Alzheimer’s disease (AD) is an incurable, progressive neurological brain disorder and is the 6th leading cause of death in the USA. Magnetic resonance imaging (MRI) is a technique used to diagnose Alzheimer’s disease in patients. Highly skilled and experienced doctors are currently required to make a decision on the health status of a patient which could be costly. There are no simple machine learning algorithms which could detect AD from MRI, we want to use deep learning to diagnose AD by using promising architectures for 3D brain images.

Challenges: Lack of preprocessed data, high dimensional input

Healthcare: Alzheimer’s Disease Stage Diagnosis, Applying 3D Convolutional Neural Networks to MRI Brain Scans

Utkarsh Tandon, Ben Moore, Mohammadhossein Shafinia

Introduction

- Alzheimer’s disease (AD) is an incurable, progressive neurological brain disorder and is the 6th leading cause of death in the USA.
- Magnetic resonance imaging (MRI) is a technique used to diagnose Alzheimer’s disease in patients.
- Highly skilled and experienced doctors are currently required to make a decision on the health status of a patient which could be costly.
- There are no simple machine learning algorithms which could detect AD from MRI, we want to use deep learning to diagnose AD by using promising architectures for 3D brain images.

Approach:

- Preprocess Data
- Autoencoder
- Transfer Learning
- 3D CNN
- Measure Prediction Accuracy
- Visualize Saliency

Dataset and Features

- ADNI is currently the largest publicly available dataset for Alzheimer’s Disease - 600 unique subjects accounting for roughly 2300 scans in total.
- Many subjects are scanned multiple times over a 3 year span in an attempt to highlight longitudinal changes.
- Subjects are classified as either AD (Alzheimer’s Disease), MCI (Mild Cognitive Impairment), or NC (Normal Control).
- Data is considered “processed” by ADNI (MPRAGE).
- MRI: 3D voxel array format
- Varying dimensions, voxel intensities, and acquisition parameters (RAW).

Model Training

VoxCNN Architecture

- Input Layer

Hyperparameters: Learning Rate = 27*10^-6, Batch Size = 10, Optimizer = Adam, Loss = Cross-entropy

Autoencoder Architecture

- 3D ResNet:
- Architectures
  - Voxnet CNN
  - 3D & 2D Resnet
  - Ground up 3D & 2D CNN
- Autoencoder
- Over complete
- Loss functions:
  - Cross-entropy
  - Kullback-Leibler divergence

Hyperparameter tuning:
- Learning rate
- Adam parameters
- Hidden units
- Batch size
- Regularization
- Weights
- Dropout
- Frozen (non trainable) Layers

Results

- Table 1: Model performance comparison
  - Accuracy (%) F1 Total F1 HC F1 AD
  - VoxCNN: 85.63 0.81 0.78 0.81
  - 2D Resnet: 86.97 0.82 0.86 0.82
  - 3D Resnet: 83.53 0.74 0.88 0.74
  - 3D CNN Baseline: 69.96 0.67 0.72 0.69

Analysis 2D Transfer Learning Saliency

- The class activation map shown above visualizes the attention of the model over the input by taking gradients with respect to the second to last layer.
- This enables the retention of spatial information in the map before it enters the dense layer.
- Bottom right: Can see that the model is focusing on matter in the hippocampus region and in the other layers we can see that the model is looking at areas of general white matter decay which are indicative of Alzheimer’s disease.
- 3D attention maps would also hopefully highlight the same information, although they are much harder to visualize.

Conclusion

- Several approaches to tackle the problem
- 3D CNNs the VoxCNN algorithm had the best results
- The 3D ResNet also had comparable accuracies however the result on validation set fluctuates
- The transfer learning provided us with the best accuracy (87%) due to the ability to augment our data easily using 2D generators.
- Autoencoder couldn’t perform well as the architecture was minimal under memory constraints - leading to poor encodings.

Future works

- Manually preprocess and clean more data
- Increase the autoencoder’s capacity so that it can properly translate encoded info down the network.

References: