Deep Learning based Classification of FDG-PET Data for Alzheimer's Disease Categories

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Introduction

Alzheimer's Disease (AD), a neurodegenerative disease is a progressive disease that affects the brain gradually with time and worsens. Reliable and early diagnosis of AD and its prodromal stages (i.e. Mild Cognitive Impairment(MCI)) is essential. Deep learning has recently been applied to the analysis of structural and functional brain imaging data [1]. Here we introduce a deep learning based classification using neural networks with dimensionality reduction techniques to classify the different stages of AD based on FDG-PET image analysis. We also experiment with demographic features and neural network configurations to attain better classification accuracies.

Methods

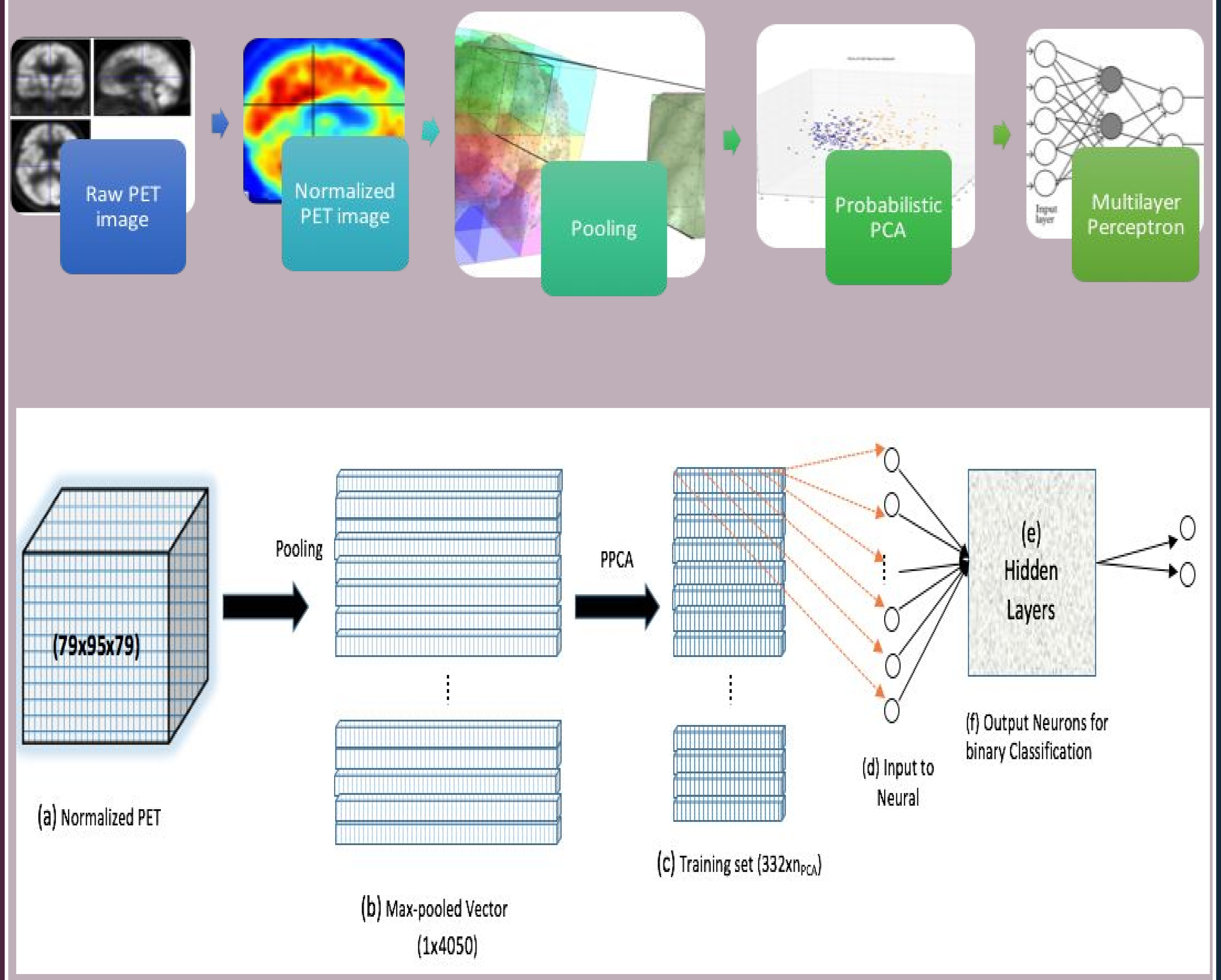

Figure 1. The pipelines (Classification and Multilayer Perceptron)

Processing Pipeline

1. The image is preprocessed and normalized to a common space. It is further max-pooled to reduce feature dimensionality.
2. Linear SVM is used to measure the extent of linear separability between features from different categories.
3. The features are further reduced to enhance classifier performance using probabilistic principal component analysis.
4. These are then passed through the simplest of all neural networks, a multi-layer perceptron for binary classification experiments
5. 10 fold cross validation is used to validate classifier performance.
6. An iterative algorithm is also devised to enhance the performance of an n-layered multi-layered perceptron.

Experiments

668 baseline patients were studied from the ADNI (Alzheimer's Disease Neuroimaging Initiative) [2]. Since EMCI, LMCI and NC features are not linearly separable, using Rectified Linear Units in the neural network induces sparsity in feature representation for network layers, enhancing linear separability. Increasing the number of hidden layers results into better classification of some classes. Max-pooled features values outperform mean-pooled feature values. Patch size of 10x10x10 was selected after varying the patch sizes from 5 to 15 to select the best size for AD/CU. The addition of demographic features such as Age, Gender, APOE (gene information) and FAQ (Functional Assessment Questionnaire) scores significantly improved performance as shown in Table 1.

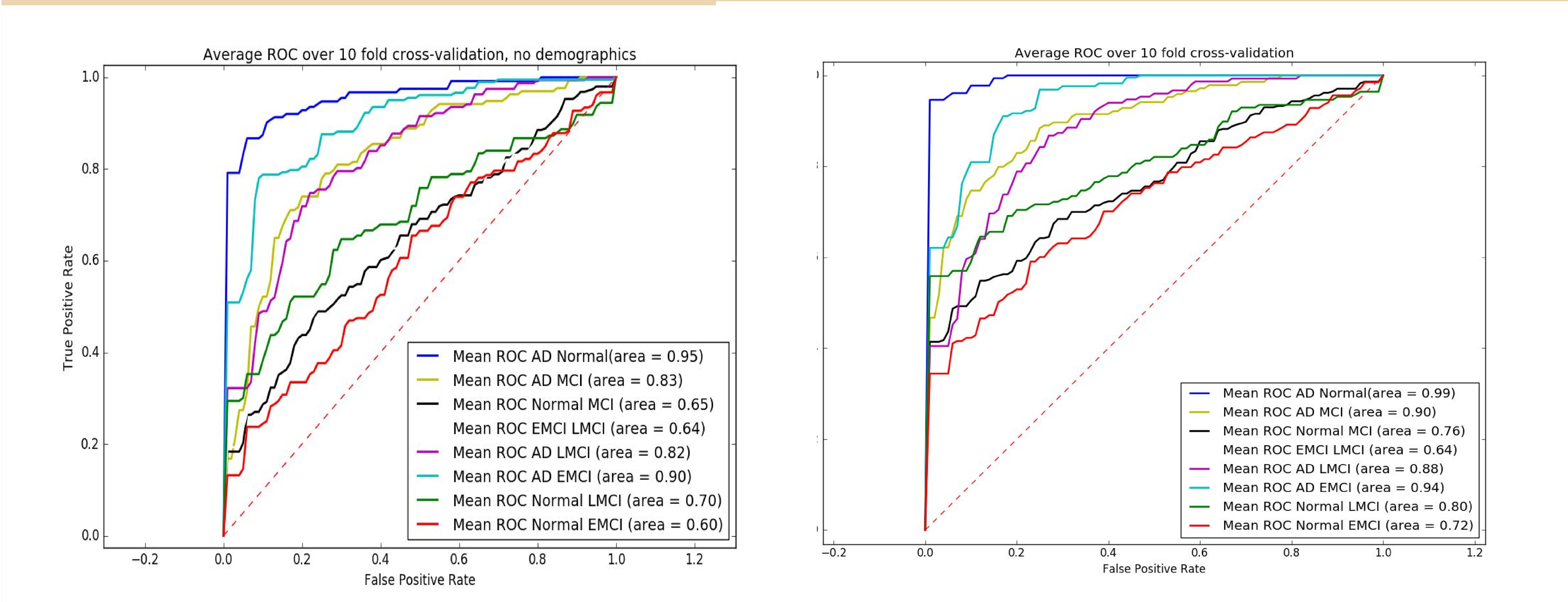

Figure 2. Comparison of the classification performance with addition of demographic features

Data	Measure	AD/CU	AD/MCI	CU/MCI	AD/EMCI	AD/LMCI	CU/LMCI	CU/EMCI	LMCI/EMCI
Max-pooled	F-1 Score	0.94	0.87	0.75	0.87	0.77	0.69	0.63	**0.68**
Max-pooled with Demographic data	F-1 Score	**0.98**	**0.91**	**0.79**	**0.90**	**0.82**	**0.83**	**0.72**	0.65

Table 1. Summary of results

Discussion

As per the Universal Approximation theorem, we should be able to find a 1-hidden layer MLP that perfectly fits over the given data. Regional analysis can further be done using Grid Long Short Term Memory (LSTM) and Parallel LSTM to enhance accuracies. Instead of PPCA, deep learning architectures could be used to learn high level feature abstractions. Other diseases could also be classified using the architecture proposed.

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2. Weiner, M.W., et al., The Alzheimer's Disease Neuroimaging Initiative: a review of papers published since its inception. Alzheimers Dement, 2012. 8(1 Suppl):p. S1-68.