Generative Adversarial Networks for Image Synthesis and Semantic Segmentation in Brain Stroke Images

Anonymous Author(s)
Affiliation
Address
email

Abstract

Brain stroke was classified as 2nd cause of death in 2016, automated methods that can locate and segment strokes could aid clinician decisions about acute stroke treatment. Most medical images datasets are limited, smalls and have a severe class imbalance, this limits the development of medical diagnostic systems. GANs (GANs) are one of the hottest topics in artificial intelligence and can learn how to produce data. This work presents a conditional image synthesis with GANs for brain stroke image analysis and class balancing; furthermore, presents a novel training framework for segmentation with GANs.

1 Introduction

Brain stroke was classified in 2016 as 2nd cause of death, 1st of disability in adults and 3rd of loss years of life according to the World Health Organization [1]. Ischemic stroke (a most common type of stroke) is caused by a partial or total restriction of blood supply to part of the brain, prolonged ischemia results in irreversible tissue death.

Health care providers generate and capture large amounts of extremely valuable data at a rate that exceeds the processing speed using traditional methods, therefore, machine learning becomes a way to integrate, analyze and make predictions based on large data sets.

However, medical images are often expensive and offer limited use due to privacy regulations; also, data sets often lack consistency in size and annotation, this makes them less useful for deep learning models by directly limiting the development of medical diagnostic systems; therefore, the generation of synthetic images would help in the analysis of medical images and provide better diagnostic systems, besides, many data sets have a severe class imbalance due to the nature of the pathologies.

In this context, we take a GANs to brain stroke image analysis, class balancing and semantic segmentation using adversarial networks.

2 Related Works

The main problem in the generation of synthetic images is to learn global and local features that capture long and short-range spatial relationships between pixels.

Currently available unconditional image synthesis works in medical images [2, 3, 4] are based in DCGAN [5] adding Pyramid Pooling [6] and Progressive Growing [7] to enforce spatial contiguity. Works in conditional image synthesis [8, 9, 10, 11] are based pix2pix framework [12].

General work for preserve global features in generated images is Self-Attention GAN [13] that uses attention maps through blocks (self-attention blocks) and spectral normalization [14].

Submitted to 33rd Conference on Neural Information Processing Systems (NeurIPS 2019). Do not distribute.

A novel work in image synthesis for data augmentation [15] uses a fine-to-coarse (from pix2pixhd framework [16]) to improve the performance of CNN segmentation model.

A recent work called SegAN [17] proposes a U-Net GAN-based framework based on the ineffectiveness of single scalar real/fake output of a classic discriminator. Instead uses a fully CNN and propose an adversarial critic network with a multi-scale L_1 loss function.

3 Approach and Current progress

Our model is fed with a database of MR Brain Ischemic Stroke Images (13200) and their segmentation, 18.38% of the total of images have a stroke (unbalanced class). The segmentation and annotation process was manual by a radiologist of the University Hospital Basel - Department of Radiology - Switzerland (owner of the dataset). The resolution of the images is 128^2 pixels and are gray-scale.

In order to learn global and local features, we decide to combine self-attention Blocks [13] and multi-scale loss L_1 [17] in a pix2pix framework [12] for image synthesis using segmentation of stroke and foreground as input and getting as output an image synthesis with a stroke for class balancing. The actual performance of the work of the image synthesis GAN can be seen in the left image of the next figure.

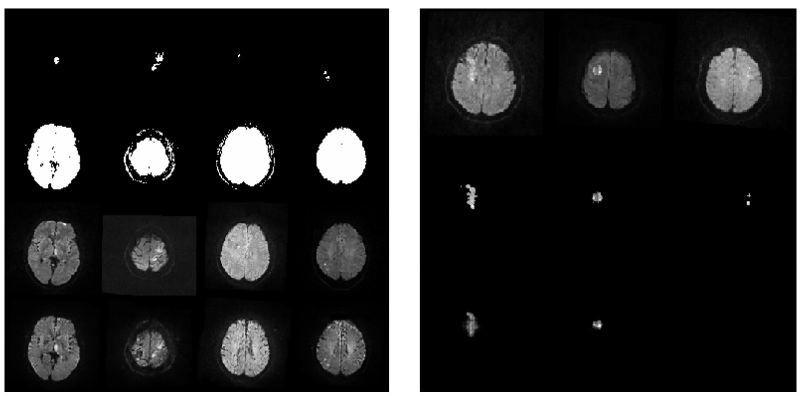

Figure 1: Left image: brain stroke image generation (1st row: stroke, 2nd: foreground, 3rd: ground truth, 4th: generated); right: brain stroke segmentation (1st row: stroke, 2nd: ground truth, 3rd: generated

Furthermore, based in SegAN [17] we build an adversarial networks (segmentor and critic) for semantic segmentation adding a Self-Attention Blocks [13] and a novel training strategy, in which the segmentor must learn the mapping of the input image to the same image masked by the label map ($image * segmentation_map$) and discriminator uses multi-scale loss L_1 for training. Actual performance of the work of the semantic segmentation GAN can be seen in the right image of the previous figure and the next table.

Table 1: Comparison to previous methods

	Dice	Precision	Sensitivity
SegAN	0.6909	0.7709	0.6515
our propose	0.7491	0.7805	0.7201

Progress work moves to improve generator performance, propose a new loss function, test with the ISLES 2018 and BRATS 2015 datasets, use an implemented image synthesis GAN for class balancing the dataset for improve segmentation GAN and implement metrics for image synthesis GAN (diversity and realism).

4 References

References

[1] Walter Johnson, Oyere Onuma, Mayowa Owolabi, and Sonal Sachdev. Stroke: a global response is needed. *Bulletin of the World Health Organization*, 94(9):634, 2016.

[2] M. Frid-Adar, E. Klang, M. Amitai, J. Goldberger, and H. Greenspan. Synthetic data augmentation using gan for improved liver lesion classification. In *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*, pages 289–293, April 2018.

[3] Camilo Bermudez, Andrew J. Plassard, Larry T. Davis, Allen T. Newton, Susan M. Resnick, and Bennett A. Landman. Learning implicit brain MRI manifolds with deep learning. *CoRR*, abs/1801.01847, 2018.

[4] Christoph Baur, Shadi Albarqouni, and Nassir Navab. Generating highly realistic images of skin lesions with gans. In *OR 2.0 Context-Aware Operating Theaters, Computer Assisted Robotic Endoscopy, Clinical Image-Based Procedures, and Skin Image Analysis*, pages 260–267, Cham, 2018. Springer International Publishing.

[5] Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*, 2015.

[6] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Spatial pyramid pooling in deep convolutional networks for visual recognition. *IEEE transactions on pattern analysis and machine intelligence*, 37(9):1904–1916, 2015.

[7] Tero Karras, Timo Aila, Samuli Laine, and Jaakko Lehtinen. Progressive growing of gans for improved quality, stability, and variation. *arXiv preprint arXiv:1710.10196*, 2017.

[8] Dakai Jin, Ziyue Xu, Youbao Tang, Adam P. Harrison, and Daniel J. Mollura. Ct-realistic lung nodule simulation from 3d conditional generative adversarial networks for robust lung segmentation. *CoRR*, abs/1806.04051, 2018.

[9] Tony C. W. Mok and Albert C. S. Chung. Learning data augmentation for brain tumor segmentation with coarse-to-fine generative adversarial networks. *CoRR*, abs/1805.11291, 2018.

[10] John T. Guibas, Tejpal S. Virdi, and Peter S. Li. Synthetic medical images from dual generative adversarial networks. *CoRR*, abs/1709.01872, 2017.

[11] Pedro Costa, Adrian Galdran, Maria Inês Meyer, Michael David Abràmoff, Meindert Niemeijer, Ana Maria Mendonça, and Aurélio Campilho. Towards adversarial retinal image synthesis. *CoRR*, abs/1701.08974, 2017.

[12] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1125–1134, 2017.

[13] Han Zhang, Ian Goodfellow, Dimitris Metaxas, and Augustus Odena. Self-attention generative adversarial networks. *arXiv preprint arXiv:1805.08318*, 2018.

[14] Takeru Miyato, Toshiki Kataoka, Masanori Koyama, and Yuichi Yoshida. Spectral normalization for generative adversarial networks. *arXiv preprint arXiv:1802.05957*, 2018.

[15] Tony CW Mok and Albert CS Chung. Learning data augmentation for brain tumor segmentation with coarse-to-fine generative adversarial networks. In *International MICCAI Brainlesion Workshop*, pages 70–80. Springer, 2018.

[16] Ting-Chun Wang, Ming-Yu Liu, Jun-Yan Zhu, Andrew Tao, Jan Kautz, and Bryan Catanzaro. High-resolution image synthesis and semantic manipulation with conditional gans. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 8798–8807, 2018.

[17] Yuan Xue, Tao Xu, Han Zhang, L Rodney Long, and Xiaolei Huang. Segan: Adversarial network with multi-scale l 1 loss for medical image segmentation. *Neuroinformatics*, 16(3-4):383–392, 2018.