ECE598 Generative AI Models - individual project - Generative adversarial networks for segmented image dataset synthesis on medical imaging

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1. Project description and goals

Background:

Image segmentation is a very popular field in the computer vision community, which develops techniques for automatic pixel-level classification on given images. Image segmentation is very useful in the medical imaging field, where radiologists try to depict the contours of the regions of interest on the radiographic images captured from the patients and assist the clinician to make a better diagnosis and treatment plan. However, semantic segmentation annotation needs large amounts of time and effort, since it needs to annotate all pixels in the image dataset. Particularly, the annotation process can be much more complicated and expensive when expertise knowledge is required. The difficulty in accessing large-scale annotated segmentation datasets limits the potential application of deep learning-based segmentation methods in practical medical problems.

Recently, several studies have extended generative adversarial networks [1,2] into low-budget image segmentation annotating factories, which could synthesize realistic image and corresponding segmentation mask pairs without much annotation work. These methods are based on StyleGAN [3], a modern GAN which could synthesize high-quality high-resolution images due to disentangled representation design, to decode the semantically meaningful intermediated feature maps from the well-trained StyleGAN generator to get the segmentation mask along with the simultaneously generated image. Ideally, if these GANs could approximate the target image and annotation domain perfectly, the generated segmented image dataset could be used as the real dataset in training the segmentation network.

For example, SemanticGAN [2] (shown in the following figure) designed an additional discriminator to force the generator to learn the pixel label distribution as well as the image distribution. In this way, it could synthesize segmented image pairs decently.

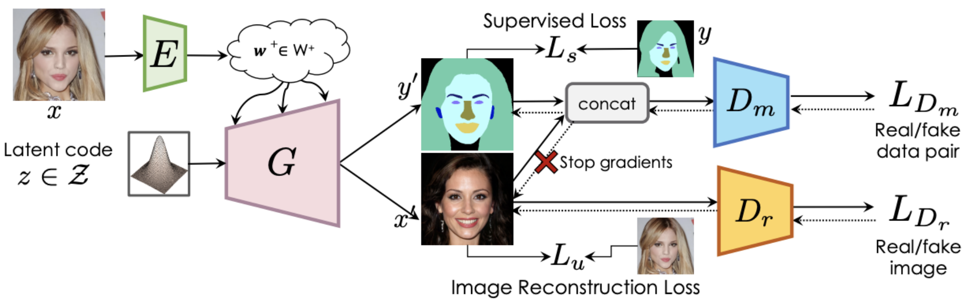

Figure 2: **Model Overview.** Generator G and discriminators D_m and D_r are trained with adversarial objectives $\mathcal{L}_G$ (not indicated here), $\mathcal{L}_{D_m}$ and $\mathcal{L}_{D_r}$. We do not backpropagate gradients from D_m into the generator's image synthesis branch. We train an additional encoder E in a supervised fashion using image and mask reconstruction losses $\mathcal{L}_u$ and $\mathcal{L}_s$.

Another method called DatasetGAN [1] (shown in the following figure) proposed a style-interpreter based on the style-based generator for decoding the segmentation mask.

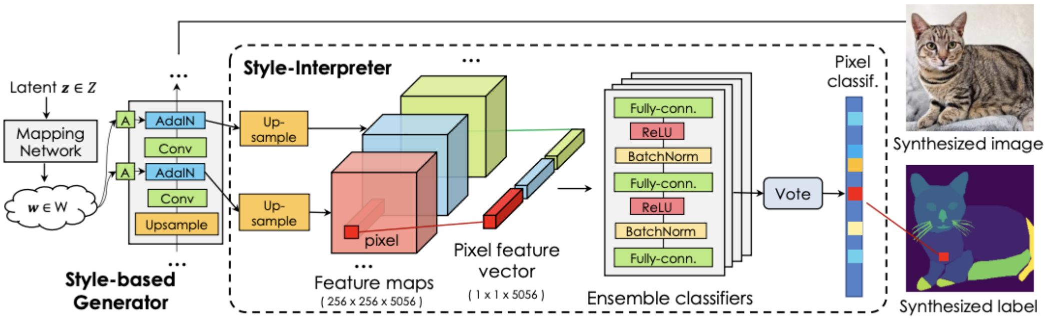

Figure 2: Overall architecture of our DATASETGAN. We upsample the feature maps from StyleGAN to the highest resolution for constructing pixel-wise feature vectors for all pixels on the synthesized image. An ensemble of MLP classifiers is then trained for interpreting the semantic knowledge in the feature vector of a pixel into its part label.

Motivation:

In this study, I’d like to transfer these GAN-based methods into medical imaging datasets, to evaluate their effectiveness in the medical imaging field. If problems happen in the replication process, I’d try to develop several modifications as the solutions. After training, the performance of the trained GAN model would be investigated to assess their feasibility in low-budget segmentation annotation.

2. Methods and training dataset

In this study, DataseGAN would be first employed. If enough time and effort are available, SemanticGAN would be investigated too.

As for the training dataset, BraTS dataset of brain MRI data and SegTHOR dataset of chest CT images might be used.

Reference:

1. Zhang, Yuxuan et al. “DatasetGAN: Efficient Labeled Data Factory with Minimal Human Effort.” *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)* (2021): 10140-10150.
3. Li, Daiqing, et al. "Semantic segmentation with generative models: Semi-supervised learning and strong out-of-domain generalization." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2021.
4. Karras, Tero, Samuli Laine, and Timo Aila. "A style-based generator architecture for generative adversarial networks." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2019.