Complex Networks in Computational Neuroscience

workshop "Computing@CSN5: applications and innovations at INFN"

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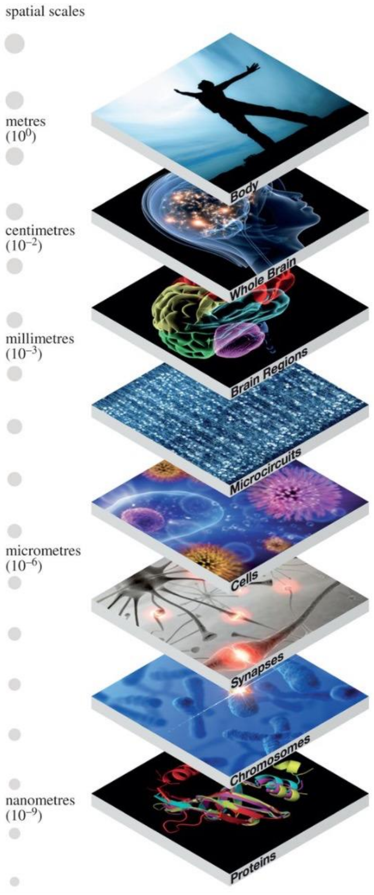
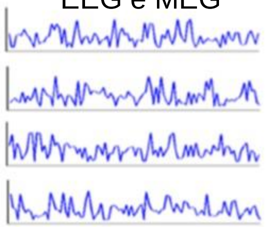
Complex Networks and machine learning



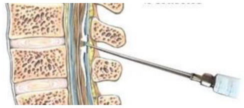
Multiple Scales

Multiple data types

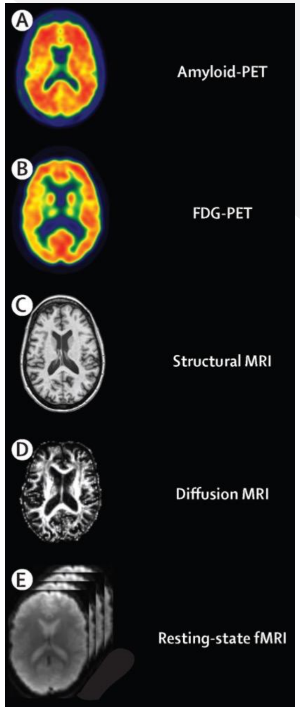
EEG e MEG



CSF



Blood test



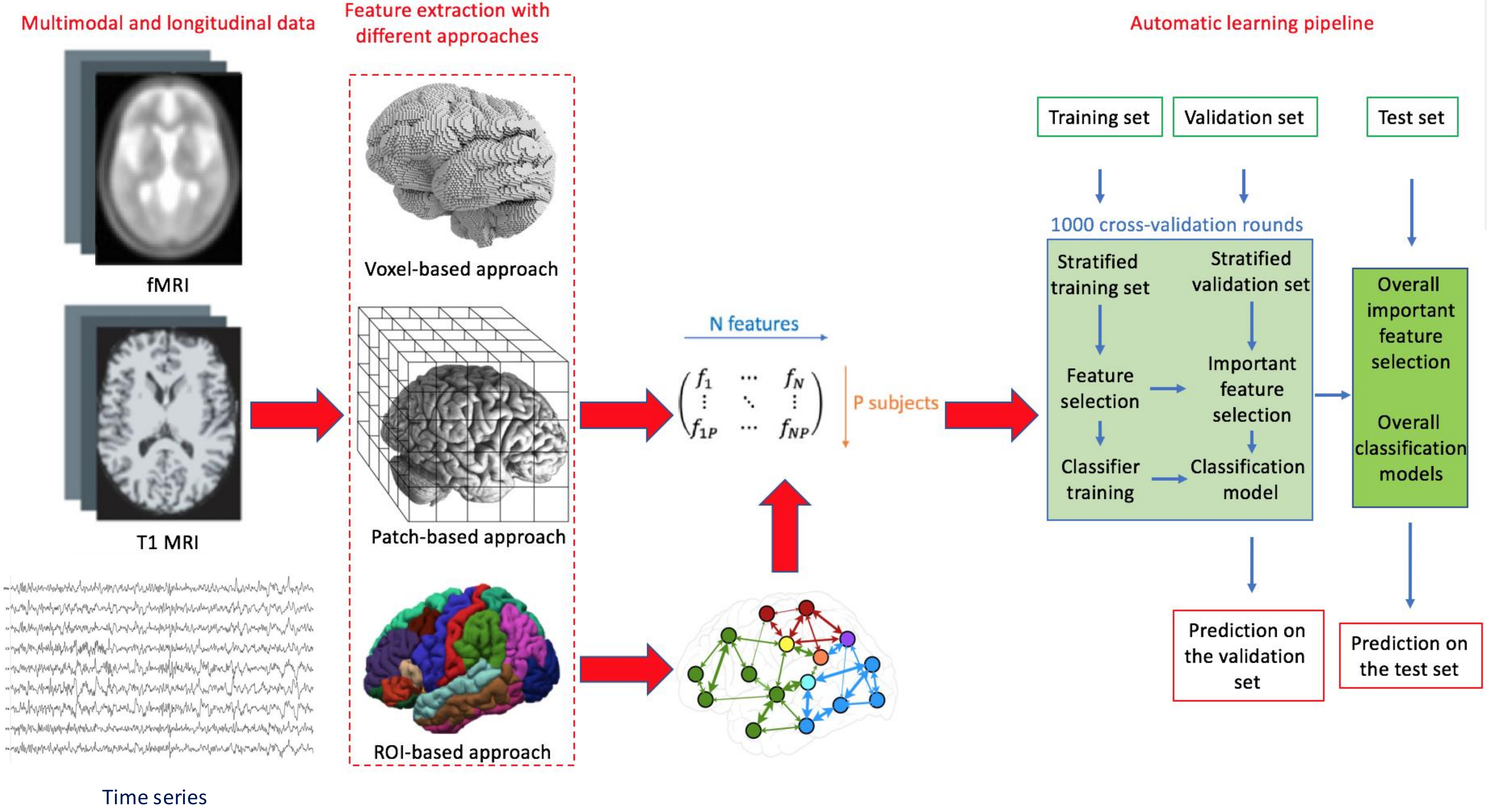
Multiple databases

ADNI

PPMi

Necessity of quantitative methods to manage, process and analyze data of complex matter and great cardinality (Big Data).

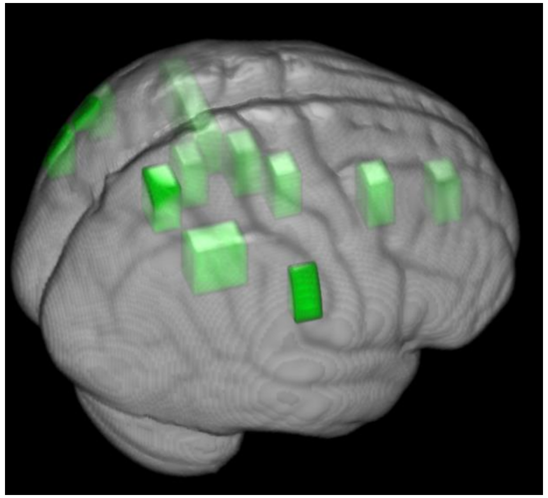
Complex Networks and machine learning



Complex Networks and machine learning

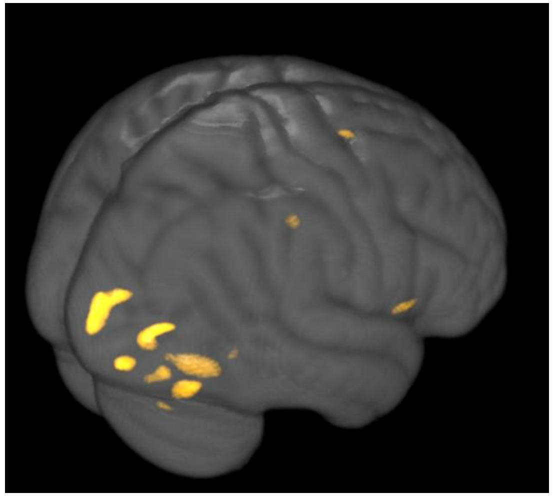
Anatomical Interpretation

By identifying which brain areas correspond to the important features obtained from the machine leaning models, it is possible to have clinical interpretations

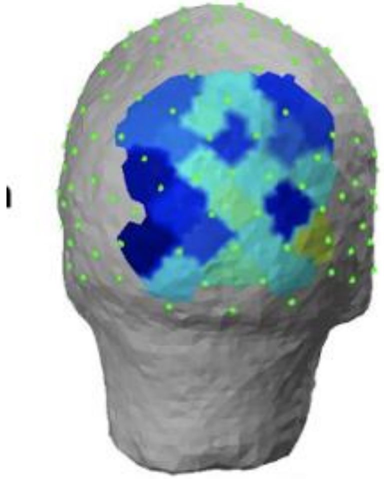


Patch level

ROI level



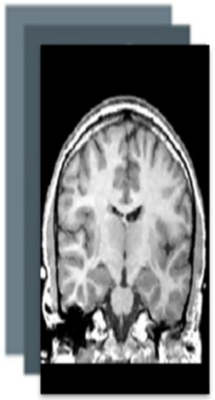
Voxel level



Sensor level

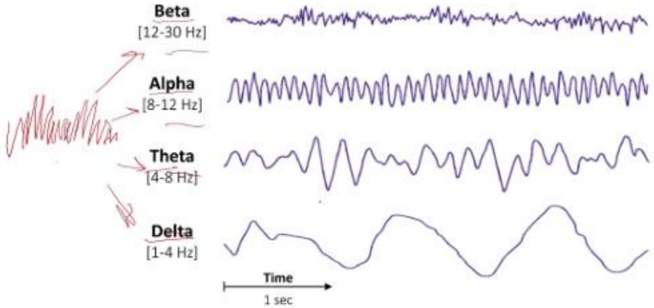
Multiplex Networks

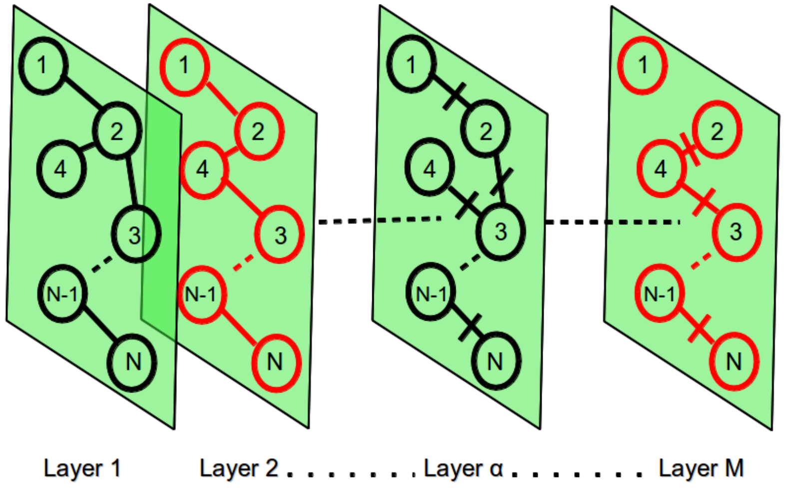
Multiple subjects



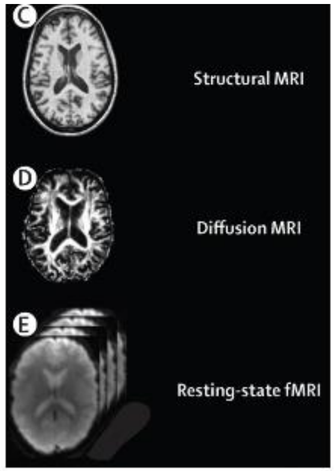
Existing approaches are not able to study the same nodes as interactions change.

Multiple frequency bands





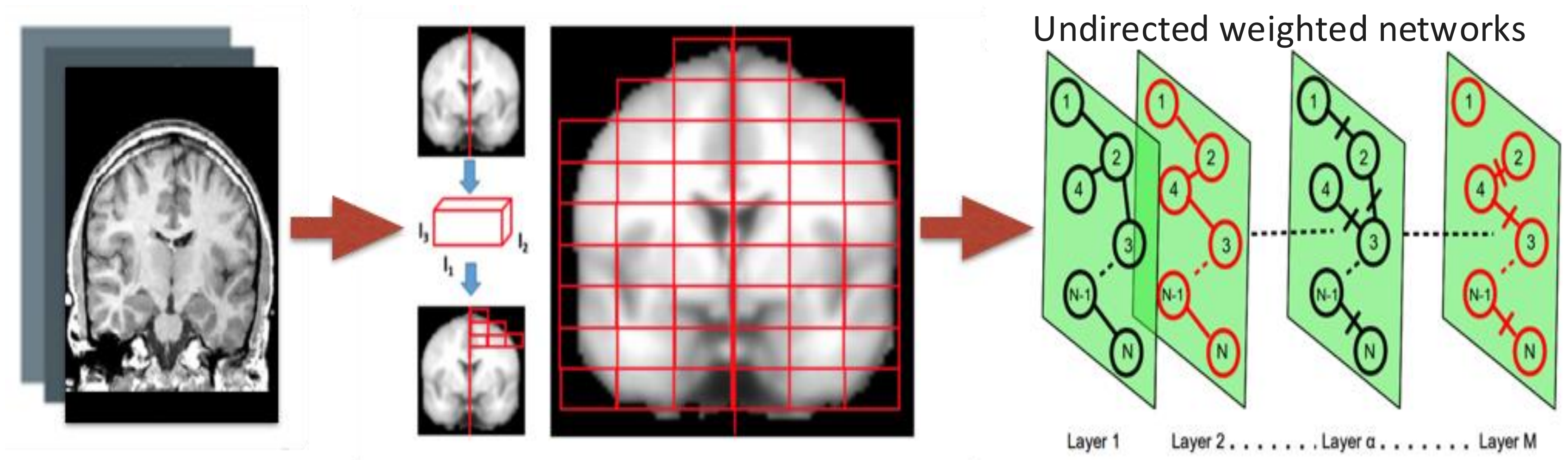
Multiple modalities



Multiplex Networks are an innovative investigation instrument able to provide context information among networks with fixed nodes and variable connections.

Alzheimer case study

Data: T1 MRI of normal controls, Alzheimer disease (AD) subjects, Mild cognitive impairment (MCI) subjects who will develop AD. These data come from Alzheimer's Disease Neuroimaging Initiative (ADNI).
Goal: early detection of the disease in order to test new treatments when they can be truly effective.



(N. Amoroso, M. La Rocca et al., Frontiers in Aging Neuroscience, 2018)

Nodes: Patches, Rectangular parallelepipeds which images can be regularly divided into

Connections: Pearson's correlation coefficient r_{ij} between pairs of nodes.

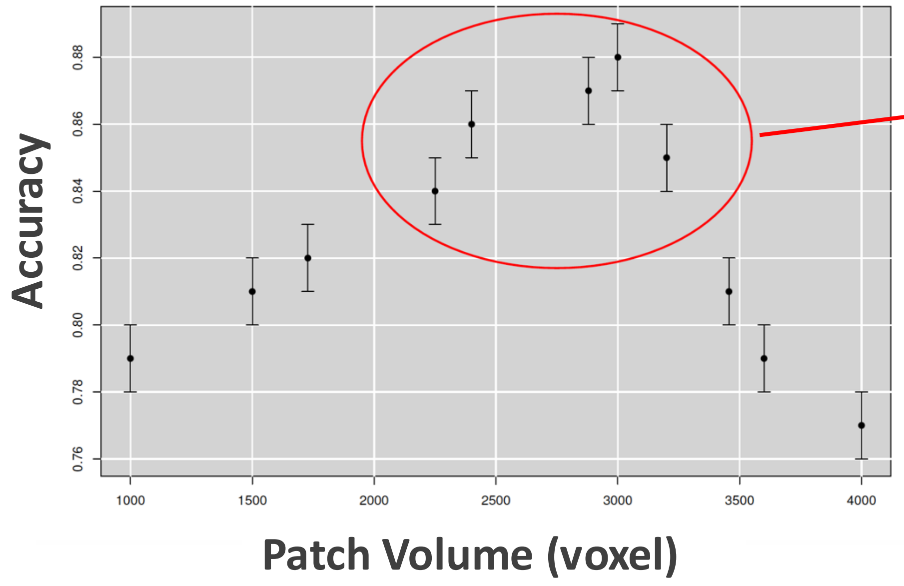
$$r_{i,j} = \frac{\sum_{k=1}^{D}(p_i^k - \bar{p}_i)(p_j^k - \bar{p}_j)}{\sqrt{\sum_{k=1}^{D}(p_i^k - \bar{p}_i)^2}\sqrt{\sum_{k=1}^{D}(p_j^k - \bar{p}_j)^2}}$$

p_i^k e p_j^k are voxel intensity at k position of the patches *i* and *j*.
D patch size.

Multi and single layer metrics concerning node importance and weight uniformity were extracted to train the machine learning system

Alzheimer case study

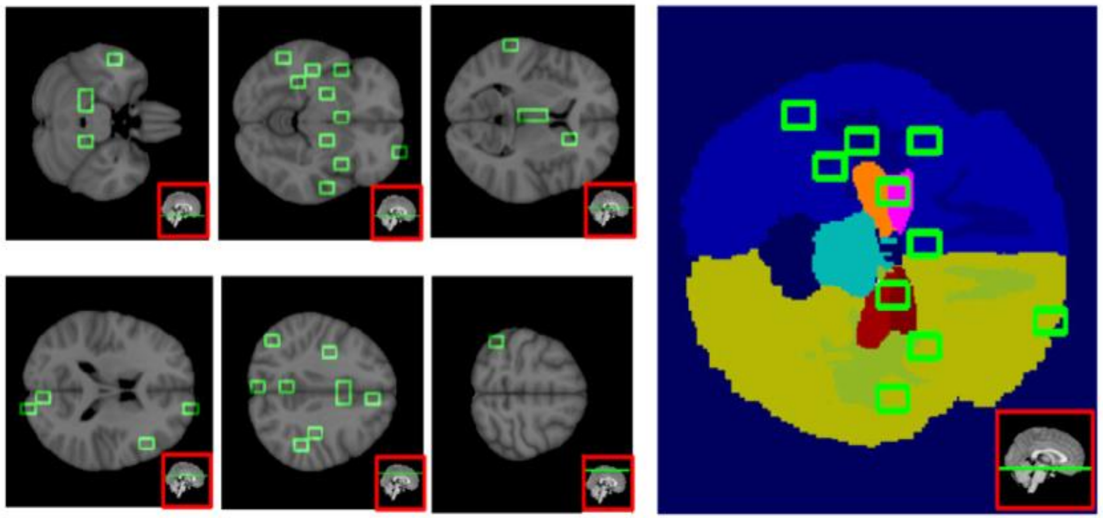
(N. Amoroso, M. La Rocca et al., Frontiers in Aging Neuroscience, 2018)



A fairly stable region in the range of [2250, 3500] voxel. The optimal performance was achieved for a volume of 3000 voxel and an accuracy of 0.88±0.01 significantly greater than that obtained with standard methods like Free Surfer (0.83±0.01).

1) identification of a privileged scale to detect disease effects.

Classification accuracy on an independent dataset	
NC-AD	NC-cMCI
0.86 ± 0.01	0.84 ± 0.01



2) Compared to standard methods, it detects more disease-related anatomical regions with an unsupervised segmentation method.

3) The method is reliable and lends itself well to becoming predictive.

An explainability AI approach to brain connectivity in Alzheimer's

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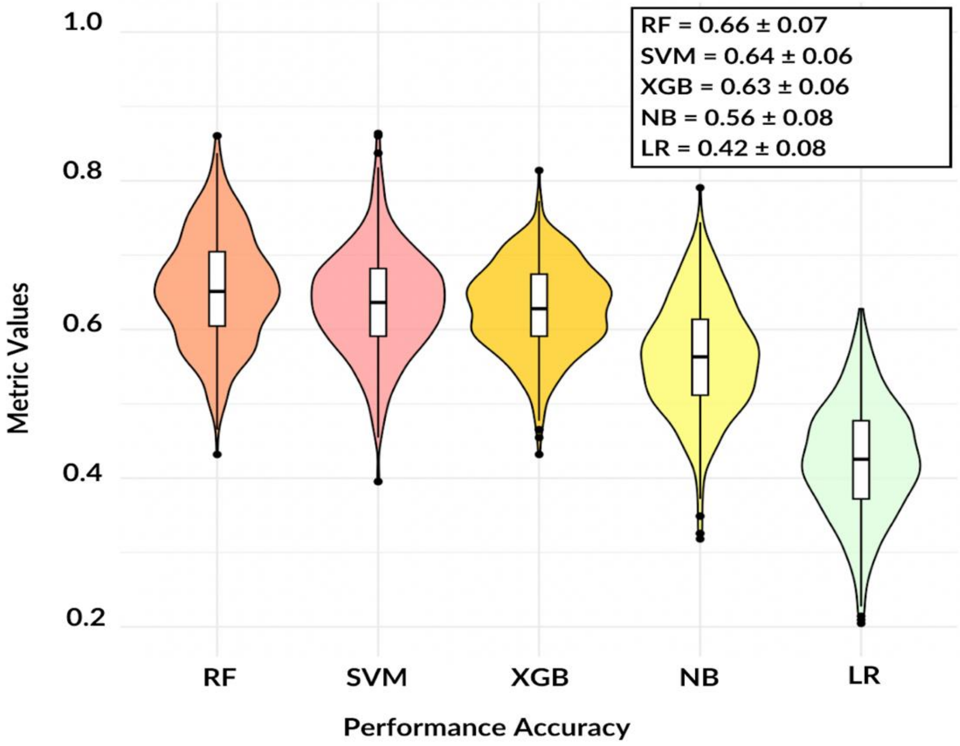
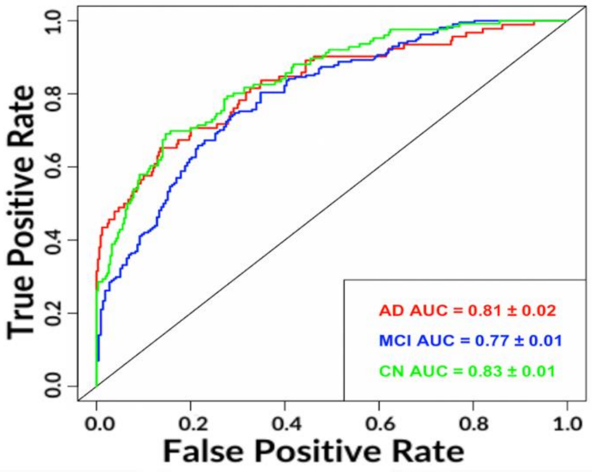
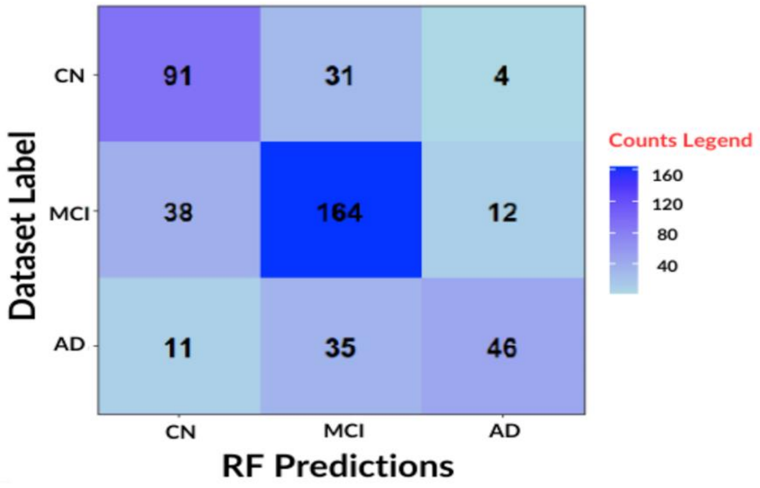
Robustness and Reliability







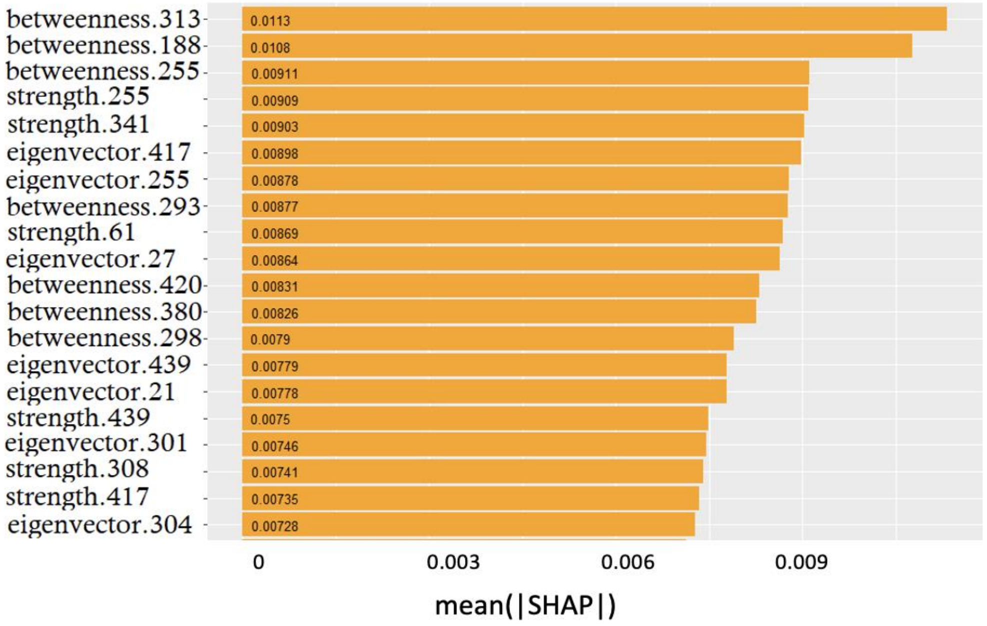
	Accuracy (%)	**AUC** (%)
Sørensen et al., 2014[7]	63.0 (57.9–67.5)	78.8 (75.6–82.0)
Wachinger et al., 2014a[7]	59.0 (54.0–63.6)	77.0 (73.6–80.3)
Ledig et al., 2014[7]	57.9 (52.5–62.7)	76.7 (73.6–79.8)
Dimitriadis et al., 2018[8] (multiclass)	61.9	-
Jimenez-Mesa et al., 2020[9]	67	-

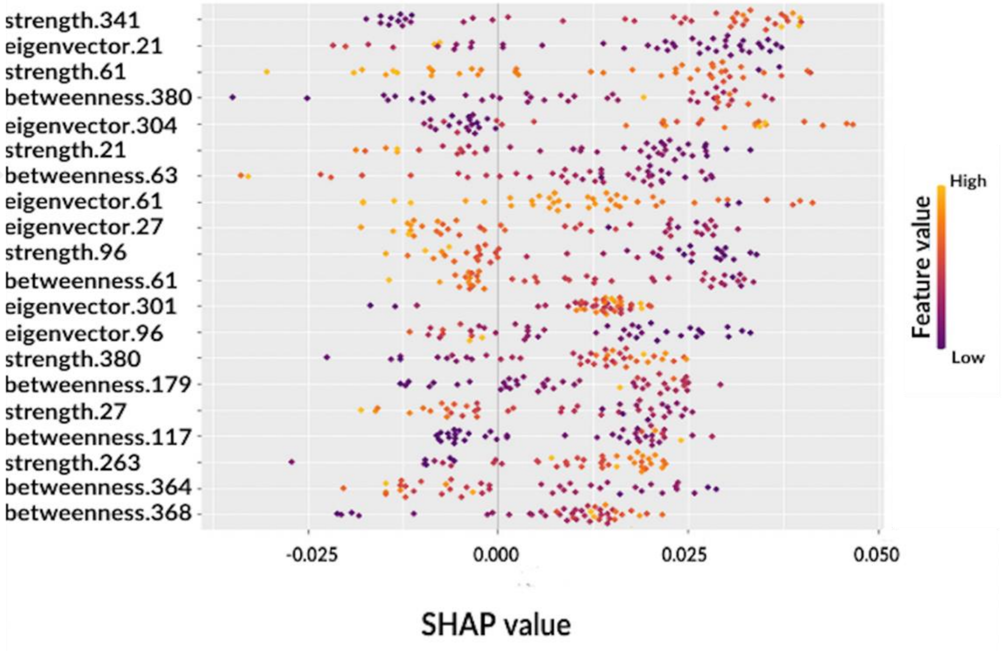
(N. Amoroso, S. Quarto, M. La Rocca et al., Frontiers in Aging Neuroscience, 2023)

[7] Bron et al. (2015). Standardized evaluation of algorithms for computer-aided diagnosis of dementia based on structural mri: the caddementia challenge.
[8] Dimitriadis et al. (2018). Random forest feature selection, fusion and ensemble strategy: combining multiple morphological MRI measures to discriminate among healhy elderly, MCI, cMCI and Alzheimer's disease patients.
[9] Jimenez-Mesa et al. (2020). Optimized one vs. one approach in multiclass classification for early Alzheimer's disease and mild cognitive impairment diagnosis.

An explainability AI approach to brain connectivity in Alzheimer's

XAI driving features





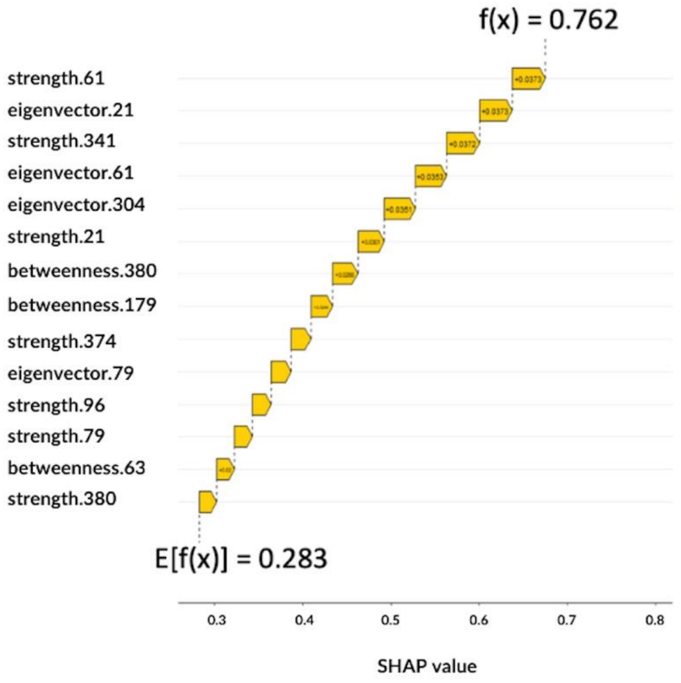
Global Feature Importance vs:	Spearman's ρ	p-value
AD Feature Importance	0.06	0.6
MCI Feature Importance	0.73	$< 2.2 \times 10^{-16}$
CN Feature Importance	0.59	4×10^{-8}

The correlation is high for all the classes but the AD class underlining how much AD subjects are heterogeneous

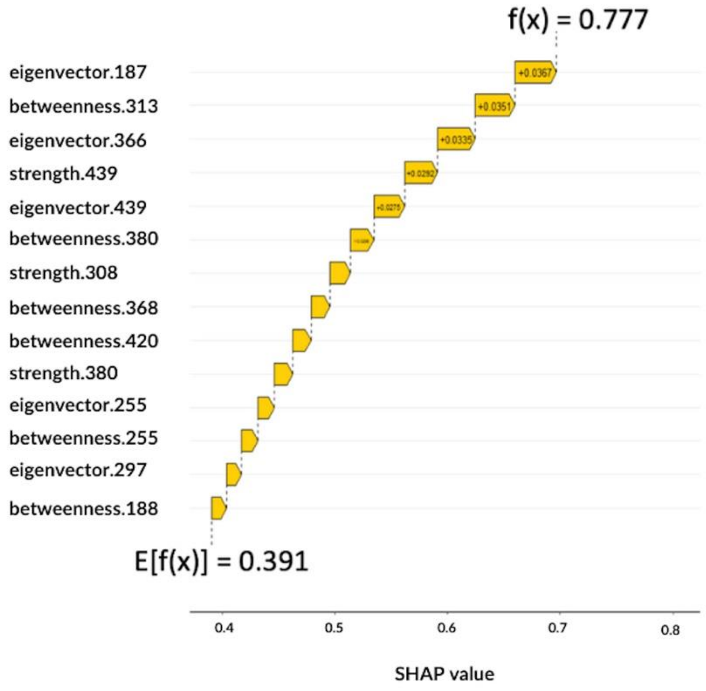
An explainability AI approach to brain connectivity in Alzheimer's

Driving features for personalized explanations

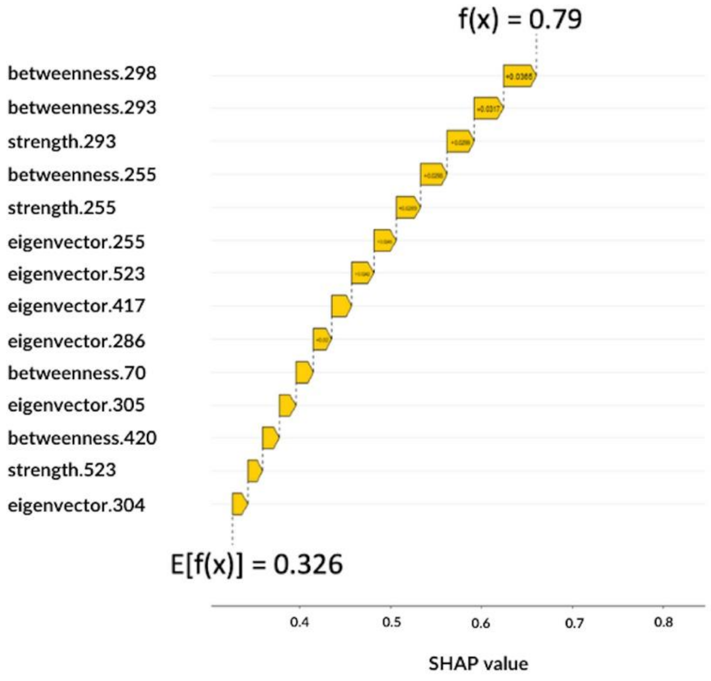
AD patient correctly classified



MCI patient correctly classified

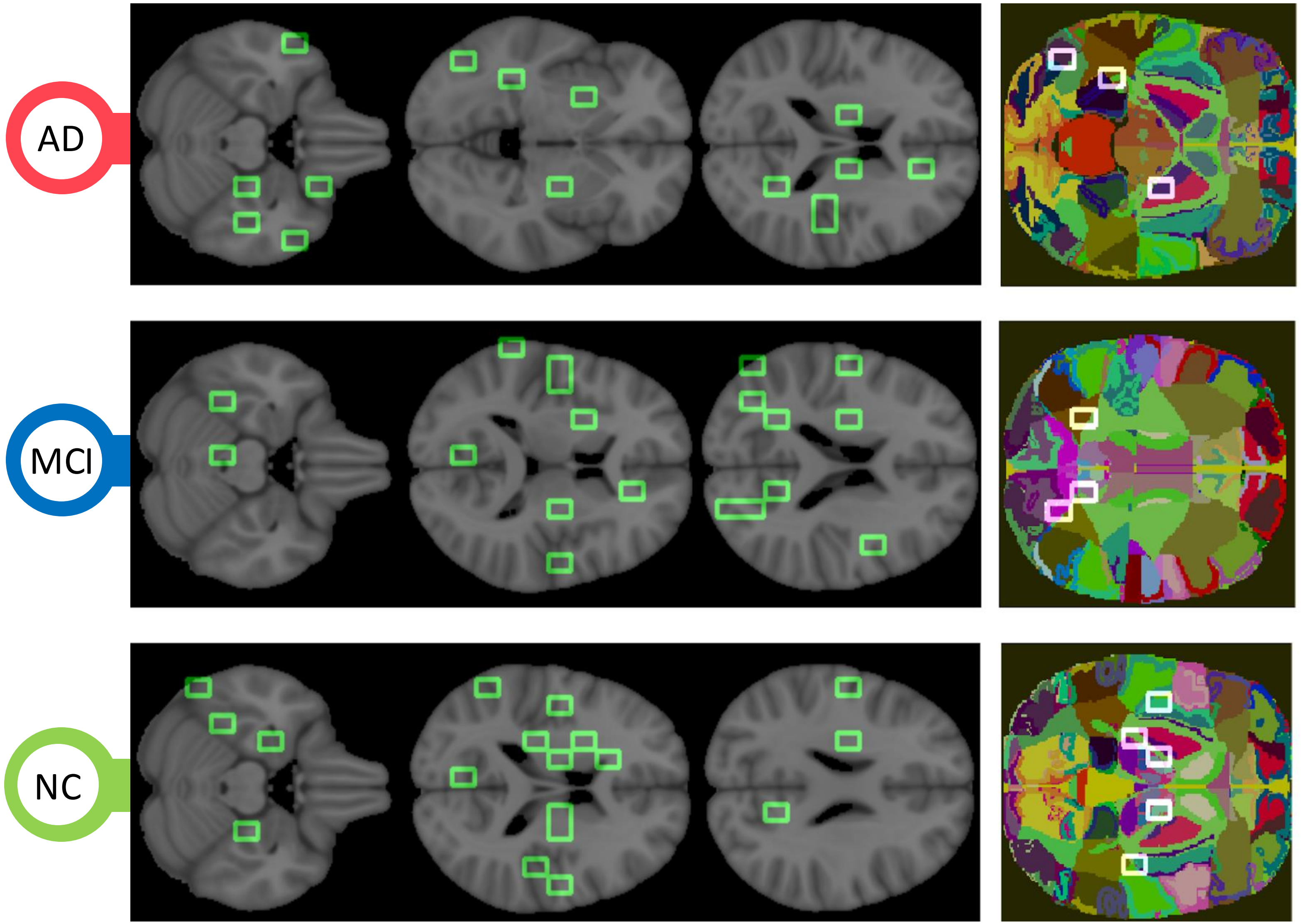


NC patient correctly classified



An explainability AI approach to brain connectivity in Alzheimer's

From network metrics to brain regions



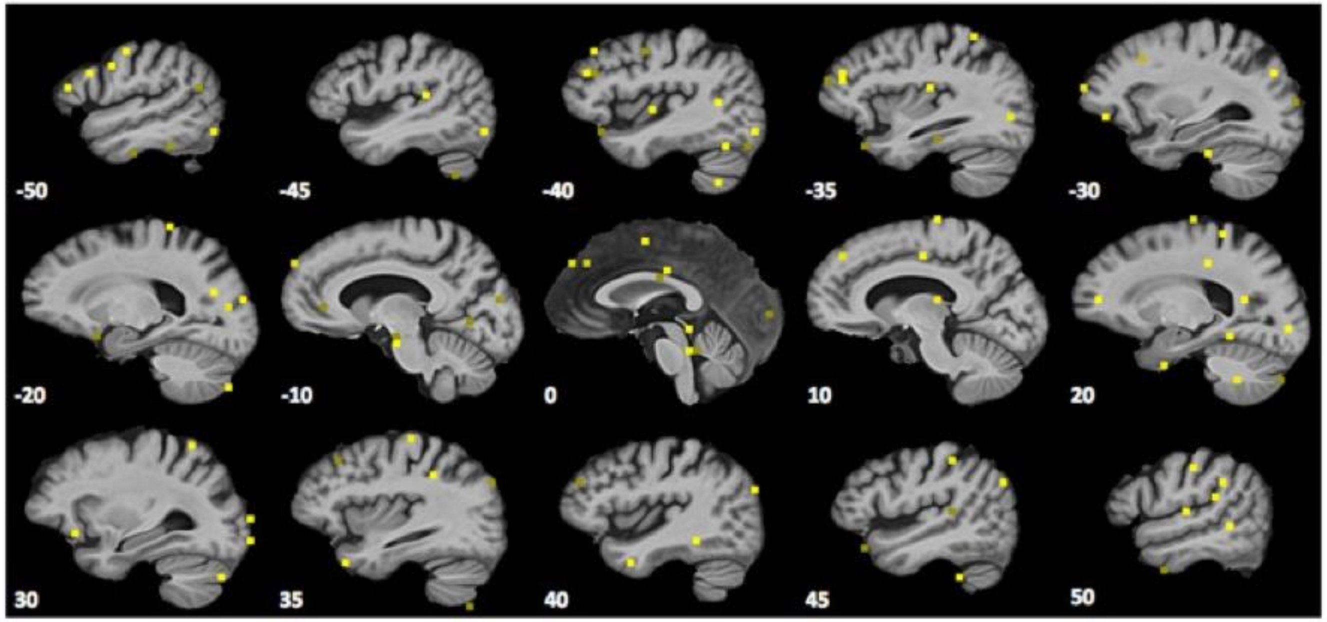
Para Hippocampal Gyrus
Amygdala
Fusiform gyrus
Middle Occipital Gyrus

Posterior Cingulate
Cuneus and Pre-Cuneus
Temporal lobe Sub-Gyral

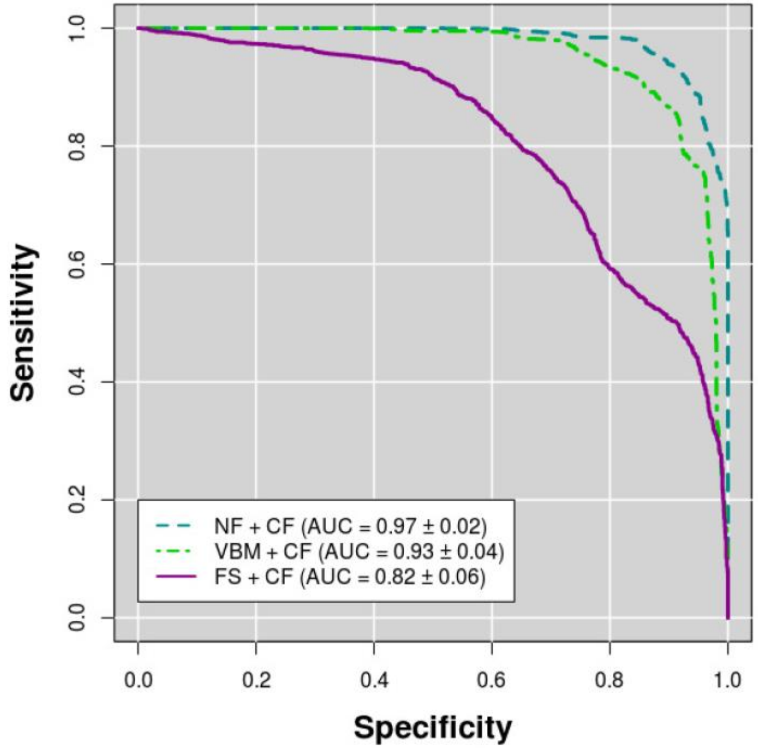
Thalamus
Insula

Parkinson case study

Data: T1 MRI of Normal controls, Parkinson disease (PD) subjects at the first stages of the disease. Data come from the Parkinson's Progression Markers Initiative (PPMI).
Goal: early detection of the disease in order to test new treatments when they can be truly effective.



This method outperform conventional methods such as FreeSurfer or Voxel Based Morphometries.



Accuracy
NC-PD
0.832 ± 0.004

The best accuracy was reached of a volume of 125 voxels.

(N. Amoroso, M. La Rocca et al., Medical image analysis, 2018)

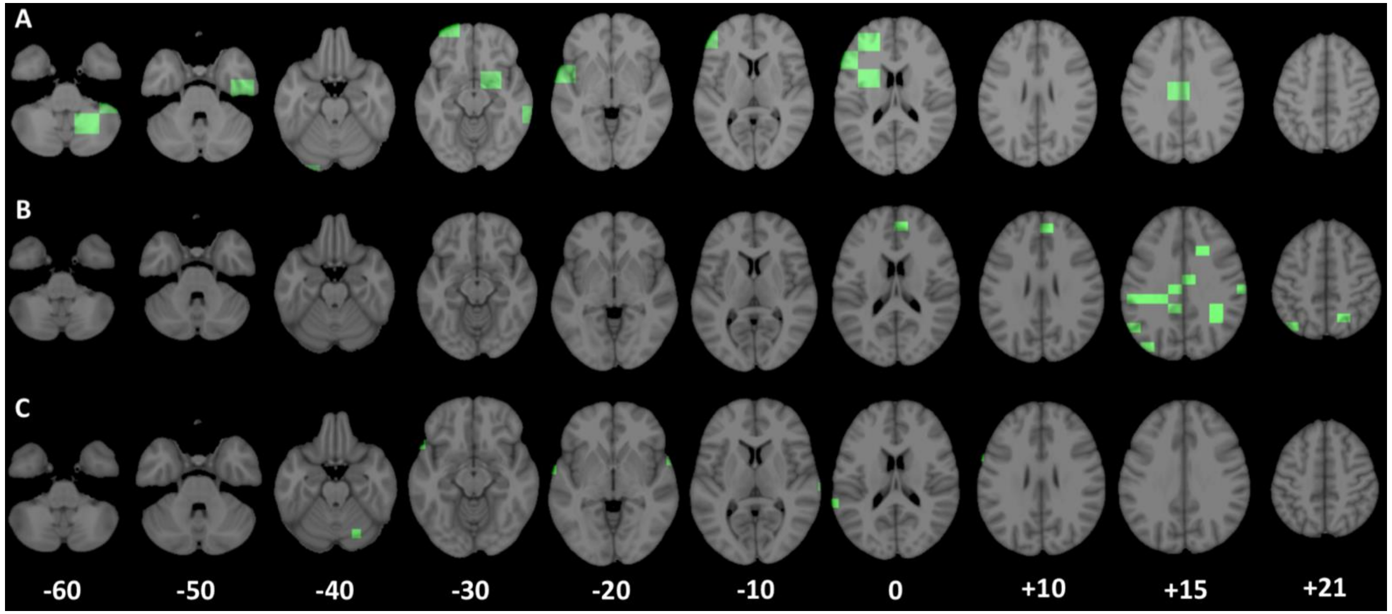
Post-traumatic epilepsy case study

Data: T1 MRI of traumatic brain injury (TBI) patients who developed seizures and seizure-free TBI patient. Data come from The Epilepsy Bioinformatics Study for Antiepileptogenic Therapy (EpiBioS4Rx) .
Goal: Identify relevant biomarkers of epileptogenesis after traumatic brain injury (TBI).

Features	Accuracy	Specificity	Sensitivity	AUC
FreeSurfer	0.67 ± 0.03	0.61 ± 0.05	0.71 ± 0.04	0.71 ± 0.03
VBM	0.60 ± 0.02	0.54 ± 0.03	0.67 ± 0.03	0.62 ± 0.03
Complex network (1000 voxels)	0.70 ± 0.03	0.74 ± 0.04	0.66 ± 0.04	0.75 ± 0.02
Complex network (3000 voxels)	0.68 ± 0.03	0.70 ± 0.04	0.67 ± 0.04	0.76 ± 0.02
Complex network (5000 voxels)	0.70 ± 0.03	0.68 ± 0.04	0.69 ± 0.04	0.75 ± 0.02

Regions related to the pathology have been confirmed in literature.

The best classification performances were obtained at three scales: 1000, 3000, and 5000 voxels, proving that the study of seizure development in TBI patients requires multi-variate analyses since brain lesions can have different sizes.



(M. La Rocca et al., Frontiers in Neuroscience, 2020)

Conclusions and future steps

- Machine learning in combination with complex networks are excellent methods to manage, analyze and compare multimodal data.

- These methods allows us to face different challenges in the field of neuroscience such as the early diagnosis of different neurological diseases.

- These quantitative models developed using complex networks are suitable to be used in the perspective of personalized medicine.

Thank you for your attention