EE-641 - Deep Learning Systems

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Project Title: Multimodal Medical Image Synthesis for Underrepresented Populations via Conditional StyleGAN

Problem Description

This project proposes the development of a Conditional StyleGAN integrated to synthesize medical images from underrepresented populations. The BraTS-Africa Challenge provides the largest publicly available dataset of annotated pre-operative glioma images from Sub-saharan African adults, including both low-grade and high-grade gliomas (LGG/HGG).

Significance

The scarcity of such medical images pose a significant challenge for training diagnostic models to those certain regions, as the lack of data can lead to poor model performance and generalizability. By generating realistic synthetic images, this valuable dataset can bridge the data gap, enabling the development of more generalized diagnostic tools.

Technical Approach:

- **Conditional StyleGAN:**

  The StyleGAN architecture from 2018, (Fig 2) will be used with improved Latent Space Mapping. The generation process will be conditioned on clinical metadata (i.e. tumor characteristics and progression stages) to synthesize images representing different glioma sub-regions. This includes the enhancing tumor (ET), non-enhancing tumor core (NETC), and surrounding non-enhancing FLAIR hyperintensity (SNFH).

- **Generator (Slice Generator)**

  The generator takes two inputs: a fixed random noise vector z, typically sampled from a Gaussian distribution of size R^d, and a one-hot encoded label vector y representing the desired MRI slice type (Axial: [1, 0, 0], Sagittal: [0, 1, 0], or Coronal: [0, 0, 1]). These inputs are concatenated to form a joint vector $[z|y]$, which is then processed through fully connected layers to transform it into a latent tensor. To ensure that the label y consistently conditions the slice generation process, y is broadcasted as an additional channel and incorporated across all layers of the network with a certain proportion (Fig. 1). The generator internally gives out a 4x4 slice and then is given to the next synthesis block where it's upscaled with a proportion of style and noise. The generator finally outputs a 256 x 256 grayscale image that corresponds to the labeled slice type specified by y. This will be evaluated against the real images to get a loss metric for weight updation in both Generator and Discriminator.

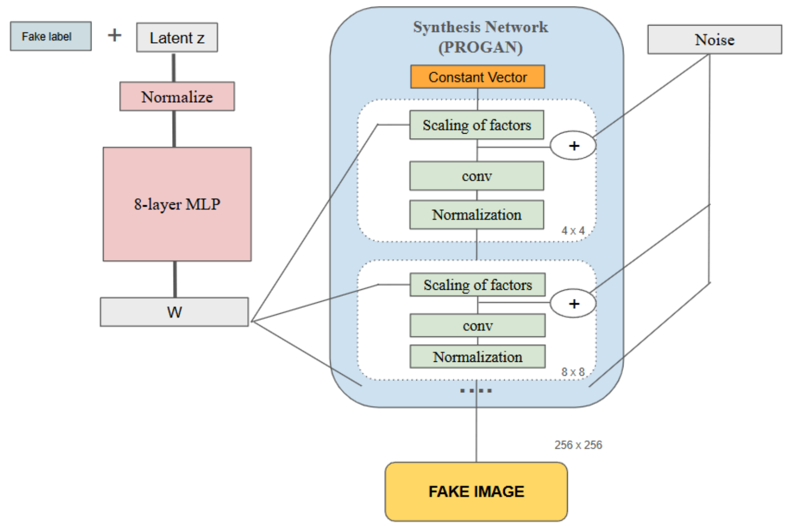

Figure 1: StyleGAN Generator

- **Discriminator (Slice Classifier)**

  The discriminator receives as input a 256 x 256 grayscale MRI slice, either real or generated, along with a one-hot encoded label vector by specifying the expected slice type. To condition the classifier on the label, y is first passed through an embedding layer to project it into a feature space. The embedded label is then concatenated with the image feature maps at an intermediate layer, allowing the network to evaluate the slice's authenticity in the context of the given label. The discriminator outputs a probability score, indicating whether the slice is real or fake, conditioned on the provided label.

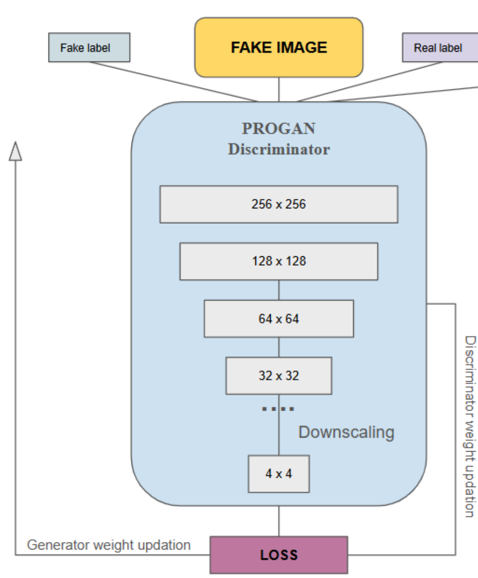

Figure 2: StyleGAN Discriminator

Dataset Description:

The BraTS-Africa dataset provides MRI scans from adult glioma patients in Sub-Saharan Africa, including both low-grade glioma (LGG) and glioblastoma (GBM/HGG) cases. The dataset includes multi-parametric MRI scans, specifically T1-weighted (T1), post-contrast T1-weighted (T1Gd), T2-weighted (T2), and T2 Fluid Attenuated Inversion Recovery (T2-FLAIR) images.

Project Timeline :

Week 1: Project Initialization and Data Preparation

- Data Acquisition and Pre-processing

Week 2: Model Development and Training Start

- Setup Development Environment
- Implementation of Conditional StyleGAN

Week 3: Training and Model Refinement

- Training of StyleGAN

Week 4: Evaluation and Project Finalization

- Model Evaluation
- Fine-tuning and Optimization
- Documentation and Reporting

References:

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