In this dissertation we aim to solve the problem of automatic diagnosis of the Attention Deficit Hyperactive Disorder (ADHD) affected subjects using their resting state functional Magnetic Resonance Imaging (rs-fMRI) data of brain. The problem is of importance as around 5-10% of the children all over the world are diagnosed with ADHD. In our approach, we model the functions of a brain as a connectivity network, which is expected to capture the information about how synchronous different brain regions are in terms of their functional activities.

We developed a simple method employing the Bag-of-Words (BoW) framework for the classification of the ADHD subjects. We represent each node in the connectivity network by a 4-D feature vector: 3-D location and the node degree. The final BoW representation of each subject is a histogram of node representations. The method is able to achieve 64% classification accuracy on the ADHD-200 data set. However, one major shortcoming of this approach is the use of features from the whole brain, which may not contain useful information.

In order to address the above shortcoming, we hypothesize that only a subset of the nodes of the network possesses important information. To identify the important nodes of the network, we developed a novel algorithm, which generates different random subset of nodes each time extracting the features from a subset to compute the feature vectors and perform classification. The subsets are then ranked based on the classification accuracy and the occurrences of each node in the top ranked subsets are measured. We improved the classification accuracy to 69.59% using this approach. One limitation of the approach is that the network features, which are computed for each node of the network, capture only the local structures ignoring the global topology of the network. Also, our method represents each voxel as a node which makes the node count of the network several thousand and increase the computational cost.

Next, in order to capture the global structure of the networks, we use Multi-Dimensional Scaling (MDS) technique to project all the subjects from an unknown network-space to a low dimensional space based on their inter-network distance measures. To reduce the network computation cost, the nodes of the network are constructed from clusters of highly active functionally homogeneous voxels which help to preserve the maximum relevant information with minimum redundancy. We achieve impressive classification accuracy (73.55%) using this method.

Finally, unlike our approach so far, we explored if structural brain images contain any useful information related to the diagnosis problem. Towards this end, we developed a new method to combine the information of structural and functional brain images in a late fusion framework. For structural data we use gray matter (GM) images of brain to input in a convolutional neural network (CNN). For the functional data we compute the average power of each voxel based on its fMRI time series. We achieve an accuracy of 79.14% using combined information.
The public is welcome to attend.