BrainSuite Tools

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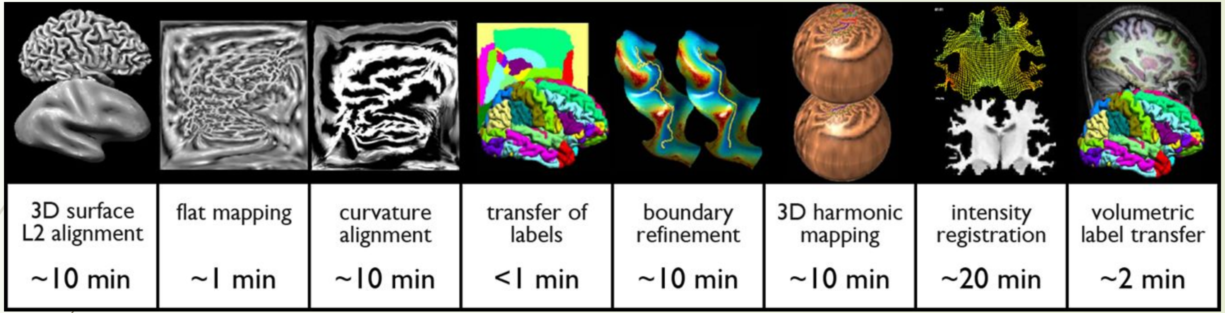
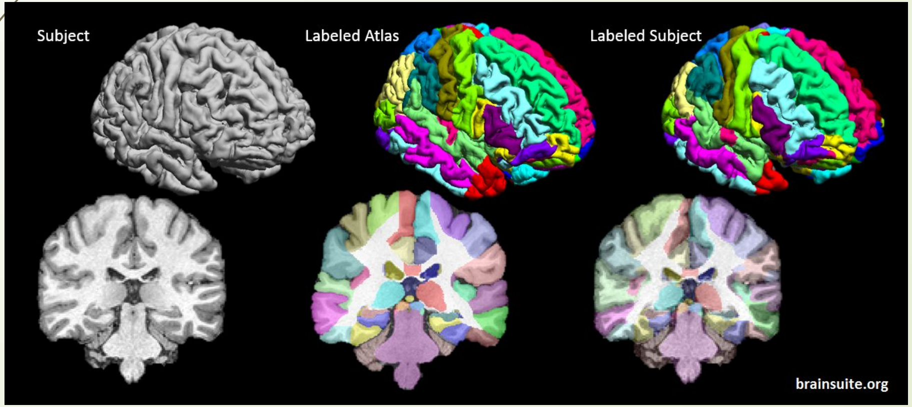
EEG and MEG methods multi-hub meeting

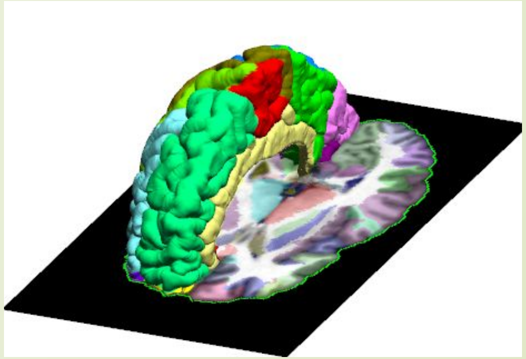
October 18th, 2023

SVReg (Surface-Constrained Volumetric Registration)

The processing sequence of SVReg module in BrainSuite



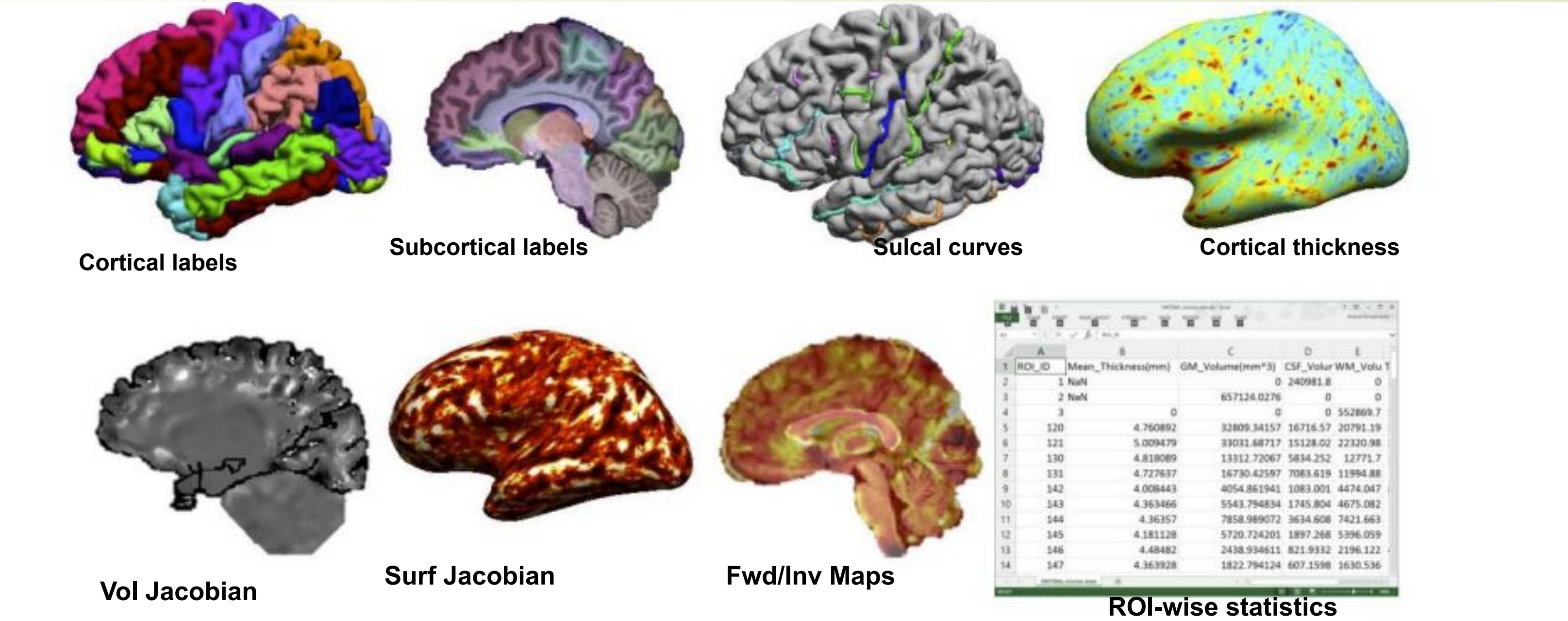




Consistent surface and volume labels

https://brainsuite.org/processing/svreg/

Outputs

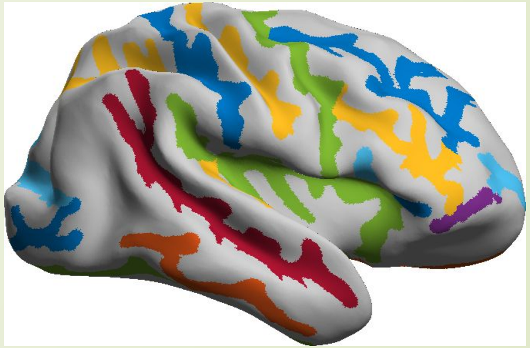

Cortical labels
Subcortical labels
Sulcal curves
Cortical thickness
Vol Jacobian
Surf Jacobian
Fwd/Inv Maps
ROI_ID Mean_Thickness(mm) GM_Volume(mm^3) CSF_Volur WM_Volu
1 NaN 0 240981.8 0
2 NaN 657124.0276 0 0
3 0 0 0 552869.7
120 4.760892 32809.34157 16716.57 20791.19
121 5.009479 33031.68717 15128.02 22320.98
130 4.818089 13312.72067 5834.252 12771.7
131 4.727637 16730.42597 7083.619 11994.88
142 4.008443 4054.861941 1083.001 4474.047
143 4.363466 5543.794834 1745.804 4675.082
144 4.36357 7858.989072 3634.608 7421.663
145 4.181128 5720.724201 1897.268 5396.059
146 4.48482 2438.934611 821.9332 2196.122
147 4.363928 1822.794124 607.1598 1630.536
ROI-wise statistics

Sulcal Demarcation

- Sulcal regions are generated by zero crossing of curvature and

- Connected component analysis in relation to the 26 sulcal curves

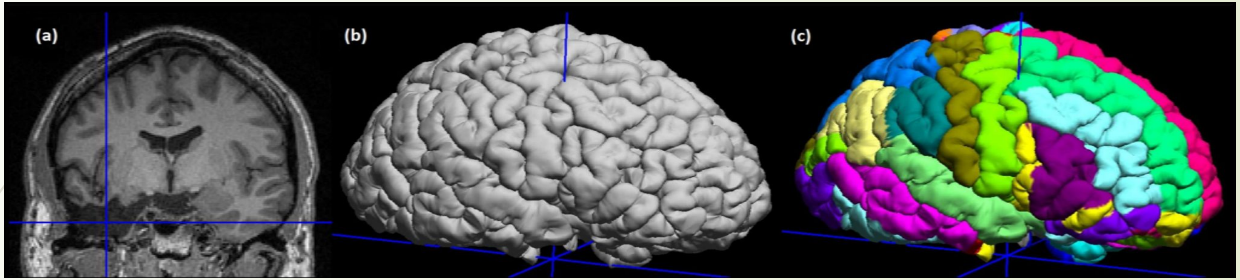
Sulcal vs Gyral regions

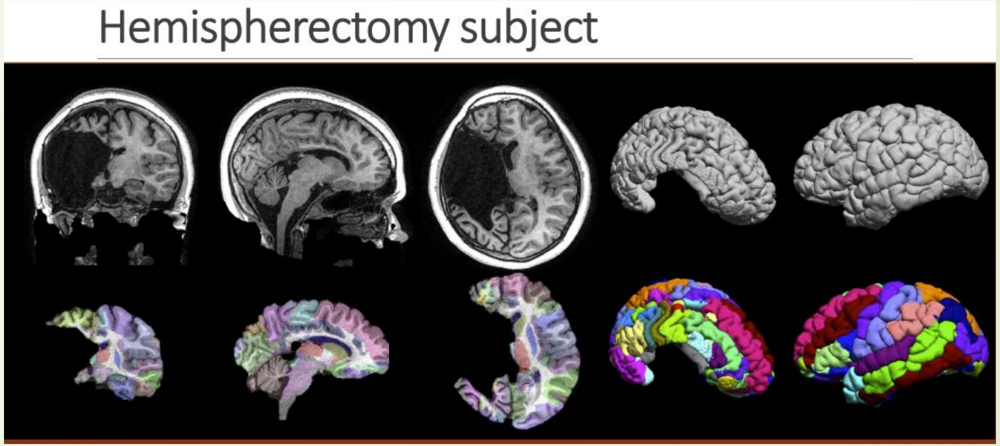


Labelled sulcal regions

https://neuroimage.usc.edu/CurveProtocol.html

Labeling of Lesion brains



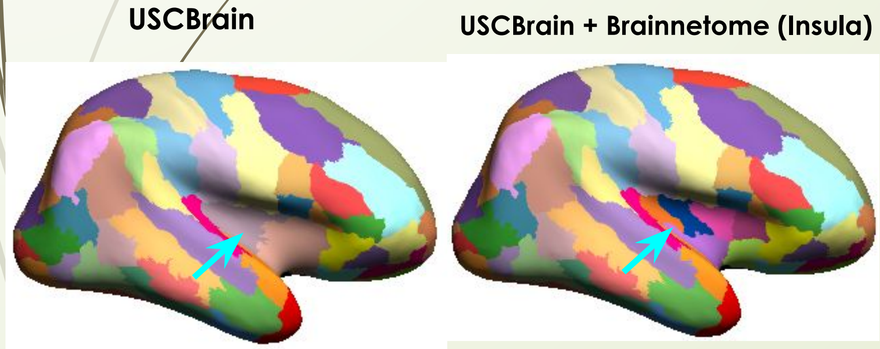


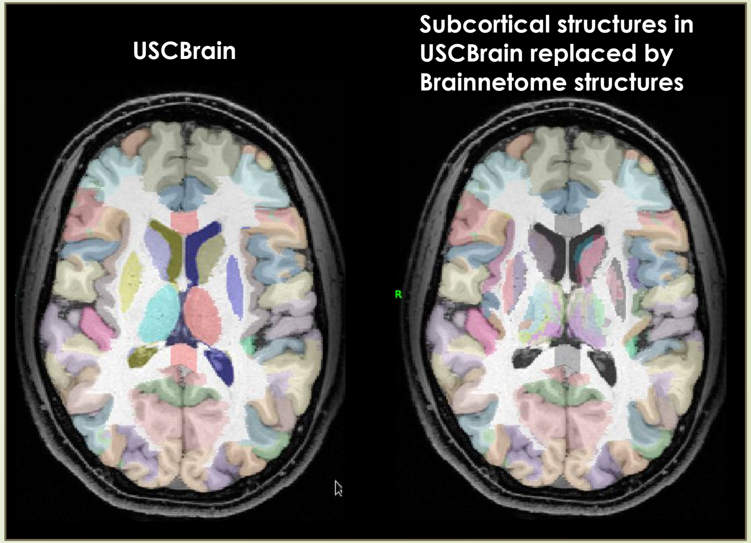
BrainSuite (SVReg) labeling works with lesion brains

Combining/Mixing Atlases

- ROIs from multiple atlases can be combined to create a mixed atlas

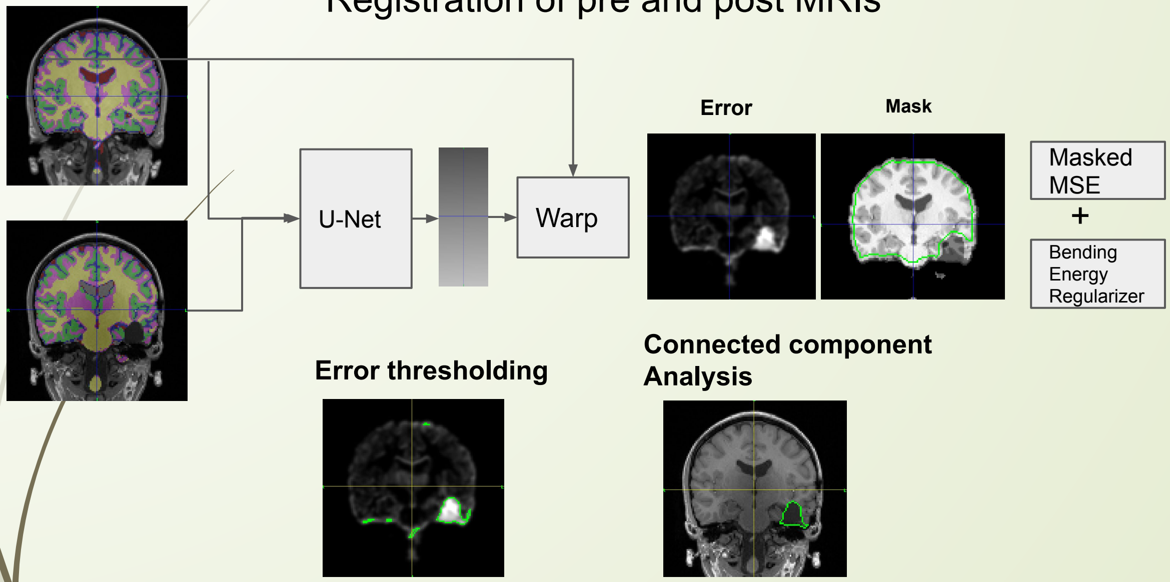
Example: Insula subdivisions and subcortical structures from USCBrain are replaced by subdivisions from Brainnetome



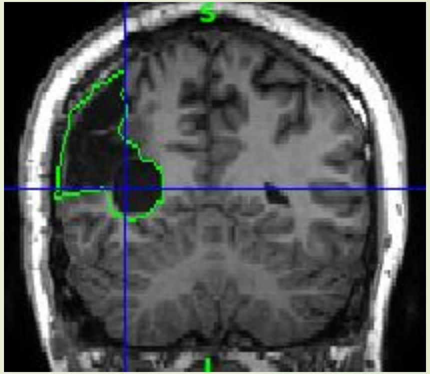


Automatic delineation of Surgical Resections on MRI using Neural Networks

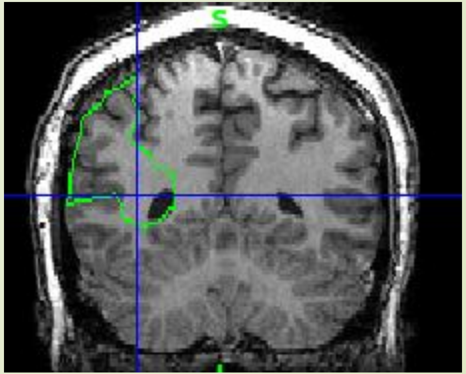
Registration of pre and post MRIs



Post-operative MRI



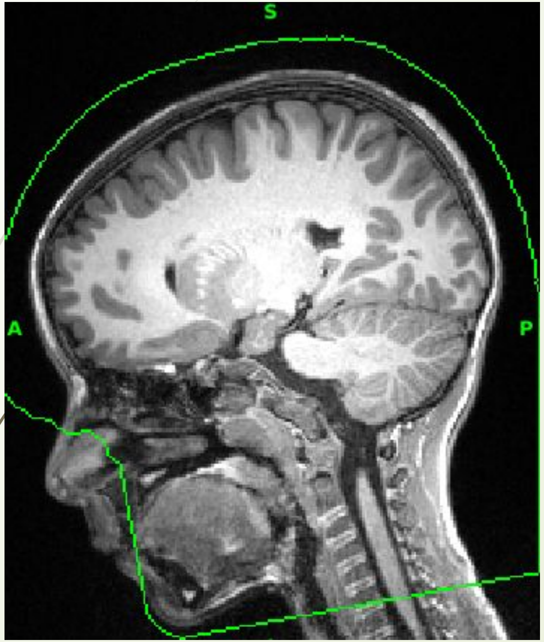
Preoperative MRI



https://github.com/ajoshiusc/auto_resection_mask

Other tools

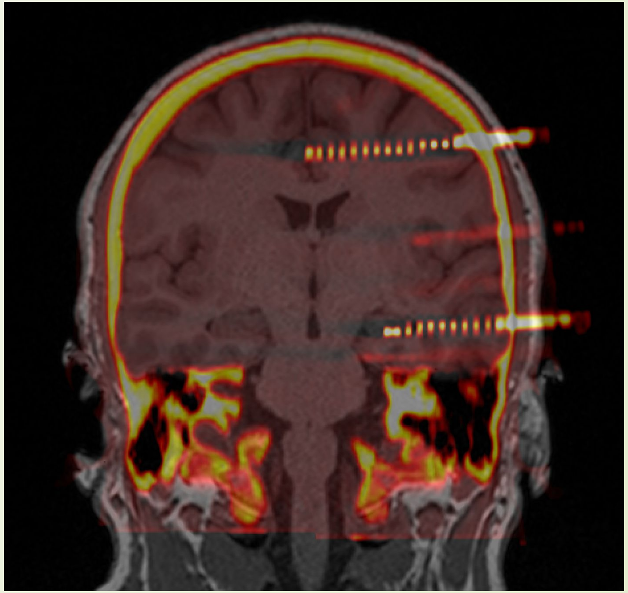
Defacing



Defaces MRIs or CT in an
EEG/MEG friendly manner

https://github.com/ajoshiusc/deface_mri

CT-MRI coregistration



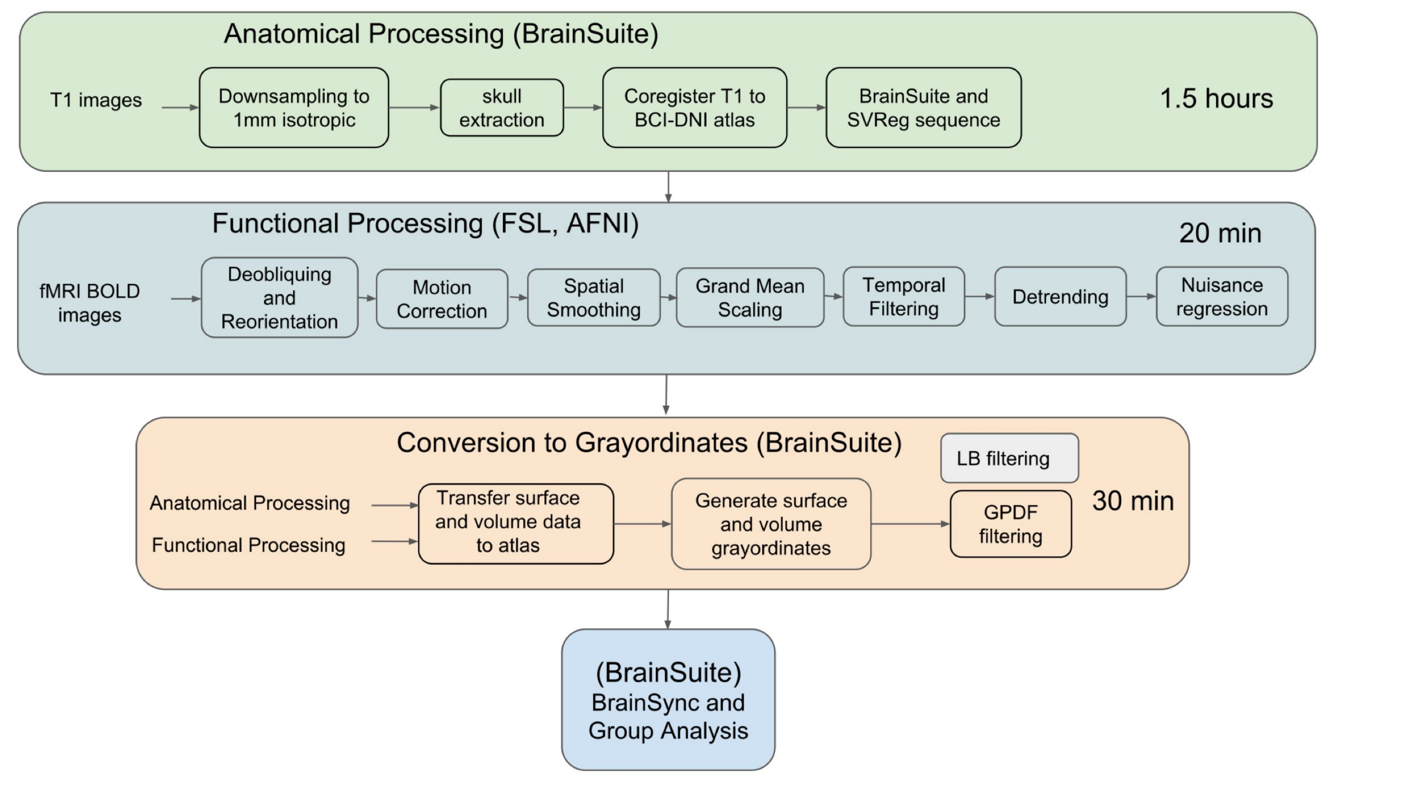
Coregisters multimodality images
using MI, MSE or CC cost functions

https://github.com/ajoshiusc/USCCleveland/tree/master/ct2mrireg

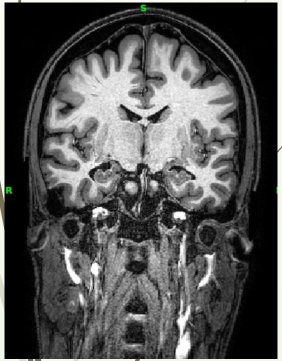
BFP (BrainSuite fMRI Pipeline)

- The BrainSuite fMRI pipeline (BFP) is an opensource software workflow for processing raw resting fMRI data.
- The pipeline processes resting fMRI and anatomical (T1) imaging data using a combination of software that includes BrainSuite, AFNI, and FSL, as well as MATLAB scripts.
- To facilitate interaction across software packages, the processed fMRI data are represented in a common grayordinate system.
- Unique features of the BFP pipeline include cortically-constrained volumetric registration, global PDF-based non-local means filtering (GPDF), and brainsync, a method for temporal synchronization of resting fMRI data across subjects.

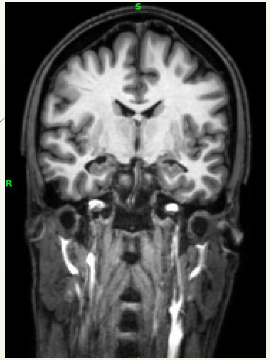
BFP Processing sequence



Anatomical processing

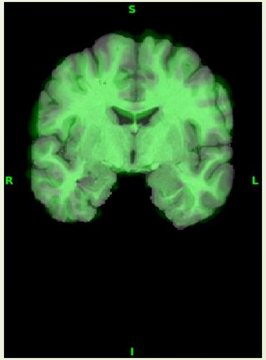


Hi-res input T1

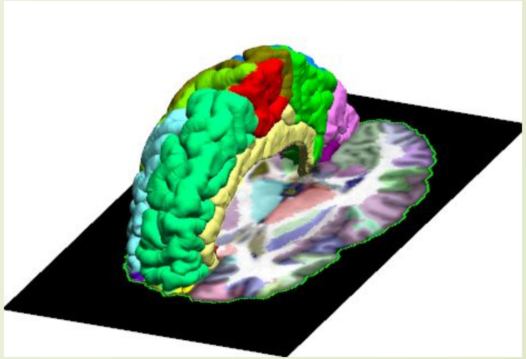


Downsampling to 1mm voxel res

Skull Stripping

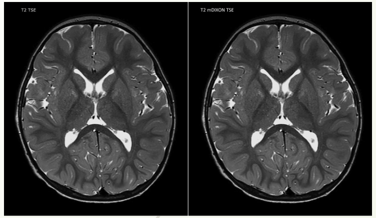


Rigid registration to BCI atlas (1mm)

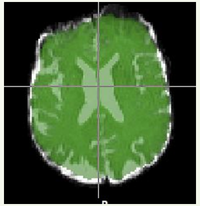


BrainSuite+SVReg using BCI atlas

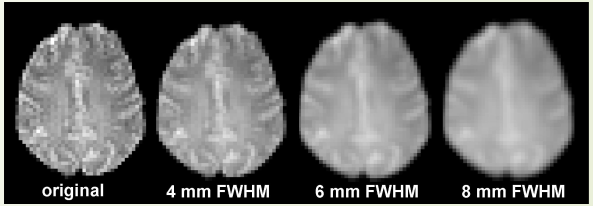
Functional preprocessing



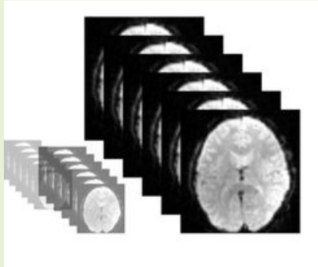
Deoblique and motion correction



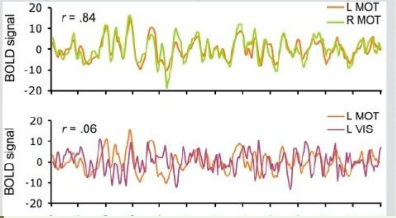
Skull Stripping



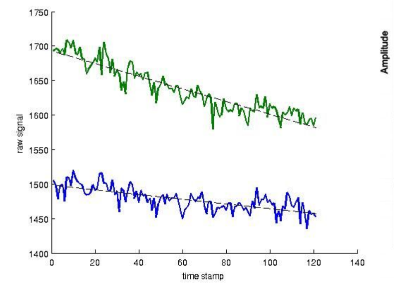
Spatial smoothing 2mm FWHM



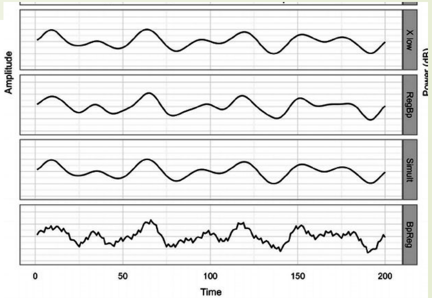
Grand mean scaling



Band pass filter (0.09 - 0.1 Hz)



Detrending (1st and 2nd order)

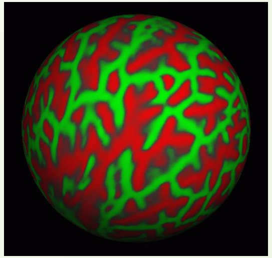


Nuisance regression using pvc label image (GSR, WM, CSF, motion)

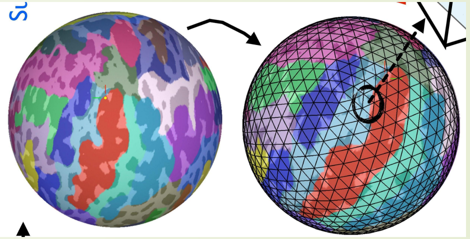
Residuals are coregistered to 3mm isotropic BCI-DNI atlas

HCP compatible Grayordinates on BCI atlas

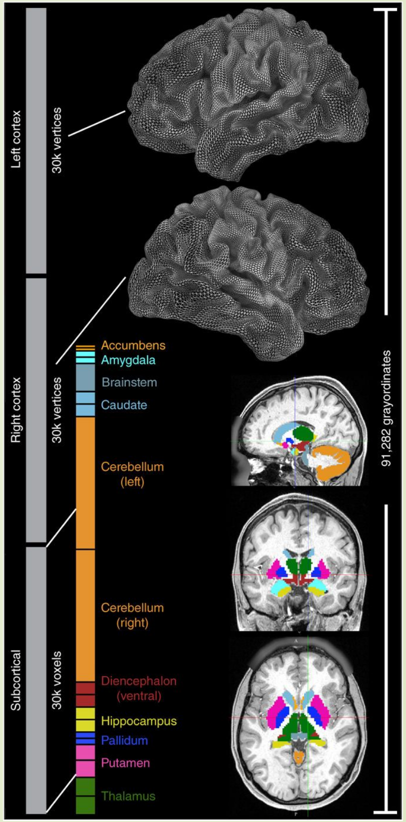
Inner surfaces
of BCI atlas

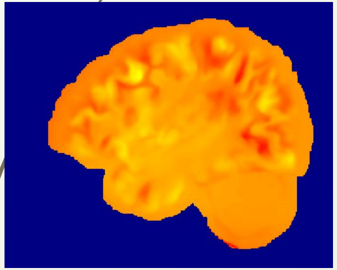


Spherical map
of BCI atlas

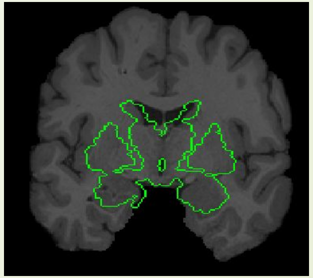


Spherical map of
grayordinates





BCI atlas to
BrainSuiteAtlas1 map

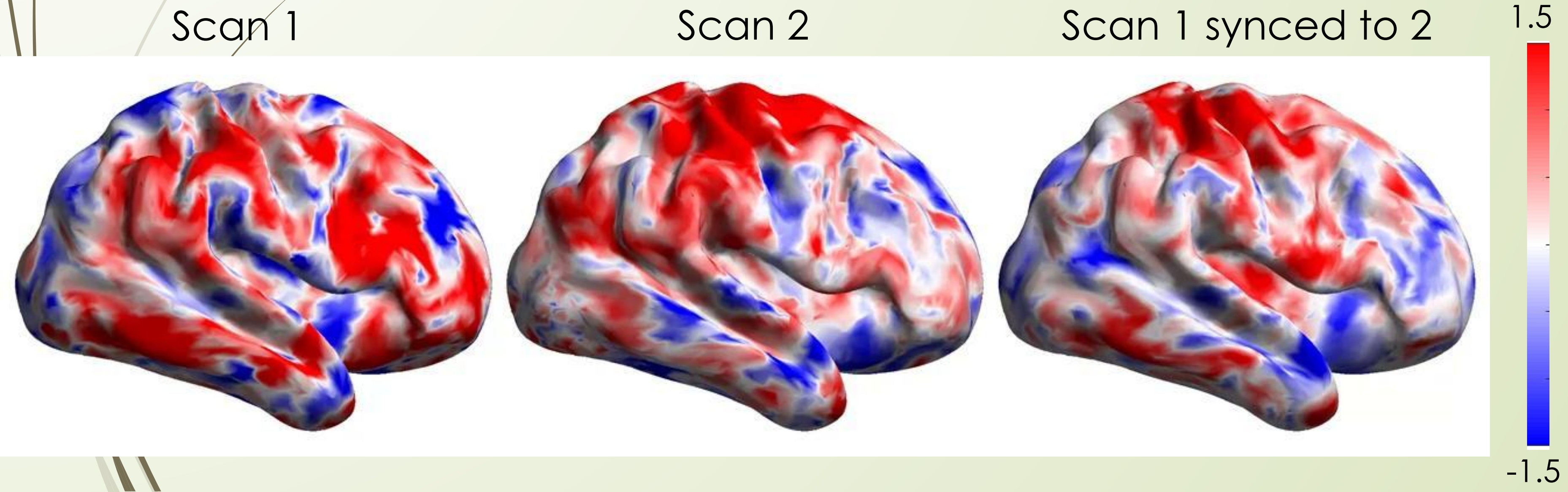


Grayordinates
in MNI space

Transfered to BCI atlas

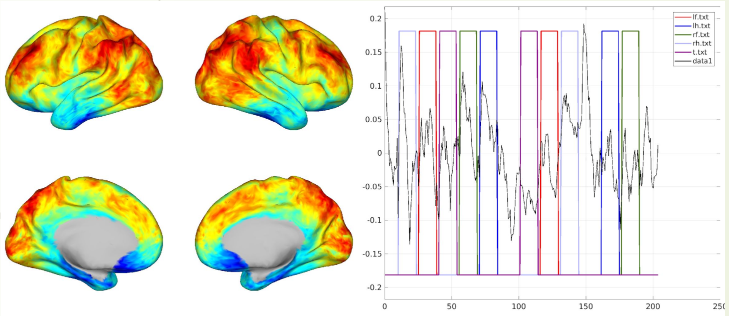
Brainsync transform

- BrainSync is a transformation of fMRI signal
  - Synchronize data across scans
  - Retains individual information
  - Allows pairwise point-wise comparisons of fMRI scans

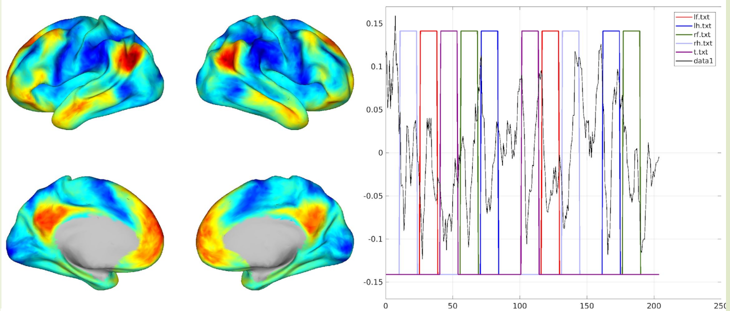


Identifying Brain Networks Using Tensor Decomposition of Multiple Subject Asynchronous Task fMRI

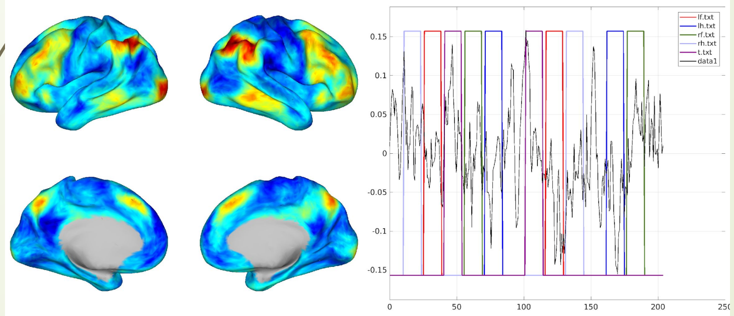
Frontal-parietal attentional control network



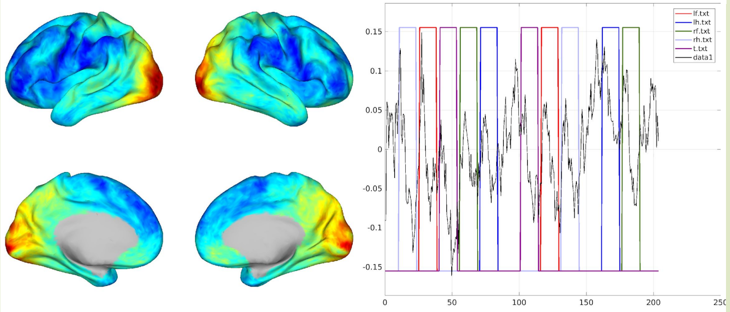
Default Mode Network



Executive Control Network



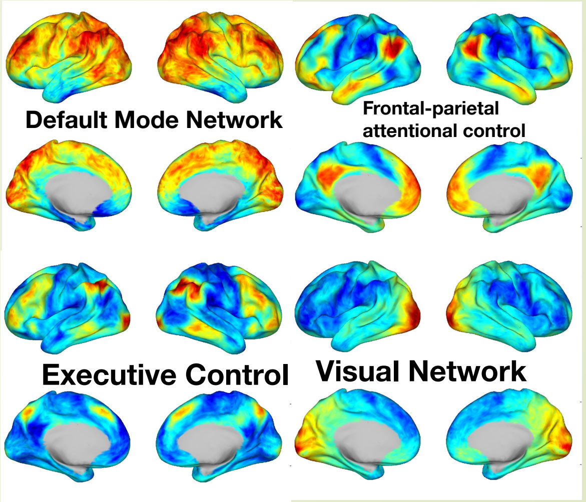
Visual Network



Li, Jian, et al. "Identification of overlapping and interacting networks reveals intrinsic spatiotemporal organization of the human brain." NeuroImage 270 (2023): 119944.

Identifying Brain Networks Using Tensor Decomposition of Multiple Subject Asynchronous Task fMRI

- Spatially overlapping and temporally correlated brain networks can be reliably identified from resting state fMRI data using the NASCAR tensor decomposition method and Brainsync temporal synchronization.
- These networks are highly reproducible across a large independent group of subjects.
- Using these networks as a set of spatiotemporal bases, one can better predict neurological/psychological measures (e.g., ADHD scores) or personal traits (e.g., IQ).



Li, Jian, et al. "Identification of overlapping and interacting networks reveals intrinsic spatiotemporal organization of the human brain." NeuroImage 270 (2023): 119944.

Post-Traumatic Epilepsy (PTE) study using BrainSuite Tools

- PTE is a common after TBI. The connection between PTE and TBI is not clearly understood.
- We aim to find anatomical and functional markers of PTE from MRI imaging data
- PTE prediction using these markers on individual level

Anatomical analysis

- We use MR imaging data to compare PTE and non-PTE groups
- We measured tissue type changes (lesions) and fMRI-based measure (ALFF)
- We developed a machine learning approach for detecting lesions

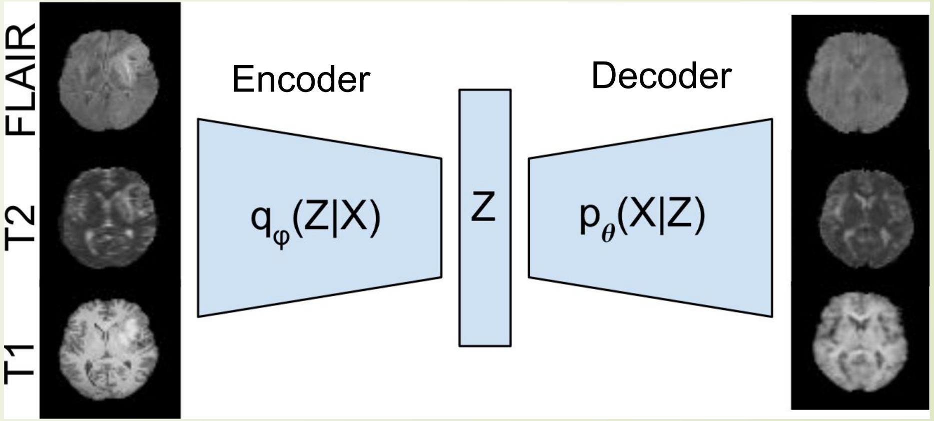
Maryland Magnets (N=150)

- This is a prospective study involving longitudinal imaging and behavioral data on TBI patients ranging from GCS 3-15 (mild to severe TBI). FLAIR/T1,T2, Diffusion, and other contrasts are available.
- Imaging and behavioral data was obtained at four time points (within 10 days of injury, 1 month, 6 months, and 18 months following injury. Both MR and fMRI are available.
- Patients with seizures (=37), measured at various time point during the study (0 days to 5 years).
- Our study population 37 PTE and 37 TBI datasets

Automatic Lesion Detection

- Variational Autoencoder (VAE) was trained on independent 138 non PTE TBI subjects

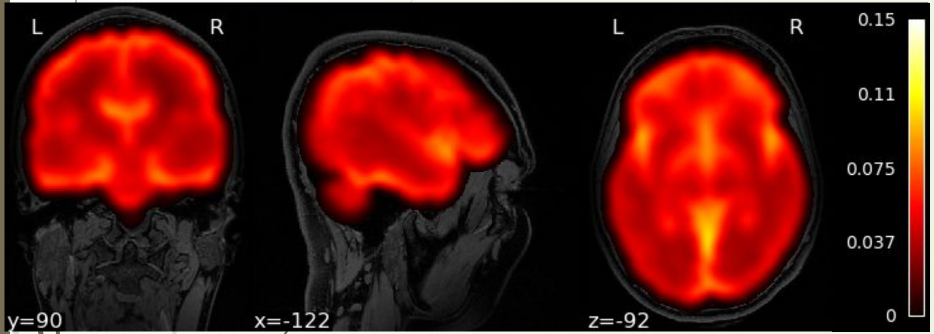
- When trained on relatively lesion free dataset, VAE learns to generate a ‘normal’ lesion free version of the input brain.



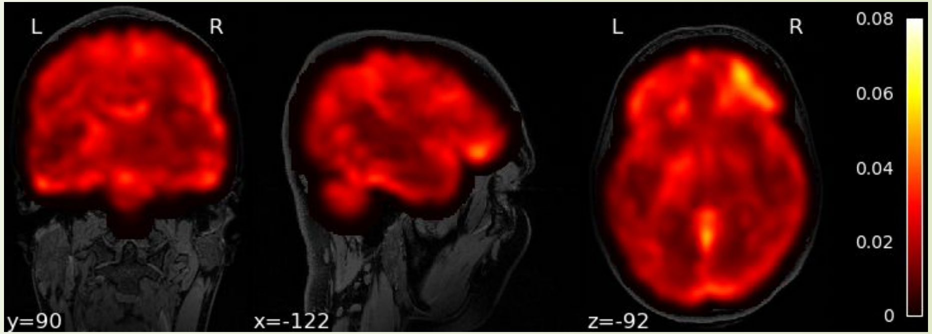
Variational Autoencoder for lesion detection

Lesion distribution

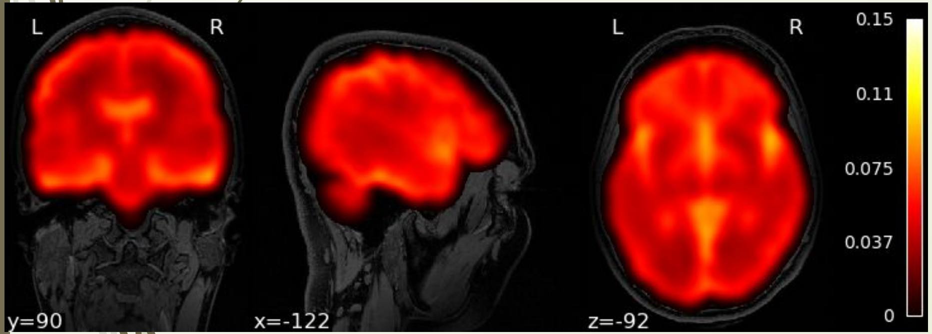
(a) average lesion distribution over non-epilepsy subjects



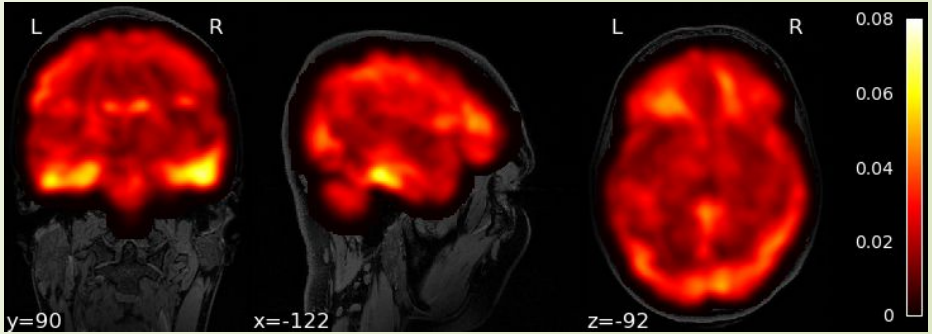
(c) std-dev of lesion distribution over non-epilepsy subjects



(b) average lesion distribution over epilepsy subjects

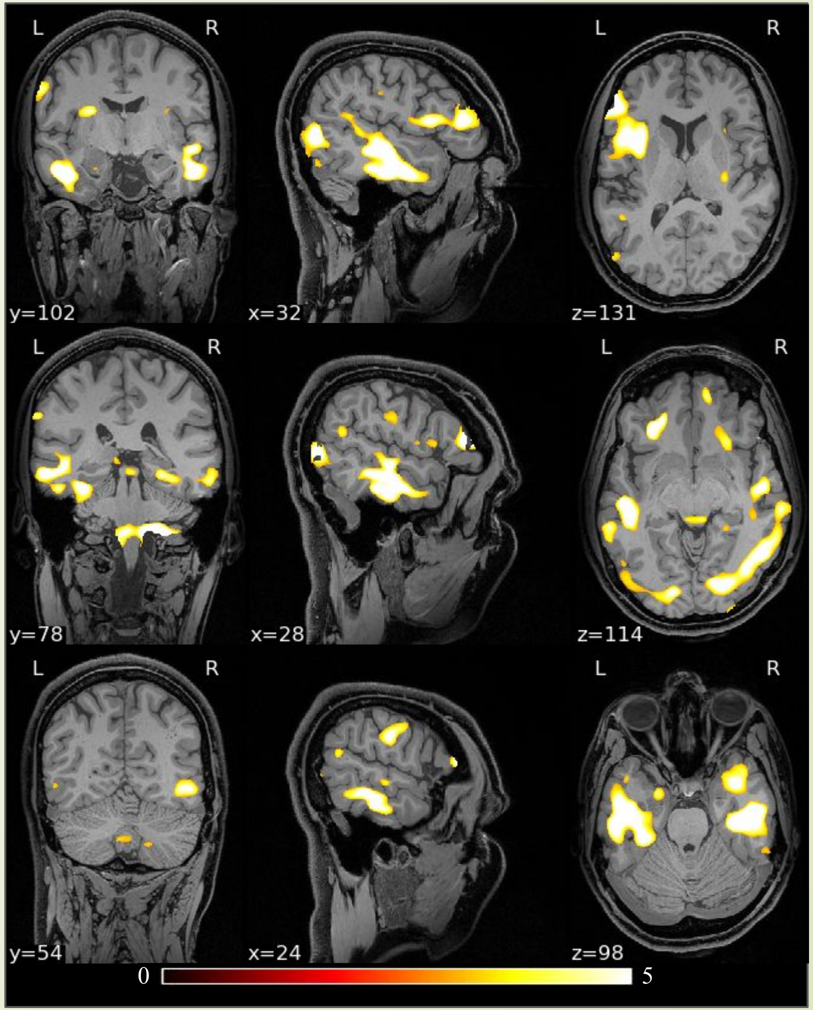


(d) std-dev of lesion distribution over epilepsy subjects



Lesion analysis results

- Voxel-based PTE vs. non-PTE group comparison of lesion maps overlaid on the USCBrain atlas.
- The color code depicts f-values, shown in a region where p-value < 0.05, resulting from the F-test (with permutations).
- Prominent significant clusters are located in the left temporal lobe, bilateral occipital lobe, cerebellum, and right parietal lobe.



ROI-wise analysis

Lobe	P-value (lesion) permutation test	P-value (ALFF) permutation test
Right Temporal	0.010	0.003
Left Temporal	0.021	0.081
Right Occipital	0.031	0.035
Left Occipital	0.127	0.009
Right Frontal	0.221	0.243
Left Frontal	0.326	0.177
Right Parietal	0.574	0.003
Left Parietal	0.654	0.069
Right Insula	0.347	0.226
Left Insula	0.546	0.724
Cerebellum	0.047	0.072

Prediction of PTE on Individual level

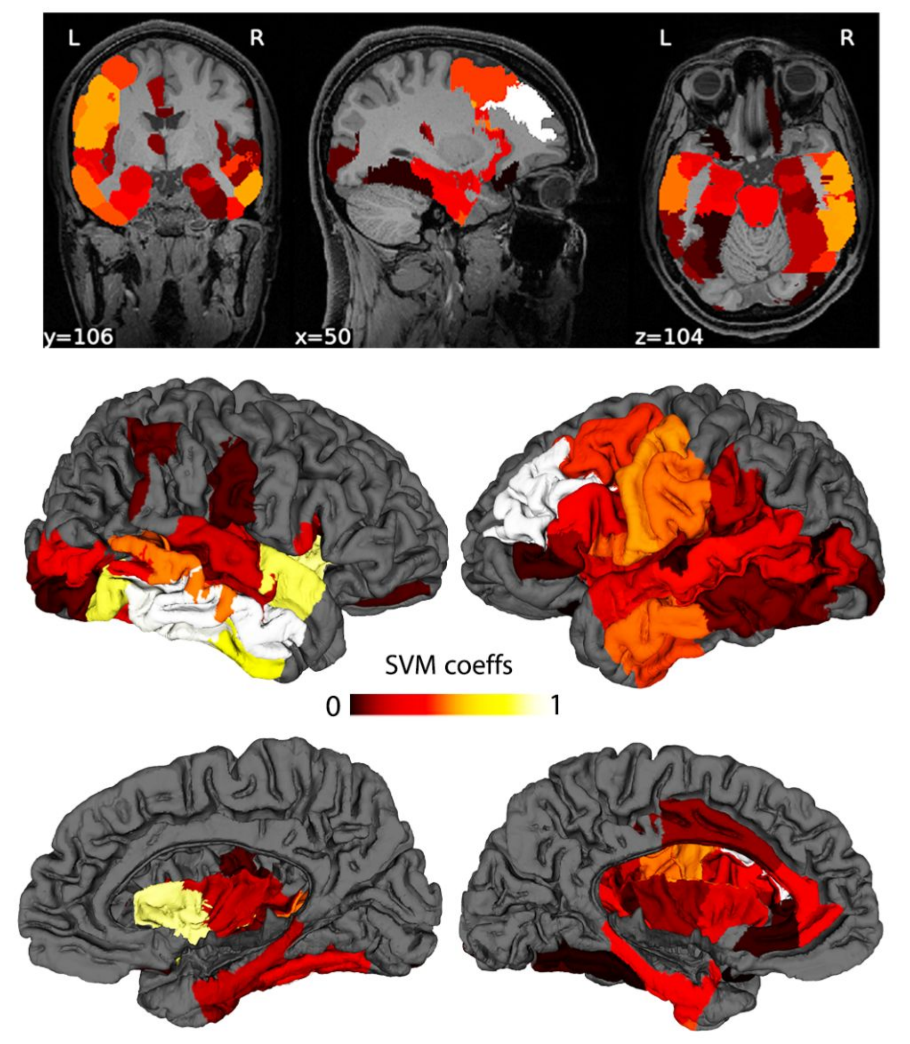
Method	Lesion	Connectivity	ALFF	Combined
KSVM	0.5486(0.0408)	0.6069(0.0691)	0.6230(0.0431)	**0.7772(0.0373)**
SVM	0.6294(0.0306)	0.5121(0.0351)	0.6321(0.0242)	0.6444(0.0333)
RF	0.5778(0.0461)	0.5514(0.0756)	0.6667(0.0324)	0.6389(0.0598)
NN	0.5002(0.0411)	0.6083(0.075)	0.5027(0.0547)	0.5625(0.0299)

Classification accuracy of PTE vs. non-PTE subjects using different classifiers and features types. Mean and standard deviation of AUC are shown for KSVM, SVM, RF and NN. The last column shows the performance obtained when the models were trained simultaneously on all three feature types

Feature Importance

The SVM Feature importance map shown as color-coded ROIs overlaid on the USCBrain atlas for lesion based prediction

Both the surface and 3D rendered ROIs are shown.



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https://brainsuite.org/