Classification of Prodromal Alzheimer's Disease using Multimodal Neuroimages based on Deep Learning

Team E

CNI Lab, SIIT Lab

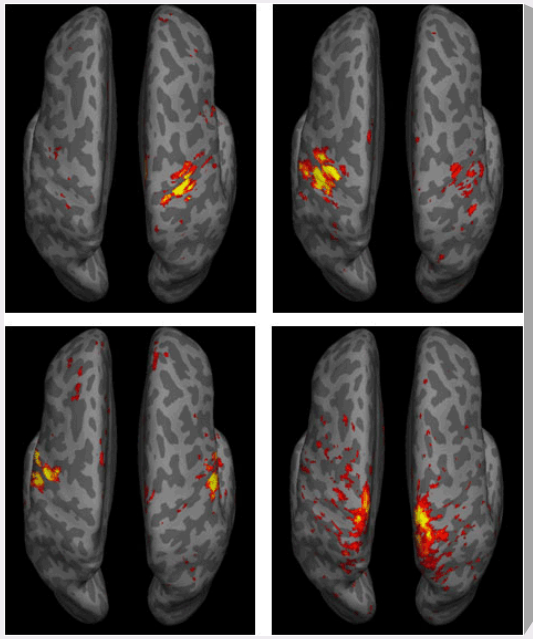
KAIST

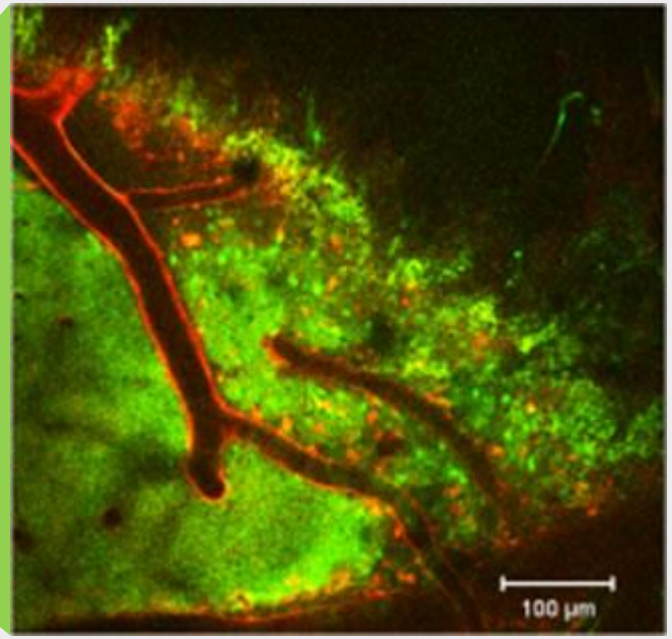
CNI LAB. Prof Jeong Yong

Human study

Brain mapping & network analysis for cognitive function

: fMRI, DTI, PET image processing



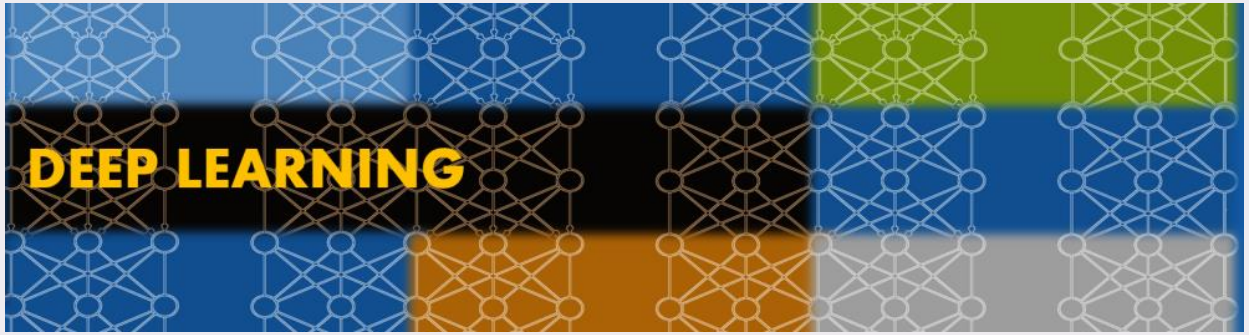


In-vivo study

Pathophysiology & treatment for neurodegenerative diseases

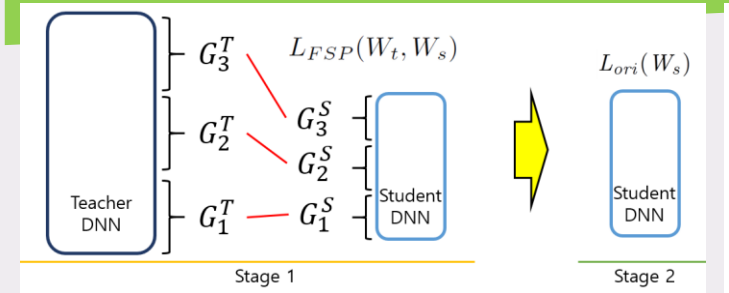
: Two-photon microscopy, VSDI

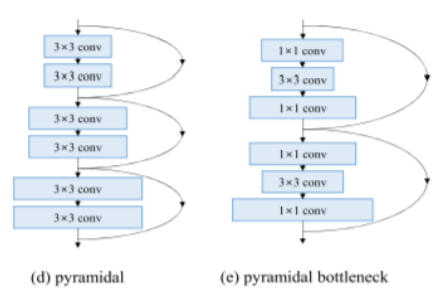
SIIT LAB. Prof Kim Junmo

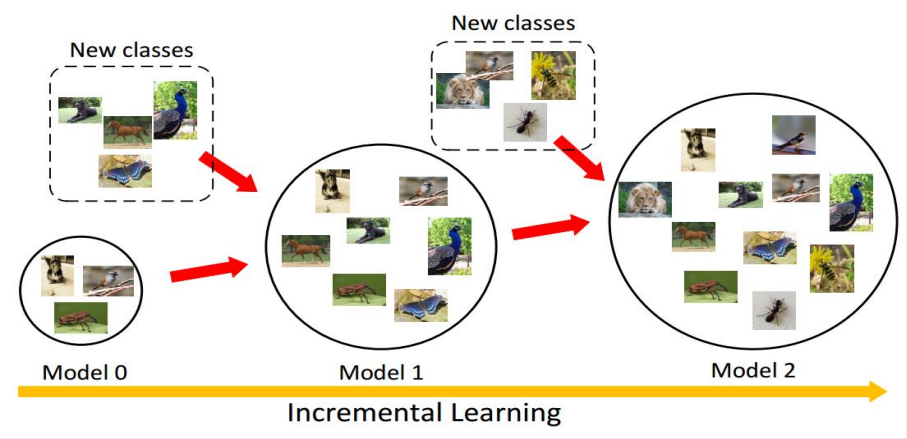


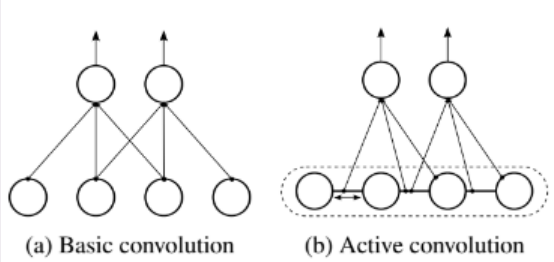
Network Development & Analysis

Knowledge distillation & Incremental learning & ...



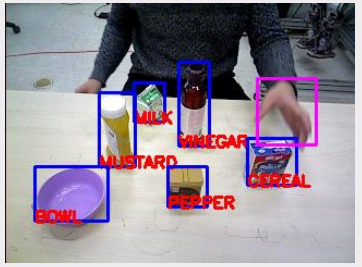






Deep Learning Applications

Object Classification & Detection & segmentation



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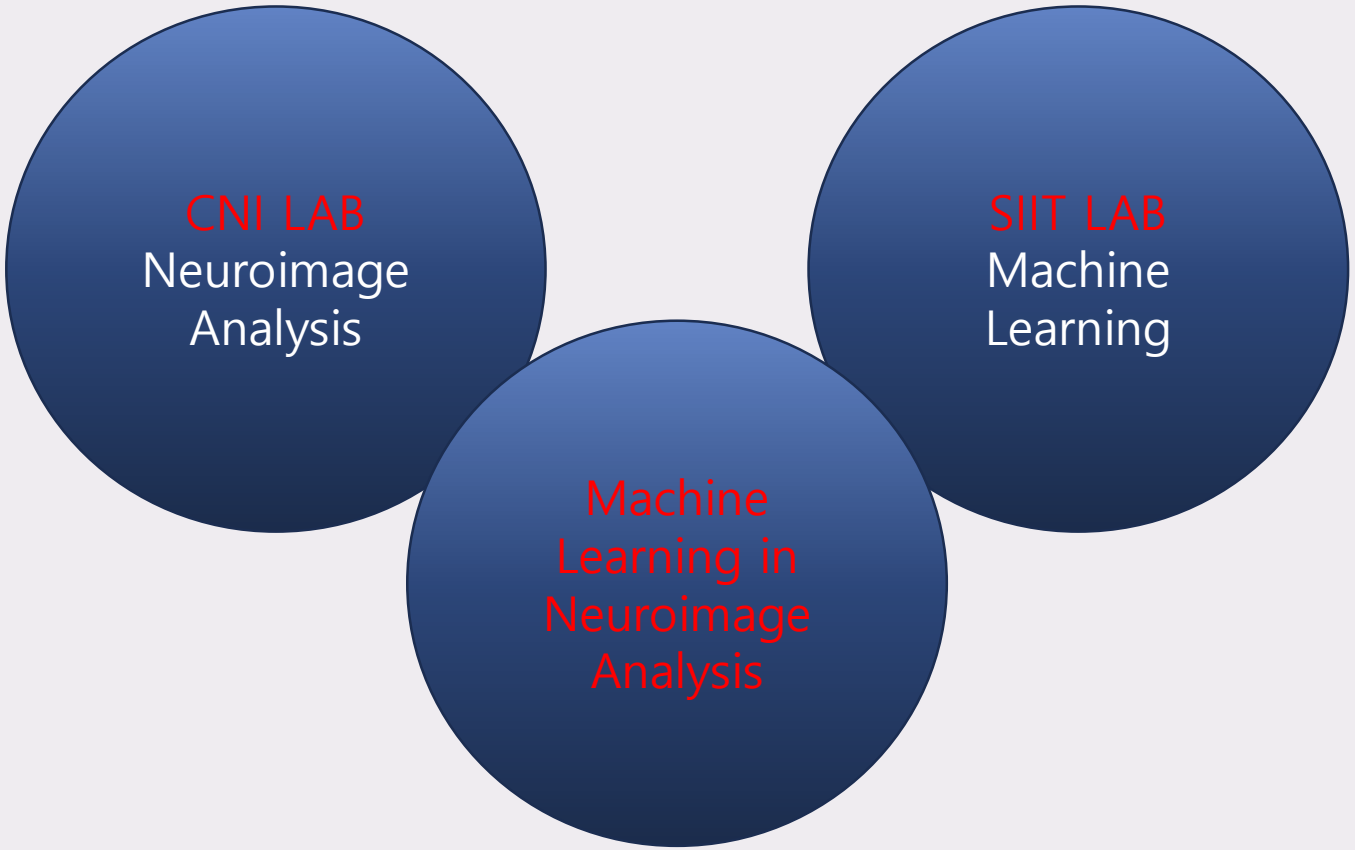
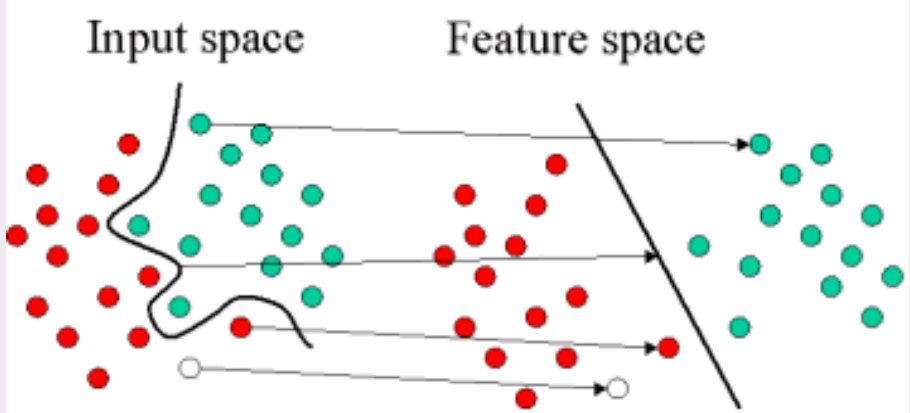
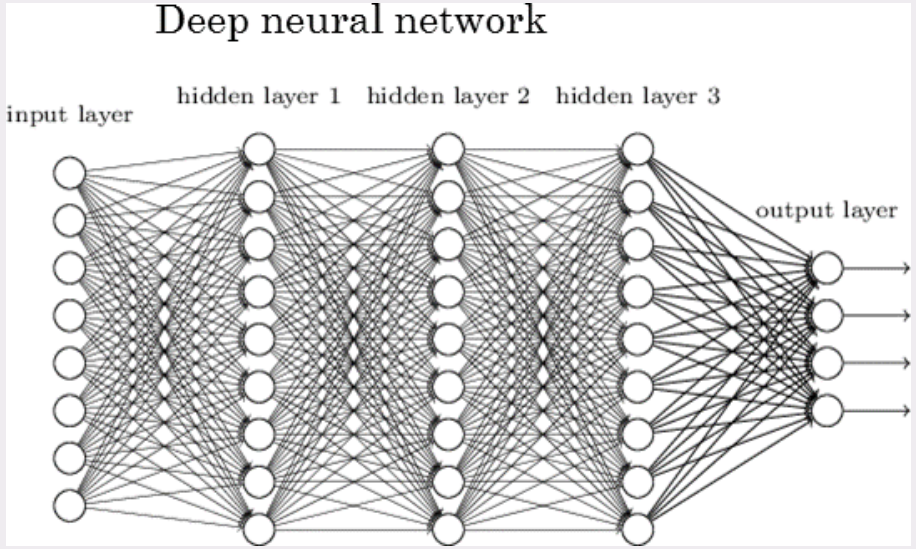


CNI LAB and SIIT LAB





Machine Learning in Neuroimage analysis

Machine learning discovers patterns in the data and use this information to make predictions on new data

Most used is the support vector machine, allowed the statistical inference at single subject using the multivariate method

Now Deep Learning is gaining considerable attention

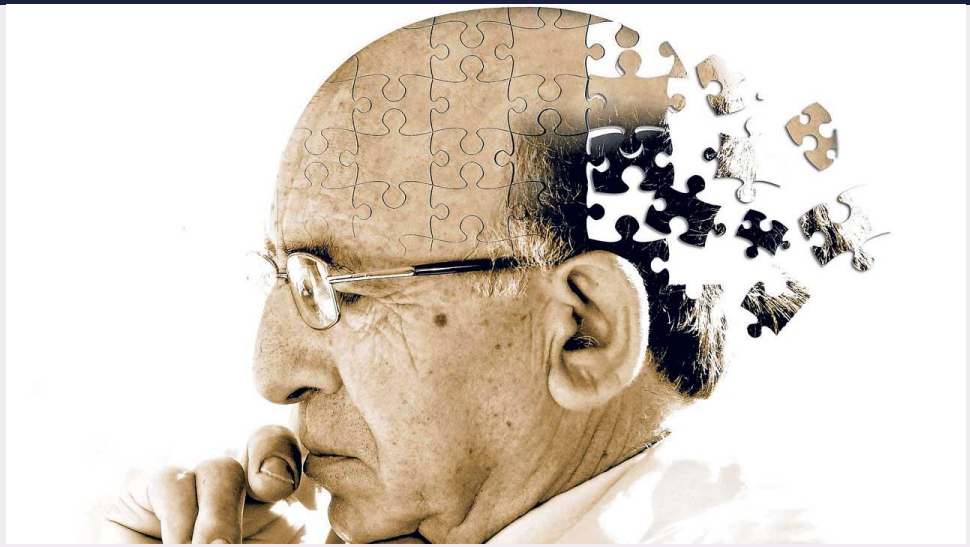
Hierarchical structure with different levels of complexity allowed higher level of abstraction

Better detector of complex, scatter and subtle patterns in the data

Neurological disorder is associated with subtle and diffuse neuroanatomical and neurofunctional abnormalities

Classification of Prodromal Alzheimer's Disease using Multimodal Neuroimages based on Deep Learning

Background

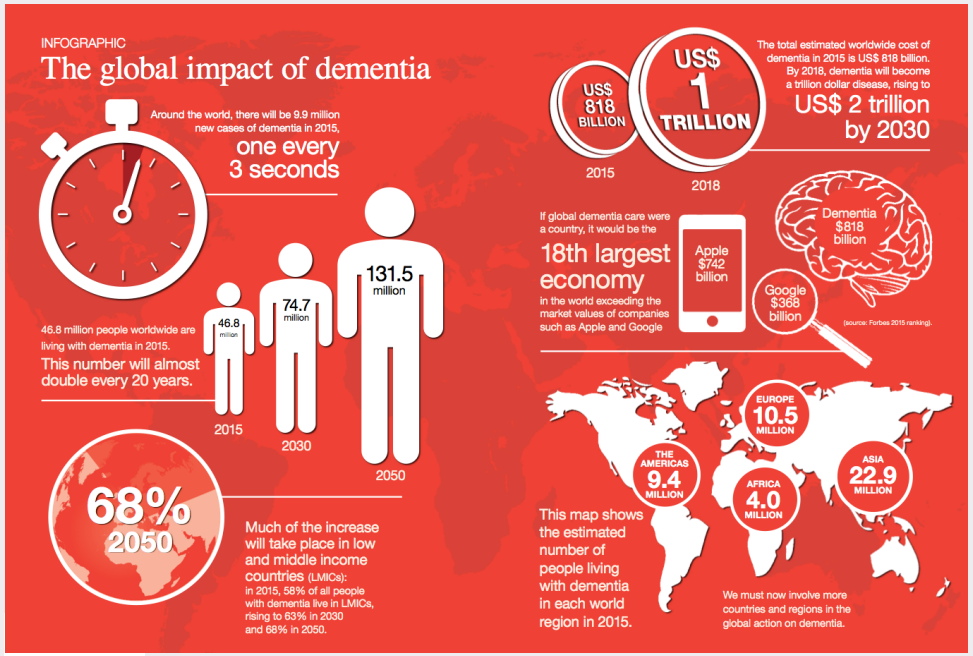


Alzheimer's disease (AD)??

Most common cause of dementia (Ferri, Prince et al. 2006)

Estimates of affecting 106 million people worldwide by 2050

However, no definite cure so far (Brookmeyer, Johnson et al. 2007)

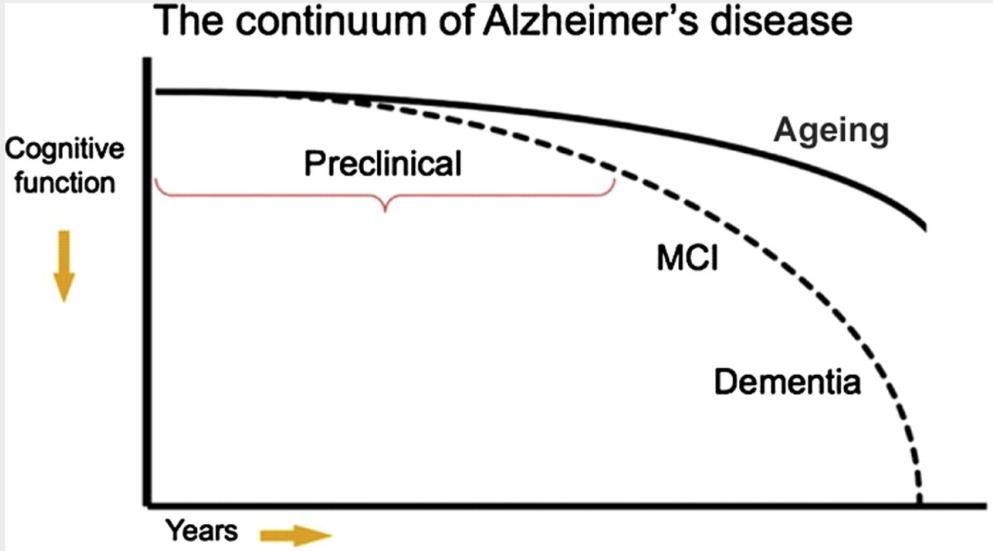


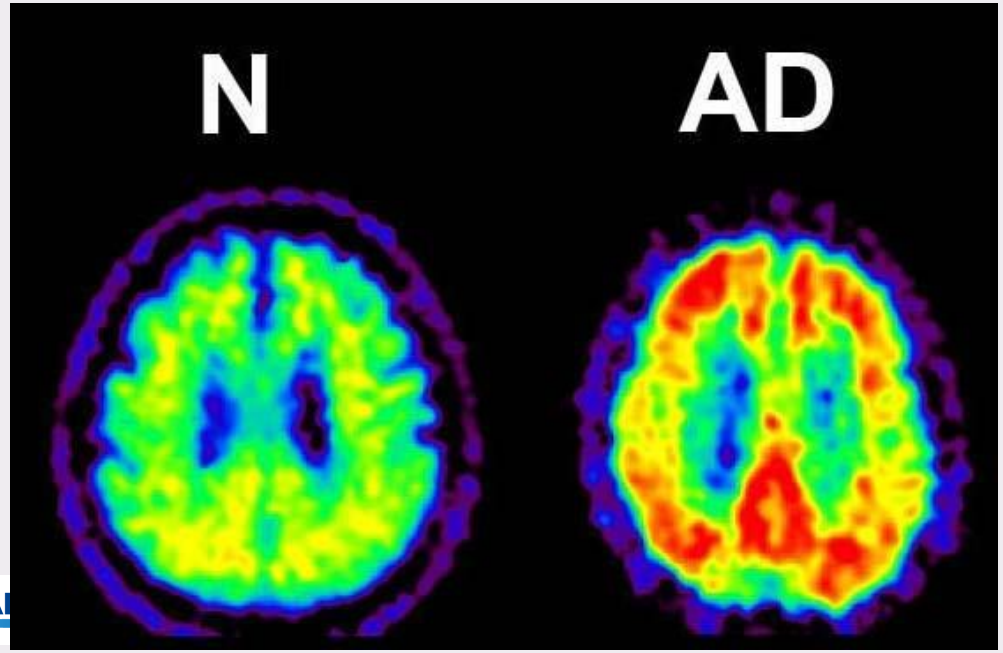
Two of key factors for developing the AD therapy is

1) Detect the disease in its earliest stage
2) Detect the accurate disease entity

Target group for AD therapy

Background





Mild cognitive impairment (MCI)??

Subject and objective cognitive impairment with preserved performance of a daily life

Transitional phase between normal and AD (Petersen et al., 1999) However they are heterogeneous!!

Prodromal AD ??

MCI with AD pathology such as A*B* in CSF or PET

Prodromal AD has 3-5 time higher risk of conversion to AD (A Okello et al. 2009)

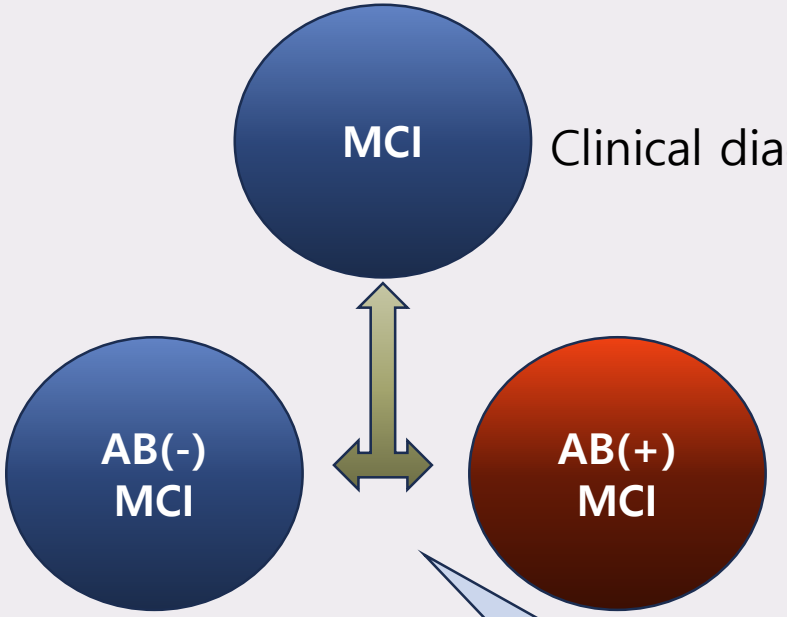
Prodromal AD is important

Could be Target group for AD therapy

1) they progress to AD

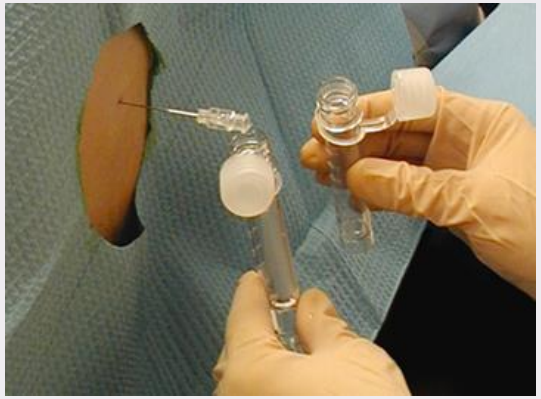
2) they are a key target group of AD therapy

Background



Clinical diagnosis

Amyloid PET or CSF tapping



Classify AB(+) MCI, prodromal AD using MRI and clinical information +fMRI, DTI

Based on Machine Learning (Deep Learning)

Previous studies - Deep Learning Approach

There are many good papers using DL in AD research

Table 1
Diagnostic studies.

Authors, year	Sample size	Technique	Features	Previous feature selection	DL architecture	Comparison	Accuracy (%)
Gupta et al. (2013)[a]	AD = 200 MCI = 411 HC = 232	sMRI	WB voxel-level	No	Sparse AE & CNN	HC vs. AD HC vs. MCI AD vs. MCI HC vs. AD vs. MCI	94.7 86.4 88.1 85.0
Payan and Montana (2015)[a]	HC = 755 AD = 755 MCI = 755	sMRI	WB voxel-level	No	Sparse AE & CNN	HC vs. AD HC vs. MCI AD vs. MCI HC vs. AD vs. MCI	95.4 92.1 86.8 89.5
Hosseini-Asl et al. (2016)[a,b]	HC = 70* AD = 70* MCI = 70*	sMRI	WB voxel-level	No	AE & CNN	HC vs. AD HC vs. MCI AD vs. MCI HC vs. AD vs. MCI	97.6 90.8 95.0 89.1
Chen et al. (2015)[a]	HC = 123 AD = 94 MCI = 121	sMRI	WB voxel-level	Yes	SAE	HC vs. AD HC vs. MCI	89.0 81.7
Liu et al. (2015a)[a]	HC = 204 AD = 180 MCI = 374	sMRI	WB region-level	Yes	SAE	HC vs. AD HC vs. MCI	82.6 72.0
Gao and Hui (2016)	HC = 117 AD = 51 Lesions = 118	CT	WB voxel-level	No	CNN	HC vs. AD vs. Lesion	87.7
Sarraf and Tofighi (2016)[a]	HC = 15 AD = 28	rsfMRI	WB voxel-level	No	CNN	HC vs. AD	96.9

2D

3D

- SAE → AE → CNN
- 2D → 3D
- Accuracy
  - 95% for AD
  - 85% for MCI

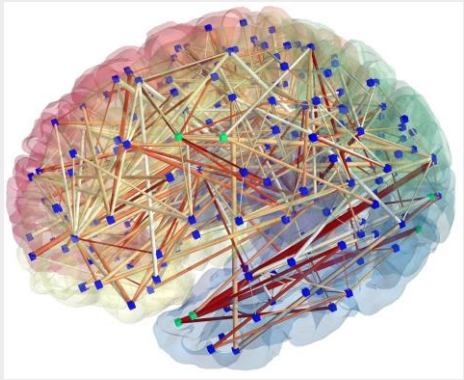
HC (Healthy Control) / MCI (Mild Cognitive Impairment) / AD (Alzheimer's Disease)
AE (Auto Encoder) / SAE (Stacked Auto Encoder) / CNN (Convolutional Neural Network)

[1] Vieira, Sandra, Walter HL Pinaya, and Andrea Mechelli. "Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: methods and applications." *Neuroscience & Biobehavioral Reviews*, 2017.

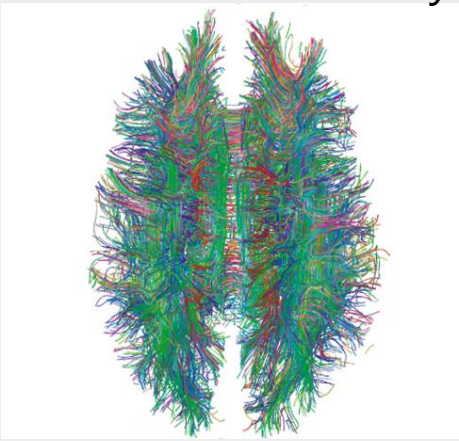
Methods

Aim1

Classify AB(+)MCI using DL based multimodal neuroimages

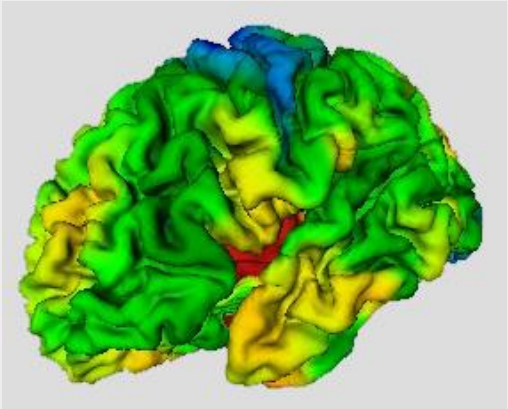


fMRI: functional connectivity map



DTI: structural connectivity map

DL based AB(+) Classifier



sMRI: regional cortical thickness

clinical information: MMSE, age, sex, ApoE4

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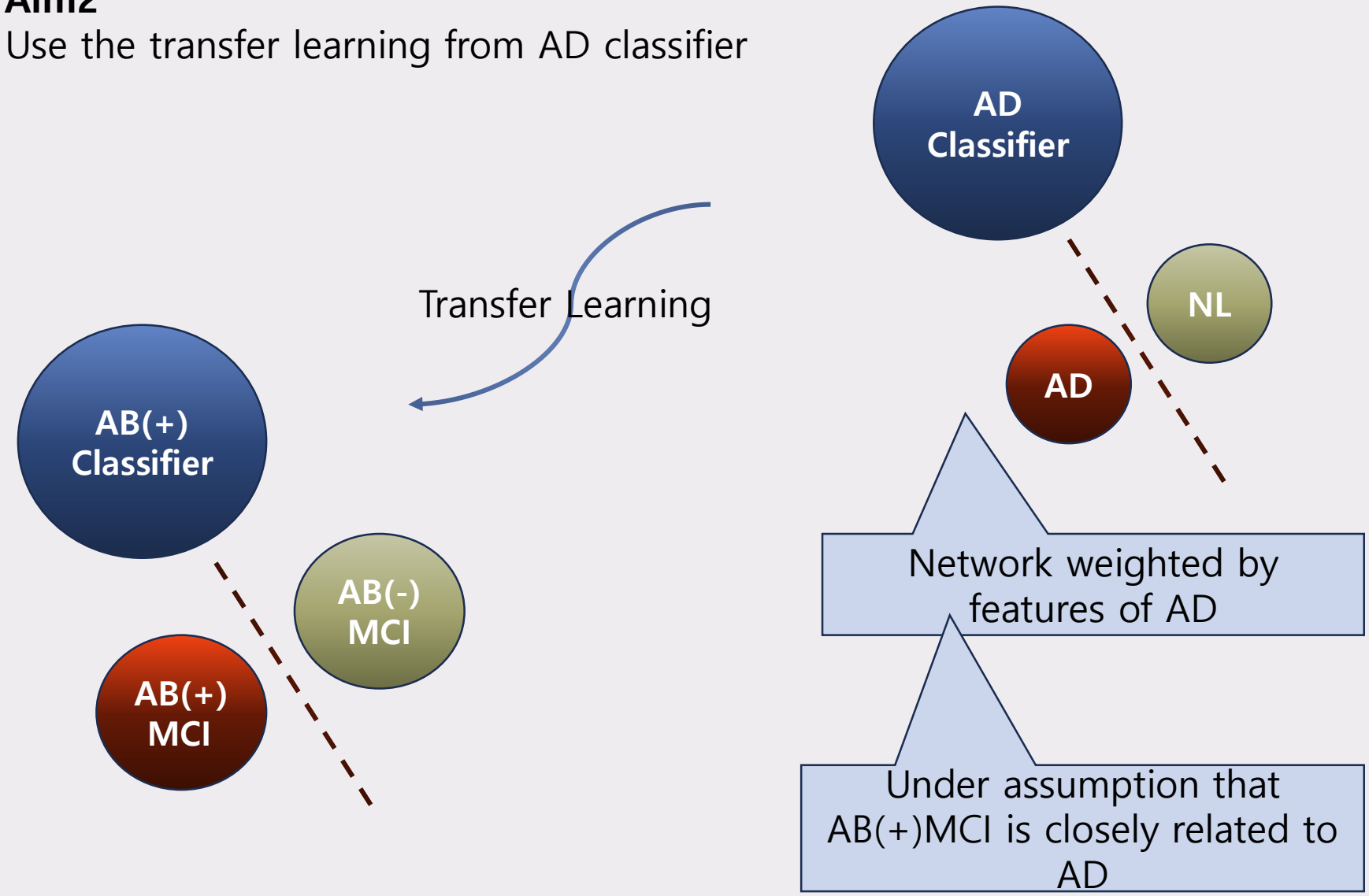
Methods

Aim2
Use the transfer learning from AD classifier

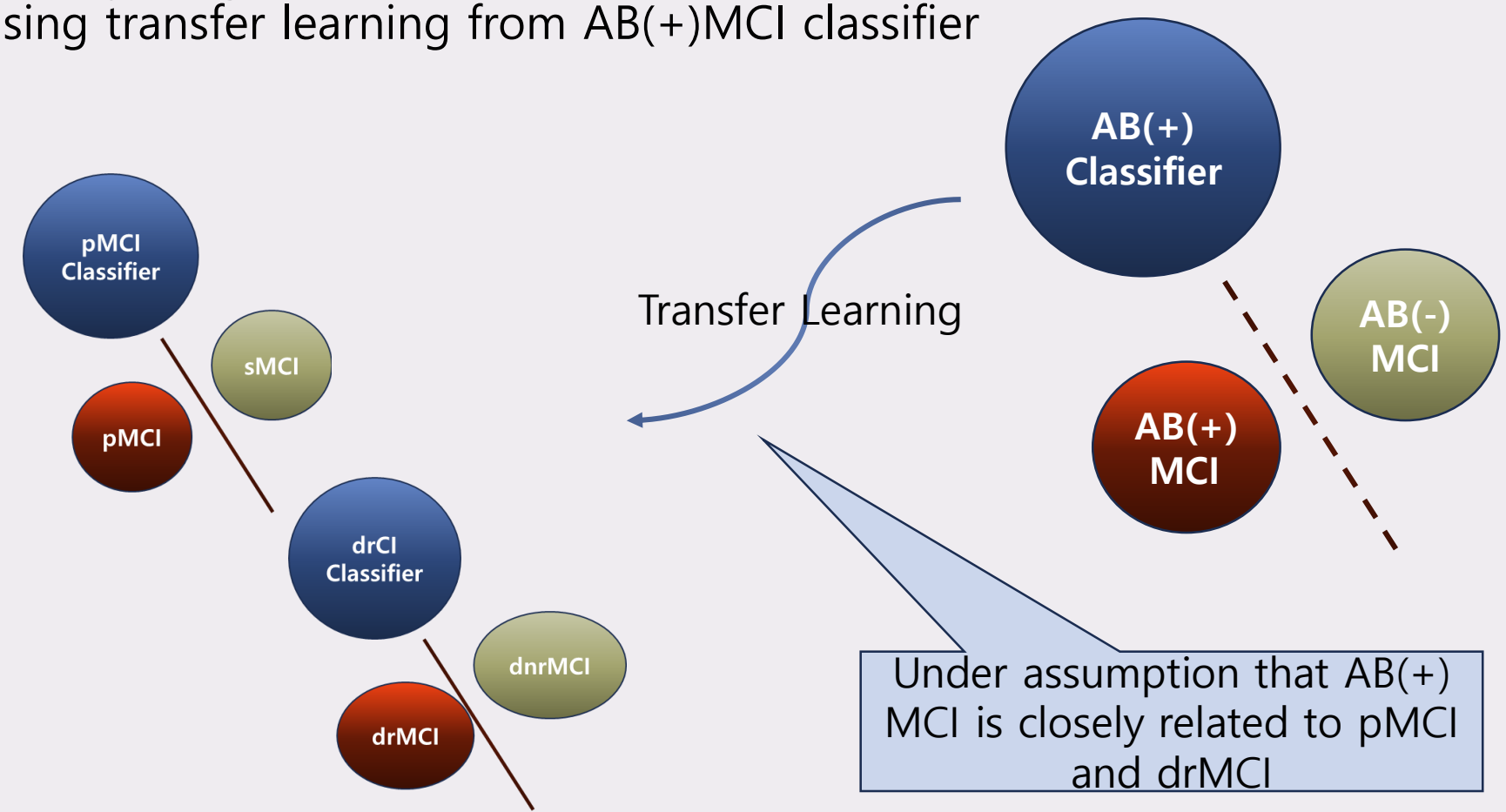


Methods

Aim3 (future work)

Classify progressive MCI (pMCI) from stable MCI (sMCI) using transfer learning from AB(+)MCI classifier

Classify drug responsive MCI (drMCI) from non-responsive MCI (dnrMCI) using transfer learning from AB(+)MCI classifier



Methods

Aim1

Classify AB(+)MCI using DL based multimodal neuroimages

Aim2

Use the transfer learning from AD classifier

Aim3 (future work)

Classify progressive MCI (pMCI) from stable MCI (sMCI) using transfer learning from AB(+)MCI classifier

Classify drug responsive MCI (drMCI) from non-responsive MCI (dnrMCI) using transfer learning from AB(+)MCI classifier

Study Plans

	5	6	7	8	9	10
fMRI data/clinical data	→	→				
DTI data		→	→			
Cortical thickness			→	→		
AD vs NL				→	→	
AB(+) MCI vs AB(+) MCI					→	→