

MRI2MRI: A deep convolutional network that accurately transforms between brain MRI contrasts

Sa Xiao¹, Yue Wu¹, Aaron Lee¹, & Ariel Rokem²

1. The Department of Ophthalmology, The University of Washington

2. The eScience Institute, The University of Washington

Contact: arokem@uw.edu | Download: <http://arokem.github.io/2018-cns-mri2mri-poster/poster.pdf>



Introduction

MRI creates images that are sensitive to different aspects of the tissue, and susceptible to different imaging artifacts. The relationships between different imaging contrasts are nonlinear and spatially- and tissue-dependent [8]. This poses several difficulties in the interpretation of multi-modal MRI. For example, analysis that requires accurate registration of images into the same coordinate frame currently requires the use of algorithms that can match images with different contrasts [5]. Moreover, a better understanding of complementary information provided in different contrasts will allow better characterization of tissue properties.

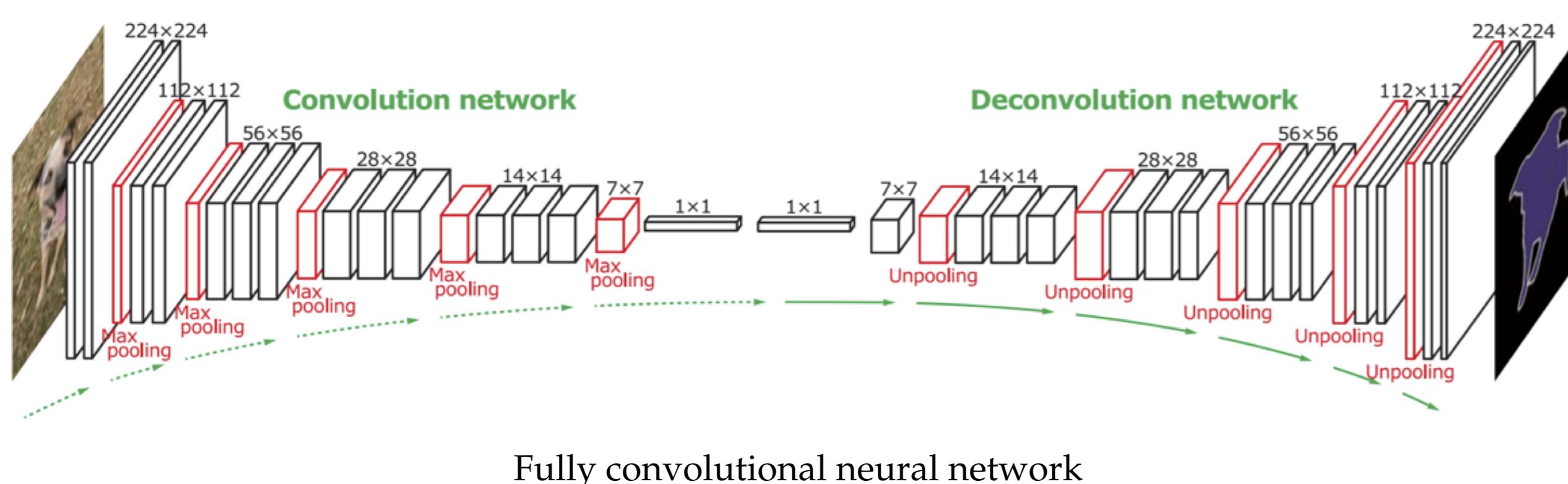
Materials and Methods

Data

We used the IXI dataset (<http://brain-development.org/ixi-dataset/>): T1w, T2w, PD, MRA, and DWI (16 directions, at b-value of 1000, one b=0) for N=567 subjects are available.

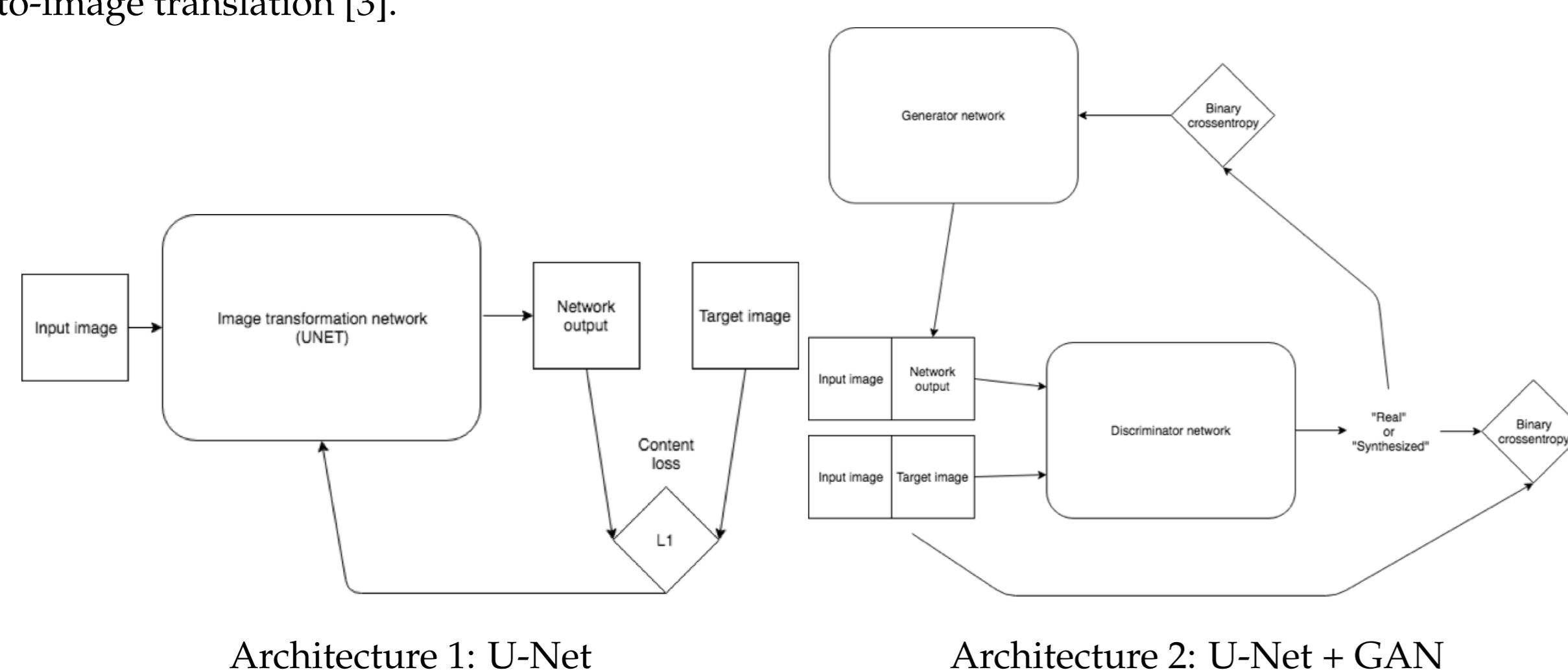
Artificial neural networks

A fully convolutional neural network was trained to learn the mapping between different MRI images in a training set (n=338). We used a U-net architecture [6]. In all cases, we used the Adam optimizer for training (with learning rate: 0.0002). The implementation used Pytorch (<https://pytorch.org>).



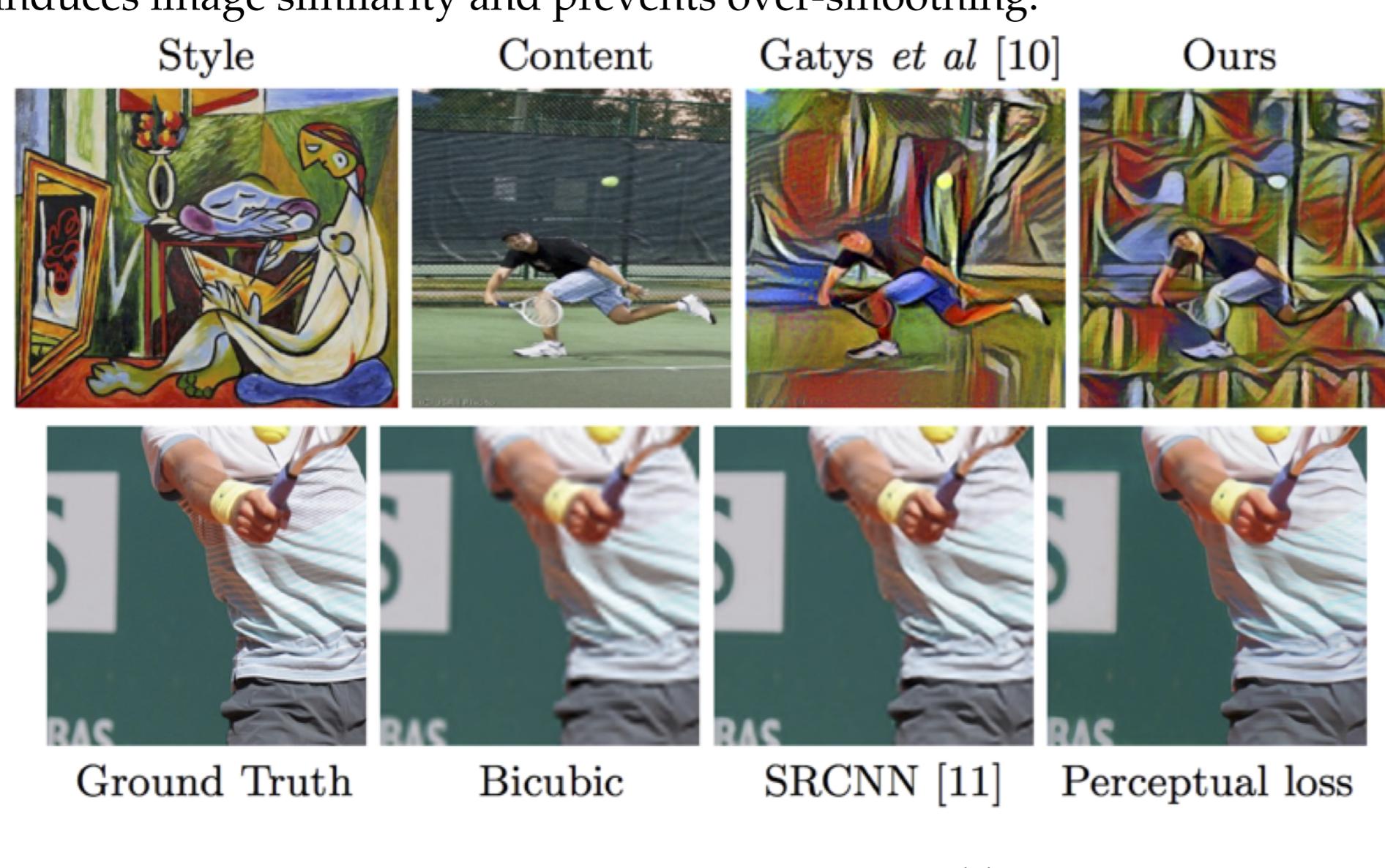
Neural network architectures

We used both the standard U-Net architecture, as well as a generative adversarial architecture for image-to-image translation [3].



Neural network loss

We used two types of loss functions: the first is a pixel-wise L1 loss. We also used a perceptual loss function [4]: the activation of the first layer of a pretrained VGG16 network [7]. The latter a cost function that induces image similarity and prevents over-smoothing.



Multi-modal registration experiments

A group of participants (n=79), set aside as a test set was used to evaluate registration. We used a state-of-the-art registration algorithm [1], implemented in DIPY [2] to register DWI b=0 to corresponding T1w images. To simulate participant motion, known rotation and translation were applied to the b=0 image and the T1w was registered to the b=0. For comparison, we also synthesized a T1w-analog from the b=0 image using the DL network and used the synthesized image with the same registration algorithm. Registration errors were calculated relative to known ground truth as mean absolute error (MAE), for translation and rotation components of the registration.

Acknowledgements

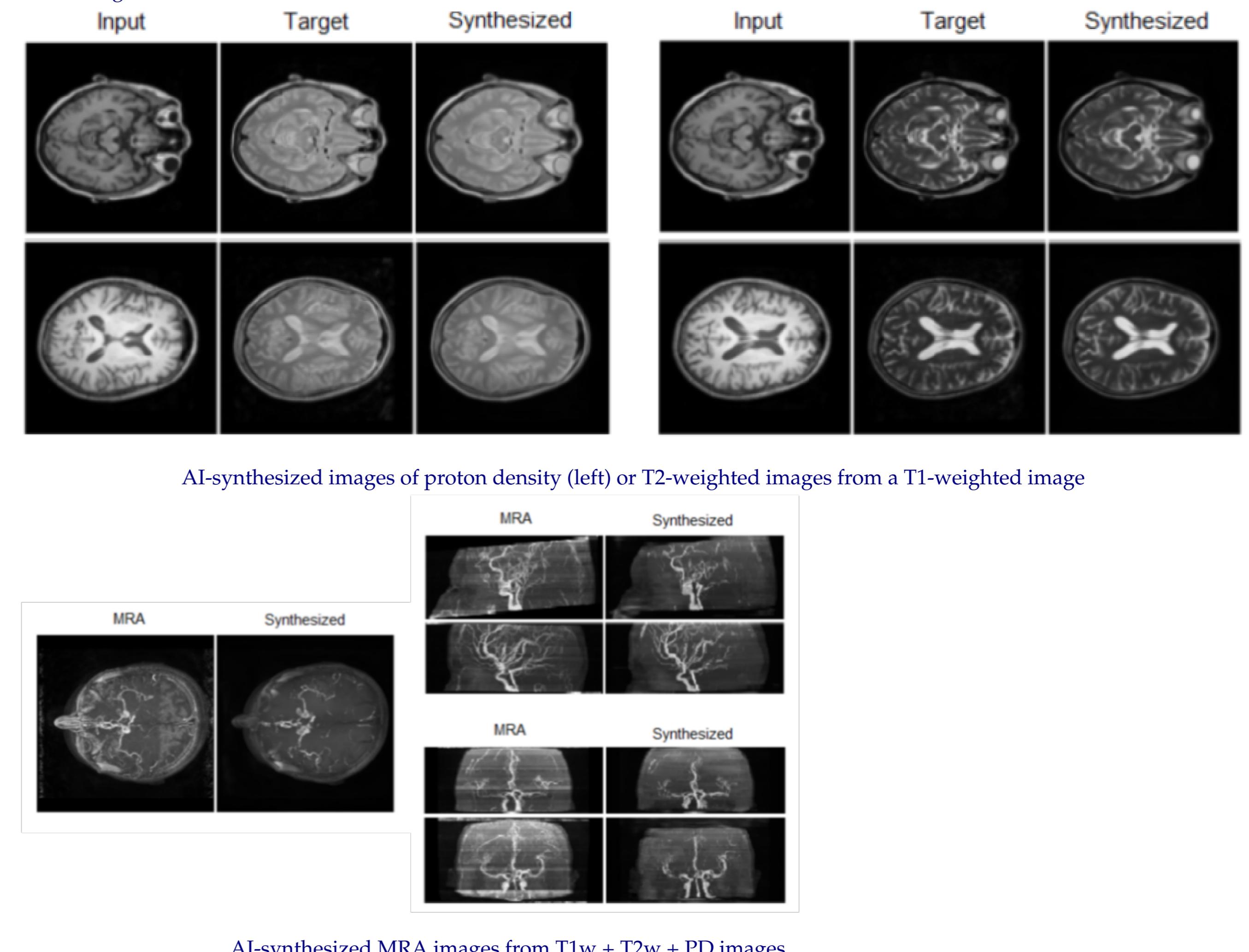
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Results

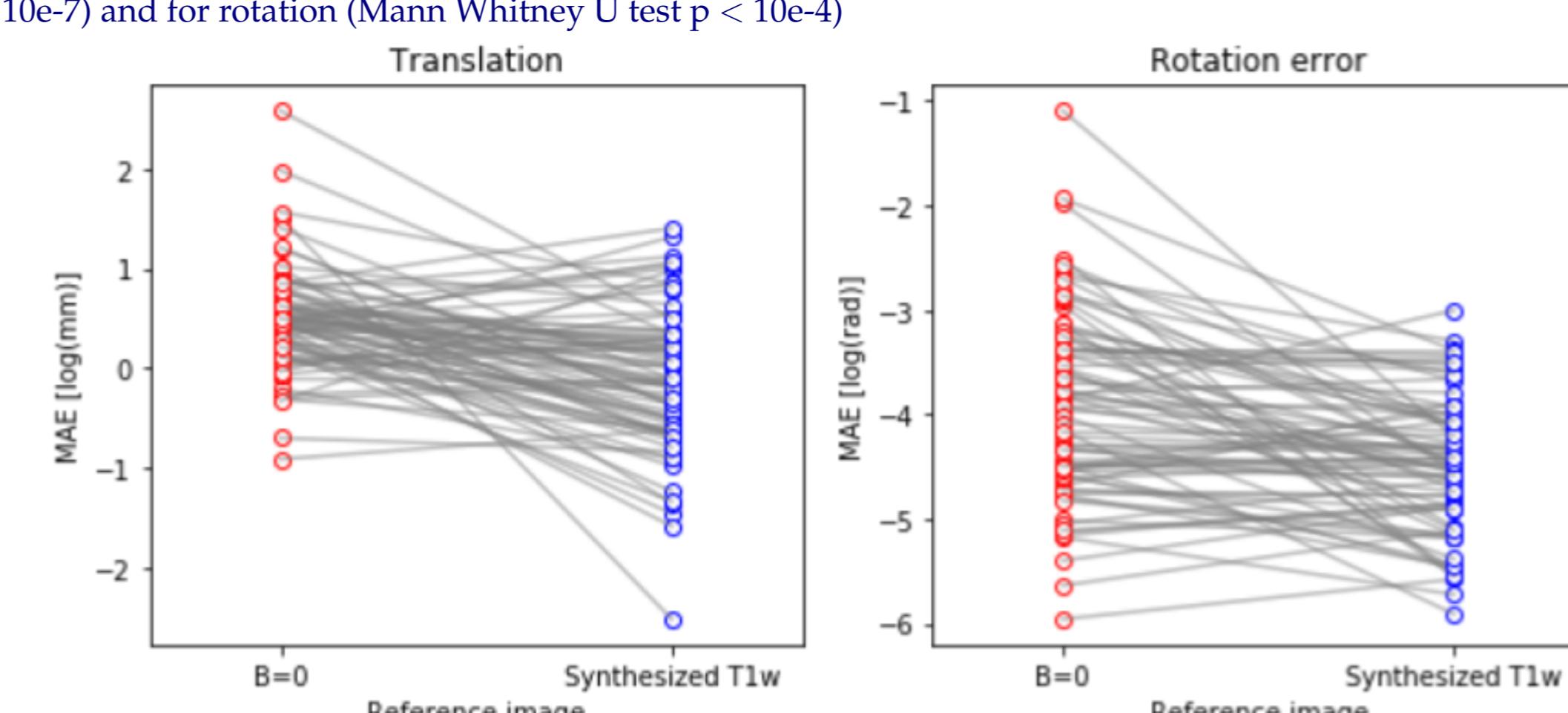
Accurate MRI image synthesis

The DL algorithm learns the mapping between different contrasts. It can be trained for either one-to-one mappings (e.g., T1w → PD, Figure 1 left, or T1w → T2w, Figure 1 right), or many-to-one mappings (e.g., T1w + T2w + PD → MRA, Figure 2). High accuracy is achieved by learning both mappings on the individual voxel level, as well as overall global structure. For example, the algorithm learns to disregard the ventricles in the mapping to MRA, despite the fact that the ventricles have similar pixel values in T1w, T2w and PD images to blood vessels.

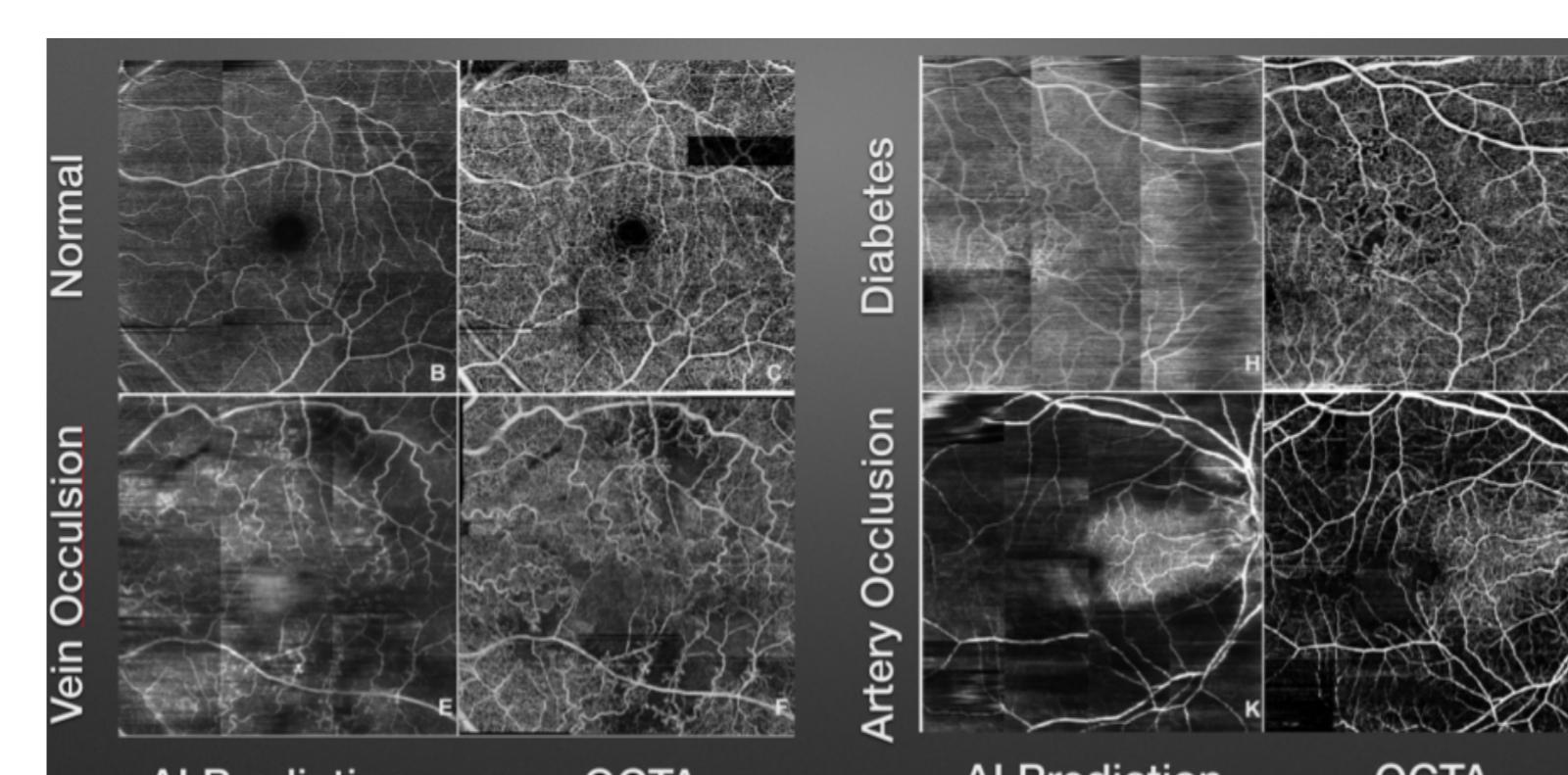


Application: multi-modal image registration

The algorithm was trained to synthesize T1w images from the DWI b=0 images. On a separate set of subjects, not used during training, we demonstrate that registration of T1w to DWI b=0 is more accurate using a synthesized T1w intermediary. This effect is shown here as mean absolute error (MAE; Figure 2) and is consistent both for the translation component (Mann Whitney U test, $p < 10^{-7}$) and for rotation (Mann Whitney U test $p < 10^{-4}$).



Other applications



AI-synthesized retinal perfusion images in patients with diseases that were not part of the training set.

Conclusions

- MRI2MRI accurately transforms between brain MRI contrasts
- This can be used to improve hard image processing tasks, such as cross-modal registration

References

- [1] B B Avants, C L Epstein, M Grossman, and J C Gee. Symmetric diffeomorphic image registration with cross-correlation: evaluating automated labeling of elderly and neurodegenerative brain. *Med. Image Anal.*, 12(1):26–41, February 2008.
- [2] Eleftherios Garyfallidis, Matthew Brett, Bagrat Amirbekian, Ariel Rokem, Stefan van der Walt, Maxime Descoteaux, Ian Nimmo-Smith, and Dipy Contributors. Dipy, a library for the analysis of diffusion MRI data. *Front. Neuroinform.*, 8:8, February 2014.
- [3] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-Image translation with conditional adversarial networks. November 2016.
- [4] Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for Real-Time style transfer and Super-Resolution. In *Computer Vision – ECCV 2016*, Lecture Notes in Computer Science, pages 694–711. Springer, Cham, October 2016.
- [5] Arno Klein, Jesper Andersson, Babak A Ardekani, John Ashburner, Brian Avants, Ming-Chang Chiang, Gary E Christensen, D Louis Collins, James Gee, Pierre Hellier, Joo Hyun Song, Mark Jenkinson, Claude Lepage, Daniel Rueckert, Paul Thompson, Tom Vercauteren, Roger P Woods, J John Mann, and Ramin V Parsey. Evaluation of 14 nonlinear deformation algorithms applied to human brain MRI registration. *Neuroimage*, 46(3):786–802, July 2009.
- [6] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-Net: Convolutional networks for biomedical image segmentation. May 2015.
- [7] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for Large-Scale image recognition. September 2014.
- [8] J Vymazal, M Hajek, N Patronas, J N Giedd, J W Bulte, C Baumgartner, V Tran, and R A Brooks. The quantitative relation between t1-weighted and t2-weighted MRI of normal gray matter and iron concentration. *J. Magn. Reson. Imaging*, 5(5):554–560, September 1995.