GAN-based Synthetic Medical Image Generation

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Wakatenokai Group G

Abstract

- Realistic synthetic brain MRI slices were genereated from original MRI slices for data augmentation using 3 different Generative Adversarial Networks (GANs)——WGAN[1], DCGAN[2], BEGAN[3]
- Physician evaluated them via Visual Turing Test and he did not distinguish real/synthetic slices
- First data augmentation approach for medical images via GANs

Motivation

- In medical imaging, available pathological images are limited; thus, data augmentation is essential
- Towards this, we use GANs for clinical purposes ——expecting same promising results for image generation as those in general computer vision
- Previous methods for data augmentation: Exploited random non-linear transformations (e.g. dense deformation field) and intensity transformations (e.g. histogram matching)
- GANs: Generate highly more realistic data giving more insights during classification regarding deformations and intensity transformations alone

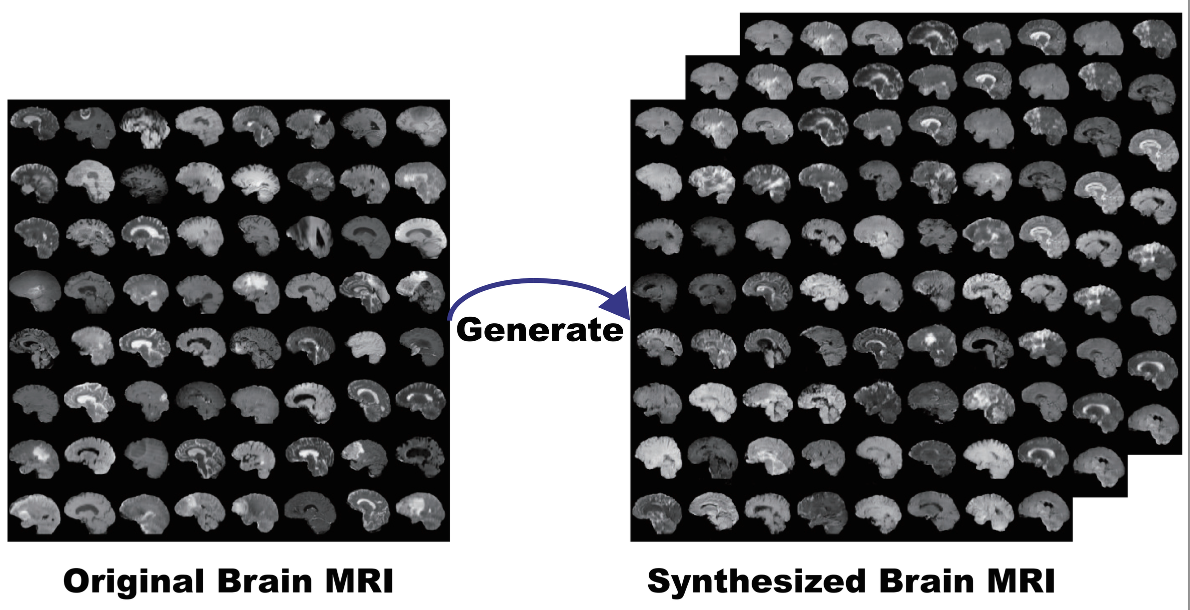


Figure: Summary of image generation for data augmentation

Dataset and Preprocess

Sagittal brain MRI slices (T1w, ceT1w, T2w, FLAIR sequences) of glioblastoma patients (HGG, most aggressive cancer in brain) on MICCAI BraTS 2016

- Training data: 220 (patients) $\times$ 4 (modalities) $\times$ 70 (slices) = 61,600 images
- Selected slices: 80 - 149th slices among whole 0 - 239th to omit useless information of end slices
- Resizing: 64 $\times$ 64 from 240 $\times$ 155 for limited computational power

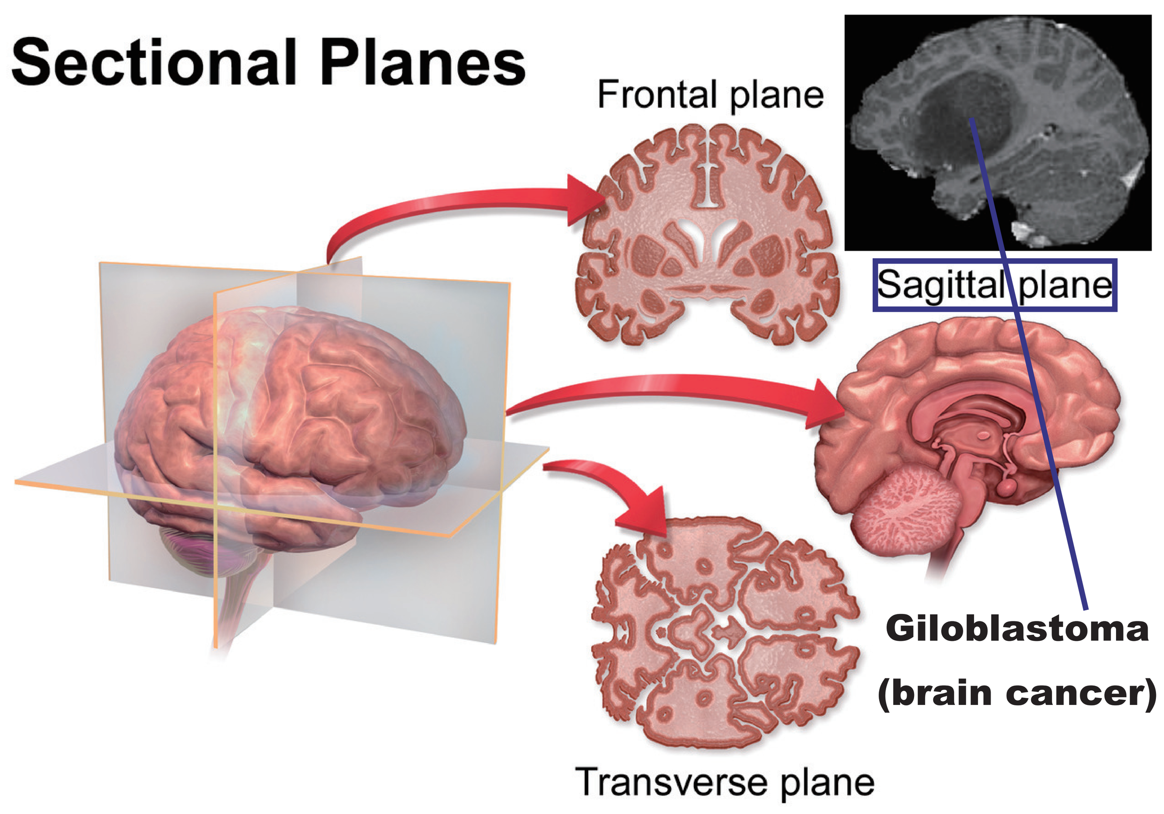


Figure: Sagittal plane

Proposed Method (WGAN)

Model

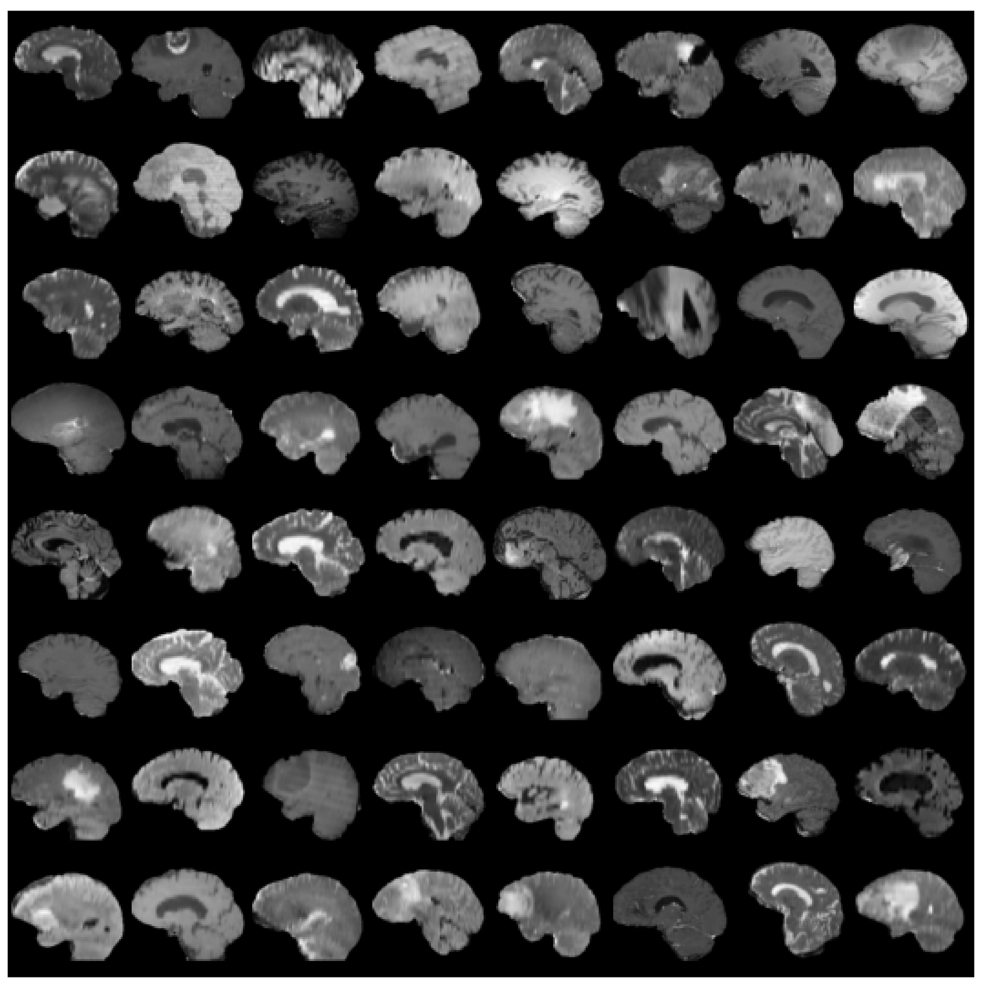
Wasserstein GAN with same network structure as DCGAN and 100 latent vectors

- Output: 64 x 64 synthesized slices

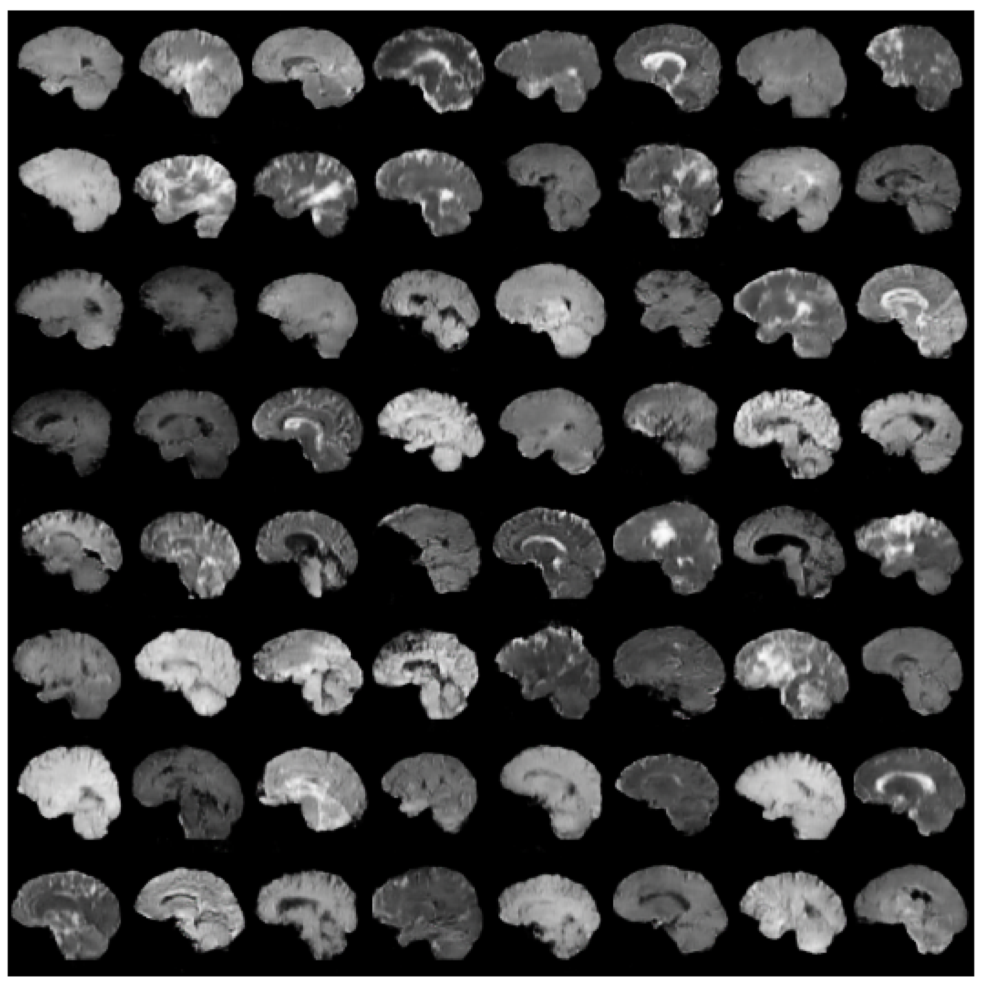
Training

- Epochs/Batch size: 100/64
- Weights: rmsprop optimizer with 5e-5 learning rate

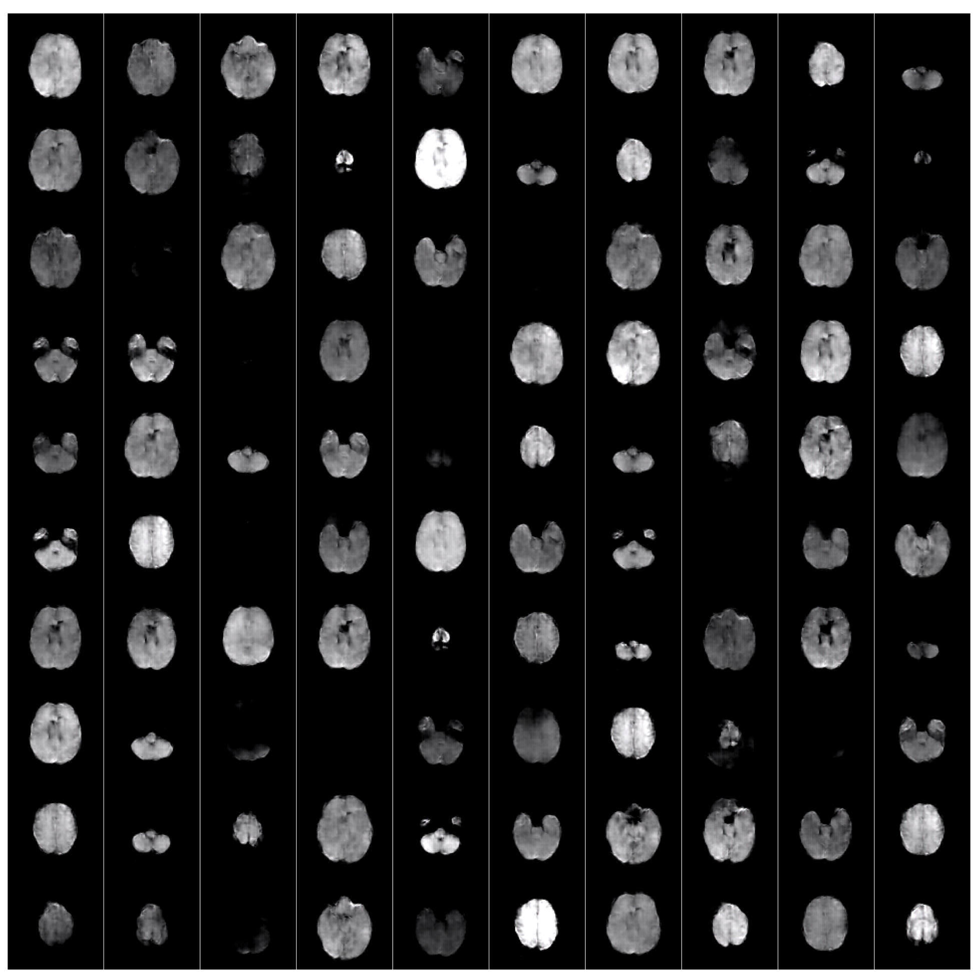
Original Brain MRI Slices



Synthesized Brain MRI Slices (WGAN)



cf. Synthesized Brain MRI Slices (DCGAN, Transverse Planes)



WGAN's Algorithm

WGAN trains critic till optimality for reliable gradient

Require: : α, the learning rate. c, the clipping parameter. m, the batch size. n_{critic}, the number of iterations of the critic per generator iteration.
Require: : w_0, initial critic parameters. θ_0, initial generator's parameters.

while θ has not converged **do**
  for $t = 0, ..., n_{\text{critic}}$ **do**
    Sample $\{x^{(i)}\}_{i=1}^m \sim \mathbb{P}_r$ a batch from the real data.
    Sample $\{z^{(i)}\}_{i=1}^m \sim p(z)$ a batch of prior samples.
    $g_w \leftarrow \nabla_w \left[\frac{1}{m}\sum_{i=1}^m f_w(x^{(i)}) - \frac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))\right]$
    $w \leftarrow w + \alpha \cdot \text{RMSProp}(w, g_w)$
    $w \leftarrow \text{clip}(w, -c, c)$
  end for
  Sample $\{z^{(i)}\}_{i=1}^m \sim p(z)$ a batch of prior samples.
  $g_\theta \leftarrow -\nabla_\theta \frac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))$
  $\theta \leftarrow \theta - \alpha \cdot \text{RMSProp}(\theta, g_\theta)$
end while

Visual Turing Test by Physician

- To quantitatively evaluate synthesized images, expert physician was asked to classify random 50 real and 50 synthetic brain MRI slices

Table: Results of Visual Turing Test for classifying real vs synthetic images performed by physician

	Selected as real	Selected as synt
Ground truth real	18	32
Ground truth synt	15	35

- Accuracy: 53% (chance = 50%)
- Sensitivity: 36.00%
- Specifity: 70.00%
- Positive likelihood ratio: 1.20
- Negative likelihood ratio: 0.91
- Disease prevalence: 50%

Physician's Comment

- Classifying real and synthetic brain MRI slices was challenging and they looked similar for me
- Examining MRI slices in detail was difficult though because of their low resolution... Show me bigger images!
- Specifying modalities with MRI slices would be preferable for better understanding

Conclusion

- Succeeded to generate realistic synthetic brain MRI slices via GANs and even physician did not distinguish them from real slices, which is promising for data augmentation

Future Work

- Sectional planes: Apply to transverse and frontal planes too
- Slice selection: Develop classifier to select slices in preprocessing
- Resizing: Use bigger size
- Quantitative image quality evaluation: Evaluate with quantitative metrics (e.g. PSNR using mean squared error and SSIM using structural similarity)
- Clinical applications: Verify whether synthesized images improve segmentation, classification, and unsupervised domain adaptation results

References:
1) Arjovsky M., et al. arXiv:1701.07875 (2017)
2) Radford A., et al. arXiv:1511.06434, ICLR2016 (2016)
3) Berthelot D., et al. arXiv:1703.10717 (2017)

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