Data Augumentation using Generative Adversarial Networks

Mayur Shastri kshastri@umass.edu

Shreyas Ganesh shreyasganes@umass.edu

1 Introduction

The challenge of obtaining massive amounts of data that is required by modern day deep learning models is one that has intrigued academicians for some time now. This problem is even more prevalent in the medical sphere, where access to high quality medical image datasets is challenging to say the least. Due to licensing and privacy concerns, the need for Data Augmentation in such a space is more necessary. Better training requires intensive Data Augmentation (DA) techniques, such as geometry/intensity transformations of original images. However, these transformed images intrinsically have a similar distribution as the original ones, leading to limited performance improvement. Thus, generating realistic (i.e., similar to the real image distribution) but completely new samples is essential to fill the real image distribution uncovered by the original dataset. In this context, Generative Adversarial Networks based DA have shown promise as it has shown excellent performances in computer vision, revealing good generalization ability, such as drastic improvement in eye-gaze estimation using SimGAN (A. Shrivastava, 2017).

2 Related work

Generative Adversarial Networks are a relatively newer class of machine learning systems. They have been used for various tasks ranging from image generation to image editing. Implemented GANS (Changhee Han, 2018) are used to augment training MRI image data to increase the accuracy of a given model used to classify the images with brain tumors. In 2018, (Maayan Frid-Adar, 2018) made use of GANs to augment their training data in order to improve the performance of their CNN model to classify liver lesions. Changhee Han (Changhee Han, 2019) shows their first GAN-based DA work using automatic bounding box annotation, for robust CNN-based brain metastases detection on 256 256 MR images.

Changhee Han (Changhee Han, 2018) is considered to be the state-of-the-art solution to this problem and in this project, we aim to validate this by implementing their findings and measuring its accuracy.

3 Work Distribution

The following is the list of project members and a tentative work distribution for the project -

1. **Shreyas Ganesh**
   Work on the proposed Progressive Growing of GANs (PGGANs) Image Generation Pre Processing For this we select particular slices of the images in the Head CT dataset, which convey the most useful information. This stage also includes distributing the data into Training, Testing and Validation data. Will also work on creating the baseline models(Neural Networks) to test the effictiveness of the GAN.

2. **Mayur Shastri**
   Work on the proposed Progressive Growing of GANs (PGGANs) Image Generation Implementaion with Loss and Gradient calculation We implement the PGGAN along with the Wasserstein loss (T. Karras, 2018) using gradient penalty. Will also work on creating the baseline models(Neural Networks) to test the effictiveness of the GAN.

4 Approach

The use of the PGGAN model is to generate similar image distributions as in the training set. PGGANs is a novel training method for GANs with a

progressively growing generator and discriminator starting from low resolution, newly added layers model fine-grained details as training progresses. We adopt this model for high resolution Head CT images that can be classified as either being haemorrhaged or not haemorrhaged. These are seperately trained for and generated.
The baseline model used for the classification problem in this project is the ResNet 50 (I. Gulrajani, 2018) classifier that is a residual learning-based CNN with 50 layers. The Head CT images are centered and cropped to 224 x 224 pixels while training the model. We adopt ResNet- 50 to detect haemorrhages in the Head CT dataset, ie binary classification of these CT images as being either haemorrhaged or not haemorrhaged.

5 Data

Our source of data for this project will be Kaggle's Head CT images dataset. This dataset contains some normal head CT slices and others with hemorrhage. There is no distinction between kinds of hemorrhages.The labels are on a CSV file. Each slice comes from a different person.. We also plan to extend our model to Kaggle's Cancer CT images dataset and also the BRATS 16 MRI images dataset.

6 Tools

We plan to use the Keras libraries for implementing the PGGAN model. Since our classification is being performed using the ResNet model we will use PyTorch to implement the model as well. As the datasets are quite large and we expect to build a quite complex model, this will require intensive compute resources, the specifics of which are not known at this time.

References

A. Shrivastava, T. Pfister, O. T. e. a. (2017). Learning from simulated and unsupervised images through adversarial training.

Changhee Han, Leonardo Rundo, R. A. Y. F. G. M. H. N. H. H. (2018). Infnite brain tumor images: Can gan-based data augmentation improve tumor detection on mr images?

Changhee Han, Kohei Murao, S. S. H. N. (2019). Learning more with less: Gan-based medical image augmentation.

I. Gulrajani, F. Ahmed, M. A. e. a. (2018). Improved training of wasserstein gans, proc. conf. on neural information processing systems.

Maayan Frid-Adar, Idit Diamant, E. K. M. A. J. G. a. H. G. (2018). Gan-based synthetic medical image augmentationfor increased cnn performancein liver lesion classification.

T. Karras, T. Aila, S. L. e. a. (2018). Progressive growing of gans for improved quality, stability, and variation.