

The role of neuroimaging beyond T1-weighted MRI in the diagnosis and prediction of neuropsychiatric disorders

Esten H. Leonardsen

26.10.23



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Neuroimaging modalities for diagnostic predictions



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Approach

(Non-T1) structural MRI (sMRI)

Diffusion MRI (dMRI)

Functional MRI (fMRI)

Molecular imaging (MOL)



Approach

(Non-T1) structural MRI (sMRI)

Diffusion MRI (dMRI)

Functional MRI (fMRI)

Molecular imaging (MOL)

DEM MS PD SCZ MDD BP



Approach

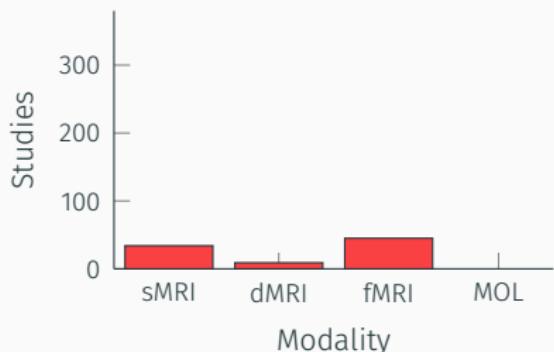
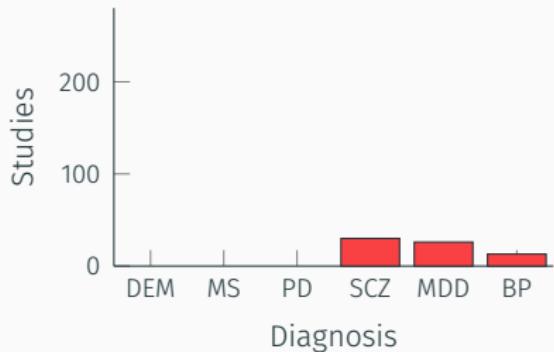
| (Non-T1) structural MRI (sMRI) | | | | | | |
|--------------------------------|-----|----|----|-----|-----|----|
| Diffusion MRI (dMRI) | | | | | | |
| Functional MRI (fMRI) | | | | | | |
| Molecular imaging (MOL) | | | | | | |
| | DEM | MS | PD | SCZ | MDD | BP |

Data



From estimating activation locality to predicting disorder: A review of pattern recognition for neuroimaging-based psychiatric diagnostics

Thomas Wolters^{a,b}, Jon K. Buitelaar^{c,d}, Christian F. Beckmann^{b,c,e}, Barbara Franke^{a,f}, Andre F. Marquand^{a,g}



Data

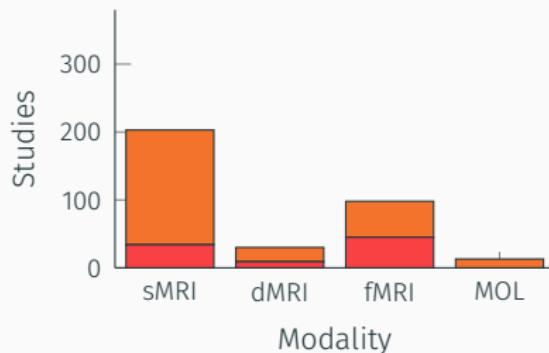
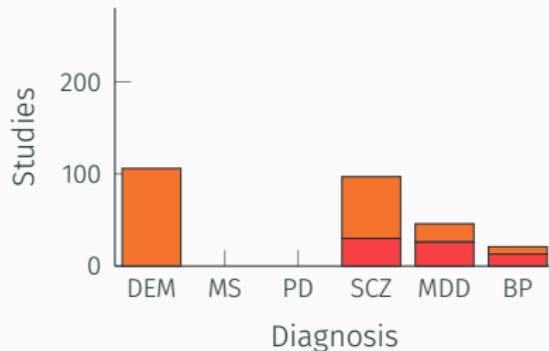


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Single subject prediction of brain disorders in neuroimaging: Promises and pitfalls

Mohammad R. Arbabi Shirani^{a,b}, [Sergey Pliš](#)^a, Jing Sui^{a,c}, [Vince D. Calhoun](#)^{a,d}



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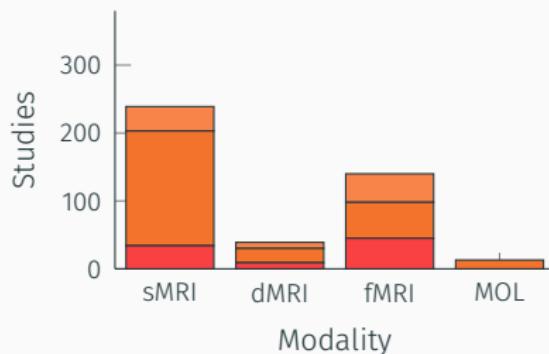
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Towards a brain-based predictome of mental illness

Barnaly Rashid, Vince Calhoun



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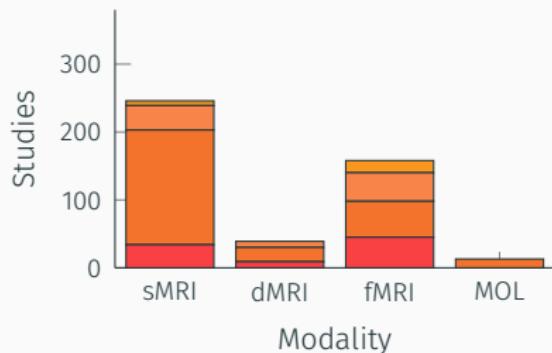
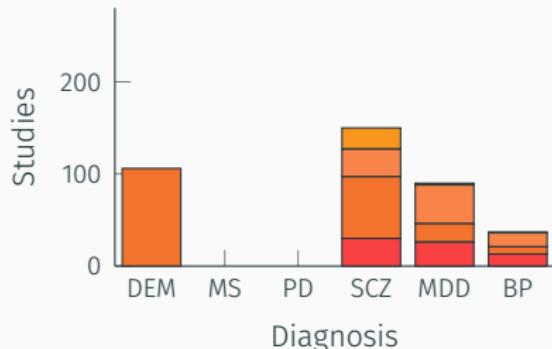
Mohammad R. ArbabiShirani^{a,b}, , Sergey Pliushch^a, Jing Sui^{a,c}, Vince D. Calhoun^{a,d}

Towards a brain-based predictome of mental illness

Barnaly Rashid, Vince Calhoun

Deep learning applications for the classification of psychiatric disorders using neuroimaging data: Systematic review and meta-analysis

Mirjam Quaak³, Laurens van de Mortel³, Rajat Mani Thomas³, Guido van Wingen²



Data



Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review

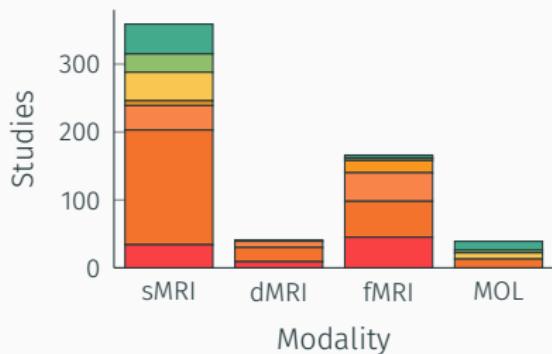
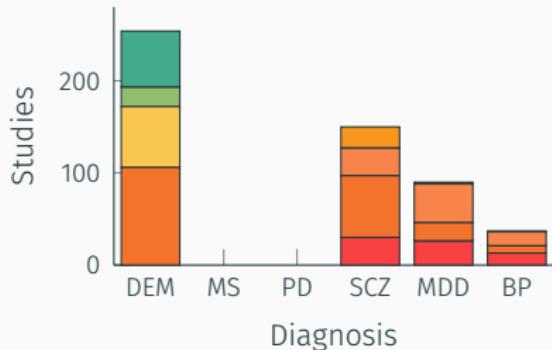
Mr Amir Ebrahimghahnavieh ³, Suhuai Luo ³, Raymond Chiong ²

Machine learning techniques for diagnosis of alzheimer disease, mild cognitive disorder, and other types of dementia

Golrokh Mirzaei ², R., Hojjat Adeli ³

Early diagnosis of Alzheimer's disease based on deep learning: A systematic review

Sina Fathi ¹, Maryam Ahmadi ², Afshaneh Dehnad ³

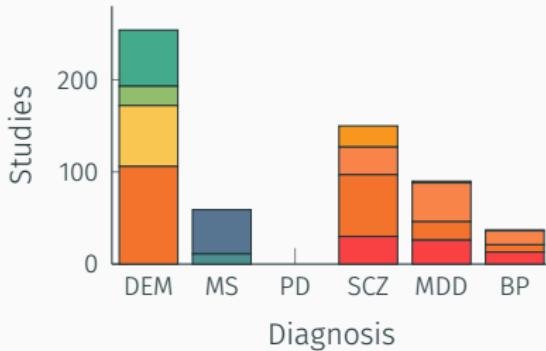


Data



Applications of deep learning techniques for automated multiple sclerosis detection using magnetic resonance imaging: A review

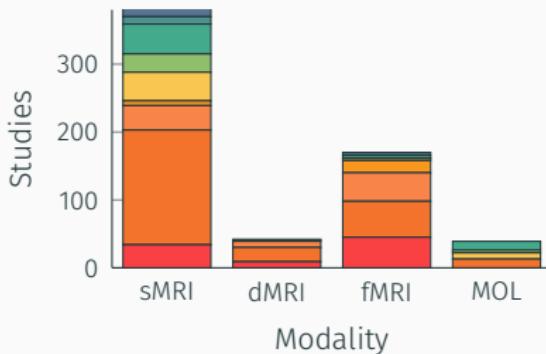
Afshin Shoebi¹, Marjane Khodatari², Mahboobeh Jafari³, Parisa Mordinian⁴, Mitra Rezaei⁵, Roohallah Alzadehsani⁶, Fahime Khozeimeh⁶, Juan Manuel Gorri⁷, Jonathan Heras⁸, Maryam Panahiazar⁹, Saeid Nahavandi⁸, U Rajendra Acharya¹⁰



Diagnosis

Multiple Sclerosis Diagnosis Using Machine Learning and Deep Learning: Challenges and Opportunities

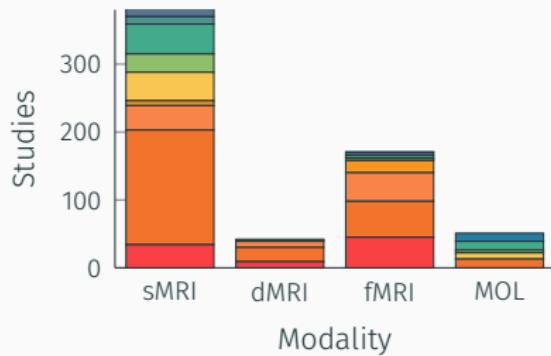
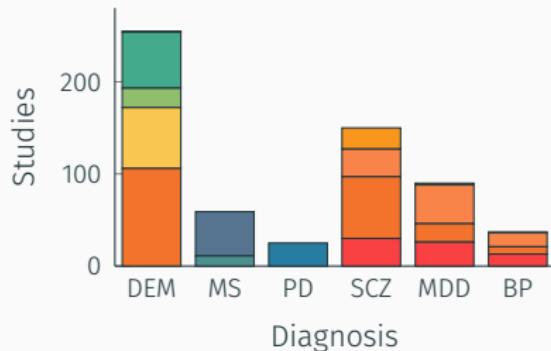
by Nida Aslam¹ , Irfan Ultil Khan¹ , Asma Basharat¹, Fatima A. Alghoot¹, Meena Aboulhous¹ , Noorah M. Alsuwayyid¹, Rawa'a K. Alturais¹, Samira Brahim², Sumayth S. Aljanes¹ and Kholeoud Al Ghendi³



Modality



Data



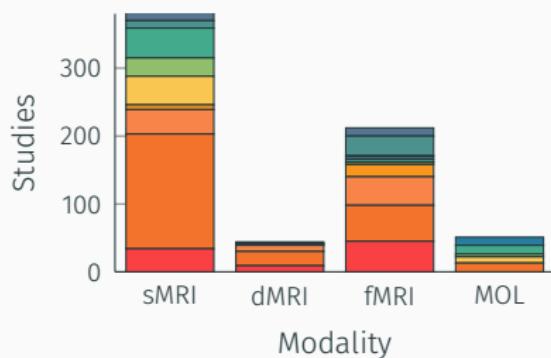
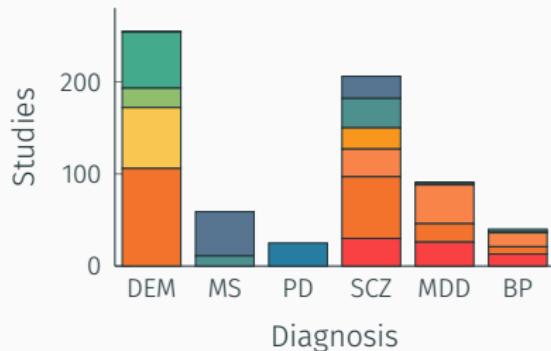
Role of Artificial Intelligence Techniques and Neuroimaging Modalities
in Detection of Parkinson's Disease: A Systematic Review
Nikita Aggarwal¹ • B. S. Saini¹ • Savita Gupta²



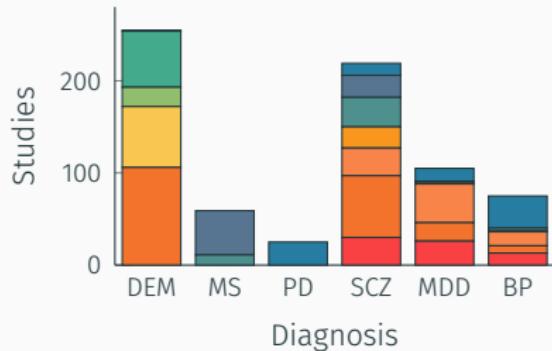
Data



Machine learning techniques in a structural and functional MRI diagnostic approach in schizophrenia: a systematic review
Renato de Faria,^{1*} Elvira Anna Carbone,^{1†} Raffaele Gastone,¹ Antonella Brusa,¹ Valentina Pugliese,¹ Cristina Segura-García,² and Pasquale De Fazio¹

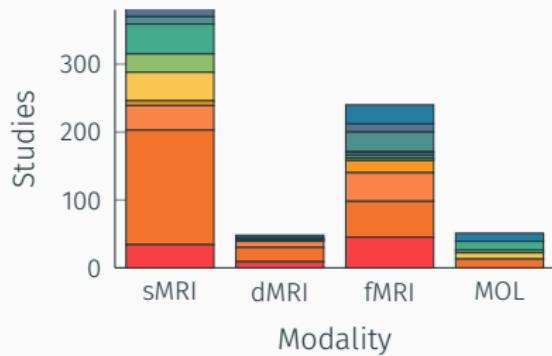


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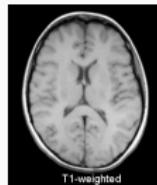


Will machine learning applied to neuroimaging in bipolar disorder help the clinician? A critical review and methodological suggestions

Laurie-Anne Claude, Josselin Houenou, Edouard Duchesnay, Pauline Favre



Other structural MRI modalities



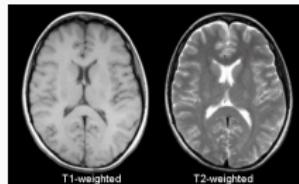
T1-weighted



Preson D. C., (2006), MRI Basics, <https://case.edu/med/neurology/NR/MRI%20Basics>



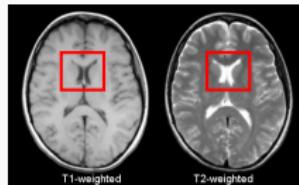
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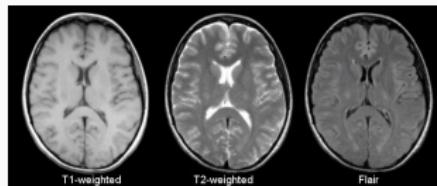
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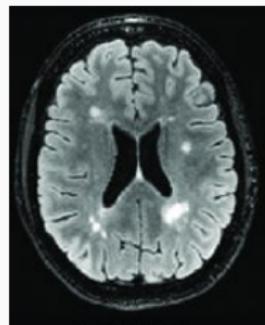
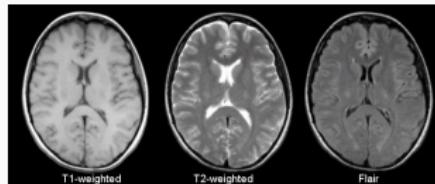
Other structural MRI modalities



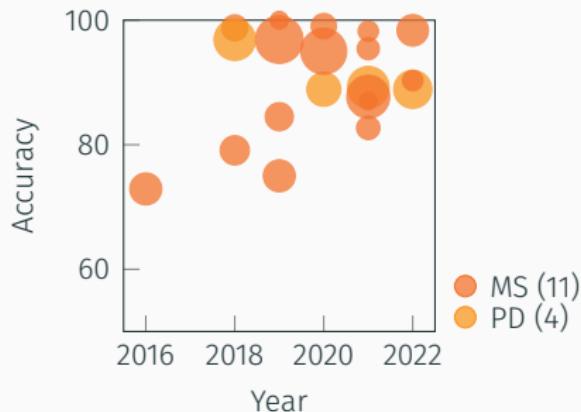
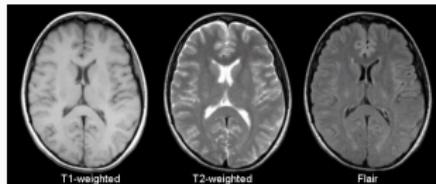
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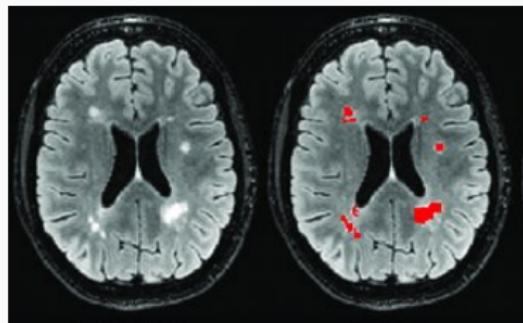
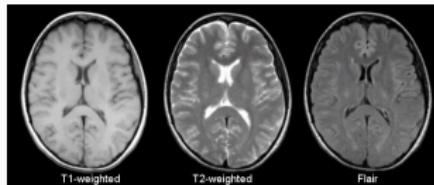
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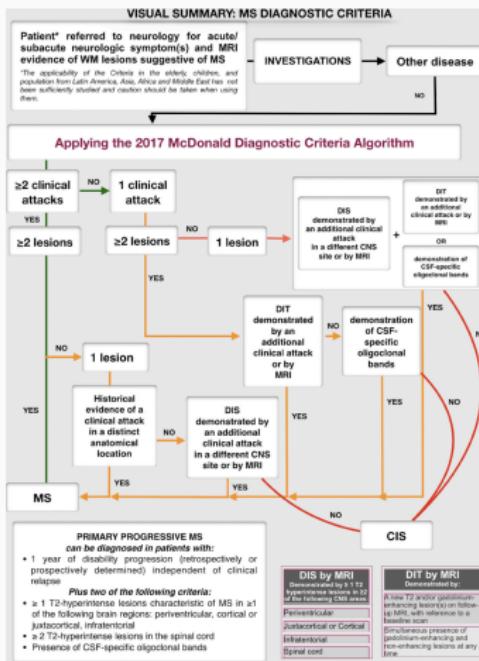
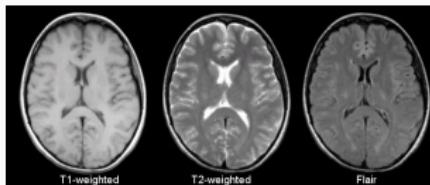
Other structural MRI modalities



Weeda, M. M., Brouwer, I., de Vos, M. L., de Vries, M. S., Barkhof, F., Pouwels, P. J. W., & Vrenken, H. (2019). Comparing lesion segmentation methods in multiple sclerosis: Input from one manually delineated subject is sufficient for accurate lesion segmentation. *NeuroImage: Clinical*, 24, 102074



Other structural MRI modalities

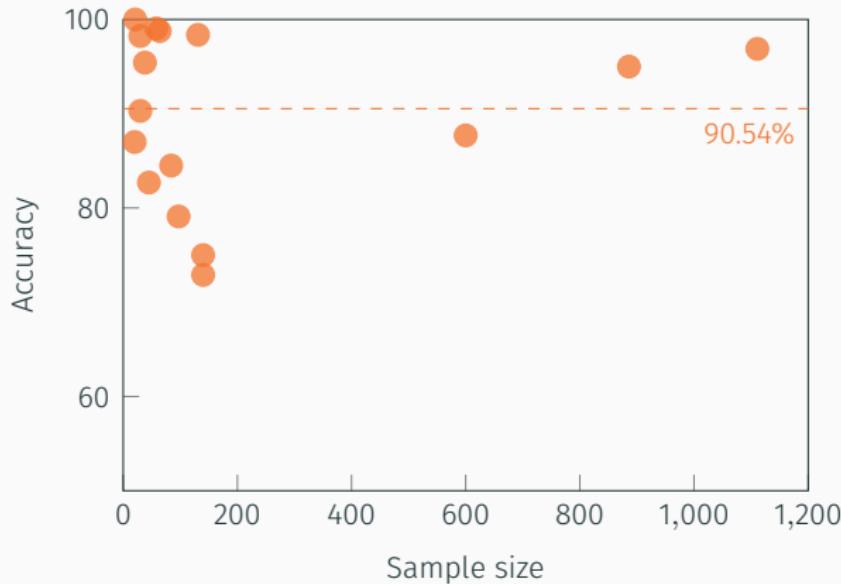


De Angelis, F., Brownlee, W. J., Chard, D. T., & Trip, S. A. (2019). New MS diagnostic criteria in practice. *Practical Neurology*, 19(1), 64-67.

Other structural MRI modalities



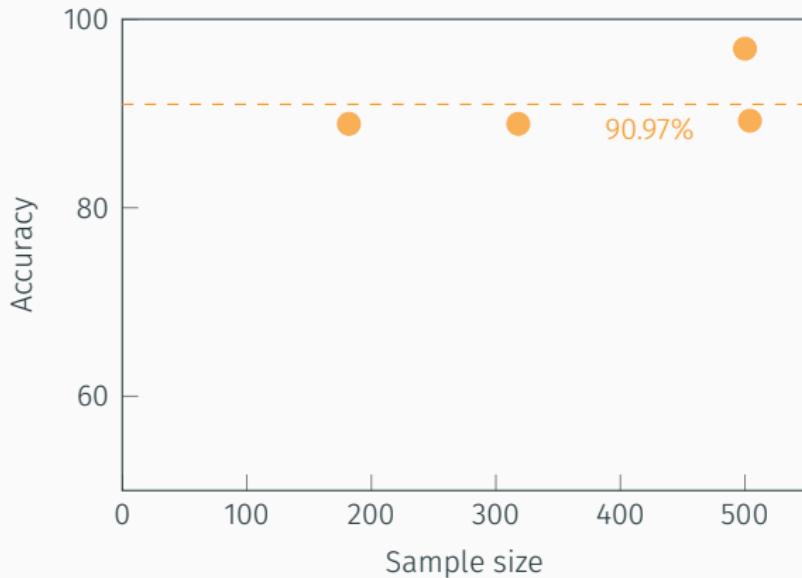
MS classification studies using T2/FLAIR



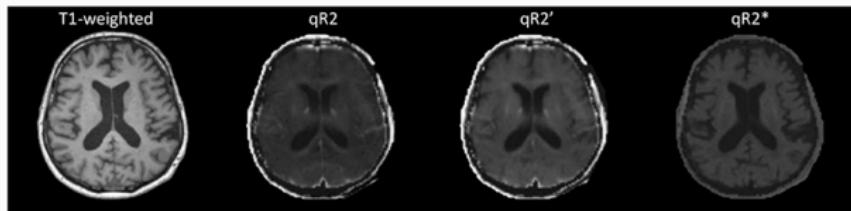
Other structural MRI modalities



PD classification studies using T2/FLAIR



Other structural MRI modalities



Talai, A. S., Sedlacik, J., Boelmans, K., & Forkert, N. D. (2021). Utility of multi-modal MRI for differentiating of Parkinson's disease and progressive supranuclear palsy using machine learning. *Frontiers in Neurology*, 12, 648548



Other structural MRI modalities



T2-weighted Image Features (based on quantitative R2, R2', and R2* Features)

| Class | TP Rate | FP Rate | Precision | Recall | F-Measure | MCC | ROC Area | Confusion Matrix | | | Accuracy |
|--------|---------|---------|-----------|--------|-----------|-------|----------|------------------|----|--------|----------|
| | | | | | | | | HC | PD | PSP-RS | |
| HC | 0.763 | 0.108 | 0.806 | 0.763 | 0.784 | 0.663 | 0.875 | 29 | 7 | 2 | 75.7% |
| PD | 0.756 | 0.207 | 0.739 | 0.756 | 0.747 | 0.547 | 0.845 | 7 | 34 | 4 | |
| PSP-RS | 0.750 | 0.072 | 0.714 | 0.750 | 0.732 | 0.665 | 0.948 | 0 | 5 | 15 | |

TP, True Positive; FP, False Positive; MCC, Matthews Correlation Coefficient; ROC AUC, Area under the receiver operating characteristic curve; HC, Healthy Controls; PD, Parkinson's disease; PSP-RS, Progressive supranuclear palsy Richardson's syndrome.



Talai, A. S., Sedlacik, J., Boelmans, K., & Forkert, N. D. (2021). Utility of multi-modal MRI for differentiating of Parkinson's disease and progressive supranuclear palsy using machine learning. *Frontiers in Neurology*, 12, 648548

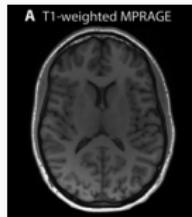


Other structural MRI modalities

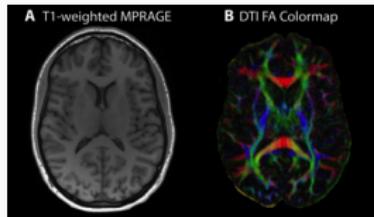
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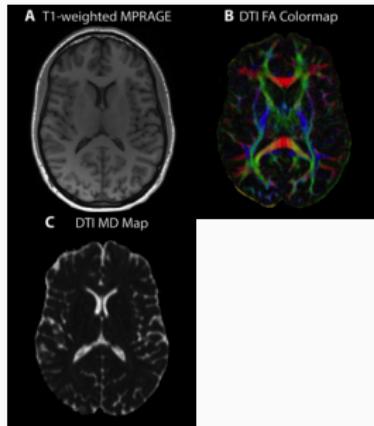
Diffusion MRI



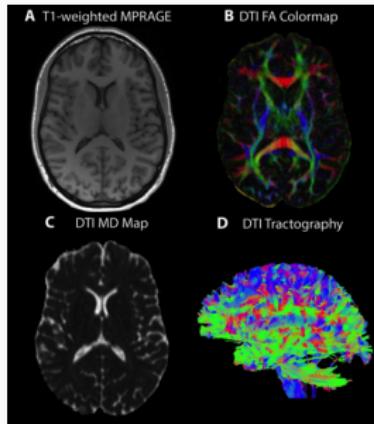
Diffusion MRI



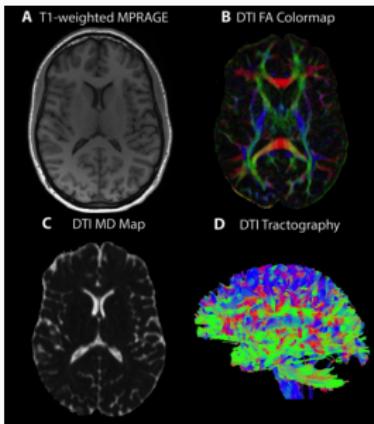
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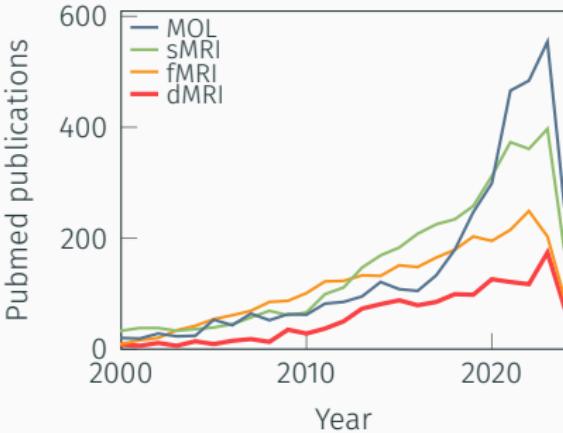
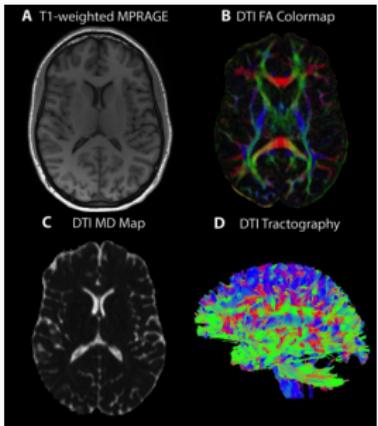
Diffusion MRI



Diffusion MRI



Diffusion MRI

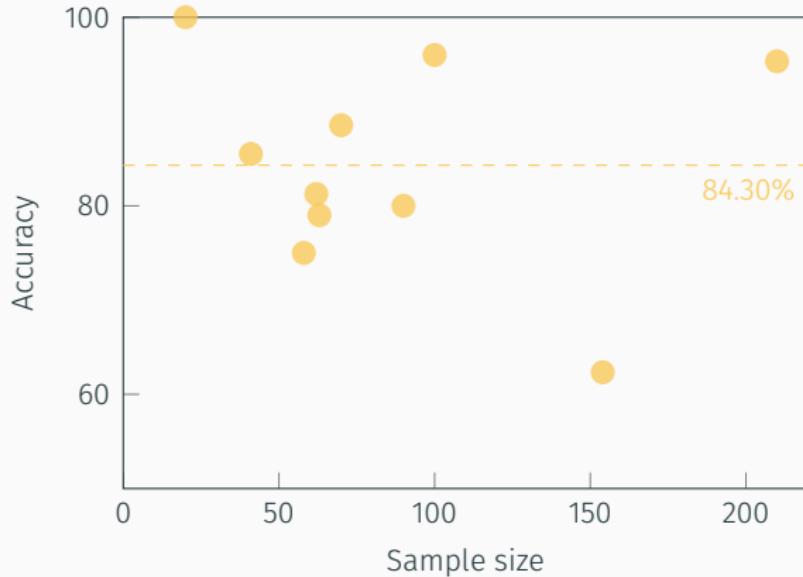


- MOL: ((molecular[Title] AND imaging[Title]) OR PET[Title] OR SPECT[Title]) AND (machine learning OR ML OR deep learning OR DL OR prediction)"
- sMRI: ((structural[Title] AND MRI[Title]) OR smRI[Title] OR T1[Title] OR T2[Title]) AND (machine learning OR ML OR deep learning OR DL OR prediction)
- fMRI: ((functional[Title] AND MRI[Title]) OR fMRI[Title]) AND (machine learning OR ML OR deep learning OR DL OR prediction)
- dMRI: ((diffusion[Title] AND MRI[Title]) OR dMRI[Title] OR DTI[Title]) AND (machine learning OR ML OR deep learning OR DL OR prediction)

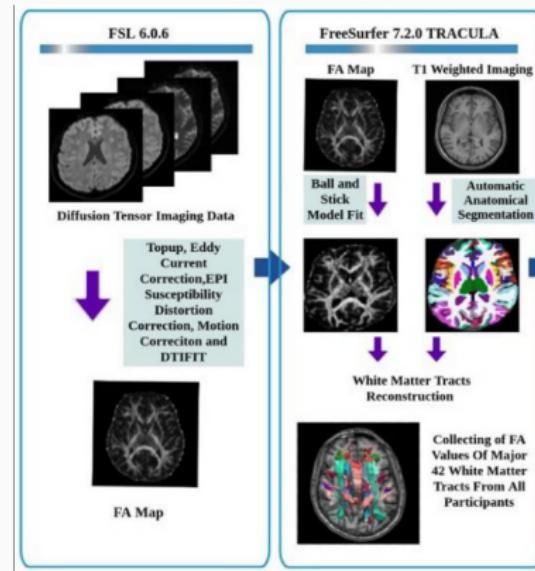




SCZ classification studies using dMRI



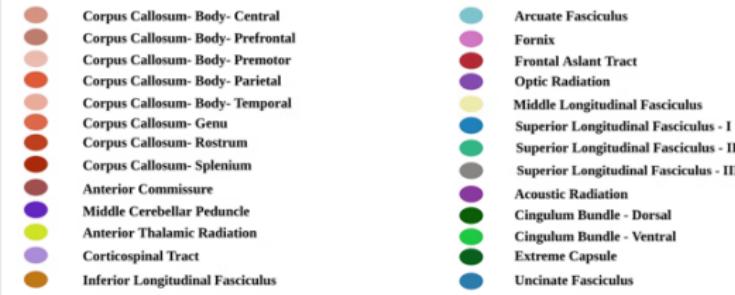
Diffusion MRI



Saglam, Y., Oz, A., Yildiz, G., Ermis, C., Kargin, O. A., Arslan, S., & Karacetin, G. (2023). Can diffusion tensor imaging have a diagnostic utility to differentiate early-onset forms of bipolar disorder and schizophrenia: A neuroimaging study with explainable machine learning algorithms. Psychiatry Research: Neuroimaging, 335, 111696



Diffusion MRI



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Diffusion MRI



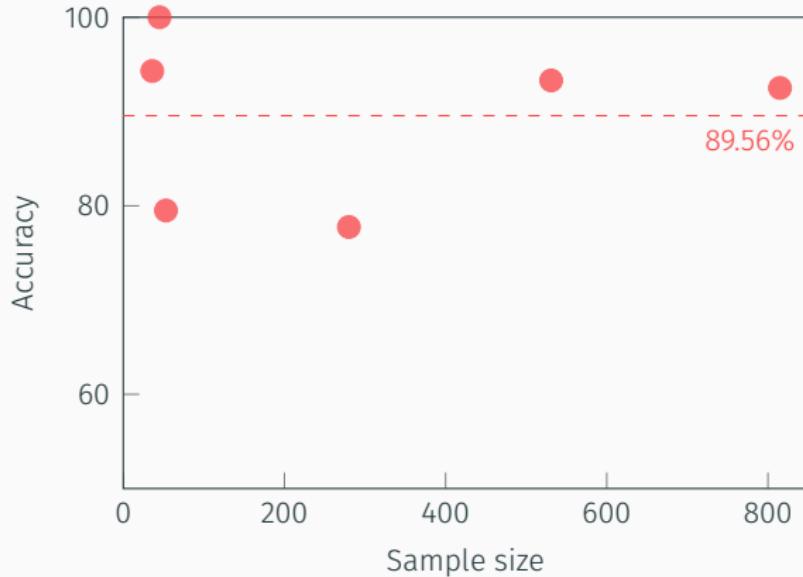
| Classifier | AUC | Accuracy | Sensitivity | Specificity | Precision | F1 score | MCC |
|---------------|------|----------|-------------|-------------|-----------|----------|------|
| SVM-linear | 0.85 | 0.80 | 0.75 | 0.86 | 0.79 | 0.77 | 0.74 |
| Random forest | 0.82 | 0.79 | 0.72 | 0.81 | 0.76 | 0.74 | 0.70 |
| SVM-Gaussian | 0.83 | 0.78 | 0.71 | 0.80 | 0.75 | 0.73 | 0.70 |
| LR | 0.78 | 0.76 | 0.70 | 0.79 | 0.73 | 0.71 | 0.68 |
| Naive Bayes | 0.75 | 0.72 | 0.65 | 0.74 | 0.68 | 0.66 | 0.62 |

Saglam, Y., Oz, A., Yildiz, G., Ermis, C., Kargin, O. A., Arslan, S., & Karacetin, G. (2023). Can diffusion tensor imaging have a diagnostic utility to differentiate early-onset forms of bipolar disorder and schizophrenia: A neuroimaging study with explainable machine learning algorithms. Psychiatry Research: Neuroimaging, 335, 111696

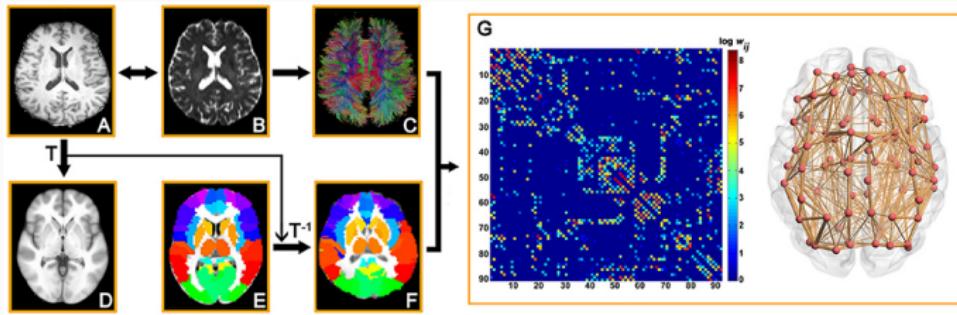




DEM classification studies using dMRI



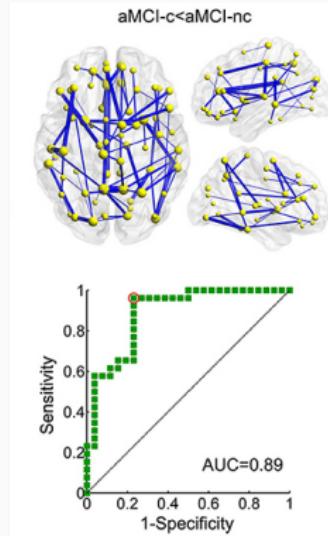
Diffusion MRI



Sun, Y., Bi, Q., Wang, X., Hu, X., Li, H., Li, X., ... & Han, Y. (2019). Prediction of conversion from amnestic mild cognitive impairment to Alzheimer's disease based on the brain structural connectome. *Frontiers in neurology*, 9, 1178



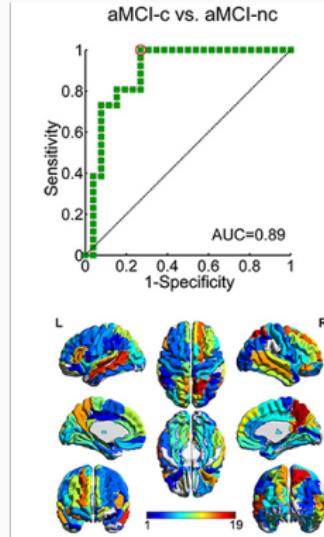
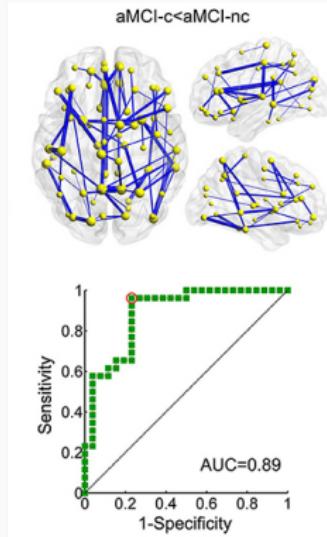
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Diffusion MRI



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Diffusion MRI

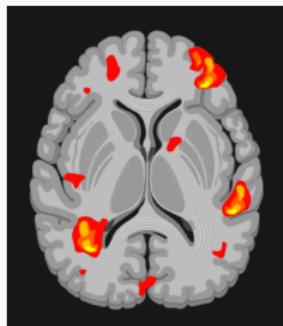
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 - Most prevalent in studies classifying MS and PD, yielding high accuracies (~90%).
 - Intimately linked with MS due to its efficacy at exposing characteristic lesions.
 - Potentially more useful than T1-weighted MRI for differentially diagnosing PD and PSP, as demonstrated by Talai et al.
- Diffusion MRI
 - Relatively few prediction studies found. Those that exist are for various disorders, mostly mental disorders (with varying accuracies, 60-100%) and DEM (80-100%).
 - Used by Saglam et al. to differentially diagnose SCZ and BP with 80% accuracy.
 - Used by Sun et al. to predict conversion from MCI to AD with 81% accuracy.



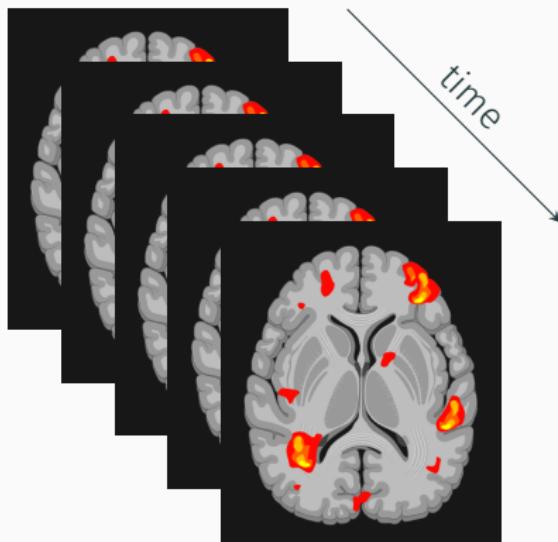
Functional Magnetic Resonance Imaging (fMRI)



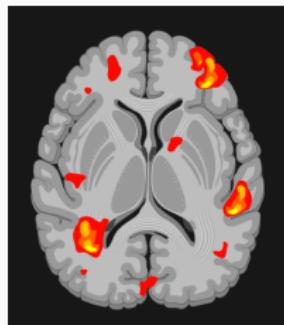
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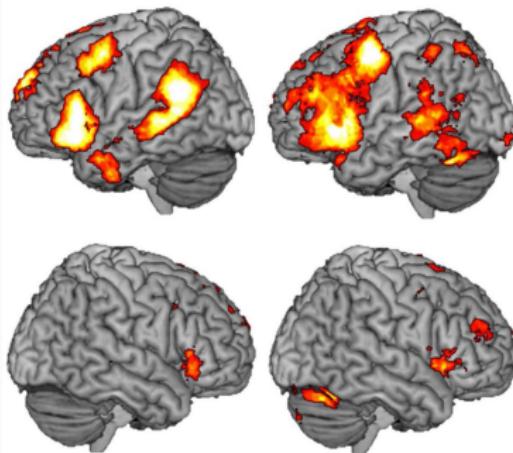


Functional Magnetic Resonance Imaging (fMRI)



rs-fMRI

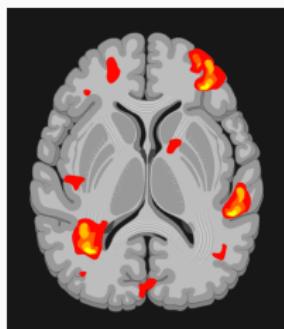
task-fMRI



Branco, P., Seixas, D., Deprez, S., Kovacs, S., Peeters, R., Castro, S. L., & Sunaert, S. (2016). Resting-state functional magnetic resonance imaging for language preoperative planning. *Frontiers in human neuroscience*, 10, 11.



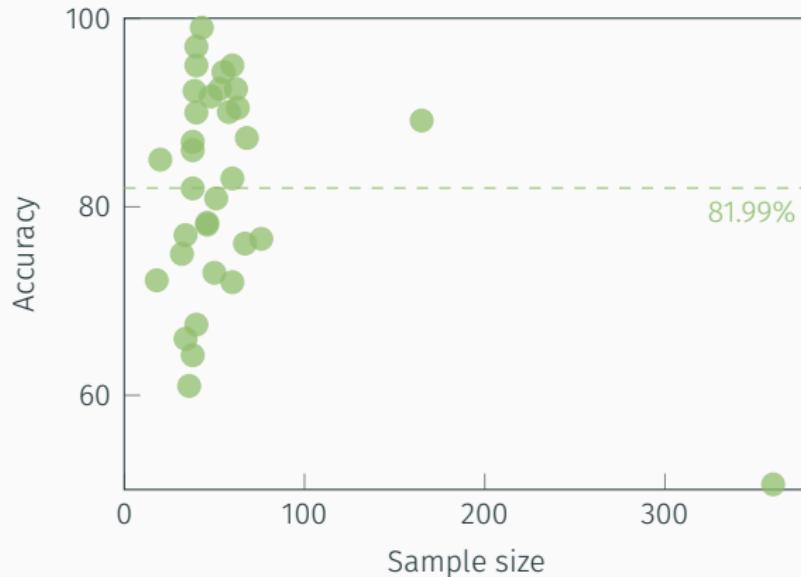
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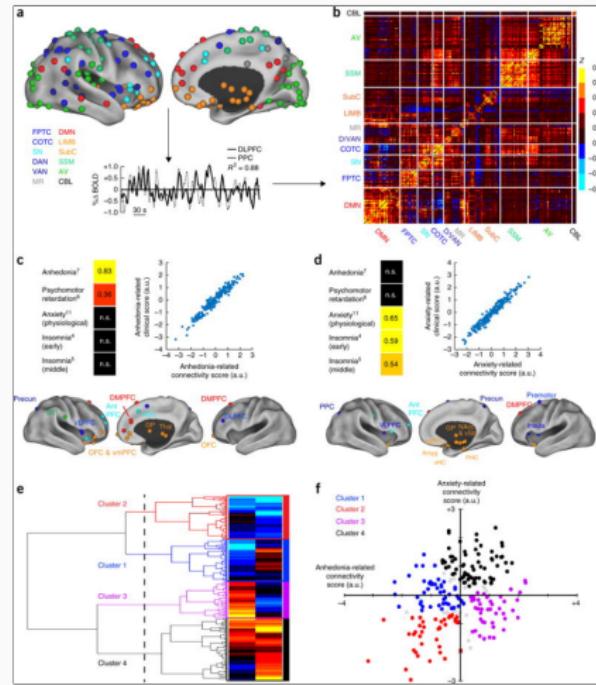
Functional Magnetic Resonance Imaging (fMRI)



MDD classification studies using fMRI



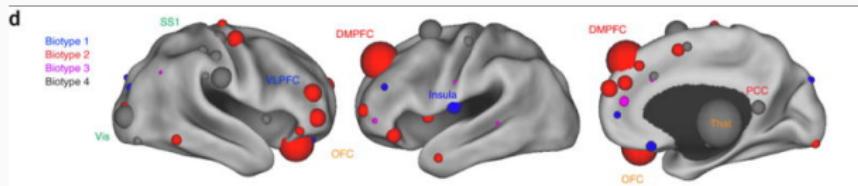
Functional Magnetic Resonance Imaging (fMRI)



Drysdale, A. T., Gosenick, L., Downar, J., Dunlop, K., Mansouri, F., Meng, Y., ... & Liston, C. (2017). Resting-state connectivity biomarkers define neurophysiological subtypes of depression. *Nature medicine*, 23(1), 28-38



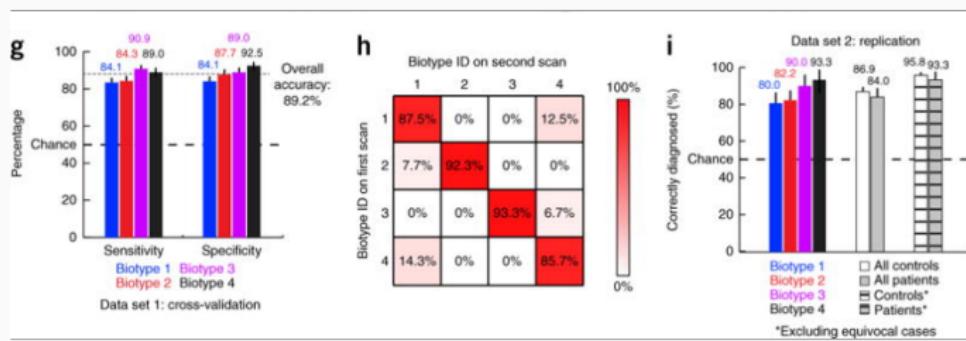
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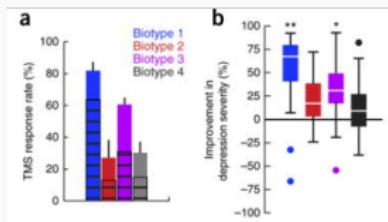
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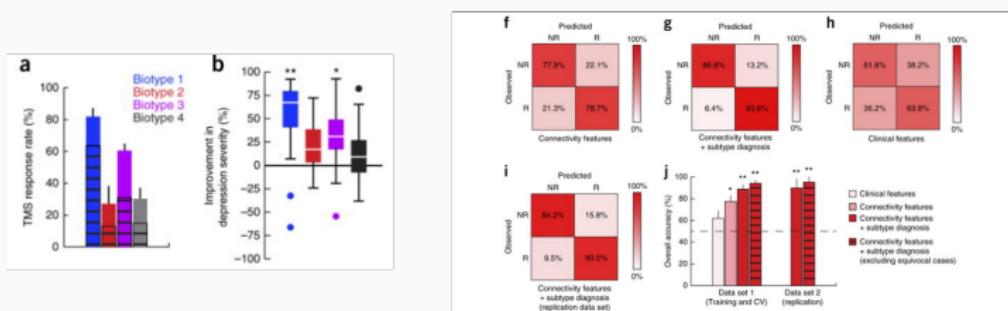
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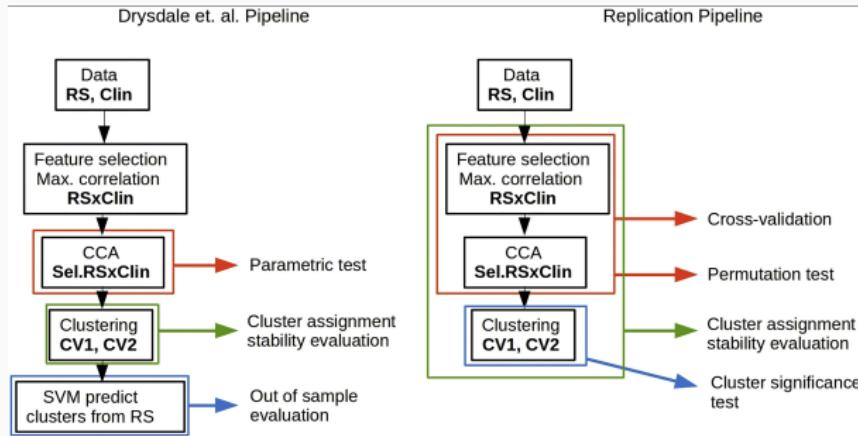
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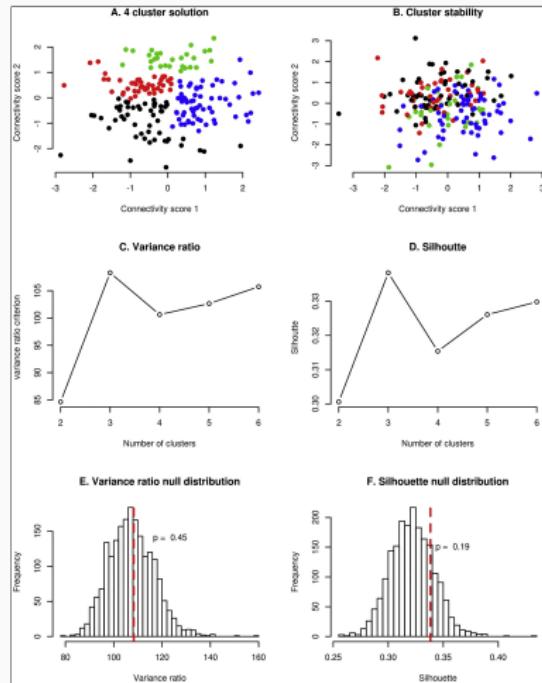
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Dinga, R., Schmaal, L., Penninx, B. W., van Tol, M. J., Veltman, D. J., van Velzen, L., ... & Marquand, A. F. (2019). Evaluating the evidence for biotypes of depression: Methodological replication and extension of. *NeuroImage: Clinical*, 22, 101796



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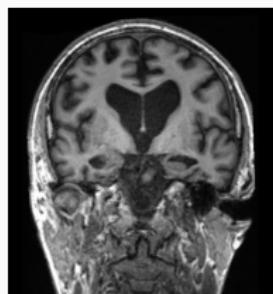


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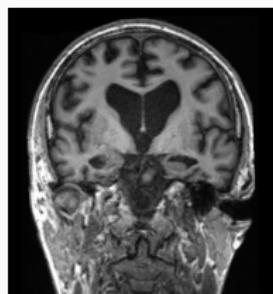
- (Non T1-weighted) structural MRI (T2/FLAIR)
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 - Intimately linked with MS due to its efficacy at exposing characteristic lesions.
 - Potentially more useful than T1-weighted MRI for differentially diagnosing PD and PSP, as demonstrated by Talai et al.
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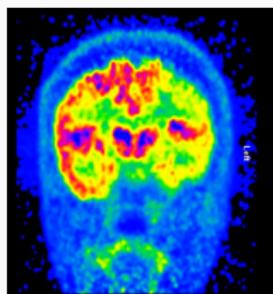
Molecular imaging (PET/SPECT)



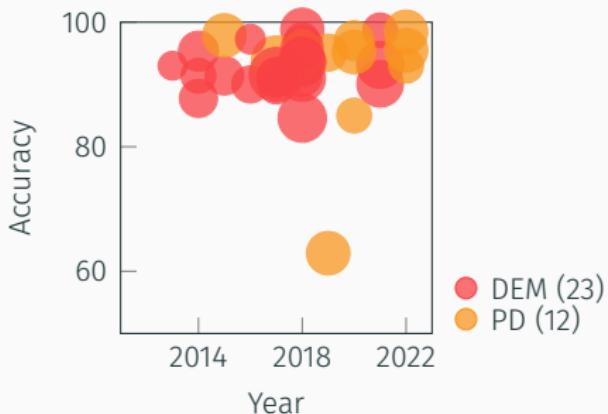
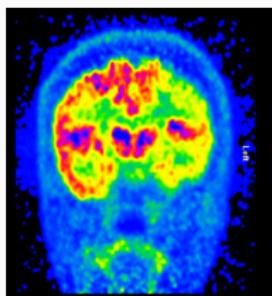
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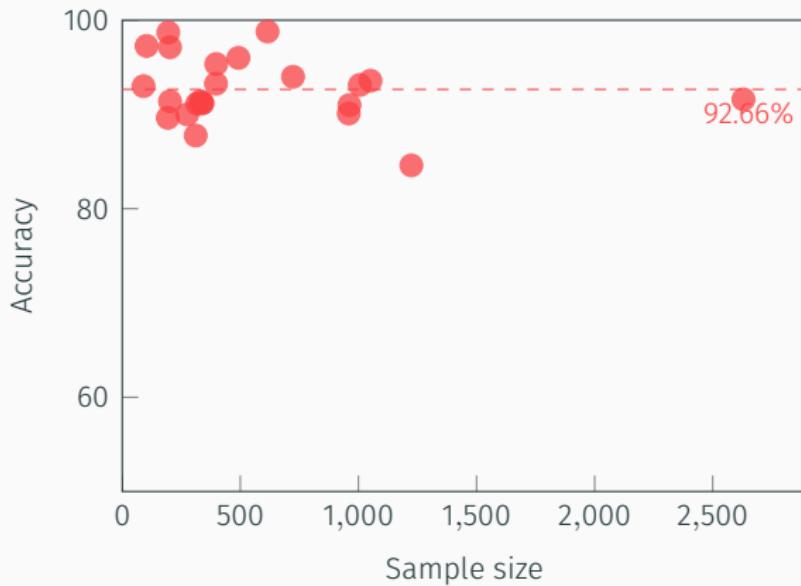
Explanation of PET



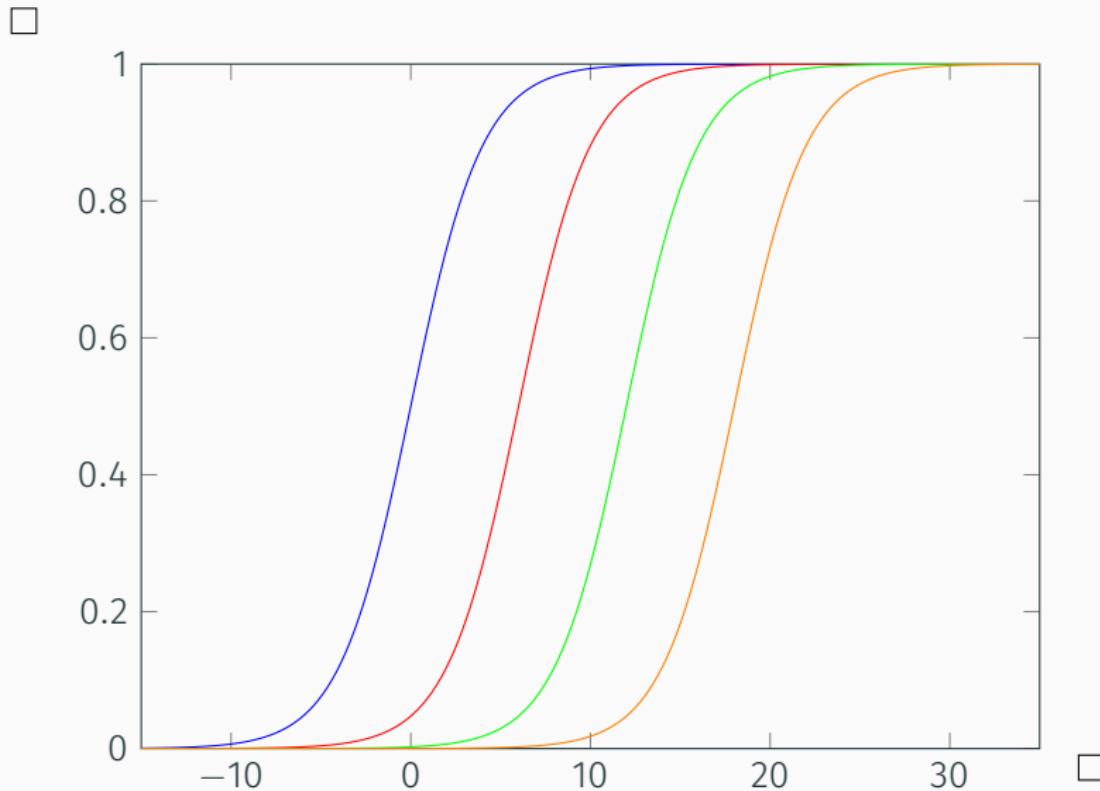
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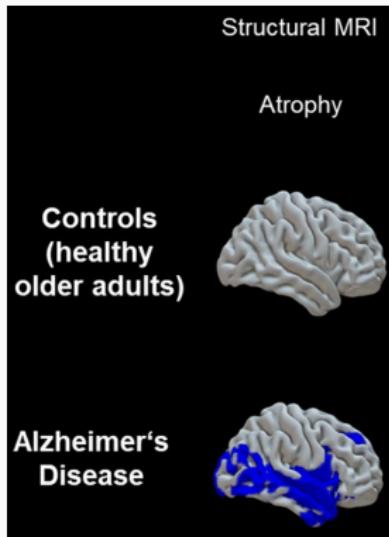
DEM classification studies using PET



Molecular imaging (PET/SPECT)



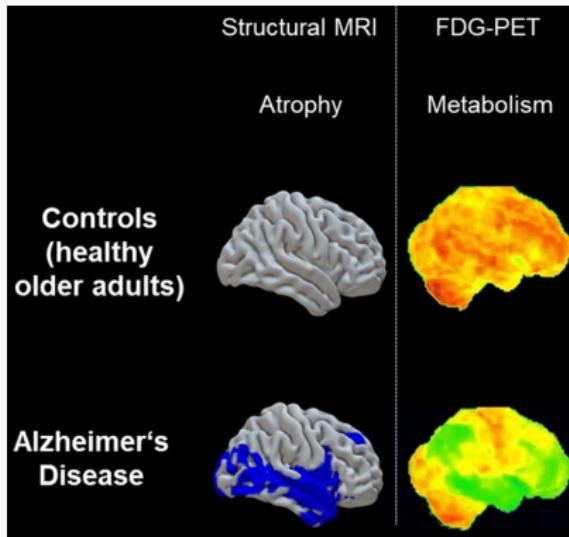
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Chételat, G., Arbizu, J., Barthel, H., Garibotto, V., Lammertsma, A. A., Law, I., ... & Drzezga, A. (2021). Finding our way through the labyrinth of dementia biomarkers. European journal of nuclear medicine and molecular imaging, 48, 2320-2324



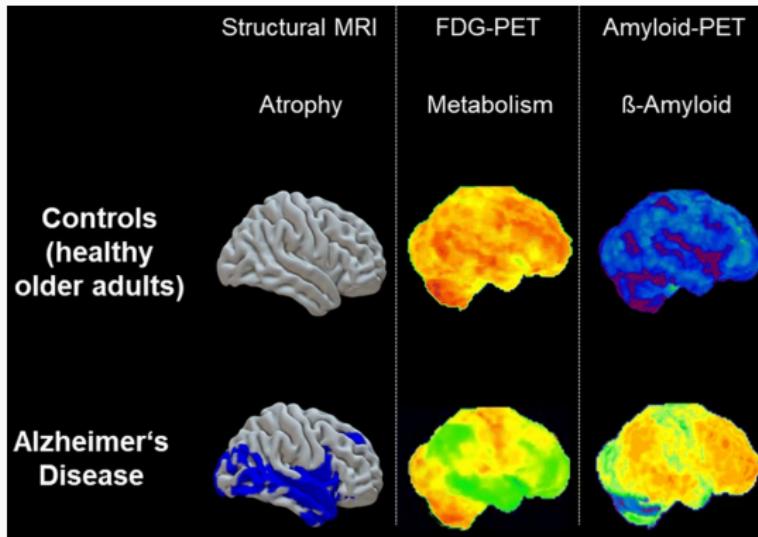
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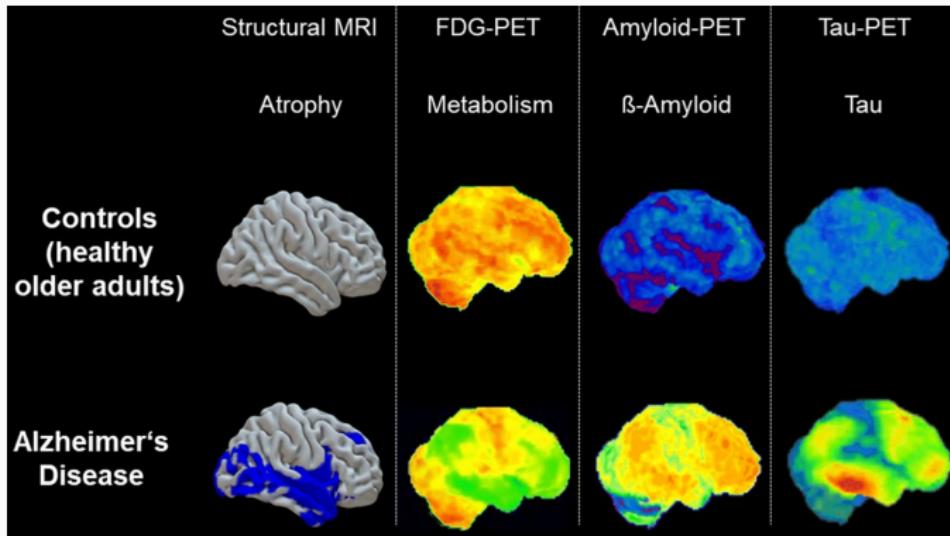
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Molecular imaging (PET/SPECT)



Molecular imaging (PET/SPECT)



"It is necessary to separate syndrome (clinically identified impairment) from biology (etiology)

AD is defined by its biology with the following implications

The disease is first evident with the appearance of β-amyloid plaques, and later neocortical tau tangles, while people are asymptomatic. Pathophysiologic mechanisms involved with processing and clearance of protein fragments may be involved very early in the disease process, but these are not yet well understood.

In living people the disease is diagnosed by disease specific core biomarkers

Unimpaired individuals with abnormal biomarker testing are at risk for symptoms due to AD.

They are not at risk for a disease they already have.

Symptoms are a result of the disease process and are not necessary to diagnose AD

AD exists on a continuum not as discrete clinically defined entities

Clinical syndromes commonly seen with AD may also be caused by disorders other than AD and therefore clinical presentation alone is not diagnostic of AD

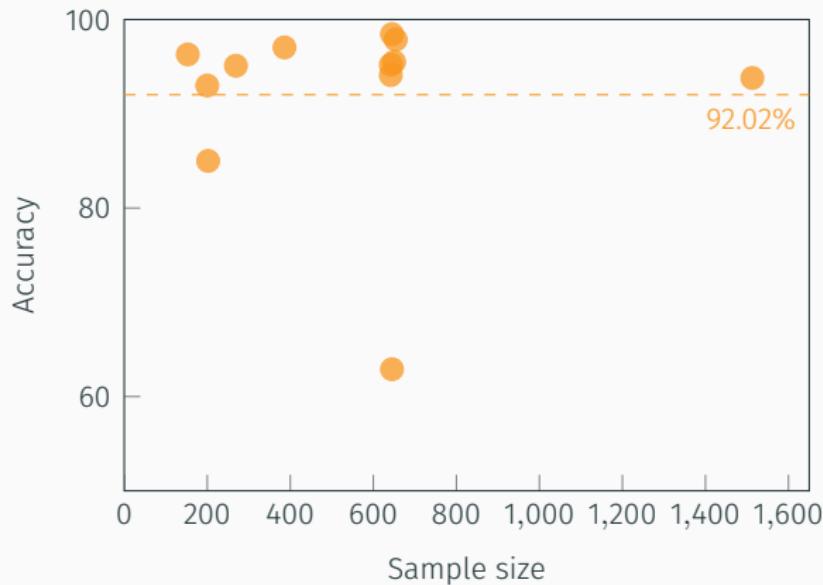
The same AD biology may result in different phenotypic presentations"



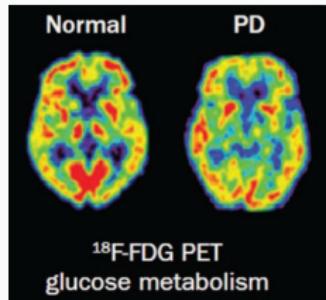
Molecular imaging (PET/SPECT)



PD classification studies using SPECT



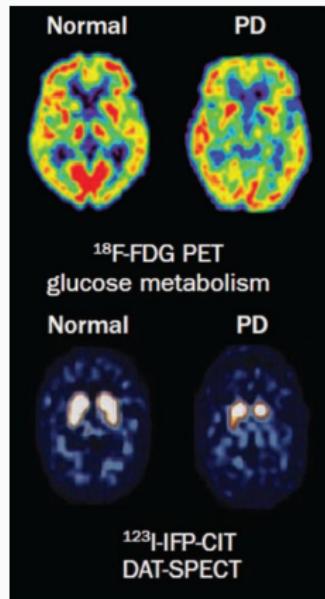
Molecular imaging (PET/SPECT)



Pagano, G., Niccolini, F., & Politis, M. (2016). Imaging in Parkinson's disease. Clinical Medicine, 16(4), 371



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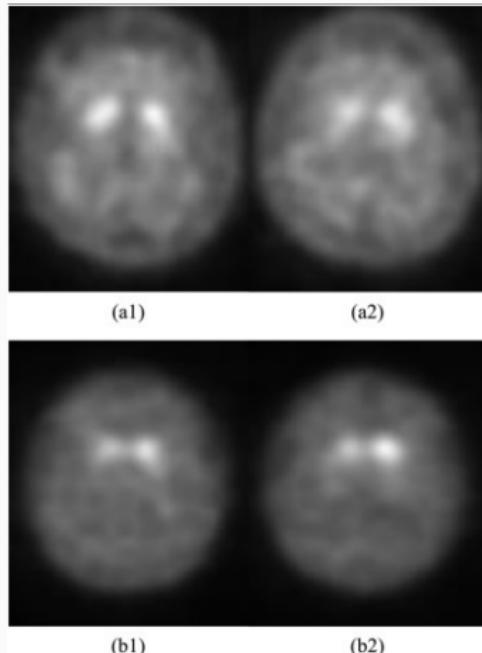
Molecular imaging (PET/SPECT)



Explanation of SPECT



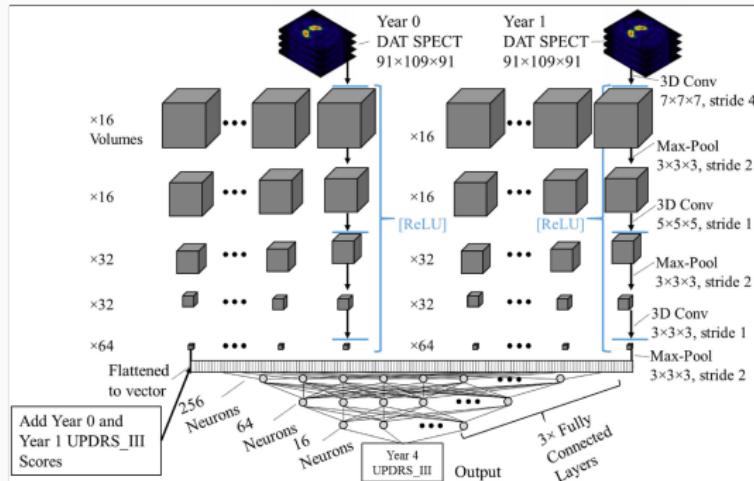
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Adams, M. P., Rahmim, A., & Tang, J. (2021). Improved motor outcome prediction in Parkinson's disease applying deep learning to DaTscan SPECT images. *Computers in Biology and Medicine*, 132, 104312



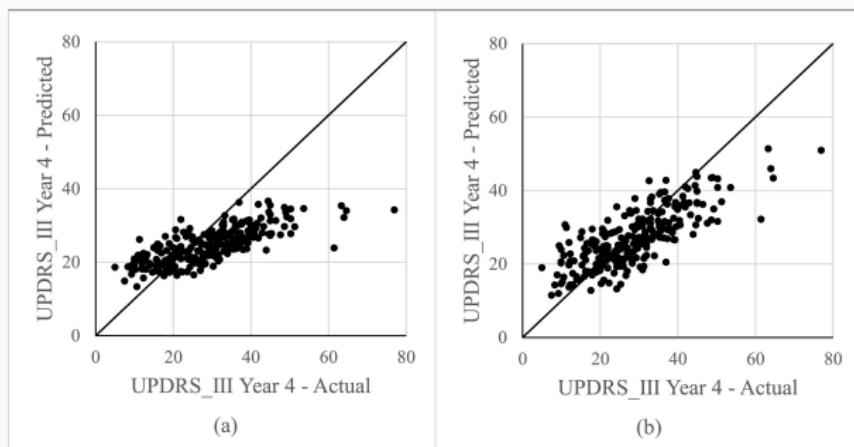
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- Molecular imaging (PET/SPECT)
 - Used in studies classifying PD and DEM with good results (accuracies >90%).
 - PET is excellent for detecting AD-related pathology, both A β plaques and TAU tangles.
 - SPECT useful to characterize degeneration of dopamine-producing cells in PD, and, as shown by Adams et al., is plausibly useful to predict prognosis.

