Synthetic Segmented Virtual Head Model Generation Using Generative Adversarial Network (GAN)

NAHIAN IBN HASAN
Elmore School of Electrical and Computer Engineering
Purdue University, West Lafayette (WL), IN, USA

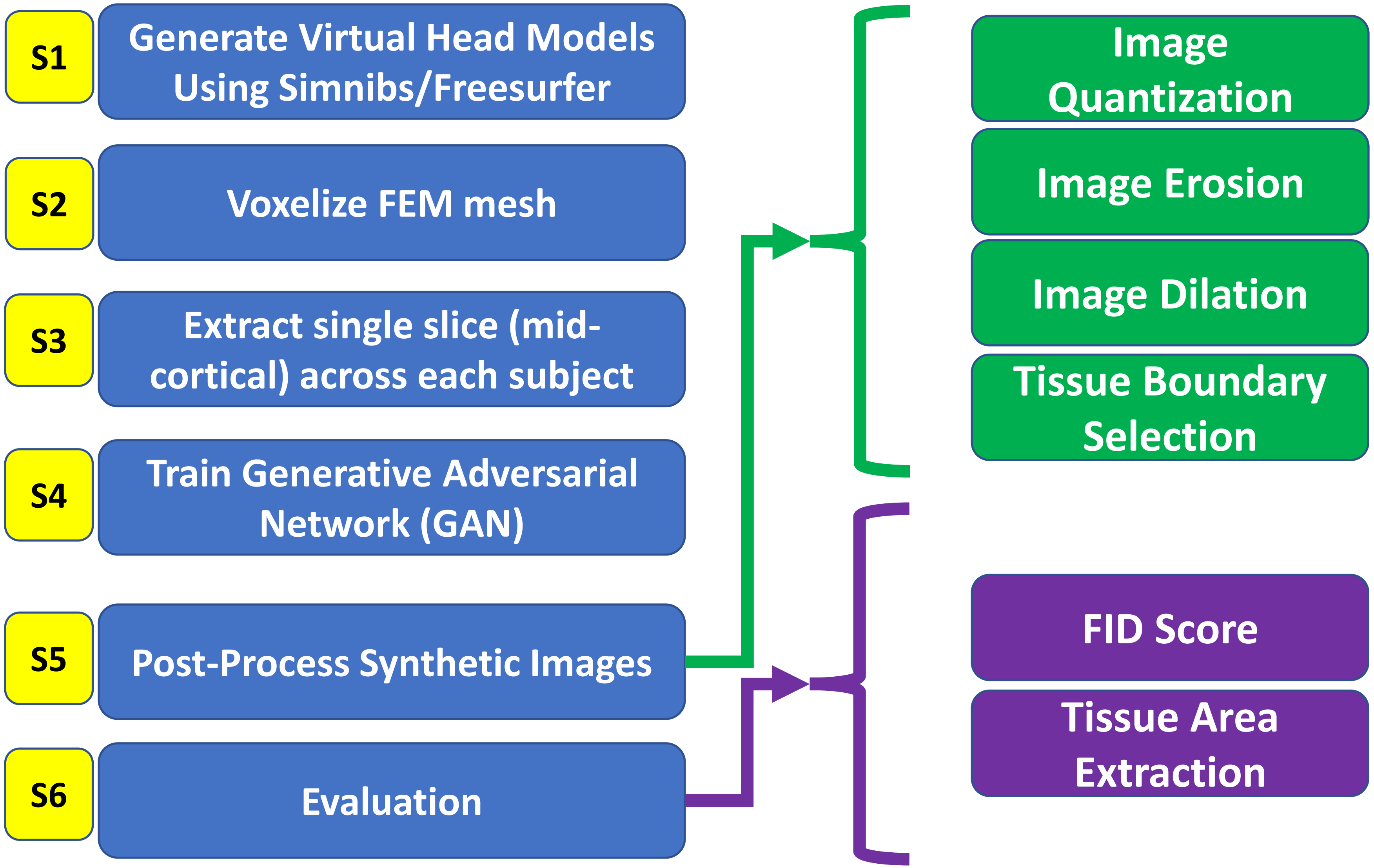
PURDUE UNIVERSITY

Project Motivation

The Purpose of Generating Synthetic Data

- Data Augmentation for MRI images for Machine Learning Projects
- Population based studies and uncertainty quantification
- Image Super-resolution (1.5T MRI → 3T/5T/7T MRI)

Project Workflow



Database Information

Database : Wu-Minn Human Connectome Project [1]

- Data Type : Structural MRI scans
- Coil Type : 3T/7T
- MRI type : T1w and T2w
- Number of Subjects : 812
- Subject Age : 22-35
- Ratio M/F : (47/53) %

[1] https://www.humanconnectome.org/study/hcp-young-adult/document/1200-subjects-data-release

Step 1 – Real Virtual Head Model Generation

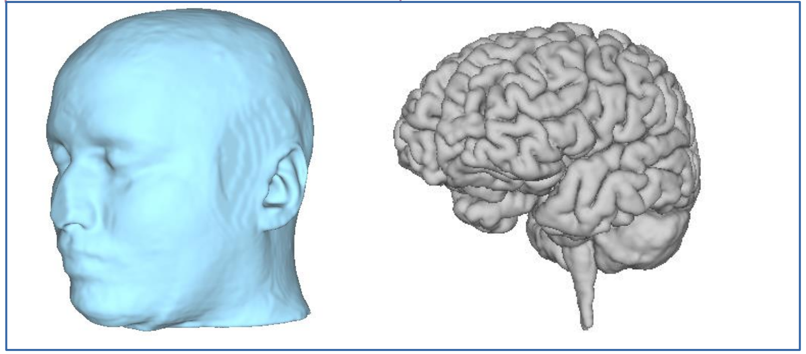
MRI Scans

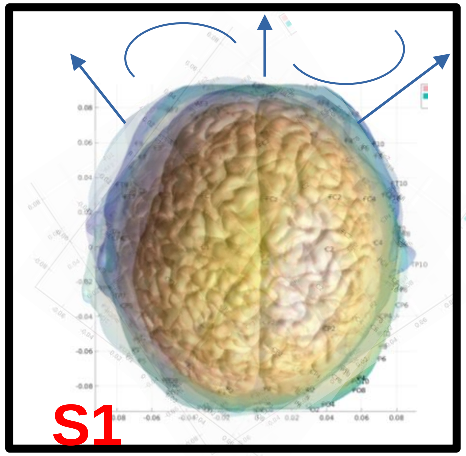
SimNIBS Uses Freesurfer* for Surface Based Cortical Tissue Segmentation

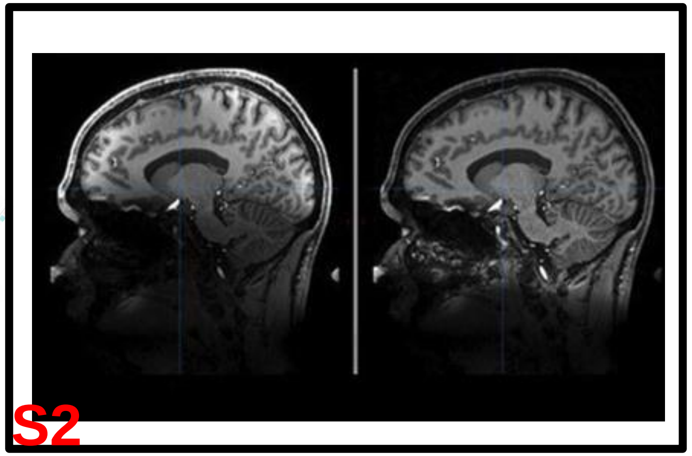
S1. Co-registration
S2. B-field in-homogeneity correction
S3. Skull-stripping
S4. Segment based on GM/WM
S5. Divide Brain into LH and RH

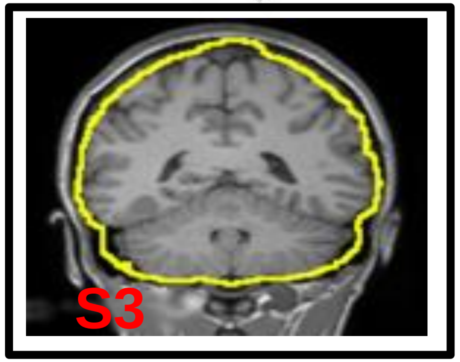
For each Hemisphere:
S6. Fill holes of the WM
S7. Deform triangle mesh to fit GM/WM interfaces

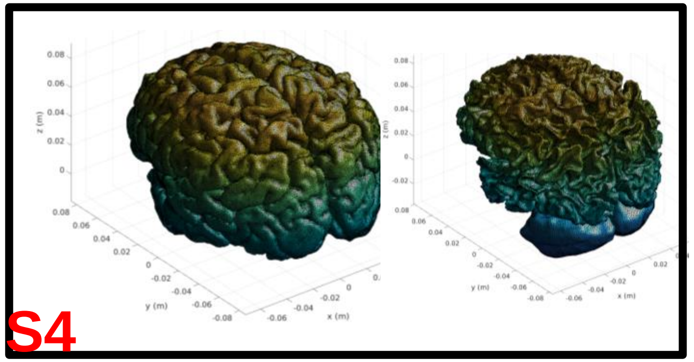
Virtual Head Model

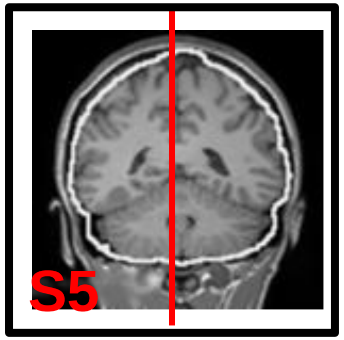


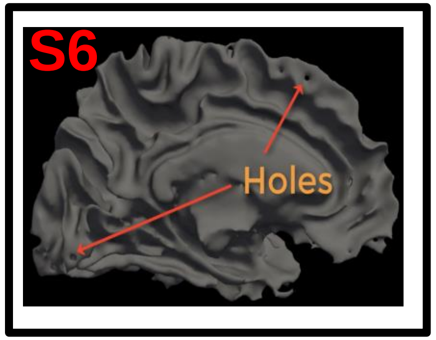






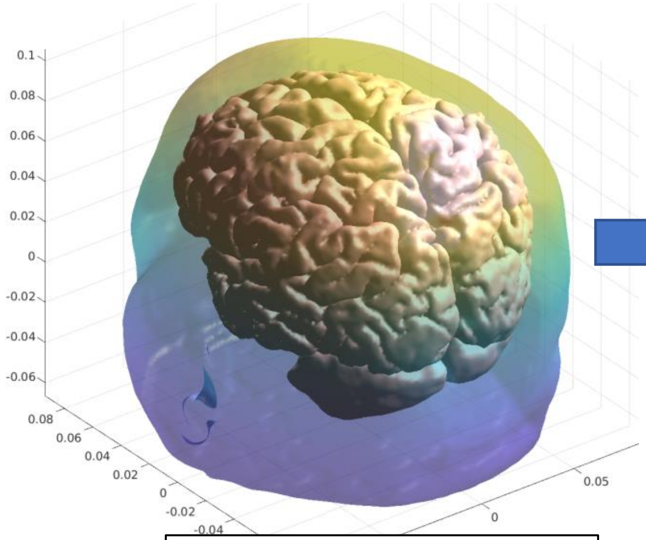




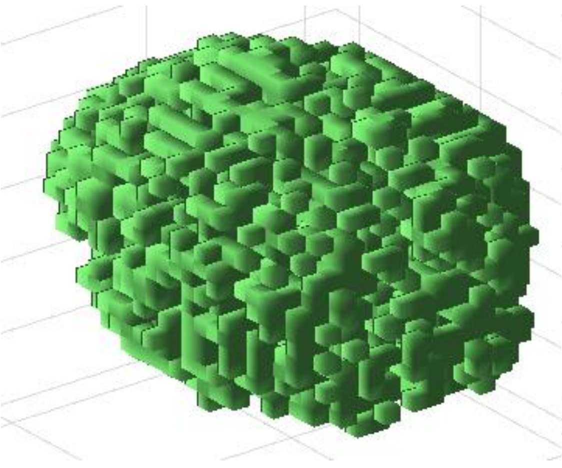


[*] Fischl, B. (2012). FreeSurfer. Neuroimage, 62(2), 774-781.

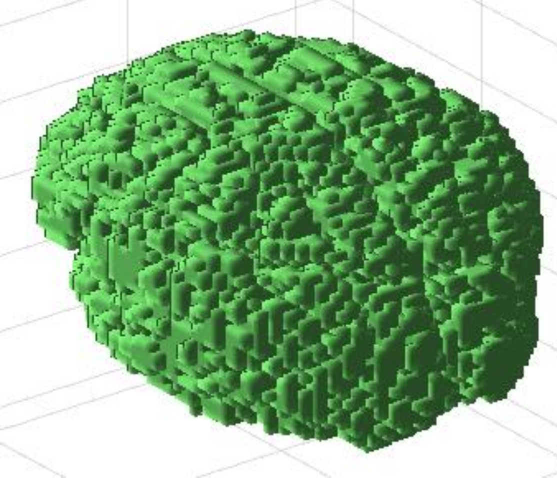
Step 2 – Voxelization of FEM Mesh



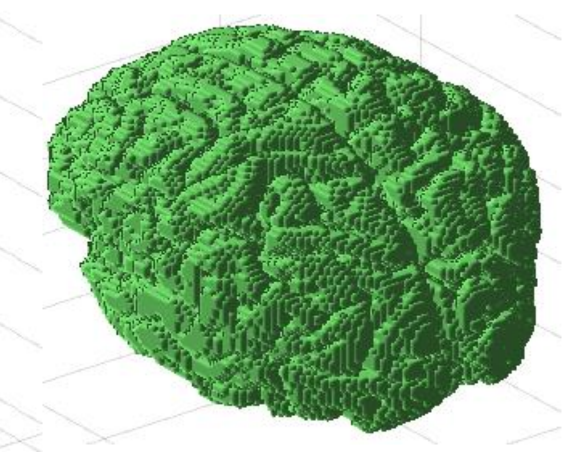
FEM Mesh for GM



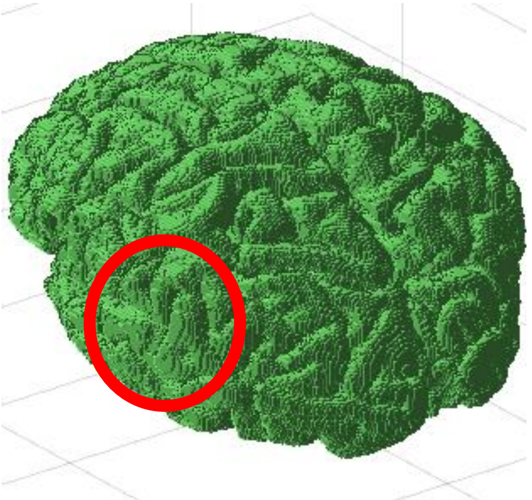
32×32×32



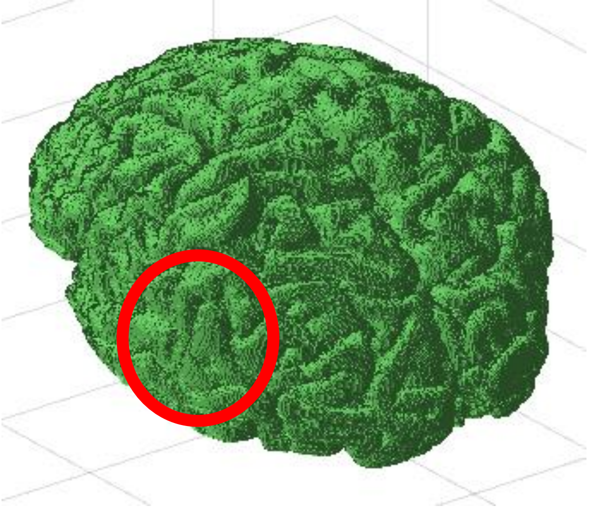
64×64×64



128×128×128



256×256×256

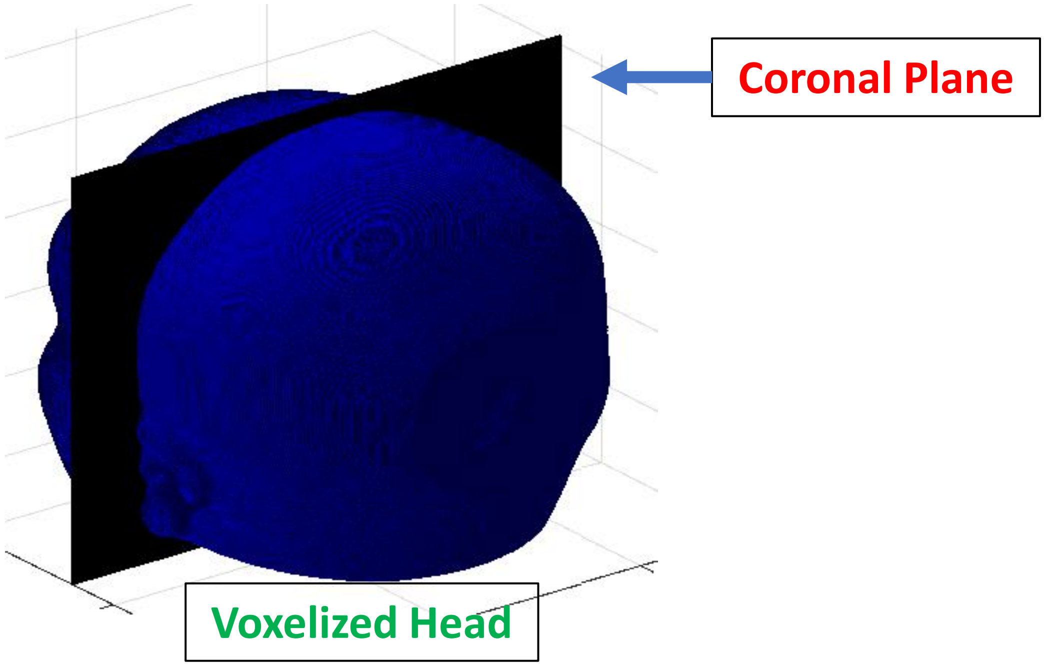


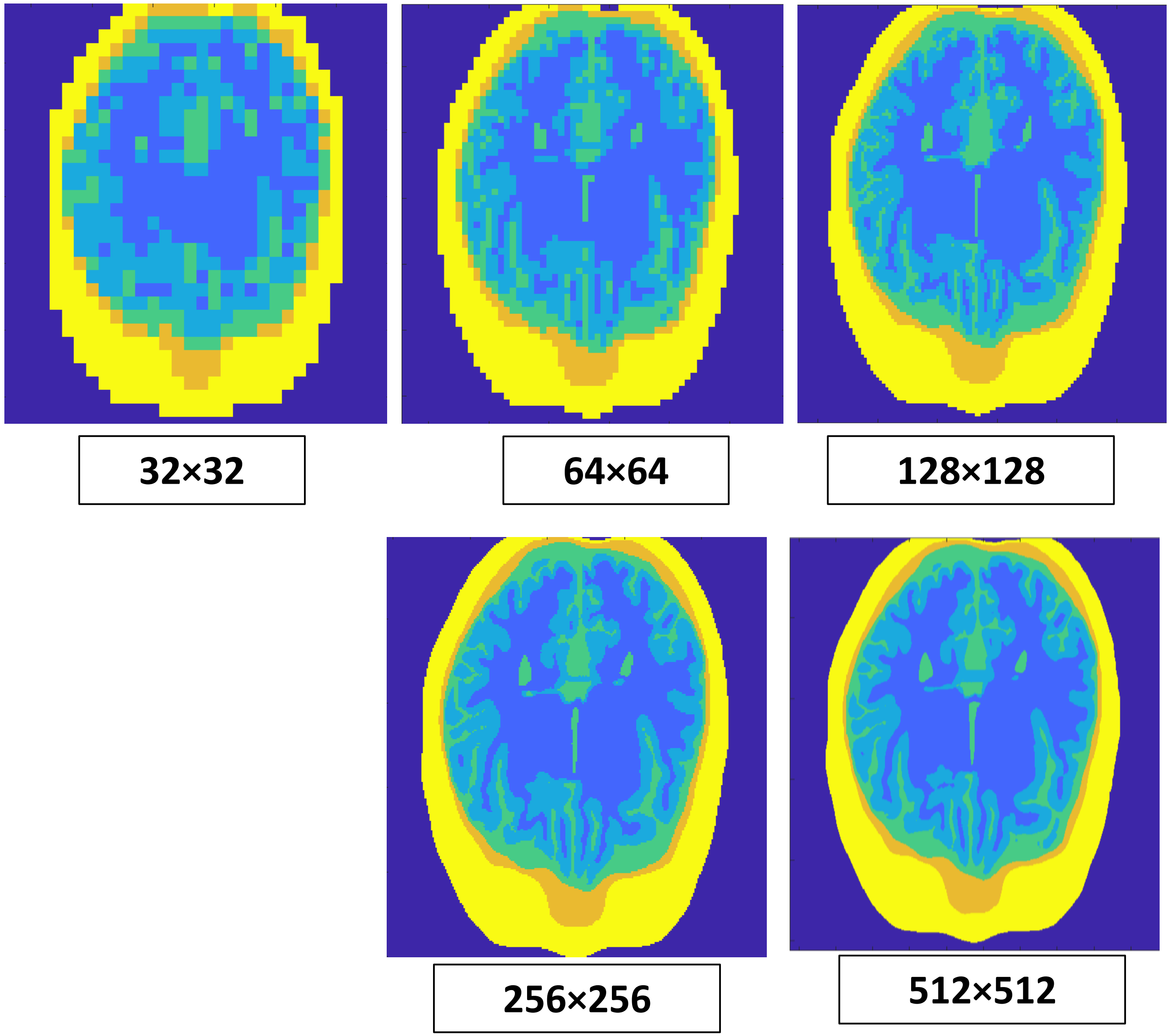
512×512×512

Effect of Voxelization Grid

- For lower grid dimensions-
  1. Uncertainty in tissue boundary
  2. Greater staircase effect
- For higher grid dimensions-
  1. Computational Effect (Higher Memory)

Step 3 – Extract Mid-Cortical Slice (Coronal Plane)

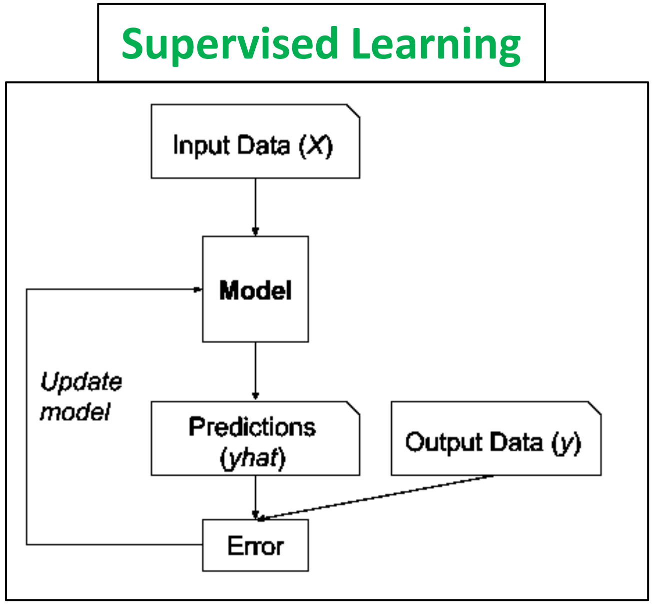


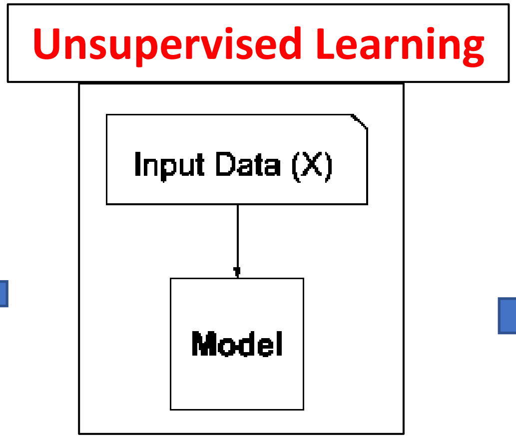


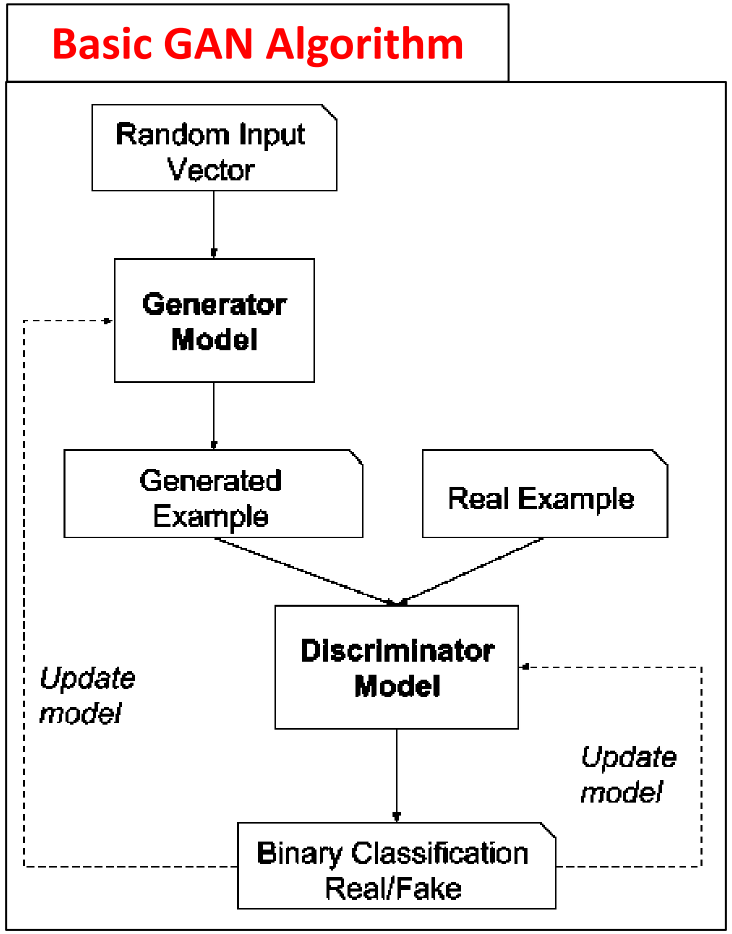
Effect of Voxelization Grid

- For lower grid dimensions-
  1. Uncertainty in tissue boundary
  2. Greater staircase effect
- For higher grid dimensions-
  1. Computational Effect (Higher Memory)

Generative Adversarial Network (GAN)





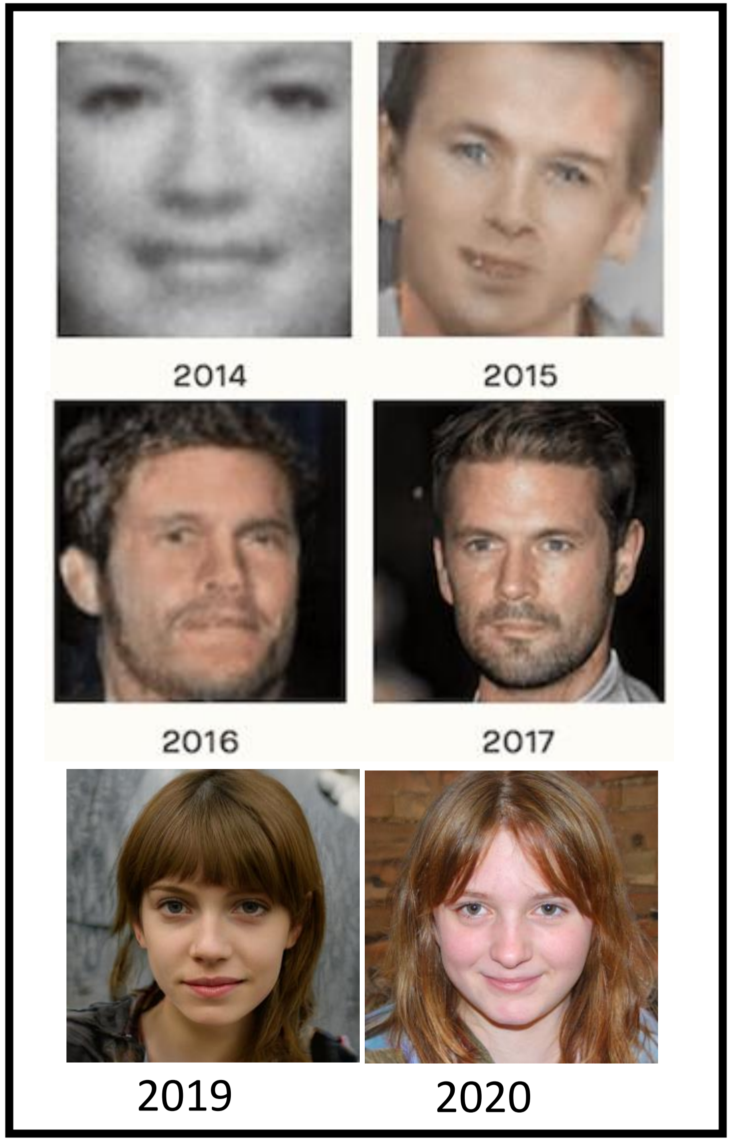


GAN Basics

- Unsupervised learning task
- Discovers and learns the regularities/ patterns in the input data
- By incorporating a secondary model, the task becomes supervised learning
- Generator: generates new data
- Discriminator: discriminates between real and generated/fake image

PURDUE UNIVERSITY | School of Electrical and Computer Engineering

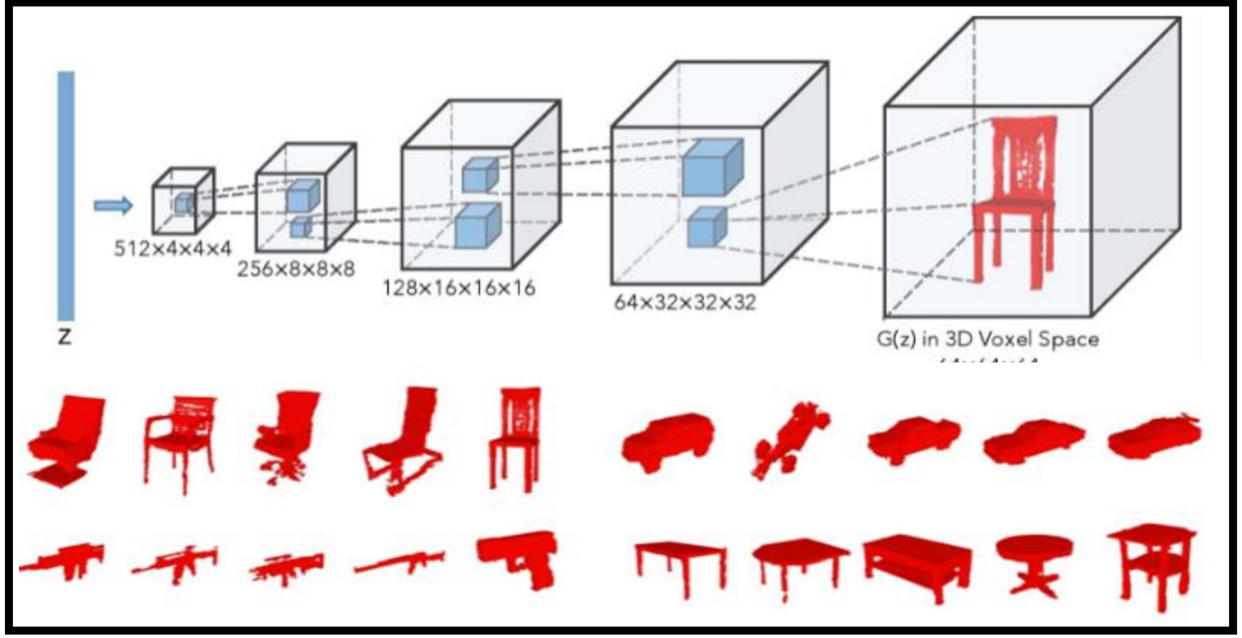
Generative Adversarial Network (GAN)-Examples



Types of GAN

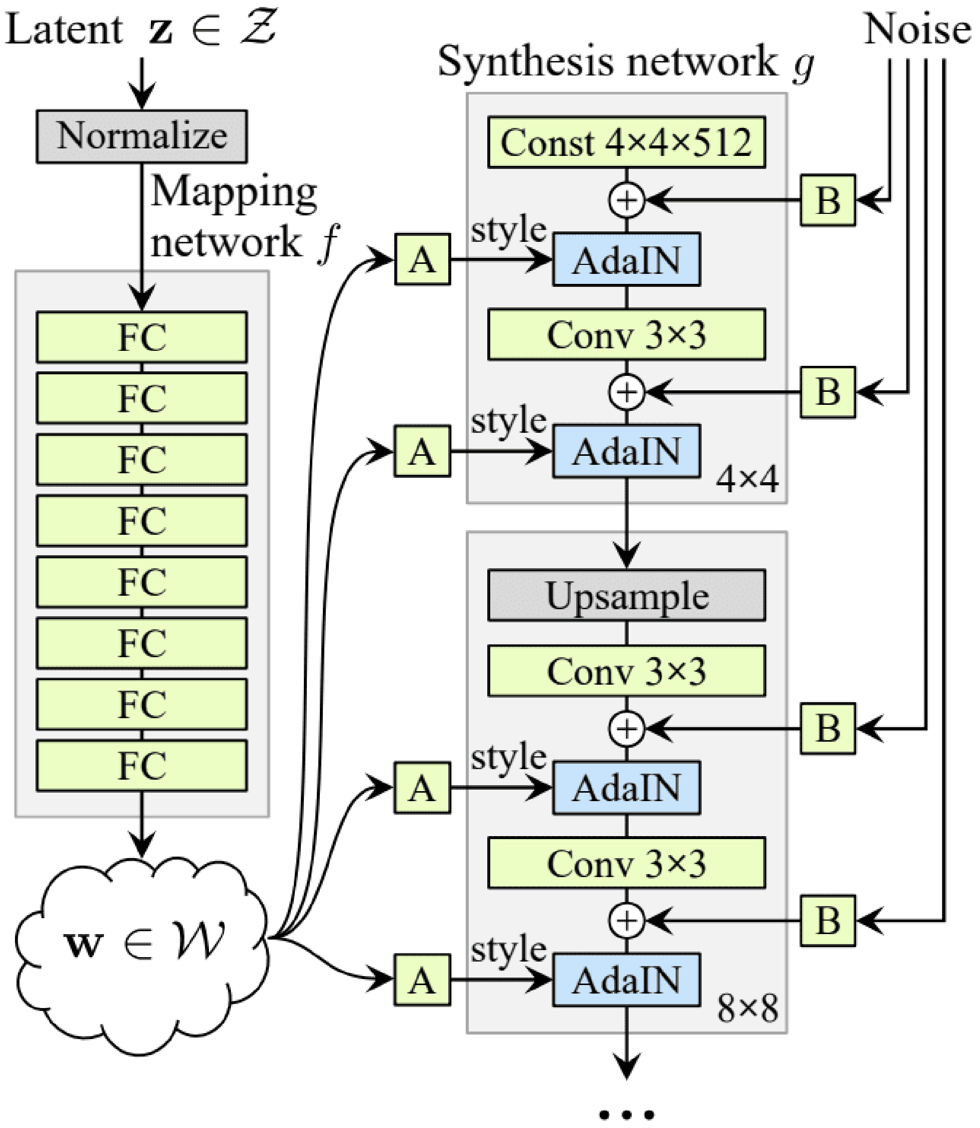
- DCGAN--------------- deep convolutional GAN
- Conditional GAN----conditional data generation
- BigGAN
- StyleGAN
- Pix-to-Pix------ Image Translation
- CycleGAN-----Image Translation
- Progressive Growing GAN

3D GAN[*]



[*]Wu, J., Wang, Y., Xue, T., Sun, X., Freeman, W. T., & Tenenbaum, J. B. (2017). Marrnet: 3d shape reconstruction via 2.5 d sketches. *arXiv preprint arXiv:1711.03129*.

Step 4 – Training Generative Adversarial Network (StyleGAN)



StyleGAN[*] Basics

- Baseline Progressive GAN.
- Addition of tuning and bilinear upsampling.
- Addition of mapping network and AdaIN (styles).
- Removal of latent vector input to generator.
- Addition of noise to each block.
- Addition Mixing regularization.

$$\boxed{\mathrm{AdaIN}(x_i, y) = y_{s,i}\frac{x_i - \mu(x_i)}{\sigma(x_i)} + y_{b,i}}$$

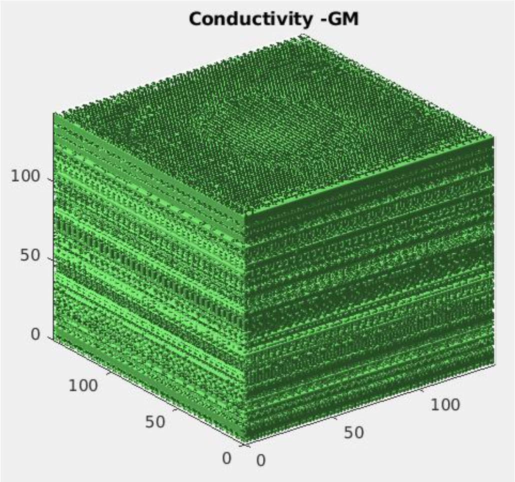
•Karras, T., Laine, S., & Aila, T. (2019). A style-based generator architecture for generative adversarial networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 4401-4410).

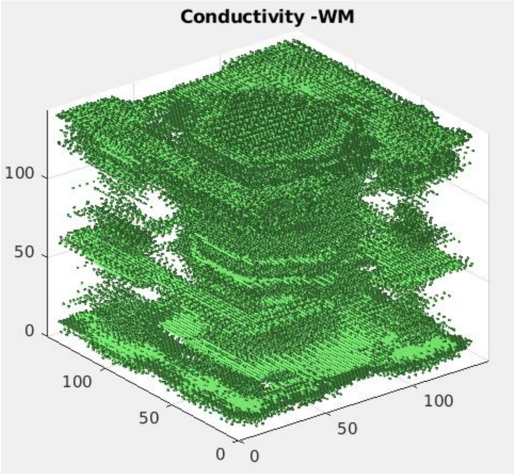
Step 4 – Training Generative Adversarial Network (StyleGAN)

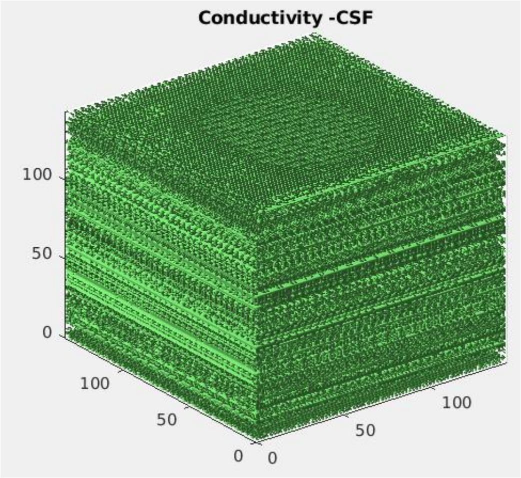
Attempt 1 (3D GAN – All Tissues)

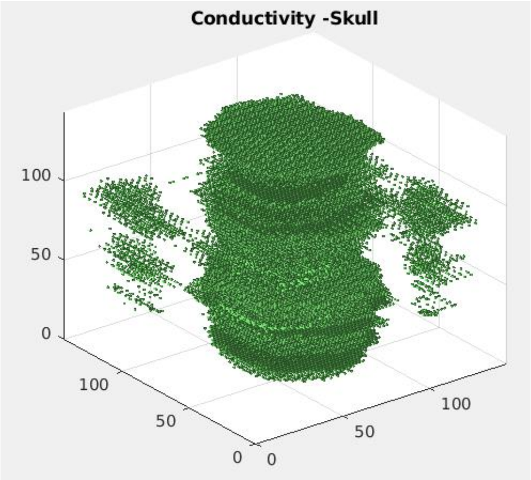
- DCGAN – 3D convolution on 3D data
- Generator Network - Unet, AlexNet,Resnet50,ResNet152, Xception

Resultant Images: random 3D data







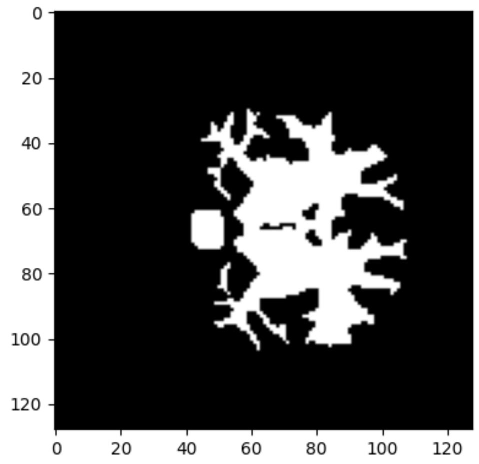


Step 4 – Training Generative Adversarial Network (StyleGAN)

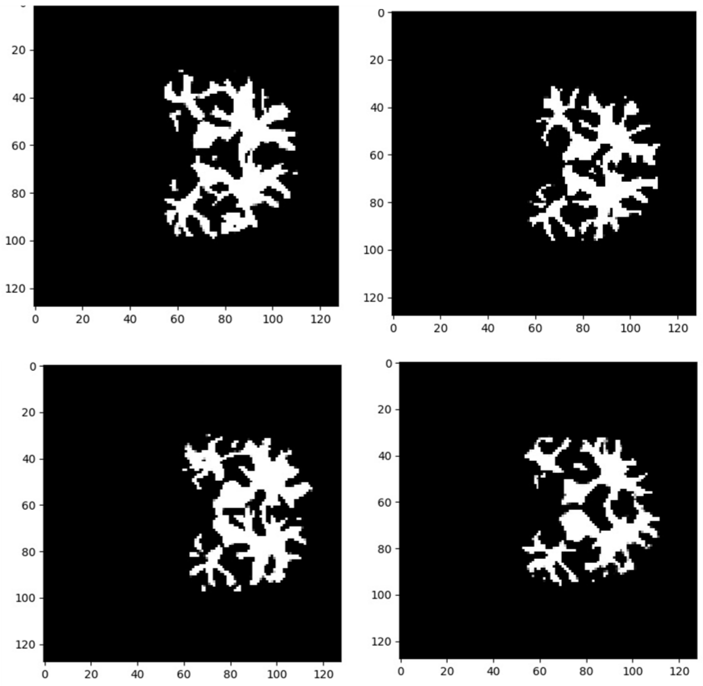
Attempt 2 (2D GAN – Single Tissue)

- StyleGAN – 2D convolution for single slice and single tissue (WM)

Resultant Images



Original WM



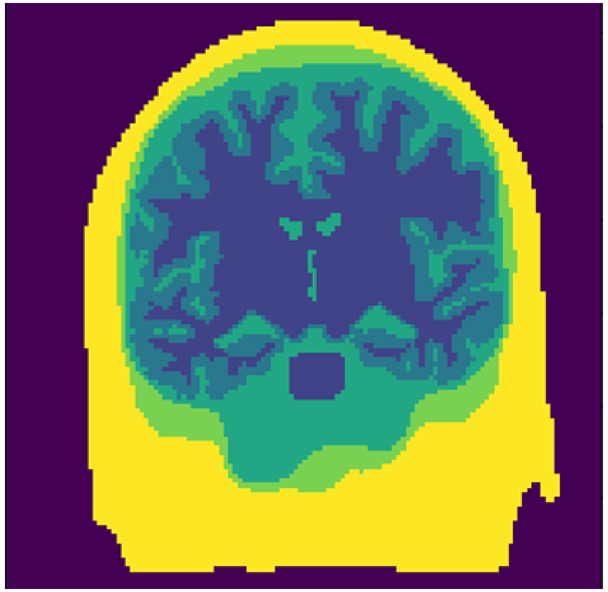
Synthetic WM

Step 4 – Training Generative Adversarial Network (StyleGAN)

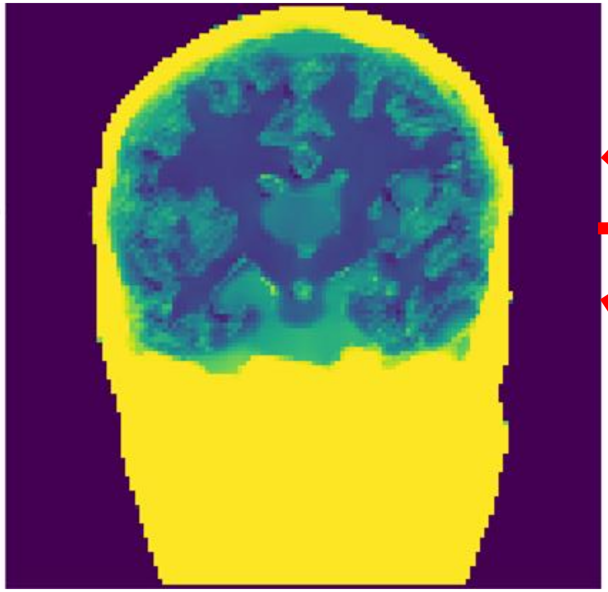
Attempt 3 (2D GAN – All Tissues)

- StyleGAN – 2D convolution for all tissues (WM, GM, CSF, Skull, Scalp)

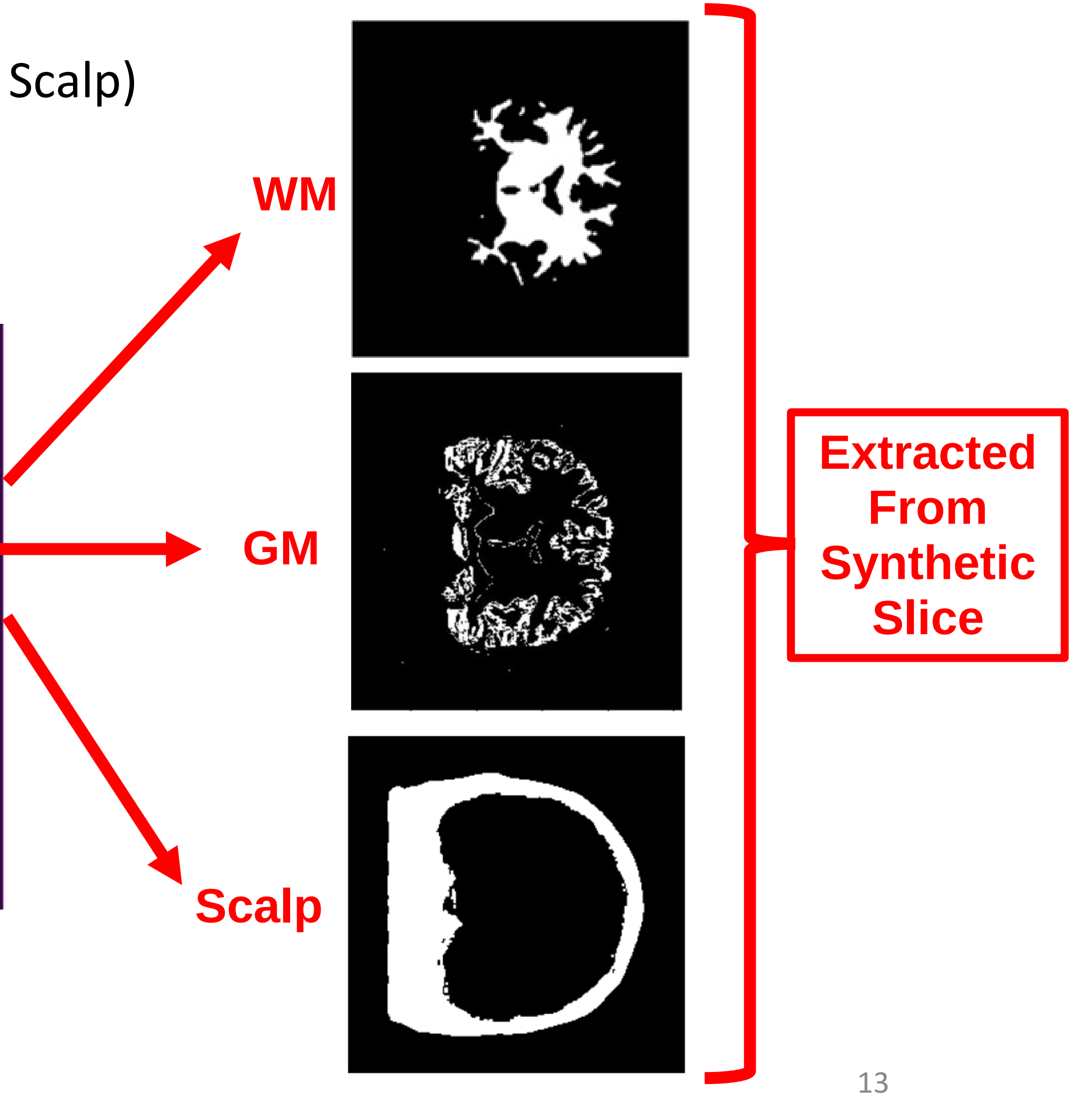
Resultant Images



Original MRI Slice

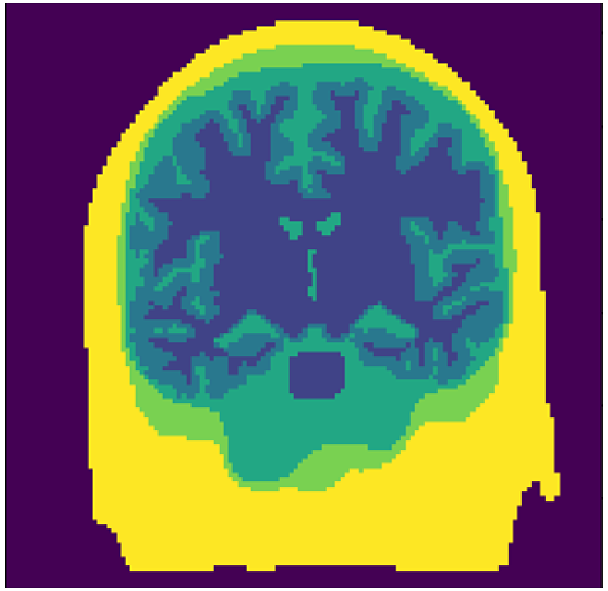


Synthetic MRI Slice

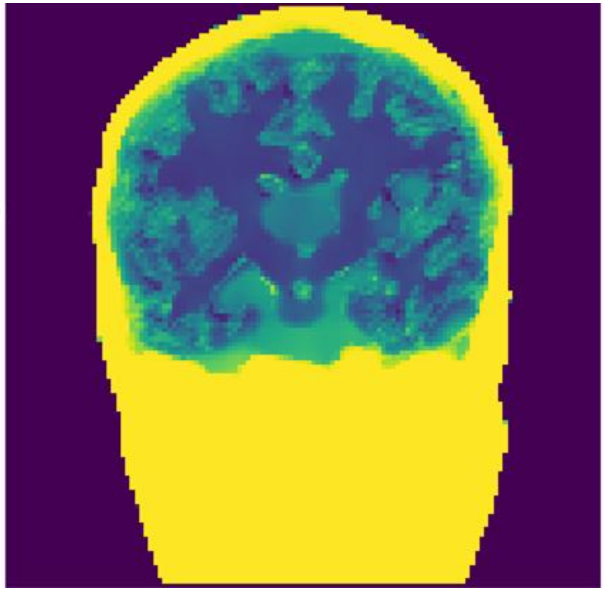


Step 5 – Post-Process Synthetic Slices

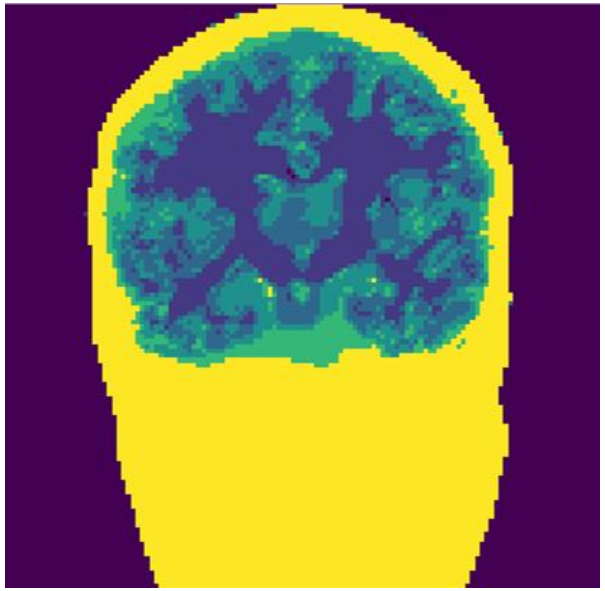
Step 5.1 – Image Quantization



Original MRI Slice



Synthetic MRI Slice



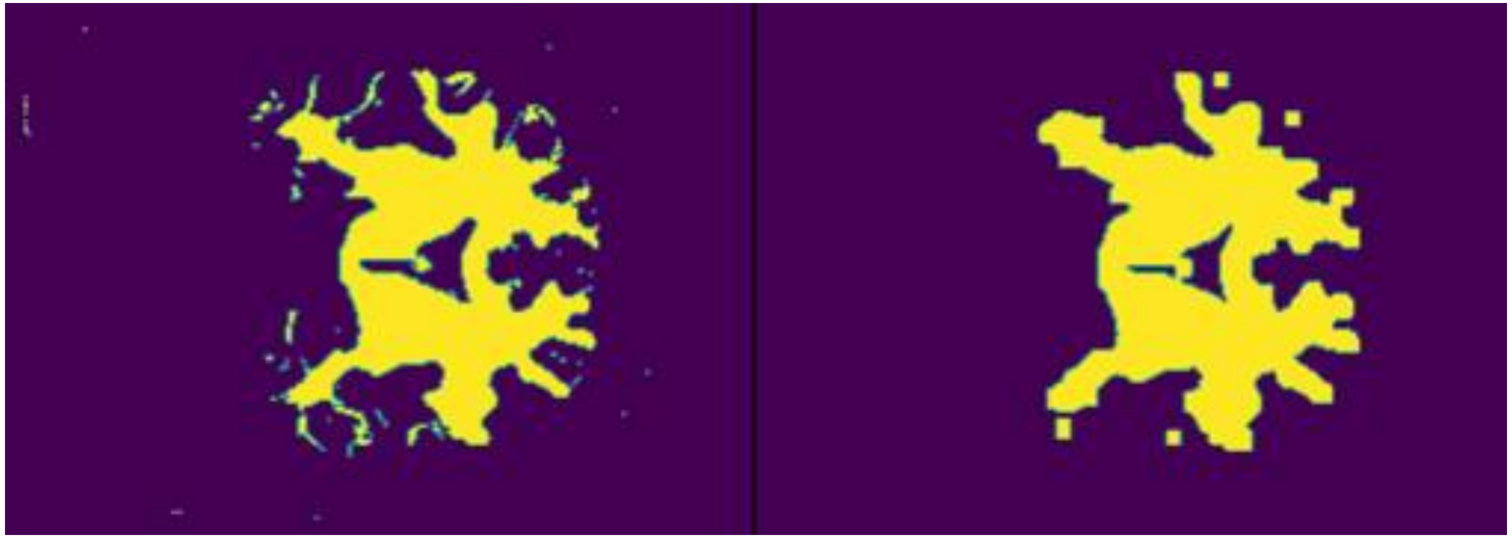
Quantized MRI Slice

Purpose of Image Quantization

- GAN generates images are floating point samples from inherent latent space
- Quantization labels each pixel of certain tissue type [1-6]
- **We implemented quantization by thresholding on histogram on generated image**

Step 5 – Post-Process Synthetic Slices

Step 5.2 – Image Erosion and Dilation

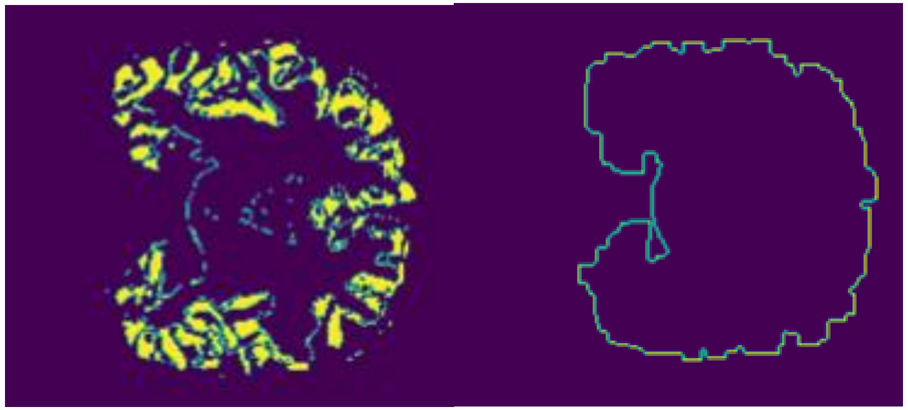


Purpose of Image Erosion and Dilation

- Image Erosion removes small noises
- Image Dilation fills the missing data points in a continuous contour.
- Erosion + Dilation = **Image Opening**
- Dilation + Erosion = **Image Closing**

Step 5 – Post-Process

Step 5.3 – Contour Selection



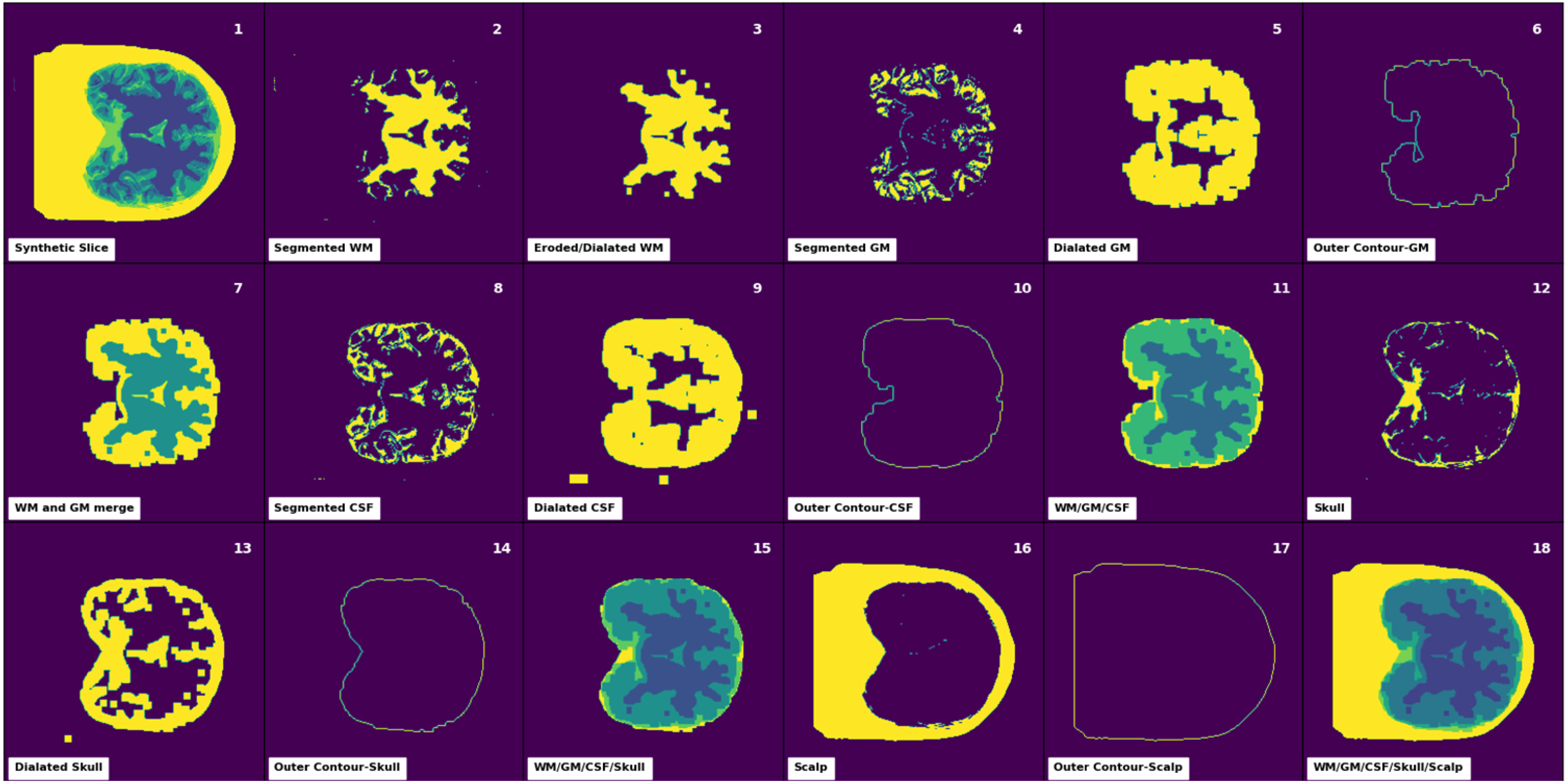
Outer Boundary - GM

Outer Boundary - CSF

Purpose of Image Contour Selection

- To find the tissue boundary

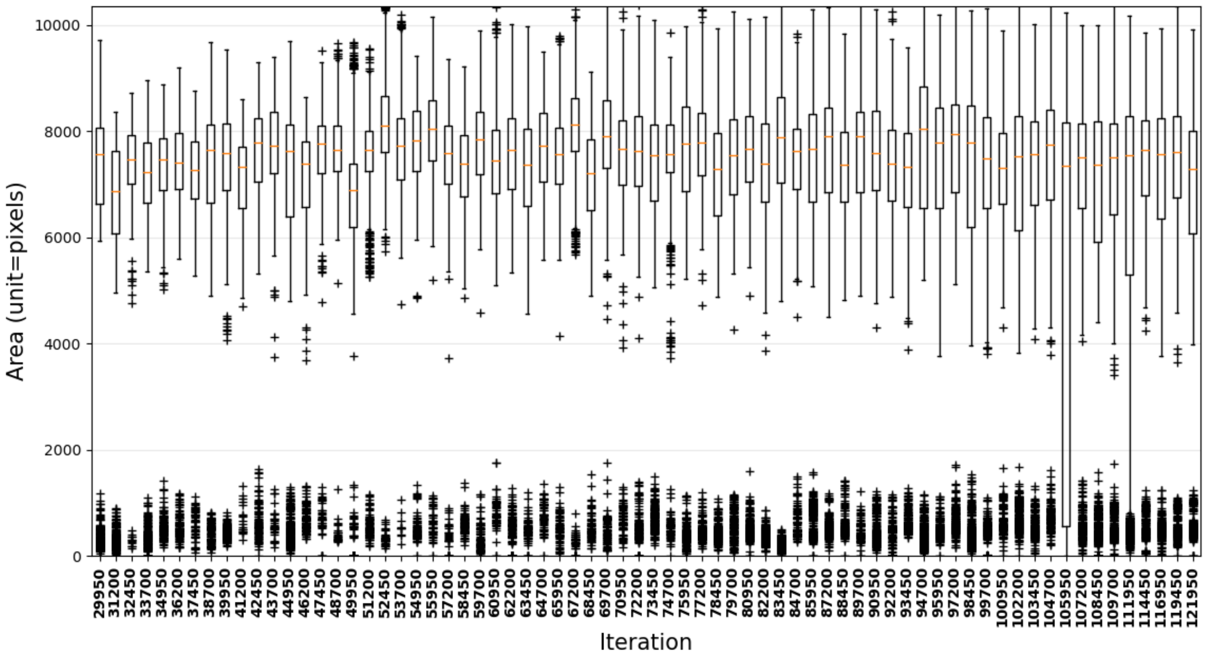
Step 5 – Summary of Post-Processing



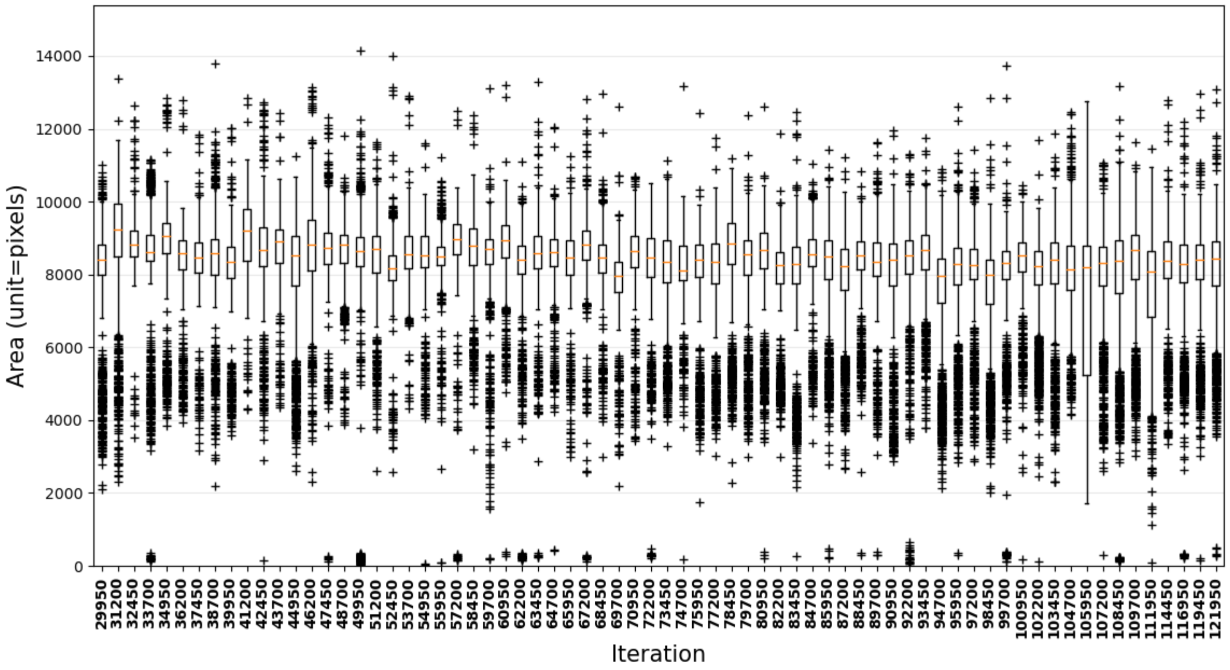
Step 6 – Evaluation of GAN-Generated Synthetic Images

Step 6.1 : Tissue Area

- Tissue Area = Number of Pixels × Pixel Area



White Matter



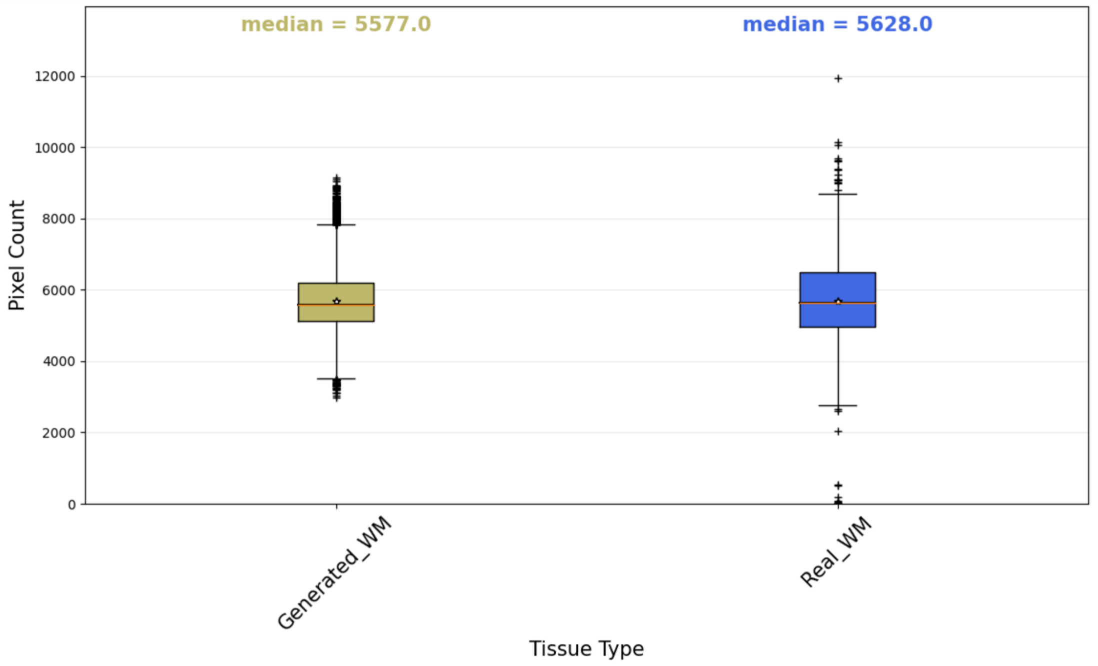
Gray Matter

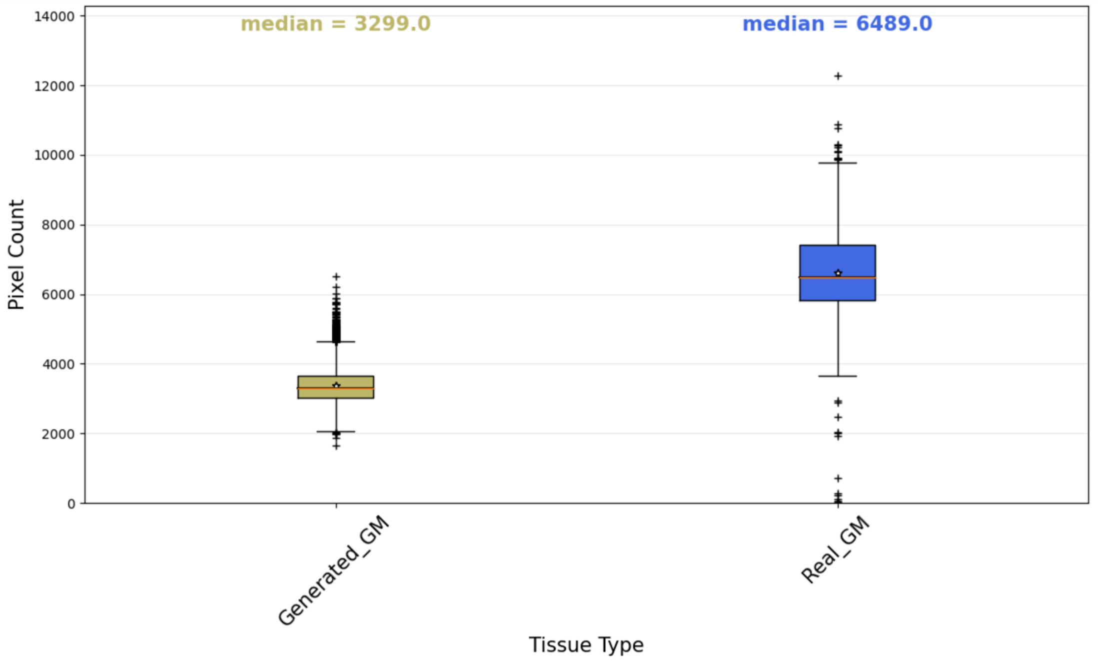
Summary: Tissue Area doesn't provide any insight about the quality of generated image

Step 6 – Evaluation of GAN-Generated Synthetic Images

Step 6.2 : Tissue Area Comparison

- Tissue Area = Number of Pixels × Pixel Area



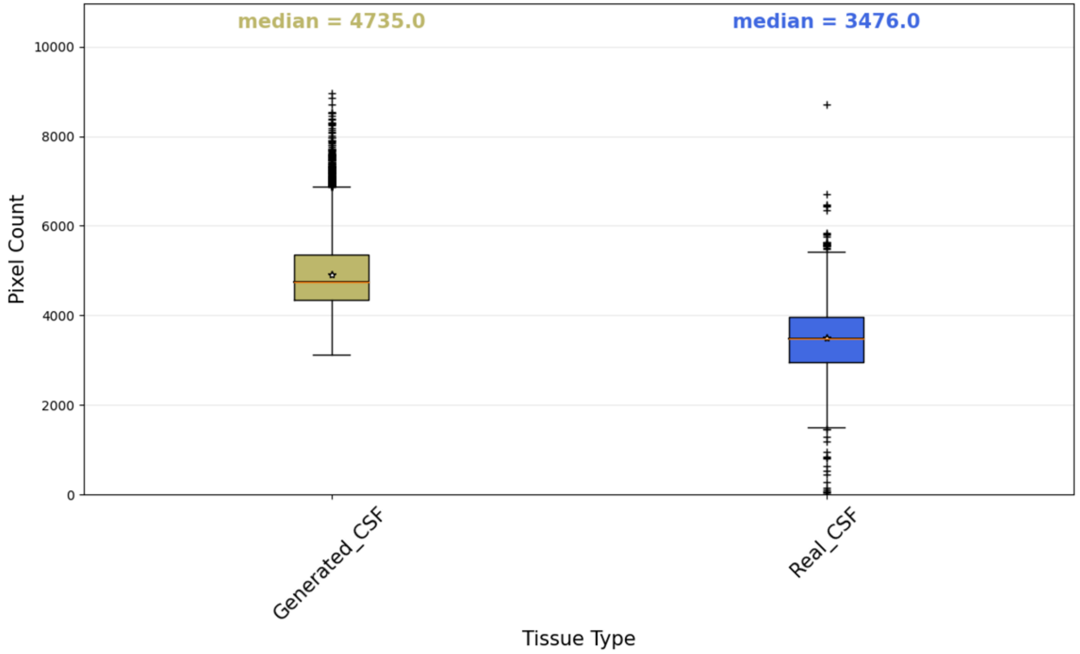


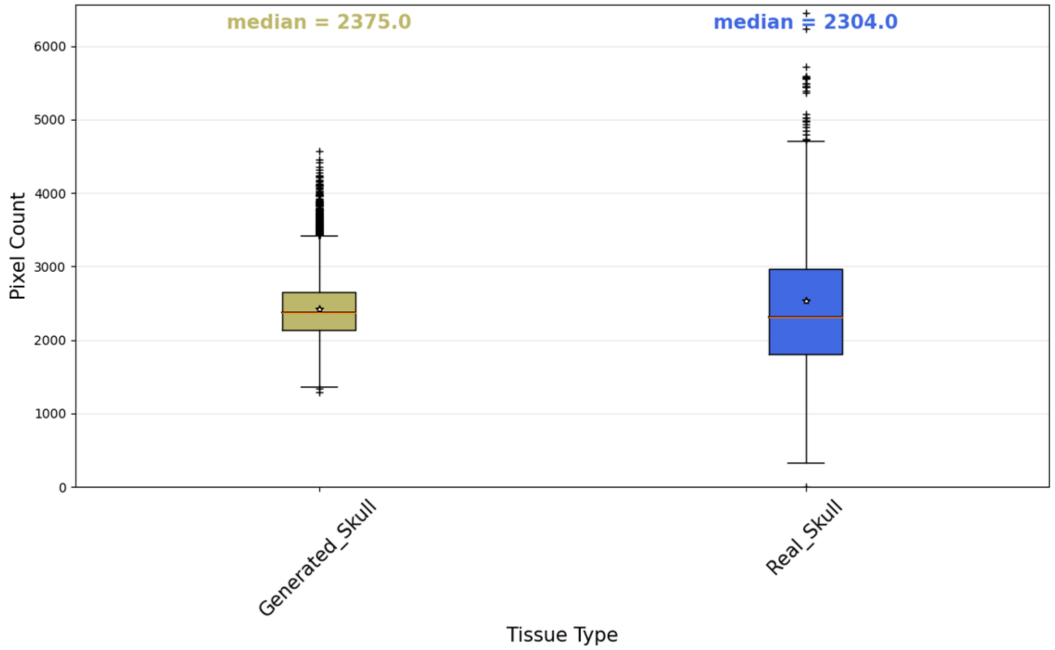
Summary: Tissue area of synthetic images resembles the tissue area of ground truth data

Step 6 – Evaluation of GAN-Generated Synthetic Images

Step 6.2 : Tissue Area Comparison

- Tissue Area = Number of Pixels × Pixel Area





Summary: Tissue area of synthetic images resembles the tissue area of ground truth data

Step 6 – Evaluation of GAN-Generated Synthetic Images

Step 6.3 : Frechet Inception Distance (FID Score)

$$d^2 = ||mu_1 - mu_2||^2 + Tr(C_1 + C_2 - 2 \times \sqrt{C_1 \times C_2})$$

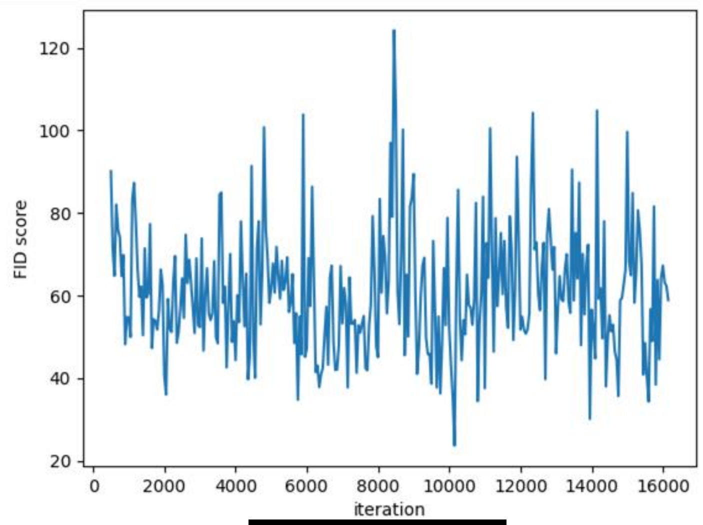
- mu1,mu2 = mean of the probability vectors at the output of Inception V3 network
- C1, C2 = covariance matrices
- Tr = Trace of the matrix

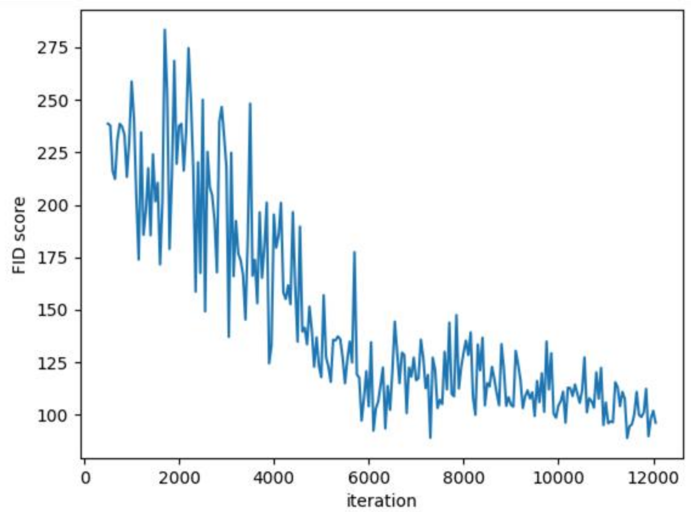
- **We want the FID score to be as low as possible**

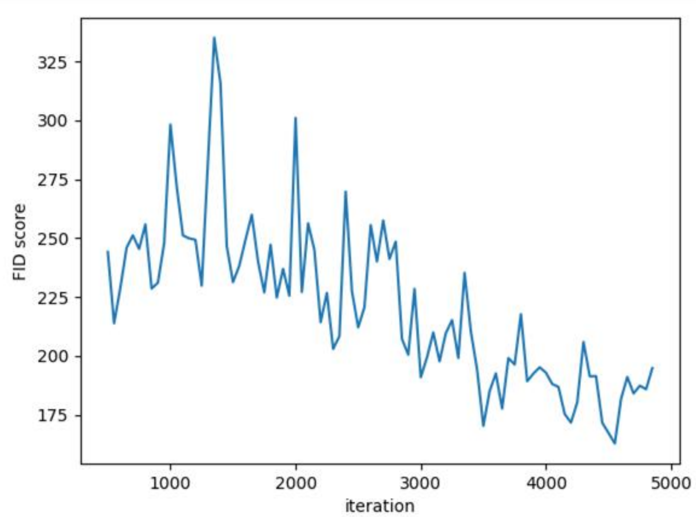
Step 6 – Evaluation of GAN-Generated Synthetic Images

Step 6.3 : Frechet Inception Distance (FID Score)

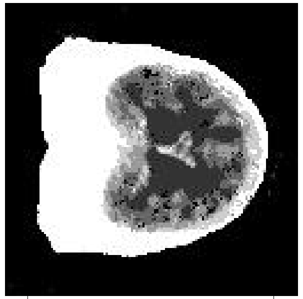
- Each iteration – 5000 generated samples



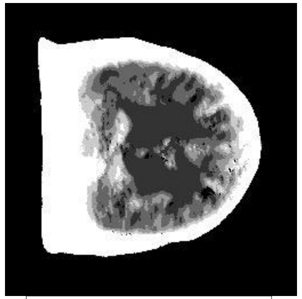




64×64



128×128



256×256

Summary of Project Outcome

1. The voxelization grid size affects the image quality, especially tissue boundary.
2. StyleGAN generated synthetic images require a substantial number of iterations before generating any meaningful image that resembles a ground truth MRI image.
3. The area of any tissue does not predict the quality of synthetic image at any training iteration.
4. The inception score does not provide a good estimation of the synthetic image.
5. The FID score improves with respect to training iterations. But it is meaningful for higher voxelization grid size.
6. **The FID score can be used as a parameter for statistical inference.**
7. Decision: Based on the current analysis the following configuration should be used for synthetic 2D MRI data generation—
    1. Network = StyleGAN
    2. Voxelization Grid Size = $256\times 256\times 256$
    3. Evaluation Metric = FID score and manual inspection

Drawback

1. The sliced images across subjects does not provide the same cortical plane across subject

Future Direction

Future Direction

1. Use MNI coordinate system to extract the same cortical plane across subjects
2. Extend the concept to generate 3D virtual synthetic head model
3. Implement the 3D StyleGAN
4. Explore Multi-GPU processing technique to accommodate 3D volumetric data

References

- Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434.
- Salimans, T., Goodfellow, I., Zaremba, W., Cheung, V., Radford, A., & Chen, X. (2016). Improved techniques for training gans. Advances in neural information processing systems, 29, 2234-2242.
- Mirza, M., & Osindero, S. (2014). Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784.
- Karras, T., Aila, T., Laine, S., & Lehtinen, J. (2017). Progressive growing of gans for improved quality, stability, and variation. arXiv preprint arXiv:1710.10196.
- Brock, A., Donahue, J., & Simonyan, K. (2018). Large scale GAN training for high fidelity natural image synthesis. arXiv preprint arXiv:1809.11096.
- Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. Advances in neural information processing systems, 27.
- Karras, T., Laine, S., & Aila, T. (2019). A style-based generator architecture for generative adversarial networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 4401-4410).
- Zhu, J. Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired image-to-image translation using cycle-consistent adversarial networks. In Proceedings of the IEEE international conference on computer vision (pp. 2223-2232).
- Isola, P., Zhu, J. Y., Zhou, T., & Efros, A. A. (2017). Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1125-1134).
- Zhang, H., Xu, T., Li, H., Zhang, S., Wang, X., Huang, X., & Metaxas, D. N. (2017). Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks. In Proceedings of the IEEE international conference on computer vision (pp. 5907-5915).

Thank You

Nahian Ibn Hasan

Graduate Assistant, Sublime Laboratory

Elmore School of Electrical and Computer Engineering

Purdue University

West Lafayette, IN, USA

Email: hasan34@purdue.edu