Supplementary Material

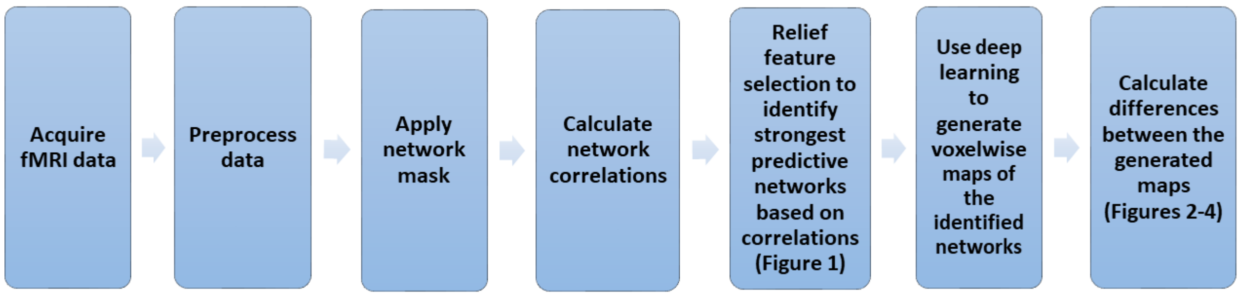
Relief Algorithm

The Relief algorithms detect conditional dependencies between attributes using a nearest neighbor approach, with features ranked by estimating how well each value distinguish between proximal comparisons. The Relief algorithm is both non-myopic and non-parametric, meaning they estimate the quality of a given feature in the context of other features, and make no assumptions regarding the distribution or sample size[1–3]. The Relief algorithm increments feature weights by the probability of the feature having different value in the neighborhood of an instance of a differing class, and decrements feature weights by the probability of the feature having different value in the neighborhood of an instance from the same class.

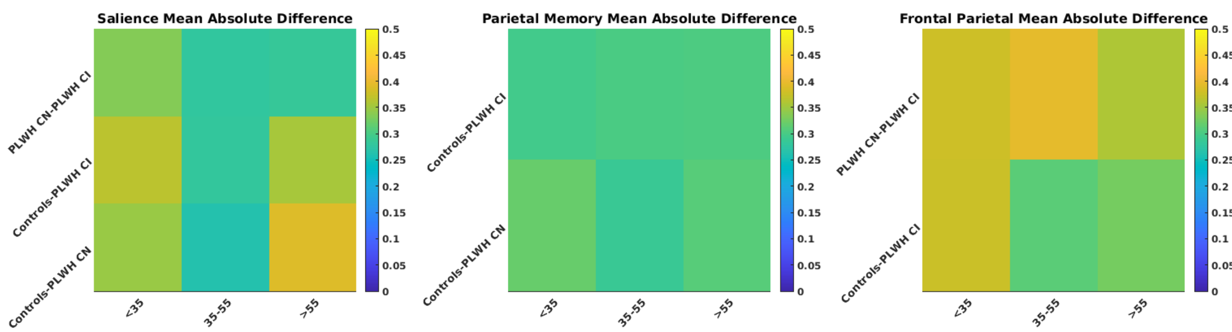
Deep learning

A total of 1,313,140 training instances were generated across all RSNs. Further, within each class 20% of the training instances were augmented by a combination of random affine transformations (rotations (±5 degrees), translations (±3 pixels), scaling (between 0.9-1.1), sheering (±3 degrees), and adding Gaussian noise (±.1)). Application of this data augmentation method has been previously demonstrated to improve out-of-sample testing and prevent overfitting[4–6]. Because the number of samples from each class (network) were not even, the 3DCNN used a cross entropy loss function with weighted classification such that each class contributed equally. This scheme will tend to deemphasize large networks (such as the DMN) and weight more heavily smaller RSNs (such as PMN). The class weights were set at: 0.25 SMD, 0.90 SML, 0.47 CON, 0.47 AUD, 0.27 DMN, 2.41 PMN, 0.47 VIS, 0.45 FPN, 0.35 SAL, 0.52 VAN, 0.52 DAN, 2.97 MET, 3.81 REW, 0.47 BGN, 0.27 THA. Twenty percent of the generated data was reserved for validation. Training terminated if the accuracy did not improve after three validations.

For inference, BOLD data from participants were inputted to the trained 3DCNN. The output comprised 15 spatial maps of the probability of classification to each of the 15 canonical RSNs. The response conditions included comparisons of the medical status of participants: HIV- minus HIV+ CN, HIV- minus HIV+ CI, and HIV+ CN minus HIV+ CI. Response conditions were also partitioned according to age: under 35 years, between 35 and 55 years, over 55 years. For each response condition, the highest-ranking features found by the Relief algorithm were selected from the spatial maps of probability for the 15 RSNs. For each compared medical status and for each age group, the probability maps selected by the Relief algorithm were compared by subtraction. In the probabilistic interpretation, as the number of neighbors increases to include all of the available data, feature weights simplify such that contextual information from features is lost and features become myopic. In contradistinction from the Relief algorithm, 3DCNN comparison results are probabilities inferred using data from all neighbors available in the data. That is, the Relief step of the analysis pipeline provides non-myopic results for the RSNs. Subsequently, the 3DCNN step of the analysis pipeline provides myopic results over voxels. The serial arrangement of feature selection followed by model induction has information retrieval benefits[1] for the probabilistic interpretation of weights generated by the Relief algorithm and subsequent 3DCNN comparisons.



Supplemental Figure 1: Flow chart outlining analysis process used in this research.



Supplemental Figure 2: Mean absolute difference heat maps associated with Figures 2-4. Due to the difference in network sizes, only non-zero voxels were considered when calculating the mean absolute difference for each network.

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