NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

School of Computer Science and Engineering
College of Engineering

Pruning deep neural networks

for encoding and decoding the human connectome

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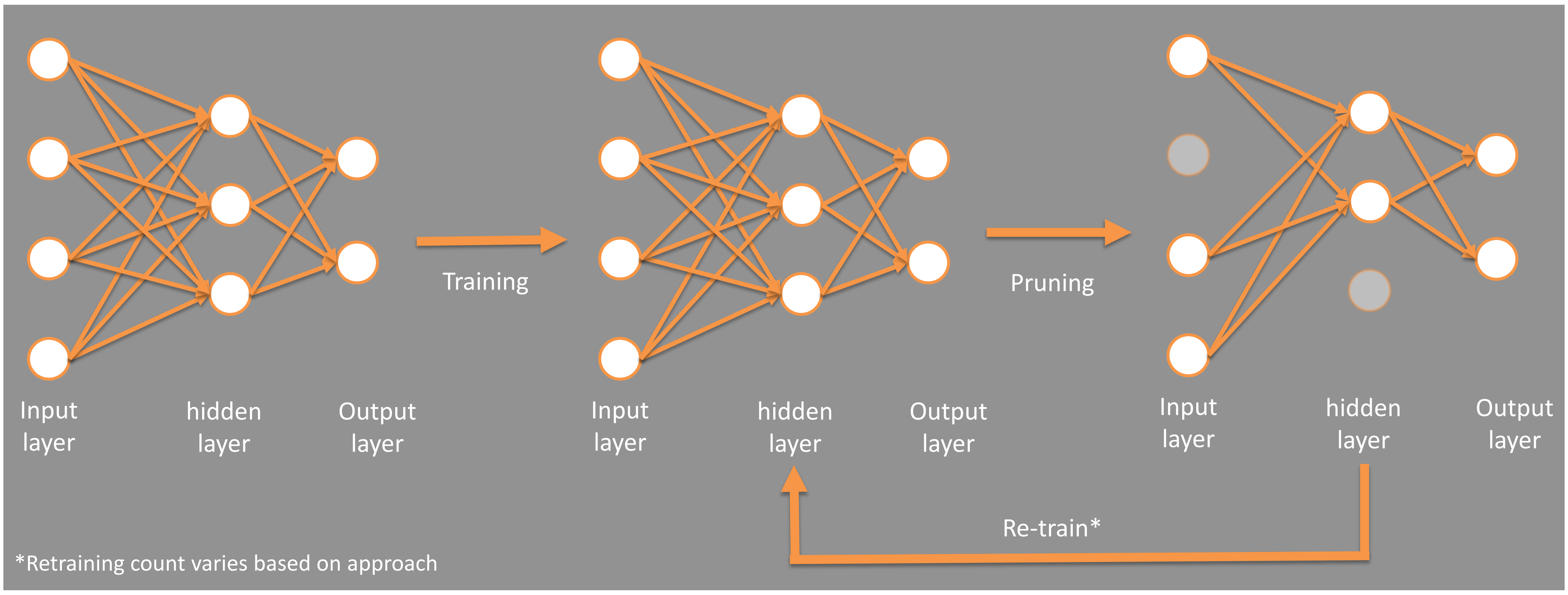

Project Objectives:

The main focus of this project is to identify biomarkers of neurodegenerative disorders such as Alzheimer's Disease (AD) and Parkinson's Disease (PD) in functional Magnetic Resonance Imaging (fMRI) scans. Deep learning models can be used to encode the human functional connectome and classify between healthy subjects and patients with diseases, followed by a decoding process to identify salient features used in the classification. However, fMRI datasets have much more features than data samples, causing models to overfit easily. Existing solutions involving pruning the neural network range from recursive feature elimination which is too slow to a one-shot pruning approach which prunes too harshly. Thus, this project will explore the viability of improved pruning methodologies to attain an improved, sparser architecture. This project also goes beyond existing work on pruning multi-layer perceptron (MLP) to propose pruning approach for convolutional neural network (CNN), which can take in dynamic functional connectivity (dFC) matrices, as well as graph convolutional network (GCN), which is a better fit for encoding functional connectomes. The pruning algorithms proposed can also generalise to non-neuroimaging datasets, which is demonstrated by applying them to datasets like MNIST, CIFAR-10 and the CORA dataset, suggesting applications beyond the initial scope defined by this project.

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Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 50)                1735850
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dropout_1 (Dropout)          (None, 50)                0
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dense_2 (Dense)              (None, 32)                1632
_________________________________________________________________
dropout_2 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_3 (Dense)              (None, 32)                1056
_________________________________________________________________
dropout_3 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_4 (Dense)              (None, 2)                 66
_________________________________________________________________
activation_1 (Activation)    (None, 2)                 0
=================================================================
Total params: 1,738,604
Trainable params: 1,738,604
Non-trainable params: 0
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Experiment	Brief description
LEAN	Re implementation of LEAN algorithm
Multiplier test	Test to confirm validity of LEAN architecture
iLEAN	iterative approach of LEAN; prune from last hidden layer to input, one layer per iteration, retraining in between each iteration
Lottery ticket hypothesis	Test to show that reinitlaising the model's original weights improves post pruned accuracy
SiLEAN	Single iterative LEAN apporach; prne all hidden layers in the first iteration, retrain, then prune the input layer in the next iteration
CCNN (edges)	Adoption of LEAN methodology for CCNN architecture; prune by the importance score of each edge in adjacency matrix
CCNN (nodes)	Adoption of LEAN methodology for CCNN architecture; prune by the summed importance score of each node in adjacency matrix
CLEAN	Mulit channel approach of CCNN; allows us to split a single data entry into several discrete portions, retaining more temporal information
GCN	A graph convolutional network approach whereby we incorporate both imaging data (fMRI) as well as non imaging data (gender, age etc.).