Please accept this submission in response to your invitation:

On behalf of the National Institutes of Health (NIH) BD2K program, we are inviting you to participate in the upcoming annual International Society for Computational Biology meeting, ISMB 2018 in Chicago, IL. BD2K will be hosting several exciting sessions on July 7th-8th, highlighting talks from NIH officials around biomedical data science, BD2K projects, and training programs. Example sessions will include:

* BD2K Power Tools: Faster, Cheaper, Better
* Building the FAIR Data Ecosystem from the Ground Up
* Advancing Biomedical Sciences through Machine Learning

**Affiliated BD2K Project:** Automatic discovery and processing of EEG cohorts from clinical records

**BD2K Grant Number:** U01HG008468

**Letter of Support:** PIs Obeid and Picone are co-PIs on this project and co-authors on this submission.

**Abstract:**

**Deep Residual Learning for Automatic Seizure Detection**

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Automated seizure detection using clinical electroencephalograms (EEGs) is a challenging machine learning problem due to several factors such as low signal to noise ratios, signal artifacts and benign variants. Commercially available seizure detection systems suffer from unacceptably high false alarm rates. Deep learning algorithms, like Convolutional Neural Networks (CNNs), have not previously been effective due to the lack of big data resources. A significant big data resource, known as TUH EEG Corpus, has recently become available for EEG interpretation creating a unique opportunity to advance technology using CNNs. The depth of a CNN is of crucial importance. State of the art results can be achieved by exploiting very deep models, but very deep models are prone to degradation in performance with respect to generalization and suffer from convergence problems. In this study, a deep residual learning framework is introduced that mitigates these problems by reformulating the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. This architecture delivers 30% sensitivity at 16 false alarms per 24 hours. This architecture enables designing deeper architectures that are easier to optimize and can achieve better performance than prior state of the art.