EXPANDING THE HORIZONS OF REHABILITATIVE NEUROSCIENCE WITH DEEP NEURAL NETWORKS

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I. Background & Significance:

In the summer of 1966, a mathematician[*] first decided to take on the challenge of translating human vision into discrete data structures. More than half a century later, this problem remains unsolved, and yet, through the very attempt of segmenting the human visual system into sub-problems, the field of *deep learning* was born: a branch of machine learning inspired by the design behind our neural networks. By imitating the way humans process visual information, deep neural networks have permanently transformed our everyday lives: from our autonomous vehicles to the image recognition algorithms that run our social media platforms. In the biomedical space, quantifying behavior is extremely time-sensitive; deep learning enables researchers to automate the analysis of videos with a speed and accuracy that surpasses human performance—giving them the potential to speed clinical trials and drug discovery.

II. Objectives & Approach:

In this paper, we will give an overview of the use of neural networks in the realm of rehabilitative neuroscience and of the computational costs required. With an open-source program, "DeepLabCut[**]," we use a pre-existing network primed to detect animal motion; our task is to train this network to recognize mouse forepaw movements and wrist rotations and then quantify performance in a behavioral task. The trained network would then be used to assess behavior in normal mice and injured mice treated with potential therapeutics for paralysis. To improve the accuracy of our model, we evaluated the effect of modifying parameters like depth, learning rate and batch size, and tested competing hypotheses like cyclical learning rates[***], where a temporary risk of a downgrade in performance is permitted for a long-term beneficial output.

III. Outcomes & Future Directions:

Through repetitive training and testing, we were able to identify the parameters at which our network trained most optimally, even if they defied the conventional wisdom regards training neural networks. An interesting future direction would be to heavily augment the dataset used to train the network to identify body parts—an approach that would prime the network to become foolproof through intermittent image distortions (rotations, matrix shears, light adjustments, etc.) that humans could easily see but easily destroy even the most robust neural network's ability to make an accurate prediction.

[*] The Summer Vision Project, by Papert, Seymour A.
[**] Mathis A, Mamidanna P, Cury KM, Abe T, Murthy VN, Mathis MW, Bethge M. DeepLabCut: markerless pose estimation of user-defined body parts with deep learning. Nat Neurosci. 2018 Sept. 21
[***]Leslie N. Smith: Cyclical Learning Rates for Training Neural Networks, eprint={1506.01186}, arXiv 201

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