NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

School of Computer Science and Engineering
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Advanced Image Understanding with Deep Learning in Real-world Applications

Data augmentation and segmentation for 3D brain MRI images

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1. Background

Image segmentation and augmentation are crucial to biomedical imaging applications, such as disease diagnosing. Many CNN methods rely on supervised learning with large labeled dataset. However, obtaining medical images is difficult due to privacy issues and labelling medical images requires significant expertise and time. Typical hand-tuned data augmentation methods, e.g., rotation and scaling, are insufficient to capture the complex variation in brain MRI data.

2. Motivation & Objectives

The state-of-art method uses registration methods to align labeled reference image to target unlabeled images. However, there is room for segmentation performance improvement, and the number of brain examples with distinct anatomical structures are restricted by spatial transformation learned.

This project aims to improve the segmentation performance (in terms of Dice score) of the current unsupervised registration model, enhance the training efficiency and propose a methodology to synthesize more reliable images with distinct anatomical structure.

3. Approach

The improvement in segmentation performance has been done in three approaches:

(1) Fine-tune the loss functions of the spatial model to learn model behaviors. We add parameter α and λ for sensitivity analysis.

$$\mathcal{L}_{us}(f, m, \phi) = \alpha\mathcal{L}_{sim}(f, m \circ \phi) + \lambda\mathcal{L}_{smooth}(\phi),$$

Figure 1. The loss functions of spatial model.

(2) Implement Siamese network to learn the similarity score between 3D brain MRI images. The architecture of the component of *3D ConvNet* is shown in Fig.4. *3D ConvNet* extracts the meaningful features from 3D brain images.

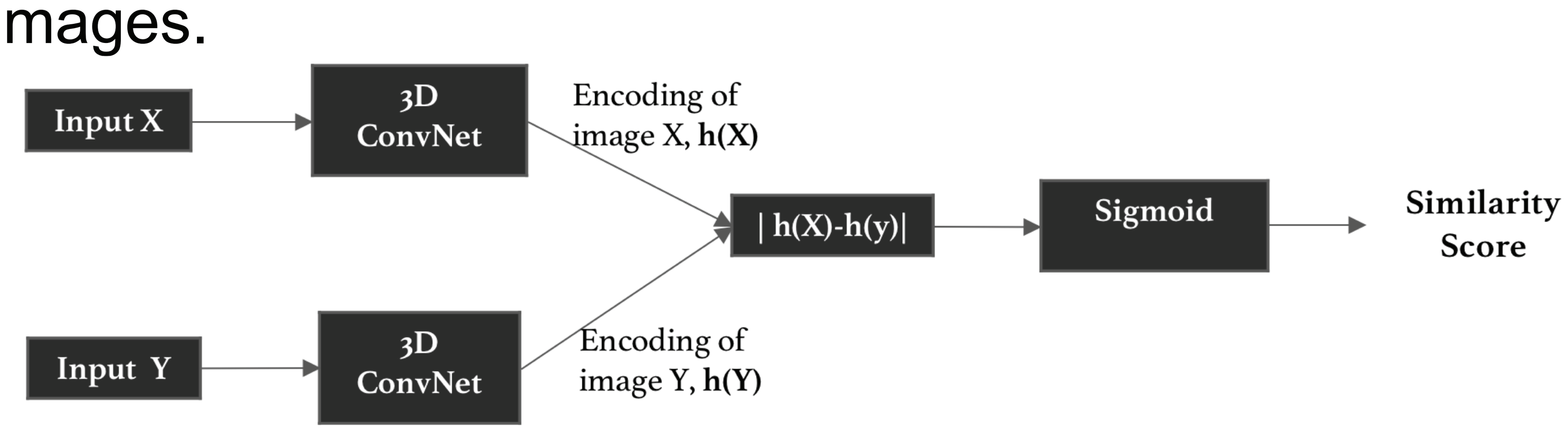

Figure 2. Siamese network architecture implemented

(3) Implement a Classification model to filter out the brain images with irregular shapes.

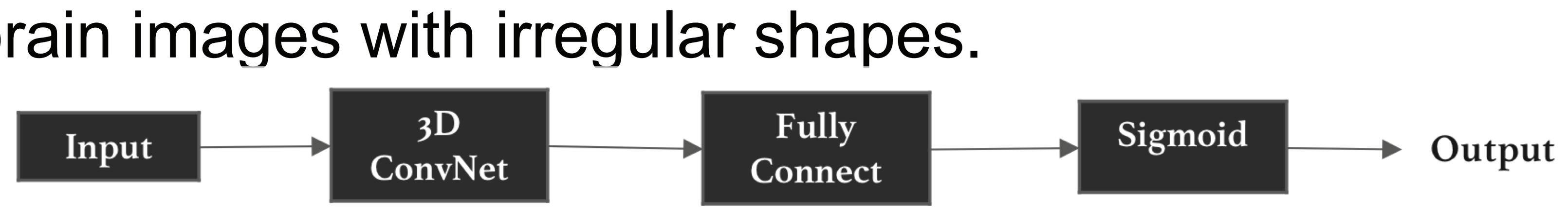

Figure 3. Classification model architecture implemented

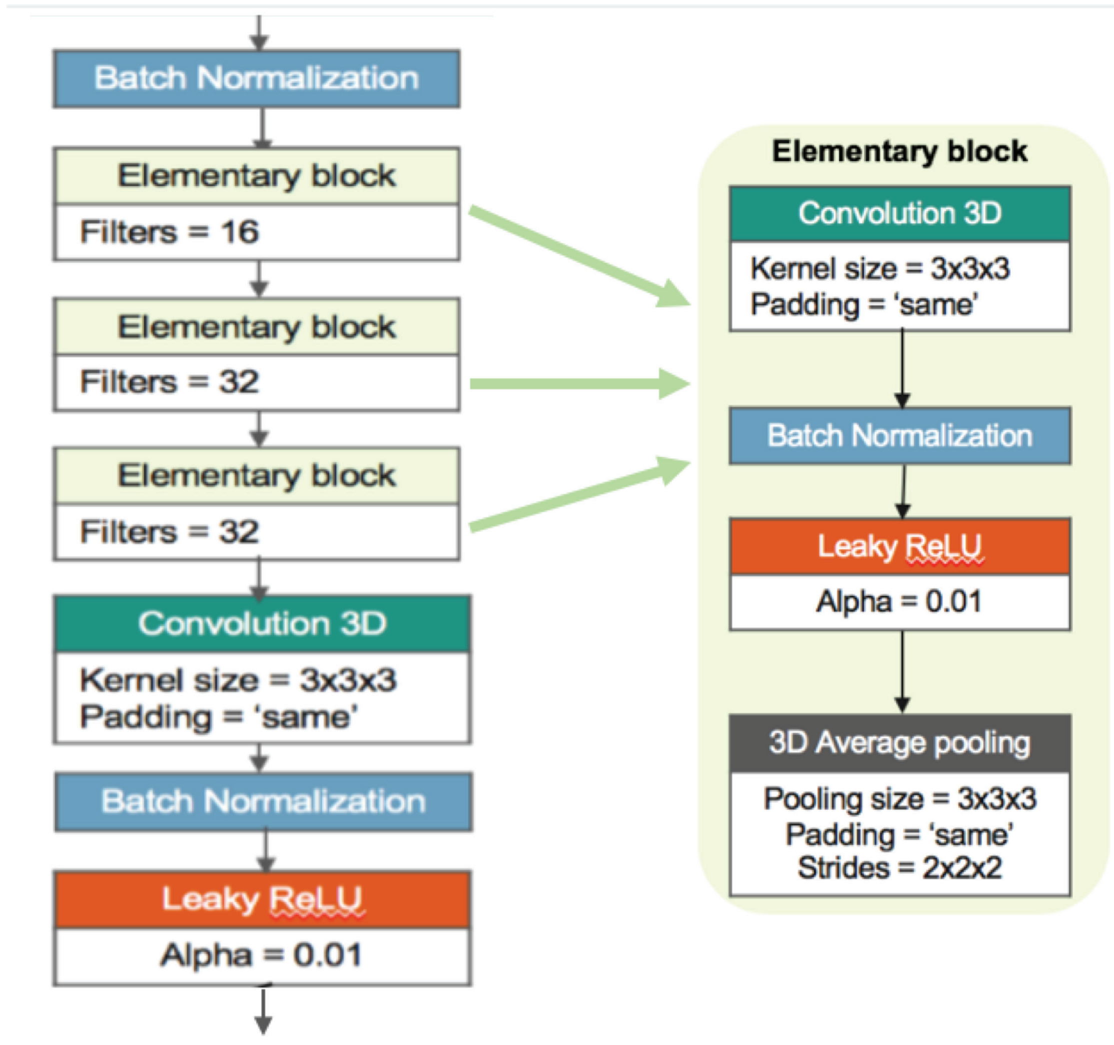

Figure 3. The left is 3D ConvNet model architecture, which is used to extract meaningful features. The right is the elementary block used in 3D ConvNet.

For synthesizing more reliable brain examples, we sample the transformation by using a continuous set of spatial transformation. We adjust the affine metrics ***F*** extracted by spatial transformation model and use it to warp the fixed atlas *x*. This generates an intermediate image between atlas *x* and unlabeled images *y*.

4. Result Analysis

For segmentation performance, all three methods outperform the baseline method in terms of mean Dice score across the validation data images.

	Original Setting	Fine-tune the loss functions	Siamese network	Classification model
Dice score	0.346	**0.439**	**0.351**	**0.389**
Dice improvement	-	**0.093**	0.005	**0.043**

Table 1. Dice score result comparison between original model settings and the models based on three research approaches

Fig.5 shows two synthesized images with distinct anatomical structures by applying ***F*** and ***0.5F***.

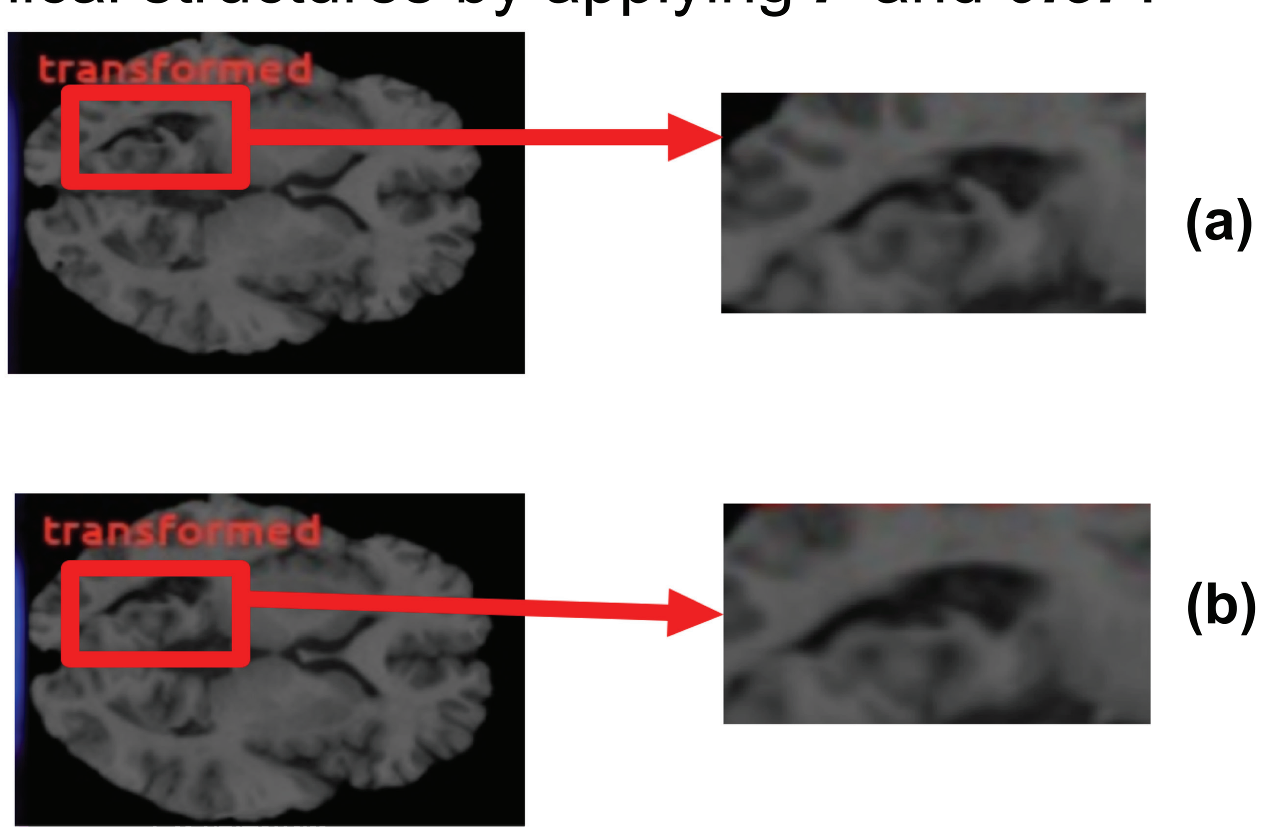

Figure 5. Synthesized brain image (a) is generated by applying affine metrics ***F***, Synthesized brain image (b) is generated by applying affine metrics ***0.5F***