Leveraging Temporal Information to better understand Alzheimer's Disease Diagnosis

Stanford CS231N Project Proposal

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1 Problem Motivation and Formulation

Magnetic resonance imaging (MRIs) on human brain have been one of the most critical method for diagnosing neurological diseases like Alzheimer's Disease (AD), as an extremely important indicator of AD is that there's usually a much faster brain deterioration trend presented for patients' brain compared to the normal ones. While modern ML technique gains huge success on analyzing MR images to help disease diagnosis, one main challenge is to study on Longitudinal MR brain image dataset. New difficulties not only lies on how to attain higher diagnosis accuracy by leveraging temporal information, but also lies on the interpretability of the result obtained by ML models.

To better utilize the temporal information, we plan to use a hybrid model involving CNN for individual image spatial feature extraction and RNN for temporal analysis across a series of images. Meanwhile, to attain better interpretability, we will explore new techniques such as new regularization loss terms to help maintain consistency among data during time. To evaluate our method, an AD/non-AD classification task will be run to see if higher accuracy is reached.

2 Research Paper Review

There has been many related research performed in this area. A early paper "Long-term Recurrent Convolutional Networks for Visual Recognition and Description", published in 2014, proposed a class of CNN-LSTM end-to-end trainable neural network suitable for large-scale visual understanding tasks, such as activity recognition.[1] One of the more recent paper "Recurrent Neural Networks with Longitudinal Pooling and Consistency Regularization", published in early 2020, has proposed novel longitudinal pooling and consistency regularization techniques to specifically focus on AD classification task through series of temporal MRI images for each individual patients.[2]

3 Project description

Data. We will use 3D fMRI data in Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset to study the long-term progression of Alzheimer's disease. The dataset contains 811 subjects (patients/control), with around 198 AD subjects, 229 Normal Control subjects, and 384 MCI subjects. Each subject will have 1-7 MR images, with time range from 3 months to 48 months. To better acquire the trend of brain structure/function deterioration, we choose images at time 0 month(baseline), 12 months, 24 months, 36 months, 48 months (if available). After data processing procedure, the format of each MR image will be 64*64*64.

Methods. As the input of our model is a sequence of MRIs of a person's brain and the length of the sequence varies among cases, we propose a CNN-RNN architecture. The CNN acts as a feature extractor on each individual image. We will explore on new ways to help the data maintain consistency during time such as adding new regularization term to the latent feature vector space or adding new layer operations. The extracted feature vector of each image in a sequence is then fed into a RNN to build a representation of the brain change trajectory over time. The overall representation of the MRI sequence is then used to classify a case as AD and non-AD.

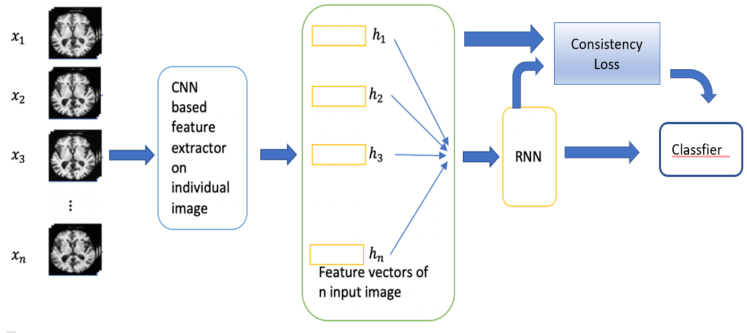

Figure 1: High-level model diagram

Evaluation. The first objective is to train a classifier that, given a sequence of MRI images of a brain, predicts the presence of AD. Considering the potential class imbalance of training and testing data, we plan to use a confusion matrix to analyze the performance of our AD classifier. We will also compare the performance of the model that leverages the temporal information embedded in the image sequence to a baseline model that only uses one image to do the classification

For better interpretability, we also plan to visualize the trend in change of brain MRIs for both AD and non-AD people. The relationship between the length of a sequence and classification accuracy is also of interest to us.

References

[1] Jeff Donahue, Lisa Anne Hendricks, Marcus Rohrbach, Subhashini Venugopalan, Sergio Guadarrama, Kate Saenko, and Trevor Darrell. Long-term recurrent convolutional networks for visual recognition and description, 2014.

[2] Jiahong Ouyang, Qingyu Zhao, Edith V Sullivan, Adolf Pfefferbaum, Susan F. Tapert, Ehsan Adeli, and Kilian M Pohl. Recurrent neural networks with longitudinal pooling and consistency regularization, 2020.