MRI data augmentation via conditional generative 3D inpainting

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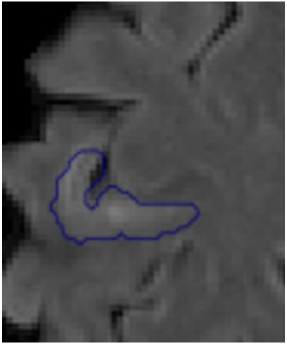
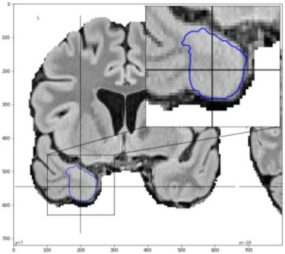
General Problem

-Despite the ever-increasing interest in applying deep learning models to medical imaging, the typical scarcity and imbalance of medical datasets can severely impact the performance of DL models.

-Generative models can be used to enrich datasets with synthetic data.

-While considering the problem we can note, that usually we lack not the data itself, but the specific region of interests, e.g. regions of focal-cortical dysplasia on MRI data.





Problem statement

Thus, the problem can be formulated in the terms of Image Inpainting.

1. $X \in \mathcal{D}, X \in \mathbb{R}^n$ – dataset
2. $X_0, \tilde{X_0} \in \mathbb{R}^n$ – initial data with zeroed region $R \in \mathbb{R}^k$ and reconstructed data.
3. $g_r : \mathbb{R}^n \longrightarrow \mathbb{R}^{n-k}$ – projection function on $\mathbb{R}^{n-k}$ subspace, corresponding to the revealed part of the image.
4. $g_h : \mathbb{R}^n \longrightarrow \mathbb{R}^k$ – projection function on $\mathbb{R}^k$ subspace, corresponding to the hidden part of the image

Our goal is to construct a function $\mathbf{f} : \mathbb{R}^n \longrightarrow \mathbb{R}^n$, such that $g_r \circ f \equiv r$ and $g_h(f(X_0))) \sim g_h(X)$, i.e. it acts as identity function on the revealed part of image and reproduce distribution of given dataset on the hidden part.

Moreover, the dataset may contain images with regions of interest belonging to different classes $c_i \in \mathcal{C}$. In this case, we want to take this into account and generate from conditional distribution $p(X|c)$.

Research directions

Function f can be constructed by parts, training a mapping from revealed part of image to hidden region. This can be done in two ways:

1. Directly in high-dimensional space $\mathbb{R}^k$, i.e. building $h : \mathbb{R}^n \longrightarrow \mathbb{R}^k$
2. In autoregressive manner, operating in the lower-dimensional spaces and conditioning next generation on previously generated slices, so that $x_i \in \mathbb{R}^l \sim g(x_{i-1}, y \in \mathbb{R}^n)$.

Related papers

1. *Towards Coherent Image Inpainting Using Denoising Diffusion Implicit Models*[1]
2. *Brain Lesion Synthesis via Progressive Adversarial Variational Auto-Encoder*[2]
3. *Brain Lesion Synthesis via Progressive Medical Diffusion: Denoising Diffusion Probabilistic Models for 3D Medical Image Generation*[3]
4. *Multitask Brain Tumor Inpainting With Diffusion Models: A Methodological Report*[4]
5. *RePaint: Inpainting using Denoising Diffusion Probabilistic Models*[5]

[1] https://proceedings.mlr.press/v202/zhang23q/zhang23q.pdf
[2] https://arxiv.org/pdf/2208.03203.pdf
[3] https://arxiv.org/pdf/2208.03203.pdf
[4] https://arxiv.org/pdf/2211.03364.pdf
[5] https://arxiv.org/pdf/2201.09865.pdf