

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

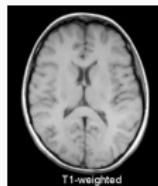
Esten H. Leonardsen

26.10.23



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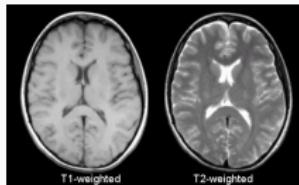
Other structural MRI modalities



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



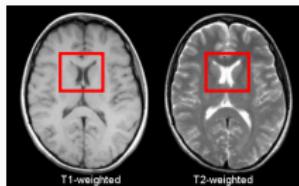
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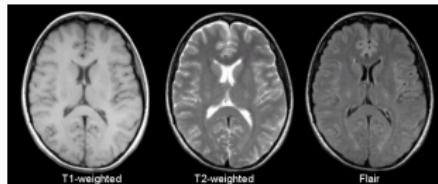
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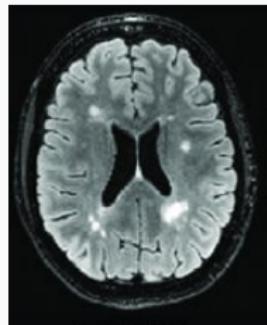
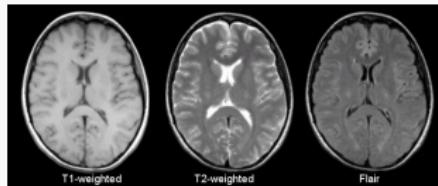
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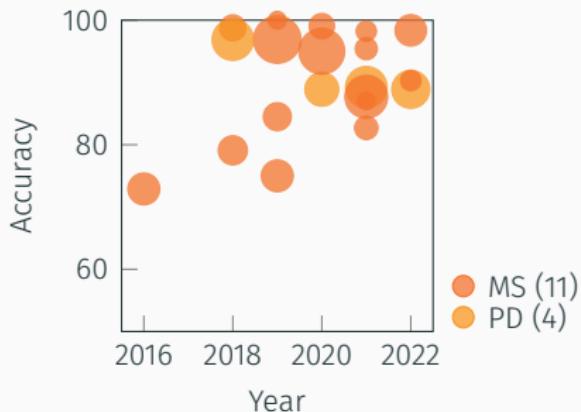
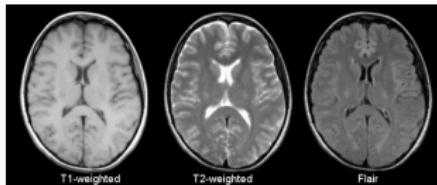
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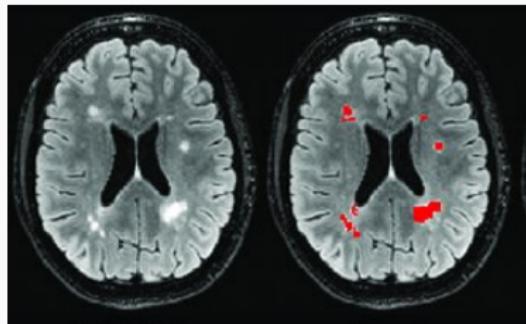
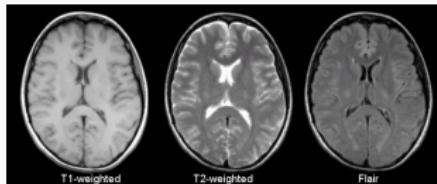
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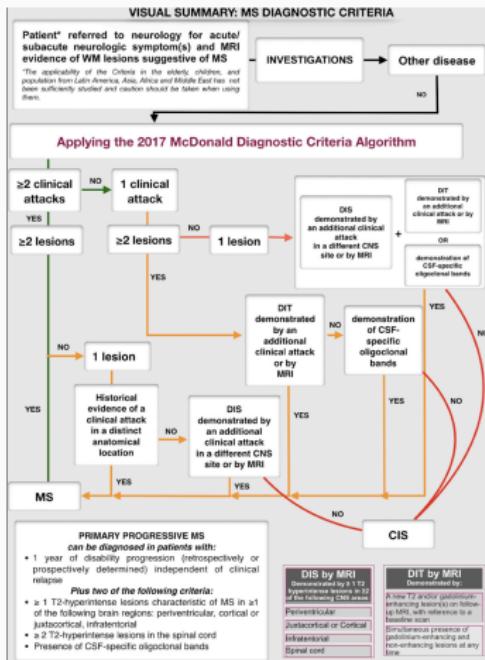
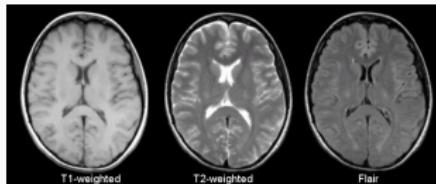
Other structural MRI modalities



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

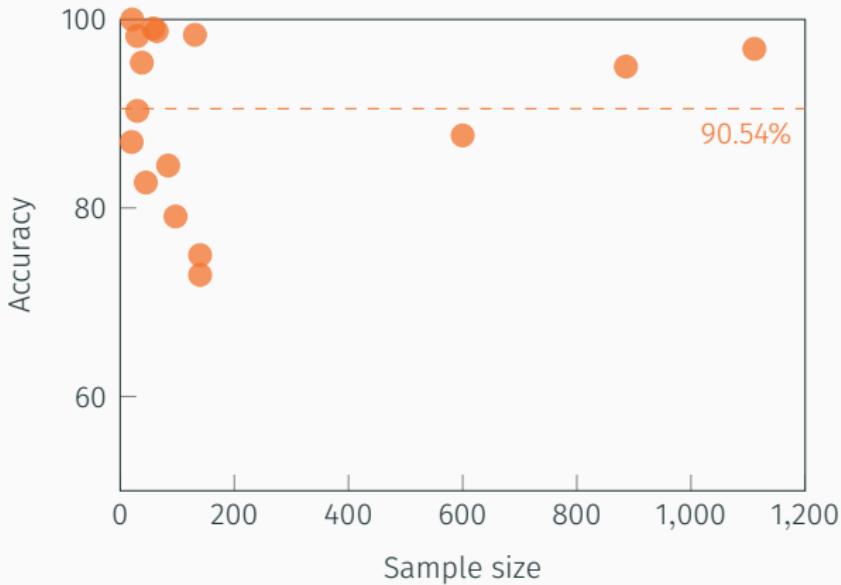


De Angelis, F., Brownlee, W. J., Chard, D. T., & Trip, S. A. (2019). New MS diagnostic criteria in practice. Practical Neurology, 19(1), 64-67

Other structural MRI modalities



MS classification studies using T2/FLAIR



Other structural MRI modalities



TABLE 3 – Accuracy, Sensitivity, and Specificity in the Prognosis of Disease Evolution for the Expert Raters and for the Proposed CNN Model on the Independent Test Set

| | Prediction of Clinical Worsening (EDSS Model) | Prediction of Cognitive Worsening (SDMT Model) | Prediction of Clinical and Cognitive Worsening (EDSS + SDMT Model) | P* |
|-------------------------|---|--|--|-------------|
| CNN deep learning | Accuracy (%) | 83.3 | 62.7 | 85.7 |
| | Sensitivity (%) | 52.9 | 60.0 | 75.0 |
| | Specificity (%) | 90.0 | 81.8 | 83.5 |
| Expert raters consensus | Accuracy (%) | — | — | 70.0 <0.001 |
| | Sensitivity (%) | — | — | 14.3 <0.001 |
| | Specificity (%) | — | — | 88.0 <0.01 |

*P value for the comparisons between the expert raters consensus and the deep learning model.



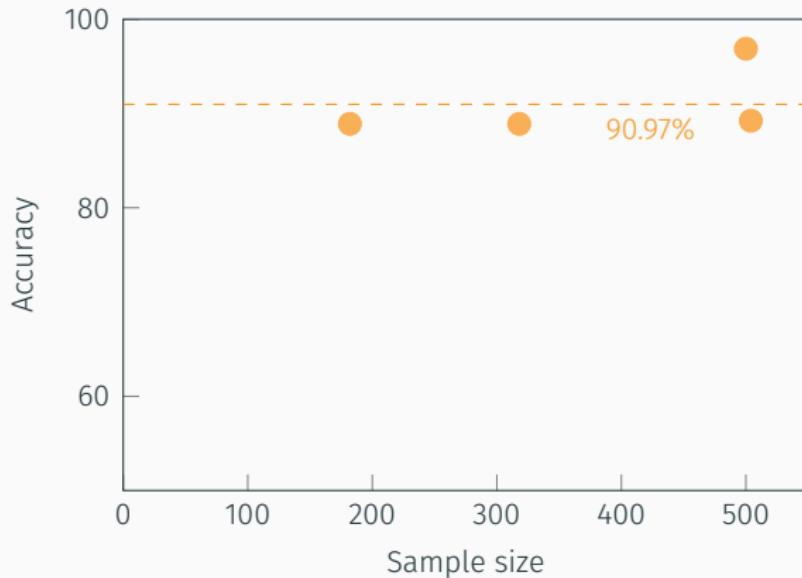
Storelli, L., Azzimonti, M., Gueye, M., Vizzino, C., Preziosa, P., Tedeschi, G., ... & Rocca, M. A. (2022). A deep learning approach to predicting disease progression in multiple sclerosis using magnetic resonance imaging. *Investigative Radiology*, 57(7), 423-432



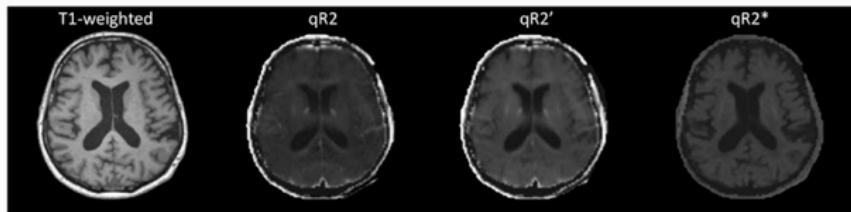
Other structural MRI modalities



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 | | |
| 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

Non-T1 weighted structural MRI

High accuracies for classifying MS and PD (>90%).

T2-weighted images used by Storelli et al. for predicting MS prognosis.

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Explanation of DTI



Diffusion MRI



Explanation of DTI



Diffusion MRI



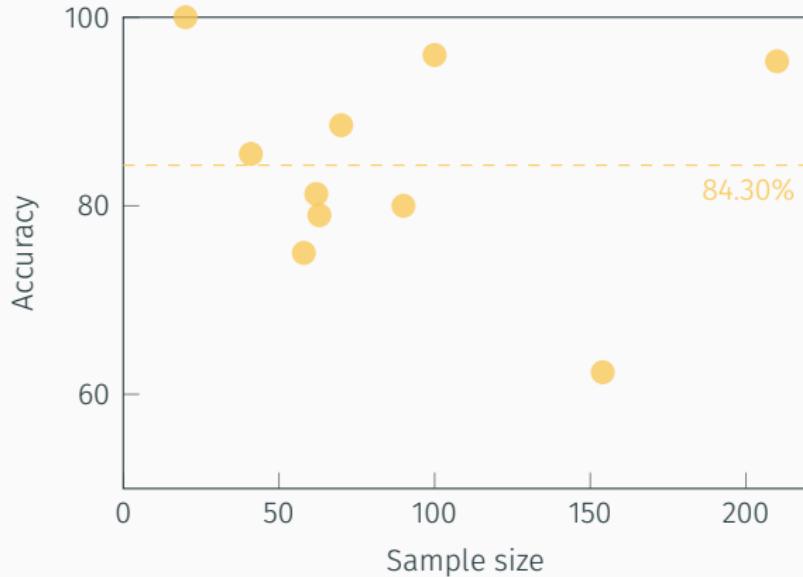
Explanation of DTI

Lack of prediction studies

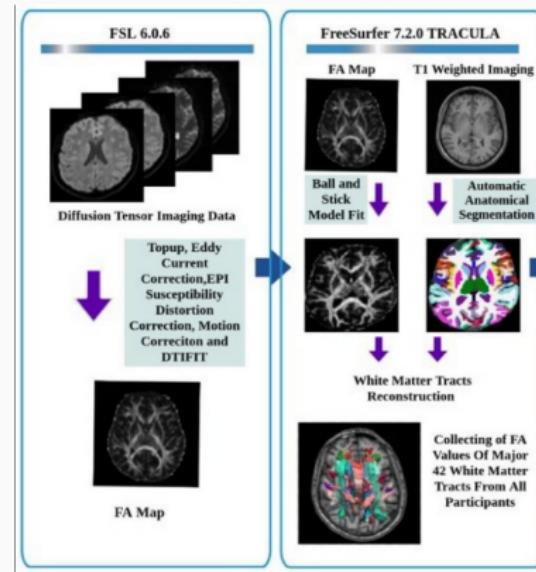




SCZ classification studies using dMRI



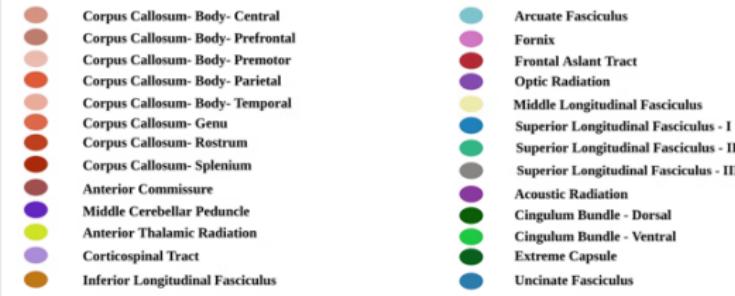
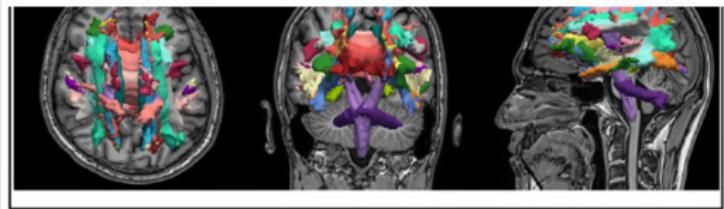
Diffusion MRI



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



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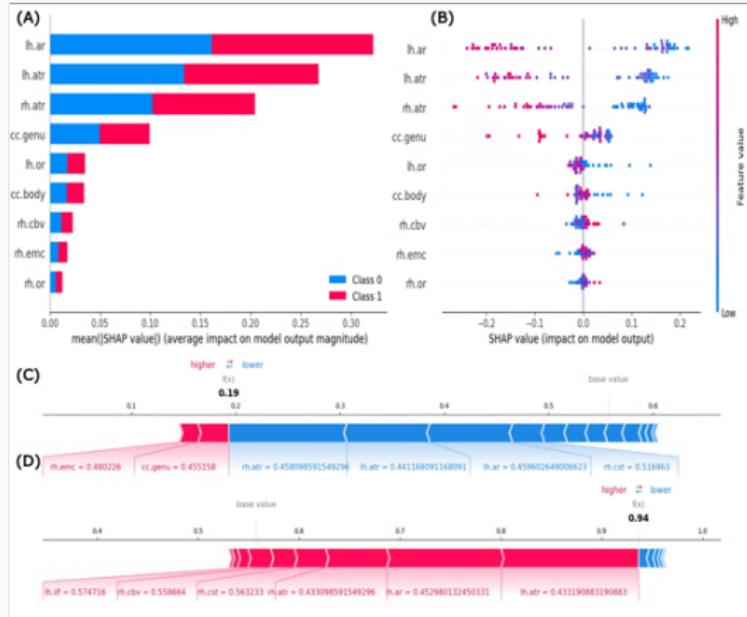


| Classifier | AUC | Accuracy | Sensitivity | Specificity | Precision | F1 score | MCC |
|---------------|------|----------|-------------|-------------|-----------|----------|------|
| SVM-linear | 0.85 | 0.80 | 0.75 | 0.86 | 0.79 | 0.77 | 0.74 |
| Random forest | 0.82 | 0.79 | 0.72 | 0.81 | 0.76 | 0.74 | 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 |

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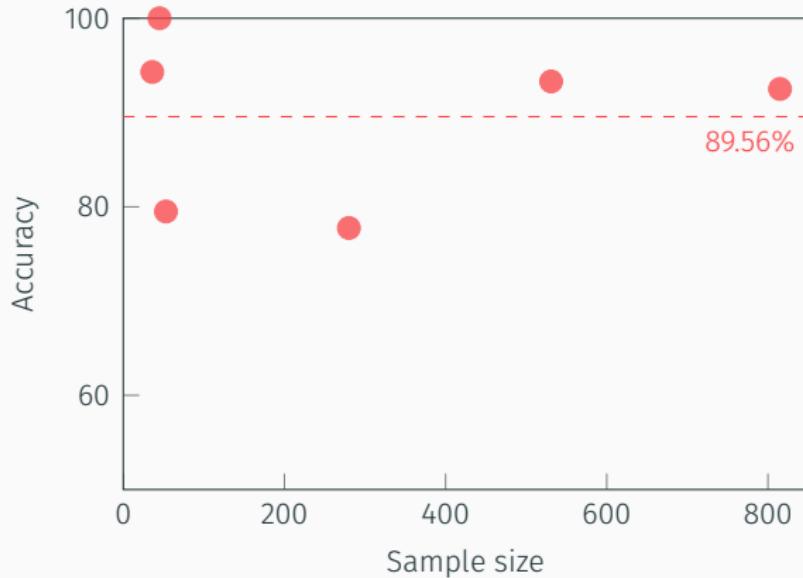


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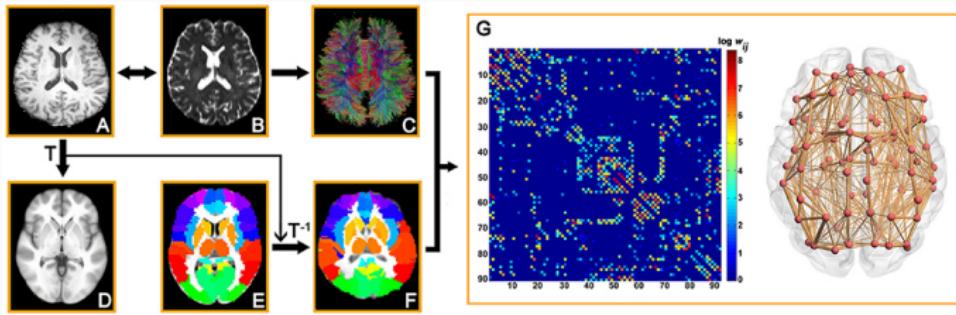




DEM classification studies using dMRI



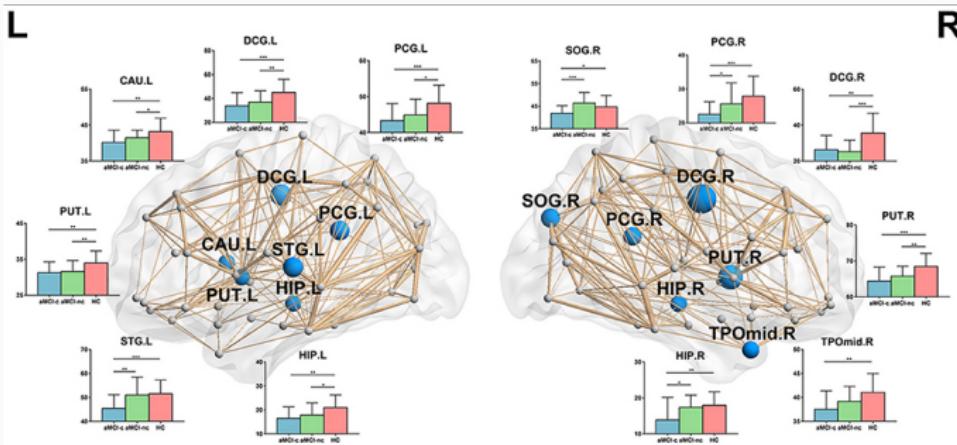
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Sun, Y., Bi, Q., Wang, X., Hu, X., Li, H., Li, X., ... & Han, Y. (2019). Prediction of conversion from amnestic mild cognitive impairment to Alzheimer's disease based on the brain structural connectome. *Frontiers in neurology*, 9, 1178



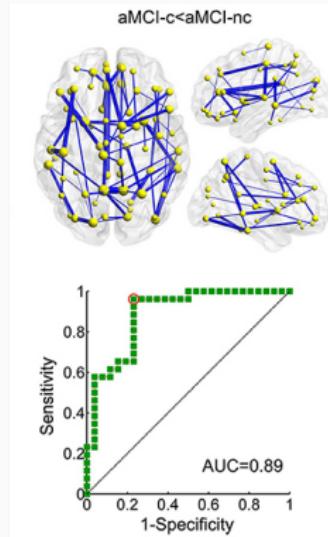
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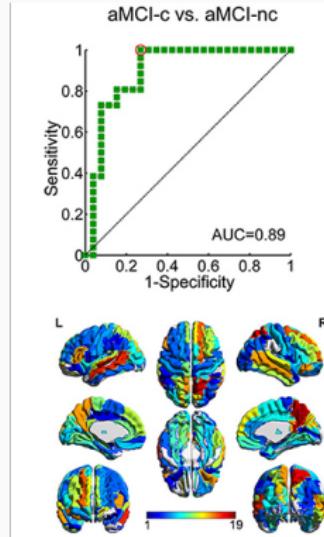
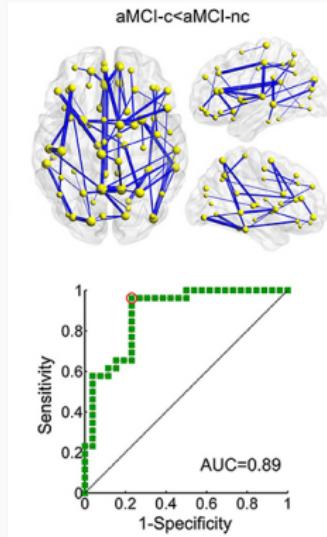
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Diffusion MRI

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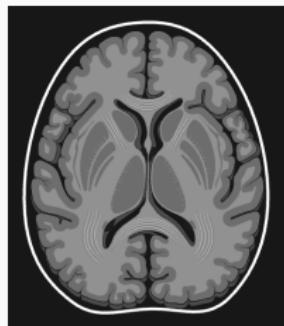
Diffusion MRI

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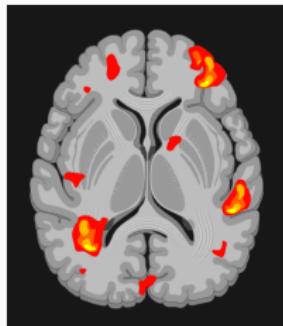
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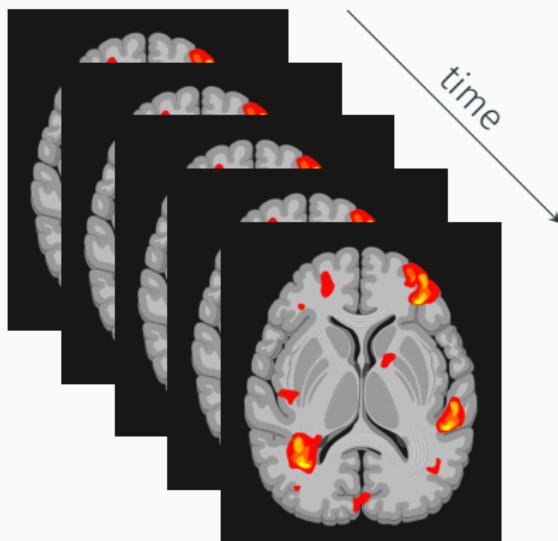
Functional Magnetic Resonance Imaging (fMRI)



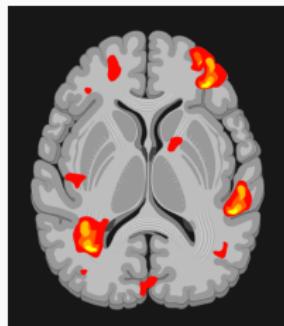
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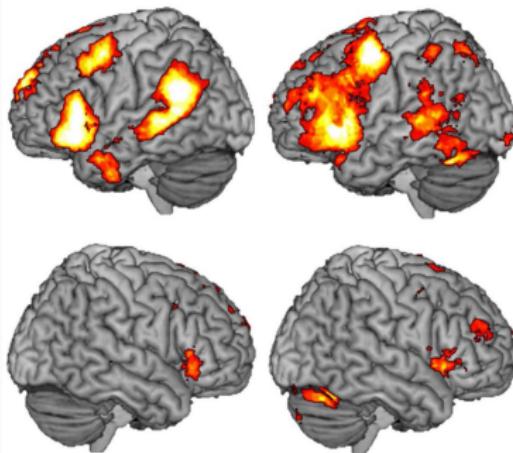


Functional Magnetic Resonance Imaging (fMRI)



rs-fMRI

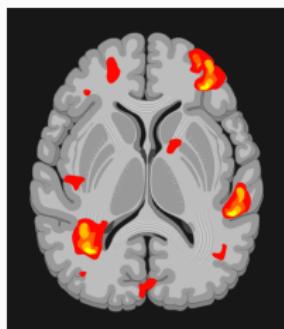
task-fMRI



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



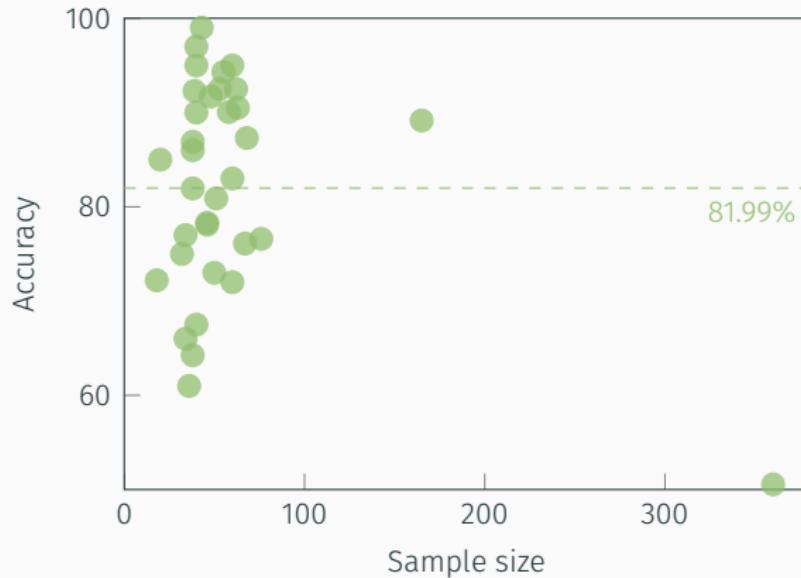
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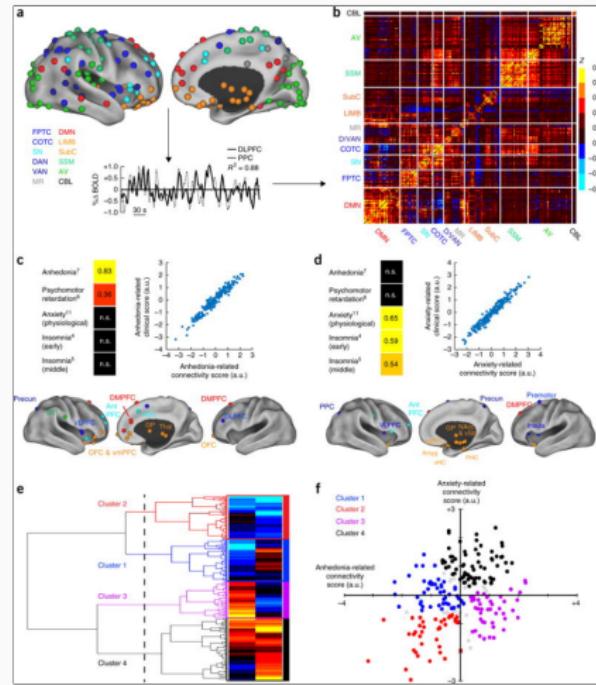
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MDD classification studies using fMRI



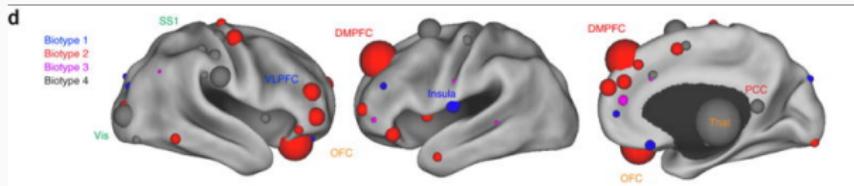
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Drysdale, A. T., Gosenick, L., Downar, J., Dunlop, K., Mansouri, F., Meng, Y., ... & Liston, C. (2017). Resting-state connectivity biomarkers define neurophysiological subtypes of depression. *Nature medicine*, 23(1), 28-38



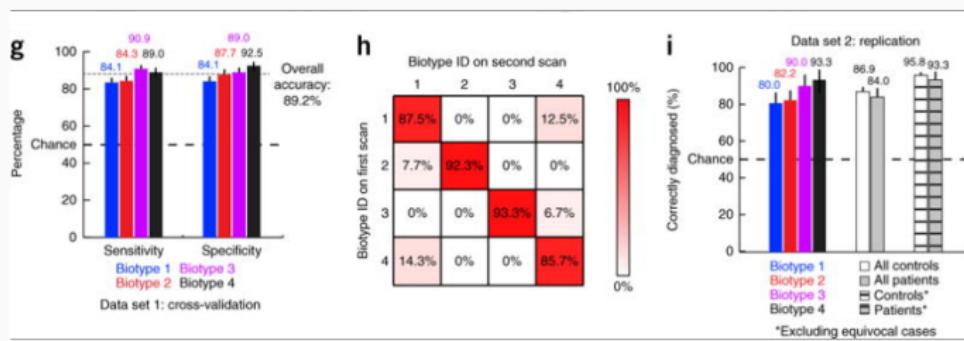
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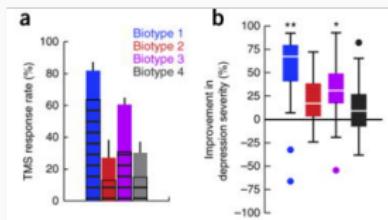
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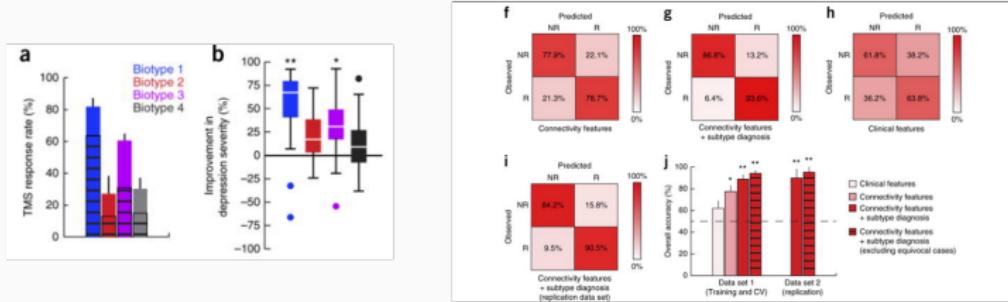
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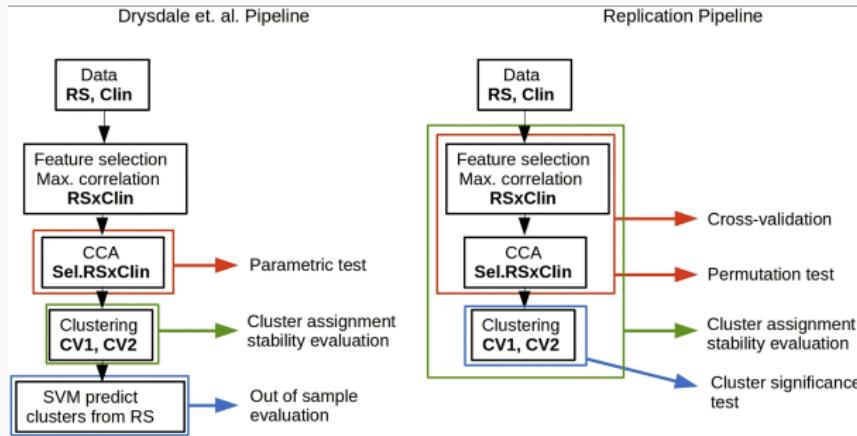
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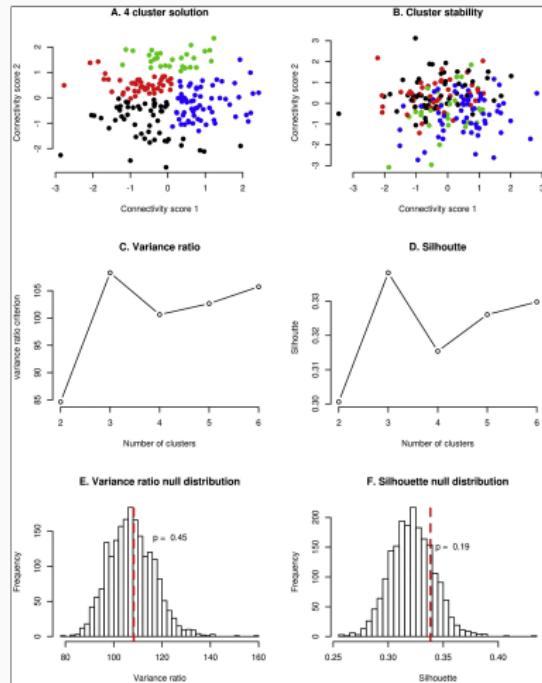
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Functional Magnetic Resonance Imaging (fMRI)

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Functional MRI

Widely used for all conditions, most prominently SCZ and MDD with varying accuracies

(60-100%) and DEM (80-100%).

Used by Drysdale et al. to detect biotypes of MDD that reacted differently to

treatment by transcranial magnetic stimulation.

However, Dinga et al. failed to replicate their results **WHY**.

