Research Proposal: Triple-GAN for Medical Data Synthesis

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1. Scientific Questions and Significance

1.1 Background

Generative Adversarial Networks (GANs), known for their success in image generation and semi-supervised learning (SSL), face challenges in SSL due to suboptimal coordination between the generator and discriminator. Additionally, the generator struggles to control the semantics of generated samples. These issues arise from the conventional two-player formulation, where a single discriminator has conflicting roles, focusing solely on estimating data without considering labels. To address these challenges, the Triple Generative Adversarial Net (Triple-GAN) [1] architecture is introduced, featuring three players: a generator, a discriminator, and a classifier. This three-player approach collaboratively defines conditional distributions between images and labels, allowing the discriminator to solely focus on identifying fake image-label pairs. Triple-GAN aims to overcome the limitations observed in traditional GANs within SSL contexts. In medical imaging, a recurring question is whether GANs can be as effective at generating workable medical data as they are for realistic RGB images.

1.2 Research Questions

1. In the realm of medical imaging, to what extent can the Triple Generative Adversarial Net (Triple-GAN) effectively generate workable medical data with controlled semantics, and how does its performance compare across various GAN architectures when applied to different medical imaging modalities?

1.3 Significance

Exploring Triple Generative Adversarial Net (Triple-GAN) is important due to current challenges in medical image analysis stemming from limited access to large annotated datasets. The study on conventional generative adversarial networks (GANs) [2] in medical image synthesis underscores their unreliability, emphasizing the need for more effective generative models. Triple-GAN's three-player architecture holds promise in addressing the shortcomings identified in traditional GANs, offering improved coordination for capturing the complexities of medical data. This exploration aligns with the overarching goal of advancing generative models to meet the unique demands of medical data, ultimately enhancing medical image analysis and research.

2. Literature Review

1. Chongxuan Li, Kun Xu, Jun Zhu, Bo Zhang, Triple Generative Adversarial Nets. Neural Information Processing Systems Conference 2017. Link

2. Skandarani, Y.; Jodoin, P.-M.; Lalande, A. GANs for Medical Image Synthesis: An Empirical Study. J. Imaging 2023, 9, 69. Link

3. Materials and Methods

0.1 3.1 Approach

Implement and evaluate the Triple GAN architecture on the medical imaging modalities tested in the study [2] (cardiac cine-MRI, liver CT, RGB retina images). Compare the generated images using Fréchet

Inception Distance (FID) and assess their utility for segmentation tasks. Investigate how Triple GAN addresses challenges identified in previous GAN studies for medical imaging.

3.2 Data Sources

Medical datasets, Automated Cardiac Diagnosis Challenge (ACDC), Segmentation of the Liver Competition 2007 (SLIVER07) and Indian Diabetic Retinopathy Image Dataset (IDRiD).

3.3 Computational Resources

High-performance computing resources, including GPUs, will be required for efficient training of the Triple-GAN architecture on medical data for which we plan to utilize Google Colab.

4. Challenges

1. Anticipate challenges in accessing the mentioned datasets.
2. Anticipate challenges in adjusting the parameters of Triple GAN for various medical imaging modalities.
3. Anticipate long training times and large memory requirements.
4. Address potential hurdles concerning segmentation accuracy and Triple GAN's capability to faithfully replicate the comprehensive features present in medical datasets.

5. Conclusion

In conclusion, this research proposal outlines a plan to implement and evaluate the Triple-GAN architecture for generating realistic and workable medical data.