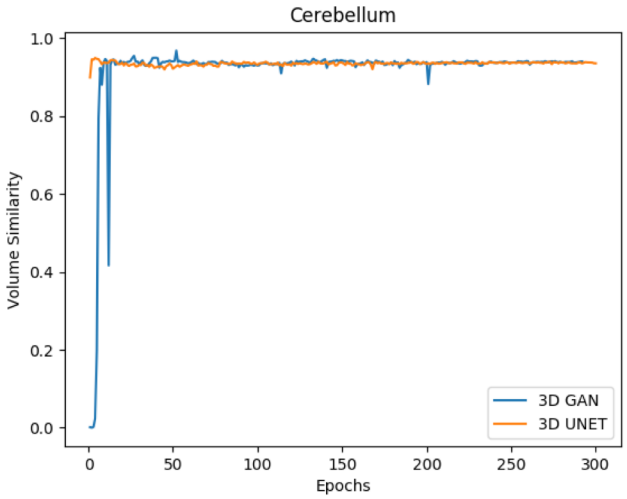


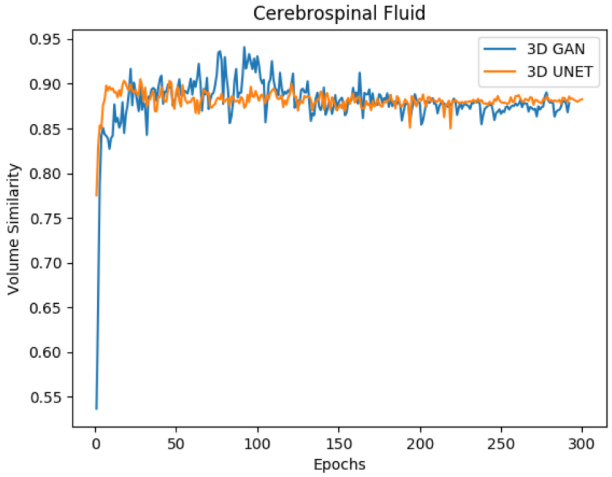


Volume Similarity









Volume Similarity