A Deep Learning Framework to Improve MRI Safety

Engineering Summer Program

Memorial Sloan Kettering Cancer Center
Weill Cornell Medicine

Nawal Panjwani, Mina C. Moghadam
The Winkler Lab at Weill Cornell Medicine

Introduction

Today, MRIs with magnetic field strengths of 1.5T and 3T are frequently used in clinical settings. Ultra-high field (UHF) 7T MRIs, which provide increased spatial resolution and sensitivity, are emerging in the field of medical imaging.

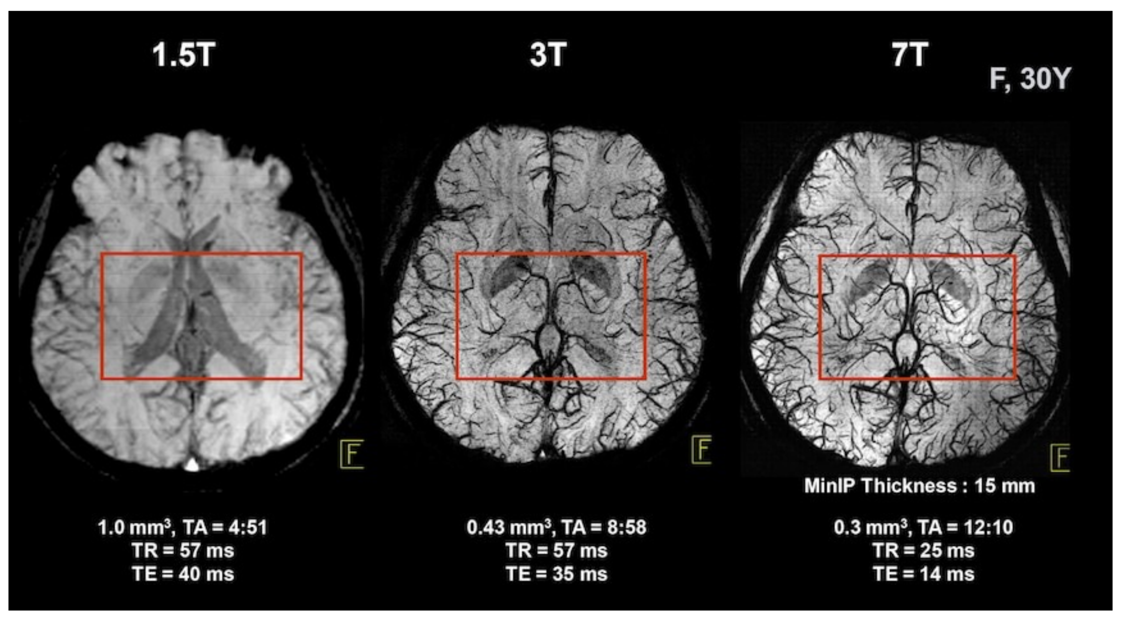

Figure 1: MRI brain scans that show the difference in spatial resolution and sensitivity between 1.5T, 3T, and 7T MRIs (Lord, 2014).

UHF MRIs, however, pose safety risks to the patient due to the nonuniform deposition of radiofrequency (RF) power in the body. This can lead to dangerous tissue heating and damage, which can be quantified by the tissue's specific absorption rate (SAR).

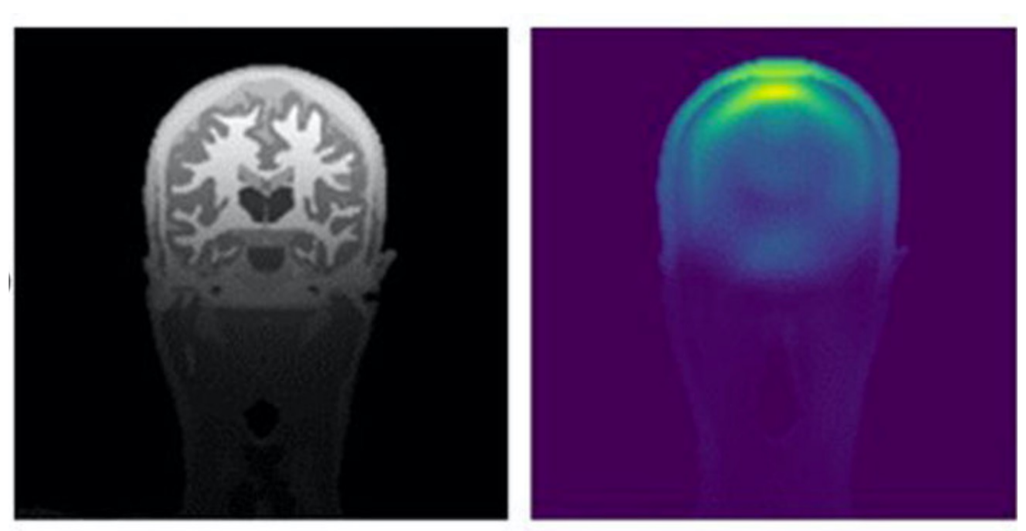

Figure 2: Anatomical scans of the head and the predicted local SAR hotspots using a 4-stage 2D U-Net architecture (Gokyar et al., 2021)

To address this safety risk, the Winkler Lab has developed a project called MRSaiFE, which takes an AI-based approach to improving MRI safety. The lab implemented a 2D U-Net architecture, which is a convolutional neural network (CNN) that precisely and efficiently segments images into a desired output. The algorithm built in this study is designed to take an anatomical body image as an input and produce a SAR prediction image as an output. In this project, the encoder backbone of the 2D U-Net is replaced with Inception-ResNet, a neural network that has shown higher accuracy and performance in image segmentation in some studies. The algorithm is trained and tested using three human body models and the SSIM and MSE are calculated and reported.

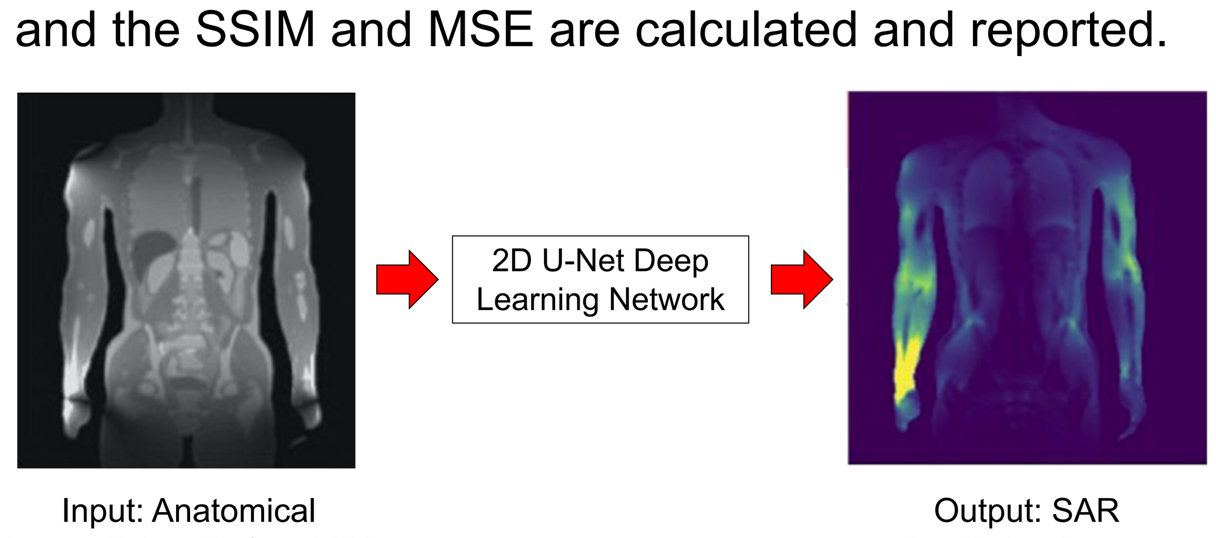

Figure 3: Local SAR hotspots predicted by the 2D U-Net deep learning network given an anatomical image (Gokyar et al., 2021).

Methods

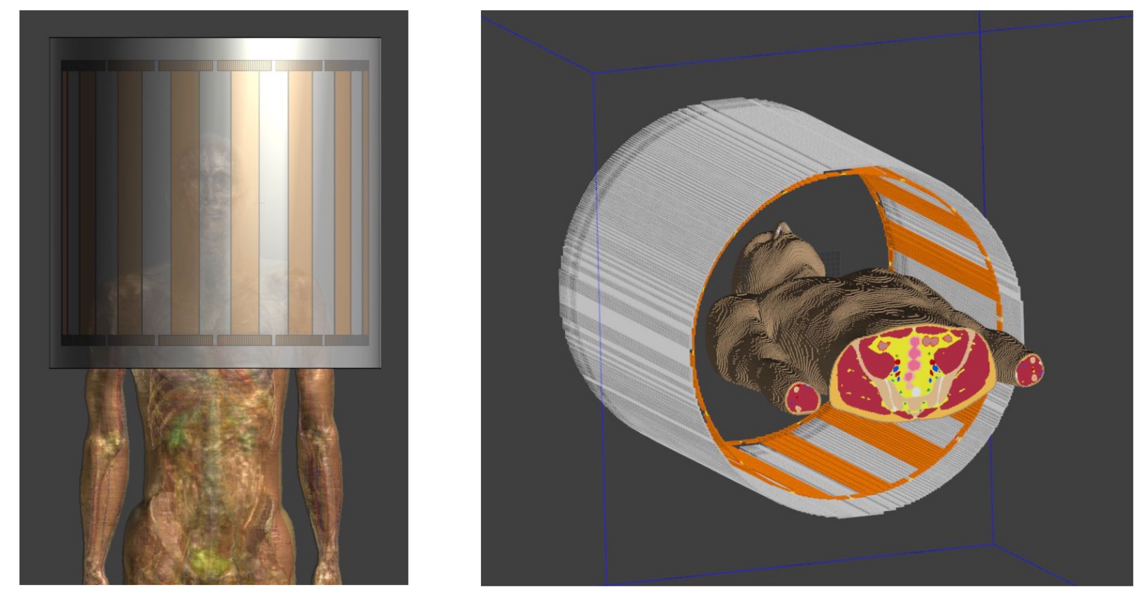

Figure 4: The input data was generated using Sim4Life simulations of 3 body models (Ella, 3-month Pregnant Woman, and Duke) at 3T body dimensions (Moghadam, 2022).

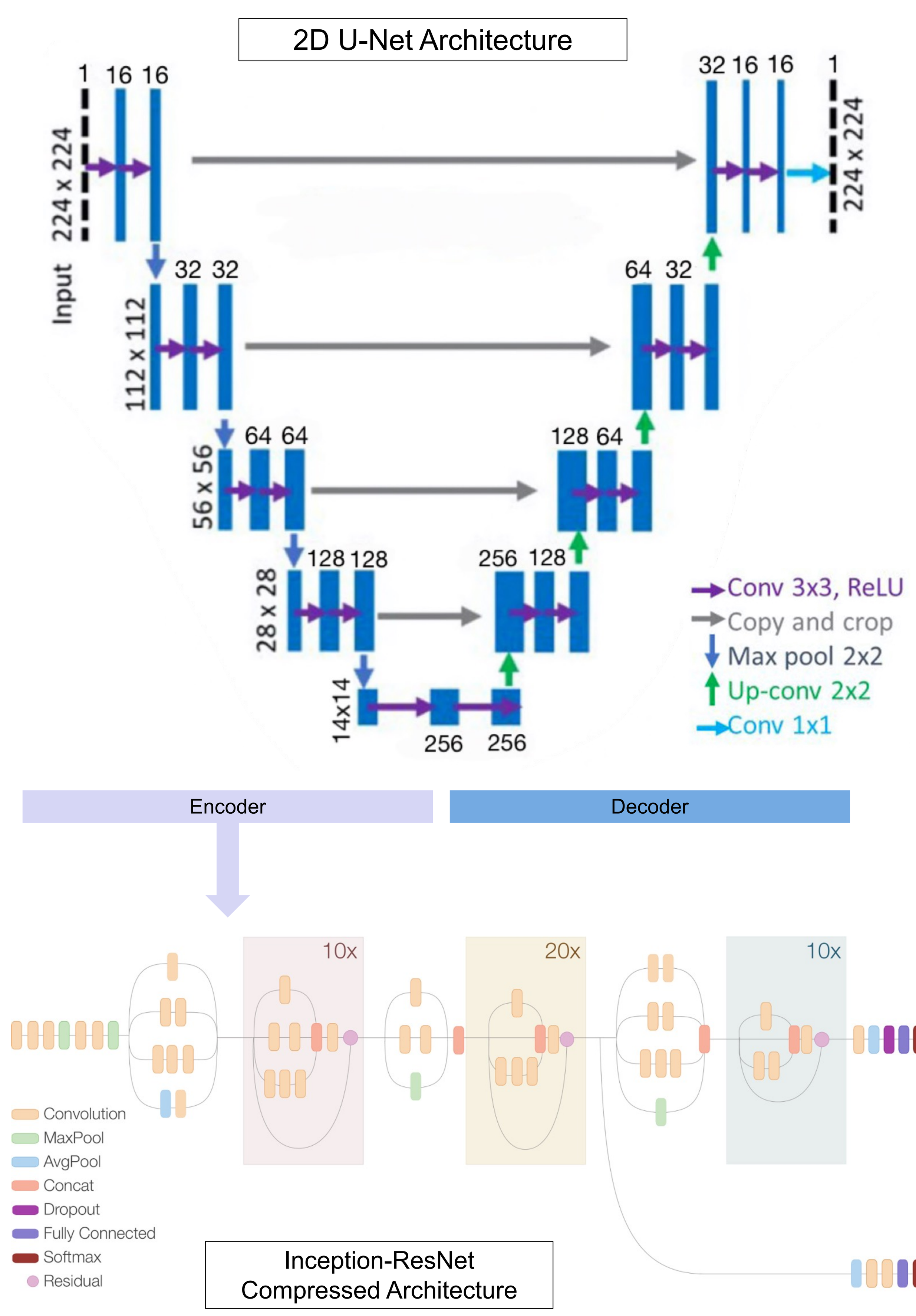

Figure 5: The encoder of the 2D U-Net was replaced with the Inception-ResNet network and the Structural Similarity Index (SSIM) and Mean Squared Error (MSE) for each SAR prediction was calculated (Alemi, 2016).

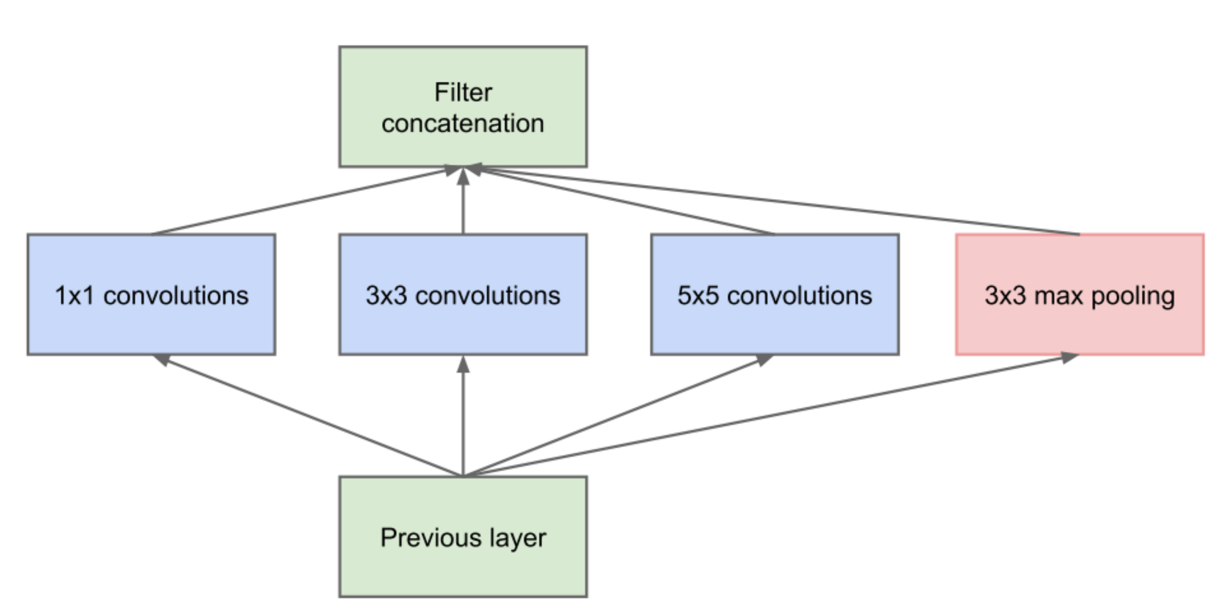

Figure 6: The image input is segmented into outputs of different dimensions due to the various filter sizes provided by Inception. With each layer of the neural network the algorithm chooses which combination of filters produces the most optimal output and concatenates them. This is called optimization and reduces the overall cost function (MSE) and increases the SSIM (Szegedy et al., 2015).

Results

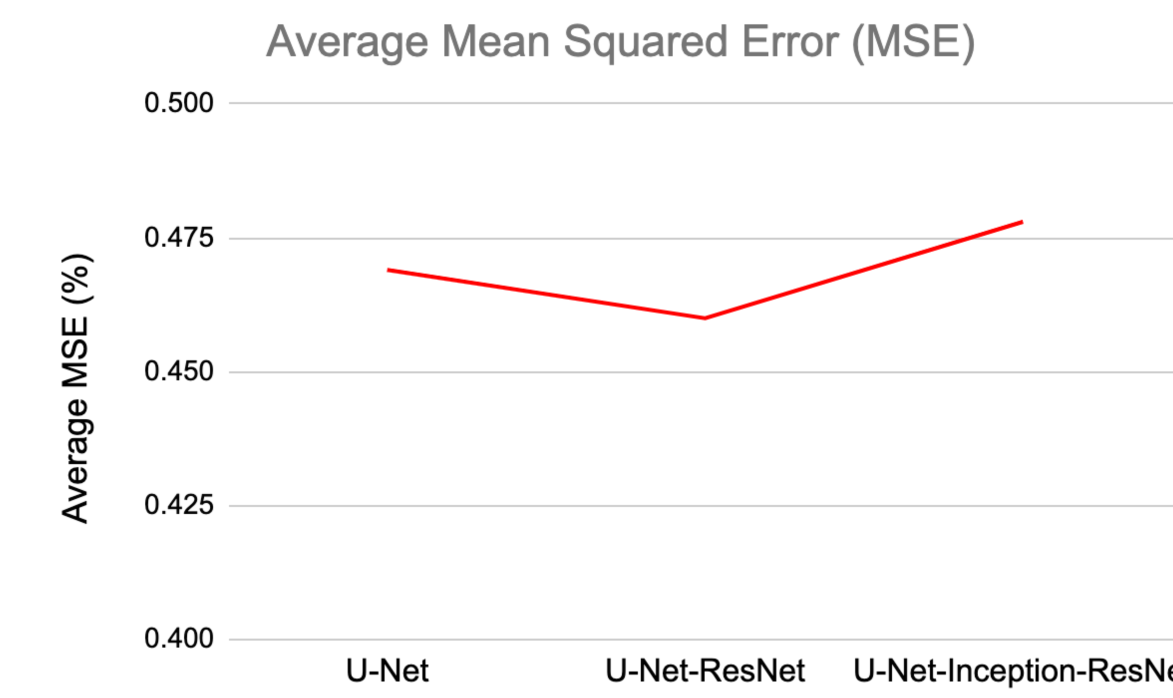

Figure 7: Comparison chart between the average Mean Squared Error (MSE) for the three neural networks.

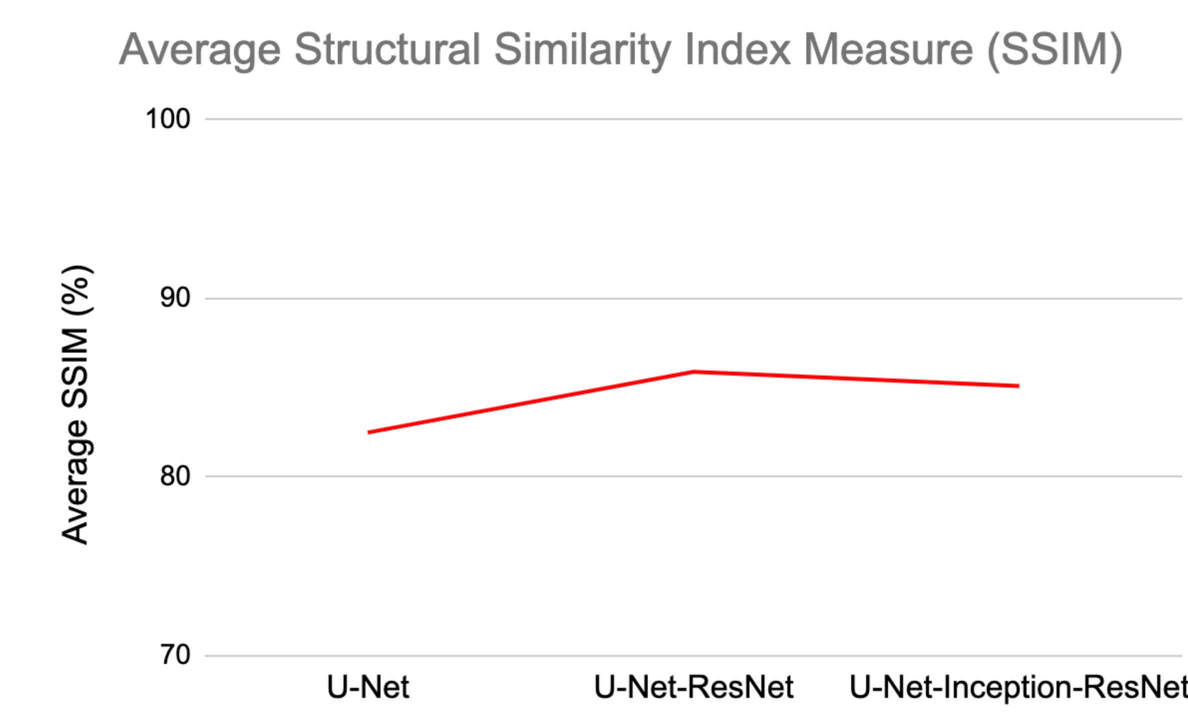

Figure 8: Comparison chart between the average Structural Similarity Index Measure (SSIM) for the three neural networks.

Discussion

This study found that neural networks with more complex architectures may not be ideal for anatomical image segmentation when the training data set is not large or generalized enough. In other words, the deep learning system may not necessarily take advantage of a more intricate model if there is a lack of input data. Compiling and implementing a larger training data set for the neural networks may result in a better SSIM. The deep learning models can also then be used to train and test on data generated by human body models at 7T. Foam padding or insulation can be placed over the patient in areas where local SAR hotspots are predicted. This can help prevent potentially dangerous tissue heating and standardize the clinical use of 7T MRIs.

References

[1] Alemi, A. (2016, August 31). *Improving Inception and Image Classification in TensorFlow*. Google AI Blog.https://ai.googleblog.com/2016/08/improving-inception-and-image.html
[2] C. Szegedy *et al.*, "Going deeper with convolutions," *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015, pp. 1-9, doi: 10.1109/CVPR.2015.7298594.
[3] Gokyar, S., Robb, F., Kainz, W., Chaudhari, A., & Winkler, S. A. (2021). MRSaiFE: An AI-based Approach Towards the Real-Time Prediction of Specific Absorption Rate. *IEEE access : practical innovations, open solutions*, *9*, 140824–140834. https://doi.org/10.1109/access.2021.3118290
[4] Lord, K. (2014, October 16). *New MRI machine may unravel mysteries of stroke*. ABC News. https://www.abc.net.au/news/2014-10-17/new-mri-machine-to-help-unravel-mysteries-of-stroke/5816738

Weill Cornell Medicine
Winkler Lab