Statistical model transfer learning for fNIRS using fMRI-trained CNN models.

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Abstract: One of the challenges of the application of deep learning models to neuroimaging is the need for extremely large (>10,000 participant) datasets for training models. In the case of fNIRS, since each instrument manufacturer and each research lab often use different probe montages and/or collection methods, the availability of very large, homogenous fNIRS datasets is not practical. In this work, we show that we can use model transfer learning to take a convolutional neural network (CNN), which has been pretrained on a very large fMRI dataset and transfer it to fNIRS using a much smaller fNIRS-specific additional training data.

Introduction: Convolutional neural networks (CNNs) are a type of machine deep learning model that have been developed and widely used over the last decade for image classification in computer vision topics. These models typically have dozens to hundreds of layers and millions of model parameters which must be estimated, which requires massive training datasets. One popular such model is the ResNet50 CNN [1], which uses 177 layers and contains 25 million parameters. This model was developed by Microsoft in 2015 using the ImageNet open image database consisting of currently 14 million labeled examples of over 1,000 different image types (e.g. cat, dog, etc.). While training these models fully from scratch requires massive amounts of training data and computational power, model transfer learning methods can be used to transfer a pre-trained model to a different domain. Model transfer is often done by freezing most of the deeper layers of a pre-trained model and then refitting only a few layers of the model using a new dataset. In this way, a model that was trained to recognize (e.g.) cats versus dogs, can be retrained to read MRI images and find tumors (e.g. see [2] for review).

Methods. We used a double model transfer learning approach. First the ResNet50 model was transferred to classify images of functional brain activity from fMRI datasets. Here, we used the open access data available from the Human Connectome Project [3], which consisted of a total of around 1,200 healthy subjects preforming a total of 7 different functional tasks (e.g. working memory, language, motor, theory of mind, etc.) with a total of 27 total functional conditions. This fMRI data was first converted into a two-dimensional image based on projection into the international 10-20 coordinate system. The input and final two layers of the pretrained ResNet50 model are then retrained based on this set of 24,600 fMRI images. Once the ResNet50 model has been transfers to classify brain imaging data using this fMRI sample, the model is transferred again from a fMRI problem to fNIRS data. Using the same E-Prime task paradigms (N-back, Theory of Mind, and Math/Language tasks only for 6 total task conditions) used in the HCP, 13 subjects were collected using fNIRS. First level statistical maps were estimated and similarly converted into 10-20 maps of brain activity. A 13-fold validation approach was used to retrain and test the model.

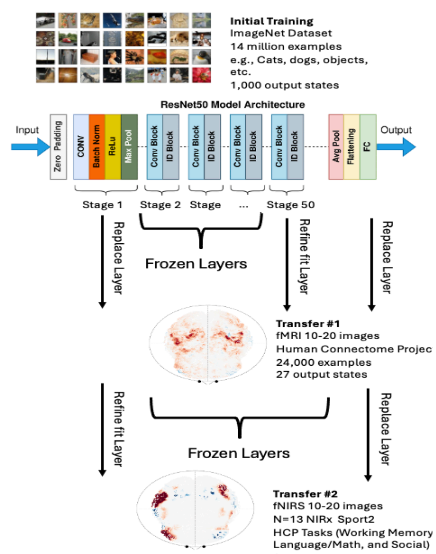

Fig 1. ResNet-50 CNN model and examples of the fMRI and fNIRS training data.

Results. At the fMRI data model (first transfer model), our CNN model is able to obtain 98% classification accuracy on the full 27-way model (random is 3.7%). For the fNIRS model (second transfer model), 72% classification was achieved on the 6-way model (random is 16.7%) using our experimental data.

References: [1]. He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778. 2016. [2]. Valverde, Juan Miguel, et al. "Transfer learning in magnetic resonance brain imaging: a systematic review." Journal of imaging 7.4 (2021): 66. [3]. Van Essen, David C., et al. "The WU-Minn human connectome project: an overview." *Neuroimage* 80 (2013): 62-79.