An overview of

GAN-BASED SYNTHETIC BRAIN MR IMAGE GENERATION

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1. Introduction

“Why do we need to generate realistic medical images completely different from the original ones? And How do it?”

1. Introduction

- CNN Training → Demands extensive medical data
- Data augmentation techniques → Reconstructed images resemble the original ones (limited performance improvement in terms of generalization abilities)
- **Generative Adversarial Networks (GAN)** → Generating realistic but completely new images

1.1 Application in Medical Imaging

Usage of Synthetic Images in Medical Imaging

- Improve diagnostic reliability

- Data augmentation in computer-assisted diagnosis as well as physician training

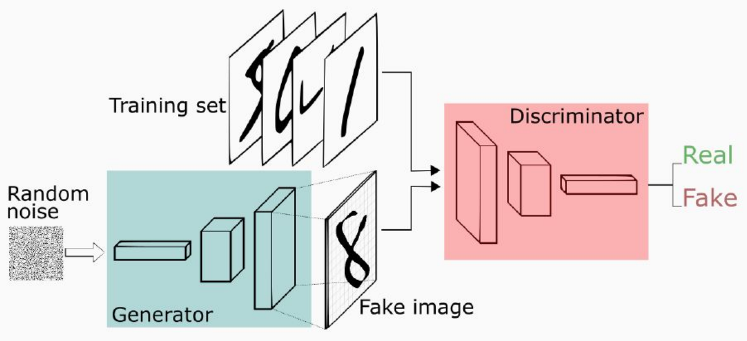
Main objective: Generate synthetic multi-sequence brain MR images using GANs.

Challenges in MR Images

- Low contrast
- Strong visual consistency in brain anatomy

2. Generative Adversarial Networks (GAN)

- Two components, the ***generator*** and the ***discriminator***:
    - The ***generator* G** needs to capture the data distribution. It learns to generate better images to fool the discriminator.
    - The ***discriminator* D** estimates the probability that a sample comes from the training data rather than from G. It learns to become better at distinguishing real from generated images.



- ***D*** and ***G*** are competing against each other
- Training is completed when D is ***completely fooled*** by G.

2. Generative Adversarial Networks (GAN)

GANs

Generate ***highly realistic images***,

No need to a well-defined objective function associated with difficult training

- ❑ Image super-resolution
- ❑ Anomaly detection
- ❑ Estimating CT images from the corresponding MRI

Variational Autoencoders (VAEs) [L. Mescheder et al.]

Have an objective likelihood function to optimize

Generate ***blurred samples*** because of the injected noise and imperfect reconstruction

3. Materials and Methods

DCGAN

WGAN

Compare the most used two GANs, DCGAN and WGAN, to find a well-suited GAN between them for medical image generation

It must avoid mode collapse and generate realistic MR images with high resolution.

Multimodal Brain Tumor Segmentation Challenge

220 High-Grade Glioma (HGG) and 54 Low-Grade Glioma (LGG) cases

Proposed GAN-based Image Generation Approach

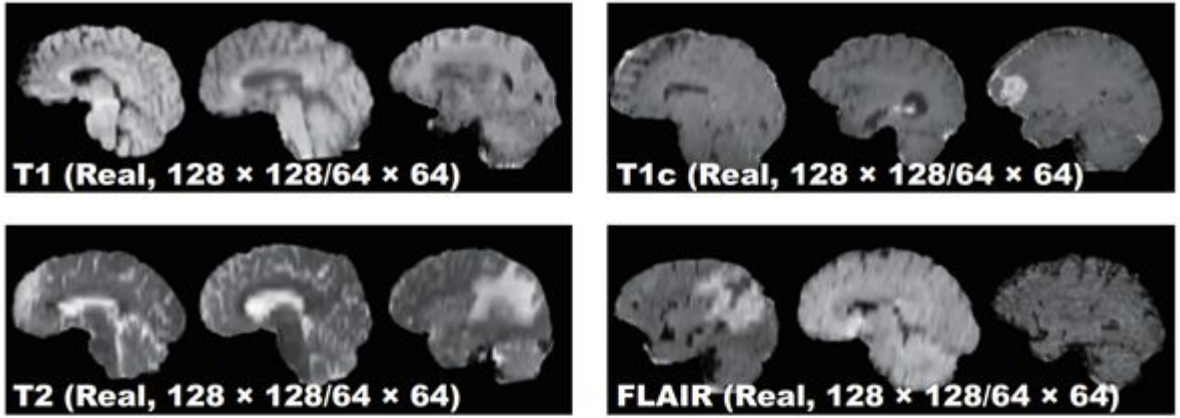


Fig. 2. Example real MR images used for training the GANs: the resized sagittal multi-sequence brain MRI scans of patients with HGG on the BRATS 2016 training dataset [20].

GAN-based MR Image Generation

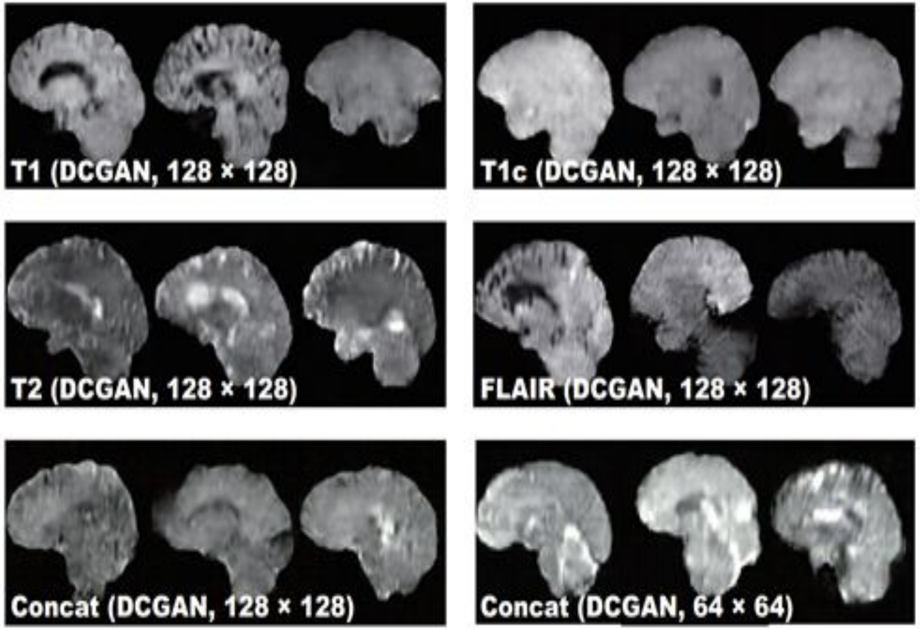
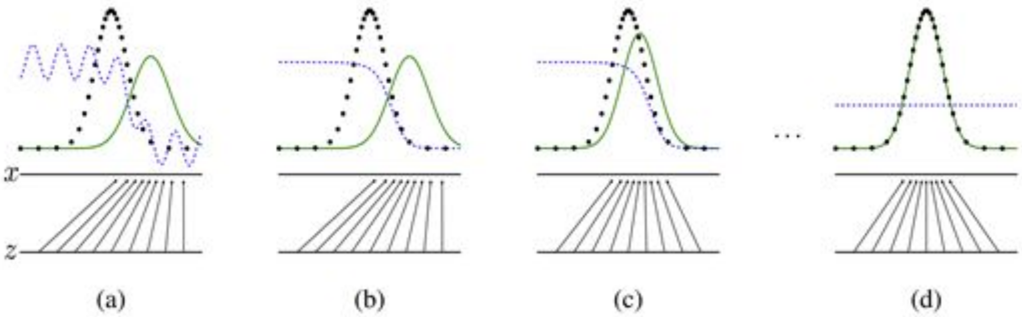


Fig. 3. Example synthetic MR images yielded by DCGAN.

DCGAN



- The generator G， the discriminator D
- The discriminator D maximizes the probability of classifying both training examples and samples from G correctly while the generator G minimizes the likelihood

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

DCGAN Implementation Details

- ELU as the discriminator, all filters of size 4×4, and a half channel size for DCGAN training. A batch size of 64 and Adam optimizer with $2.0 \times 10{-}4$ learning rate were implemented

$$W(p_g, p_r) = \inf_{p \in \prod(p_g, p_r)} \mathbb{E}_{(\boldsymbol{x}, \boldsymbol{x}') \sim p} \|\boldsymbol{x} - \boldsymbol{x}'\|,$$

WGAN

Wasserstein-GAN that minimizes a reasonable and efficient approximation of the EM distance, and we theoretically show that the corresponding optimization problem is sound

WGAN Implementation Details

- We use the same DCGAN architecture for WGAN training. A batch size of 64 and Root Mean Square Propagation (RMSprop) optimizer with $5.0 \times 10{-}5$ learning rate were implemented.

4. Results - MR Images Generated by DCGAN

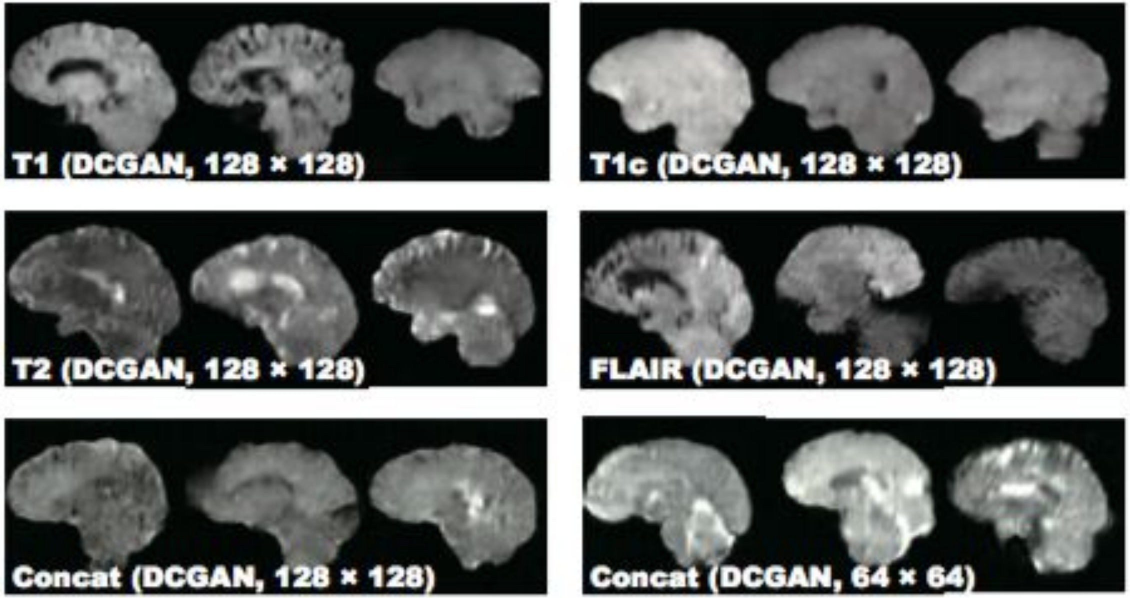


Figure: Example synthetic MR images yielded by DCGAN

4. Results - MR Images Generated by WGAN

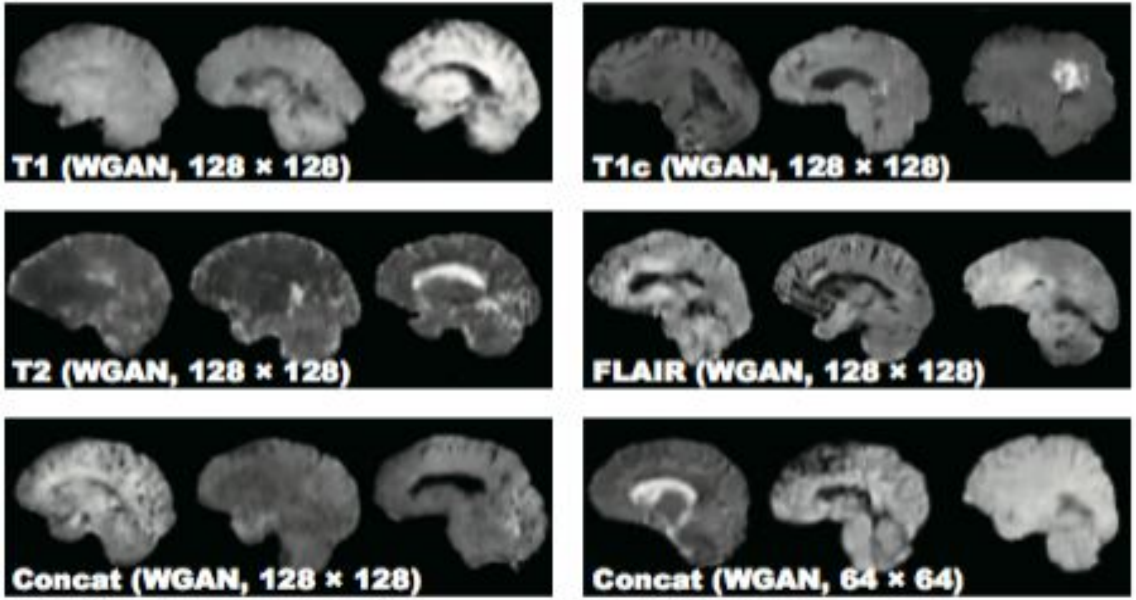


Figure: Example synthetic MR images yielded by WGAN

4. Results - Visual Turing Test Results

Table. Visual Turing Test results by a physician for classifying real vs synthetic images. It should be noted that proximity to 50% of accuracy indicates superior performance (chance = 50%).

	Accuracy (%)	Real Selected as Real	Real as Synt	Synt as Real	Synt as Synt
T1 (DCGAN, 128 × 128)	70	26	24	6	44
T1c (DCGAN, 128 × 128)	71	24	26	3	47
T2 (DCGAN, 128 × 128)	64	22	28	8	42
FLAIR (DCGAN, 128 × 128)	54	12	38	8	42
Concat (DCGAN, 128 × 128)	77	34	16	7	43
Concat (DCGAN, 64 × 64)	54	13	37	9	41
T1 (WGAN, 128 × 128)	64	20	30	6	44
T1c (WGAN, 128 × 128)	55	13	37	8	42
T2 (WGAN, 128 × 128)	58	19	31	11	39
FLAIR (WGAN, 128 × 128)	62	16	34	4	46
Concat (WGAN, 128 × 128)	66	31	19	15	35
Concat (WGAN, 64 × 64)	53	18	32	15	35

5. Conclusion

- GAN, especially WGAN, can generate 128x128 multi-sequence brain MR images, which are used for data augmentation and physician training, mainly due to the generalization ability of WGAN, but DCGAN is unsuitable due to the inferior realism and mode collapse in terms of intensity.
- For data augmentation, although realistic images can better understand the geometric/intensity transformation in classification, more realistic images do not always ensure better data augmentation, so appropriate image resolution and sequence must be found.

6. Reference

[1] Changhee Han, Hideaki Hayashi, Leonardo Rundo, Ryosuke Araki, Wataru Shimoda, Shinichi Muramatsu, Yujiro Furukawa, Giancarlo Mauri, and Hideki Nakayama. Gan-based synthetic brain mr image generation. In *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*, pages 734–738. IEEE, 2018.

Thank you!