Alzheimer’s Disease Detection using Deep Learning

NeuroGnosis

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Motivation

- Alzheimer's disease (AD) is an irreversible and progressive neurodegenerative disorder that gradually impairs memory, communication, and daily activities like speech and mobility.
- Early detection of AD is crucial for timely intervention and management of the disease can result in significant quality of life improvements.
- Advanced techniques like machine learning hold promise for accurate, early AD detection compared to the traditional methods.

Machine Learning for Early AD Detection

- Traditional models like SVMs, decision trees, and random forests applied to MRI features can distinguish AD from cognitively normal (CN), but struggle with mild cognitive impairment (MCI).
- Deep learning techniques automatically learning from raw 3D MRI data have outperformed traditional approaches and shown better generalization.
- Combining multiple modalities like MRI, PET, CSF, genetics, and cognitive tests can further boost diagnostic performance, but increases complexity.

Research | Open access | Published: 03 August 2022

Early diagnosis of Alzheimer's disease using machine learning: a multi-diagnostic, generalizable approach

Vasco Sá Diogo, Hugo Alexandre Ferreira & Diana Prata for the Alzheimer's Disease Neuroimaging Initiative

Article | Open access | Published: 17 October 2022

Generalizable deep learning model for early Alzheimer's disease detection from structural MRIs

Sheng Liu, Arjun V. Masurkar, Henry Rusinek, Jingyun Chen, Ben Zhang, Weicheng Zhu, Carlos Fernandez-Granda & Narges Razavian

Previous Work

- Traditional machine learning models like support vector machines and logistic regression achieved around 65-80% AUC for the MCI vs CN task.
- While progress has been made, accurately distinguishing MCI from cognitively normal individuals using machine learning on neuroimaging and multimodal data is an ongoing challenge that requires further research and validation.

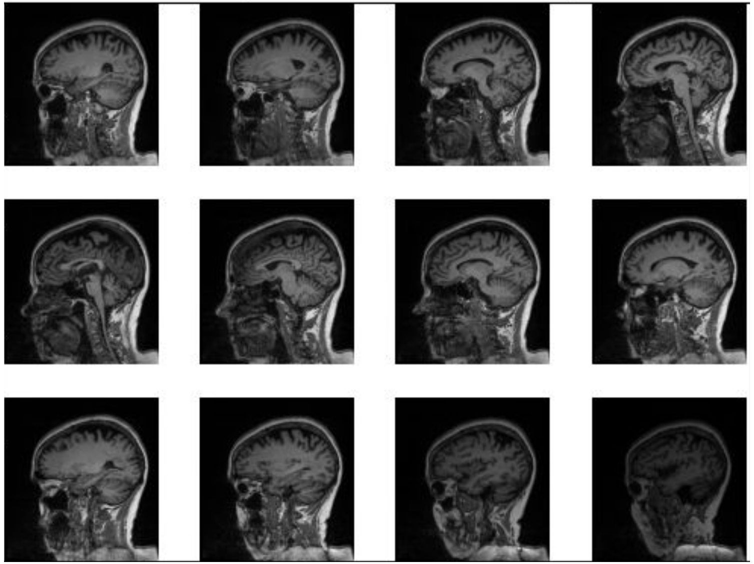
Application	Model	group	Acc	AUC	Spe	Sen
CN vs MCI	linear SVM	ac-SLIC	0.691	0.793	0.531	0.817
	group lasso SVM + SAR		0.708	0.779	0.691	0.721
MCIs vs MCIc	linear SVM	ac-SLIC	0.615	0.675	0.597	0.649
	group lasso SVM + SAR		0.654	0.683	0.642	0.676
MCI vs AD	linear SVM	ac-SLIC	0.639	0.705	0.673	0.588
	group lasso SVM + SAR		0.657	0.705	0.673	0.632

https://www.sciencedirect.com/science/article/pii/S1053811918304658?via%3Dihub

Dataset Description

- Alzheimer's Disease Neuroimaging Initiative (ADNI) is a landmark longitudinal study.
- ADNI collects multimodal data including MRI, PET, CSF biomarkers, genetics, and cognitive assessments.
- We used "Accelerated Sagittal MPRage MRI" scans from ADNI3 study.
- Our dataset contains total number of 183 MCI (Mild Cognitive Impairment) and 378 CN (Cognitively Normal) subjects.
- This dataset contains multiple MRI sessions for some of the subjects in different dates.
- Each MRI session has ~200 slices of the brain.

Some example slices from a random patient

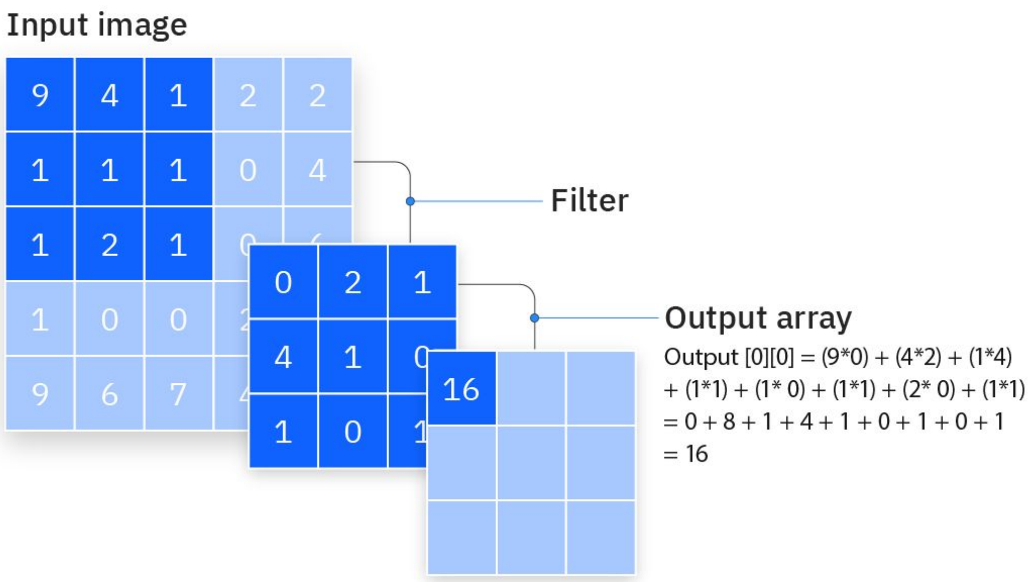


Data Preparation

- As some subjects had multiple sessions of MRI scanning, so we kept only one session per patient.
- From each session, we only used the middle 65 slices after ordering them accordingly, and converting them to pixel arrays.
- Each data point corresponds to a subject's MRI scans in one session.
- We split train/validation/test set (70/15/15).

Convolutional Neural Networks (CNNs)

- CNNs are a type of deep learning architecture primarily used for image and video analysis tasks.
- They excel at automatically learning the summarized features from raw pixel data.



CNNs: Key Components

Convolutional Layers:

- Apply learnable filters (kernels) to the input image to extract local features.
- Filters slide over the input (stride determines the step size), performing element-wise multiplications and summing the results.
- Capture spatial dependencies and learn translation-invariant features.

Pooling Layers:

- Downsample the spatial dimensions of the feature maps.
- Commonly used pooling operations include max pooling and average pooling.
- Help to reduce computational complexity and provide translation invariance.

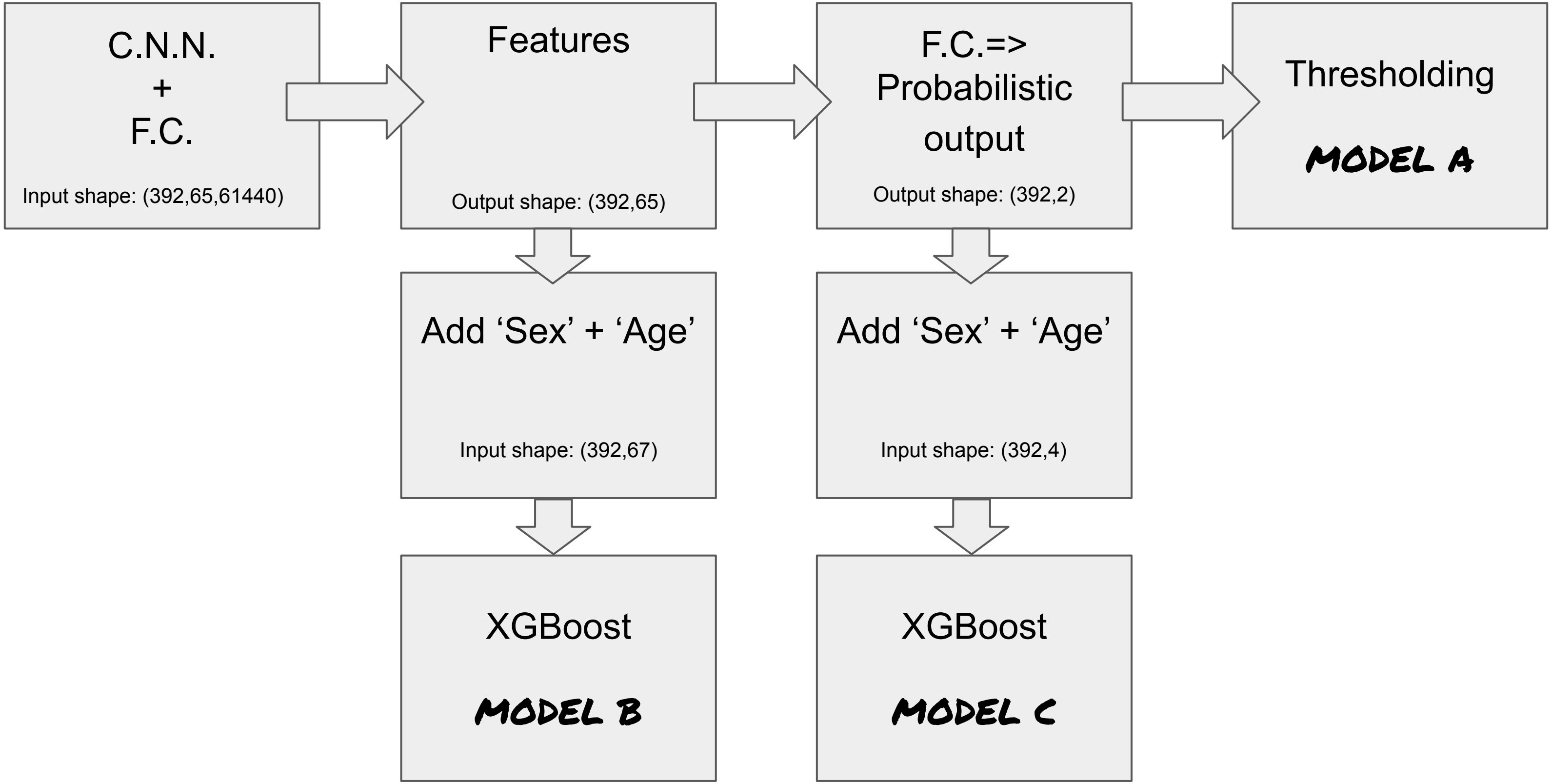
Activation Functions:

- Apply non-linear transformations to the output of convolutional layers.
- Common activation functions include ReLU (Rectified Linear Unit), sigmoid, and tanh.
- Introduce non-linearity, allowing the network to learn complex patterns.

Fully Connected (FC) Layers:

- Flatten the output of the convolutional and pooling layers into a 1D vector.
- Connect neurons in the current layer to all neurons in the previous layer.
- Perform high-level reasoning and classify the extracted features.

Different Models



Model Performance Report

AUC graph/table comparison of the model variations

	Accuracy	AUC	Precision	Recall	F1	Regularization
CNN+FC	0.62	0.58	[0.69,0.48]	[0.72,0.45]	[0.7,0.47]	L1 + Dropout + Weighted loss function
CNN+XGB	0.63	0.61	[0.71, 0.5]	[0.7, 0.52]	[0.7, 0.51]	Weighted loss function
CNN+FC+XGB	0.65	0.59	[0.68, 0.56]	[0.85,0.32]	[0.76, 0.41]	L1 + L2 + Dropout + Weighted loss function

Next steps:

To further enhance the impact and robustness of the Alzheimer's disease prediction model, several future directions are proposed:

- Preprocessing Improvements: Explore additional preprocessing techniques to improve the quality and information content of the MRI scans.
- Model Optimization: Experiment with different CNN architectures, hyperparameter tuning, and ensemble techniques to improve model performance.
- Multi-Modal Approach: Incorporate other types of data, such as clinical information, genetic data, or cognitive test results, to provide a more comprehensive understanding of Alzheimer's disease and potentially enhance prediction accuracy.
- Dataset Expansion: Expand the dataset to include more diverse samples and stages of Alzheimer's disease, ensuring the model's generalizability and robustness.

THANK YOU

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- XGBoost Documentation