NiCHART: A Software Suite to Translate Neuroimaging Big Data to Individualized Biomarkers in Disease

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Introduction:

Growing availability of open-access, large-scale neuroimaging data in healthy development and disease allows for rapid discovery of radiologic, neurologic, and psychiatric insights . This is especially true in the context of machine learning (ML), which promises improved prediction of diagnoses, prognoses, disease subtypes, and more. However, harnessing ML to pursue such precision medicine efforts remains a challenge for many neuroimaging scientists – barriers in coding skills, field-specific knowledge of state-of-the-art methodology, and access to large-scale neuroimaging data all limit the rate of biomarker discovery. We introduce niCHART (NeuroImaging Computational Harmonization and ARtificial intelligence Toolbox), a mutually-compatible ecosystem of state-of-the-art methods allowing for holistic processing of multi-modal MRI images as well as calculation of statistical and ML-based imaging-derived phenotypes (IDPs). Ultimately, niCHART will allow for improved reproducibility and accessibility of neuroimaging analysis as well as allow end-users to contextualize their own data among open-access, curated neuroimaging big data.

Methods:

niCHART integrates all-in-one software pipelines for pre-processing, harmonization, and statistical analysis of structural MRI, diffusion MRI, and functional MRI (Figure 1). Image pre-processing components consist of a validated structural MRI atlas-based segmentation pipeline, fMRIPrep, XCPEngine, QSIPrep (q-space image preprocesing), sopNMF (stochastic orthogonally projectie non-negative matrix factorization), and pNet (personalized networks) [1-7]. Post-processing components include generalized ComBat family harmonization methods, SPARE (Spatial Pattern of Abnormality for Recognition) IDP methods, smileGAN (SeMI-supervised cLustEring via Generative Adversarial Network), and more [8-12]. Additionally, niCHART develops a statistical and ML-based dimensional system based on a large reference population and automatically projects end-user image data into this dimensional system. These niCHART dimensions capture multivariate imaging patterns of brain heterogeneity covering both normative aging and disease.

Results:

niCHART reference data consists of pooled and harmonized multi-modal imaging data from 62,859 individuals across 24 studies (Figure 2). These reference individuals are demographically diverse with respect to age, sex, race, and underlying health conditions. Statistically-extracted IDPs include atlas-based anatomical and network segmentations, data-driven parcellations, structural covariance networks, and network metrics. In neurodegeneration, additional ML IDPs include deep learning metrics describing spatial patterns of atrophy related to normal aging, Alzheimer disease, and cardiovascular disease as well as metrics for subgroup identification within Alzheimer disease patients. In neuropsychiatry, ML IDPs include indices related to normal development, depression, autism spectrum disorder, and schizophrenia. Statistical harmonization models for IDPs have been pre-trained on this reference data and allow for automated harmonization of end-user data to the reference data, which allows for improved reproducibility and more valid inference.

Conclusions:

niCHART offers an accessible and feature-rich software suite for processing and analysis of neuroimaging data to translate state-of-the-art methodology to the individual-subject level. niCHART's panel of statistical and ML IDPs allow end-users to automatically extract high-level, individualized information from complex imaging data and contextualize their subjects among demographically and phenotypically diverse reference subjects. This machinery promises to accelerate research in precision medicine and dimensional phenomics.

Disorders of the Nervous System:

Neurodegenerative/ Late Life (eg. Parkinson’s, Alzheimer’s)

Lifespan Development:

Early life, Adolescence, Aging

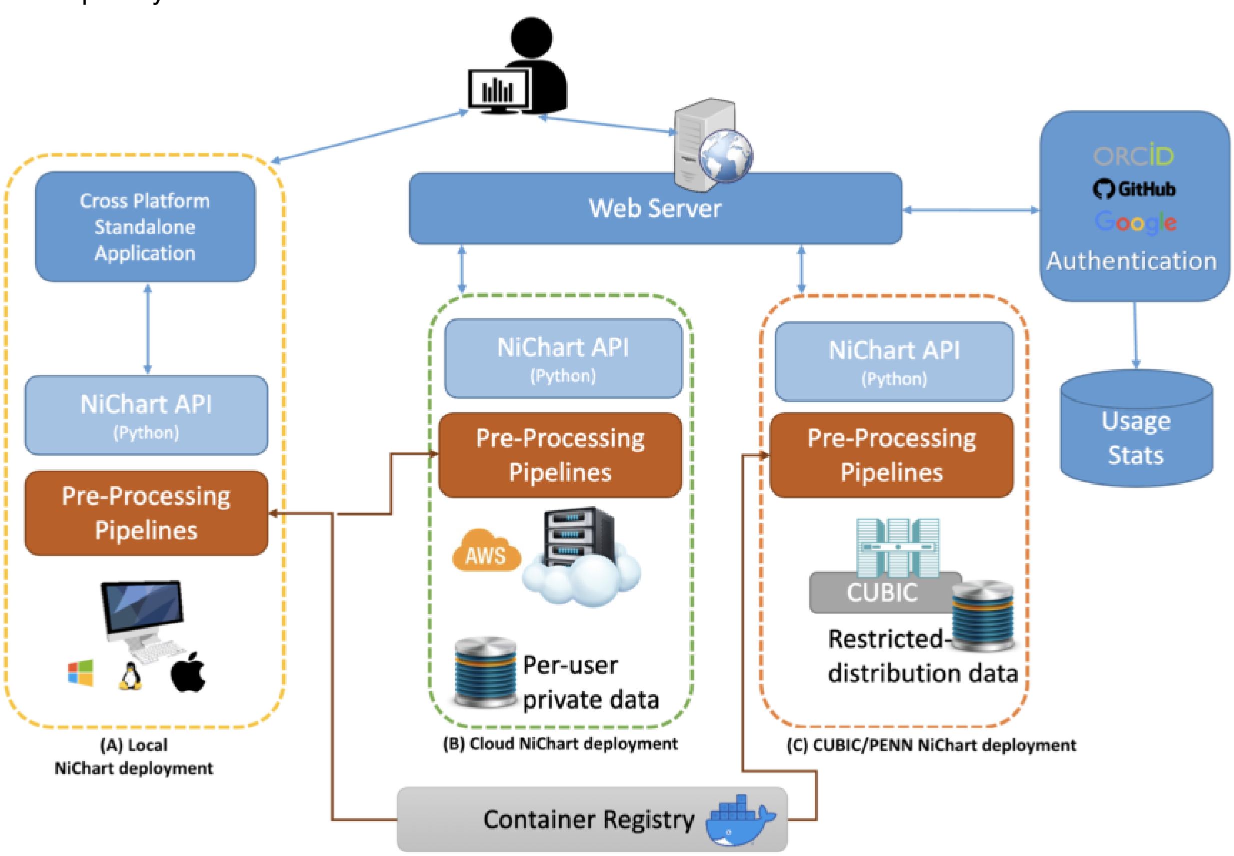
Neuroinformatics and Data Sharing:

Databasing and Data Sharing [2]
Workflows [1]
Informatics Other

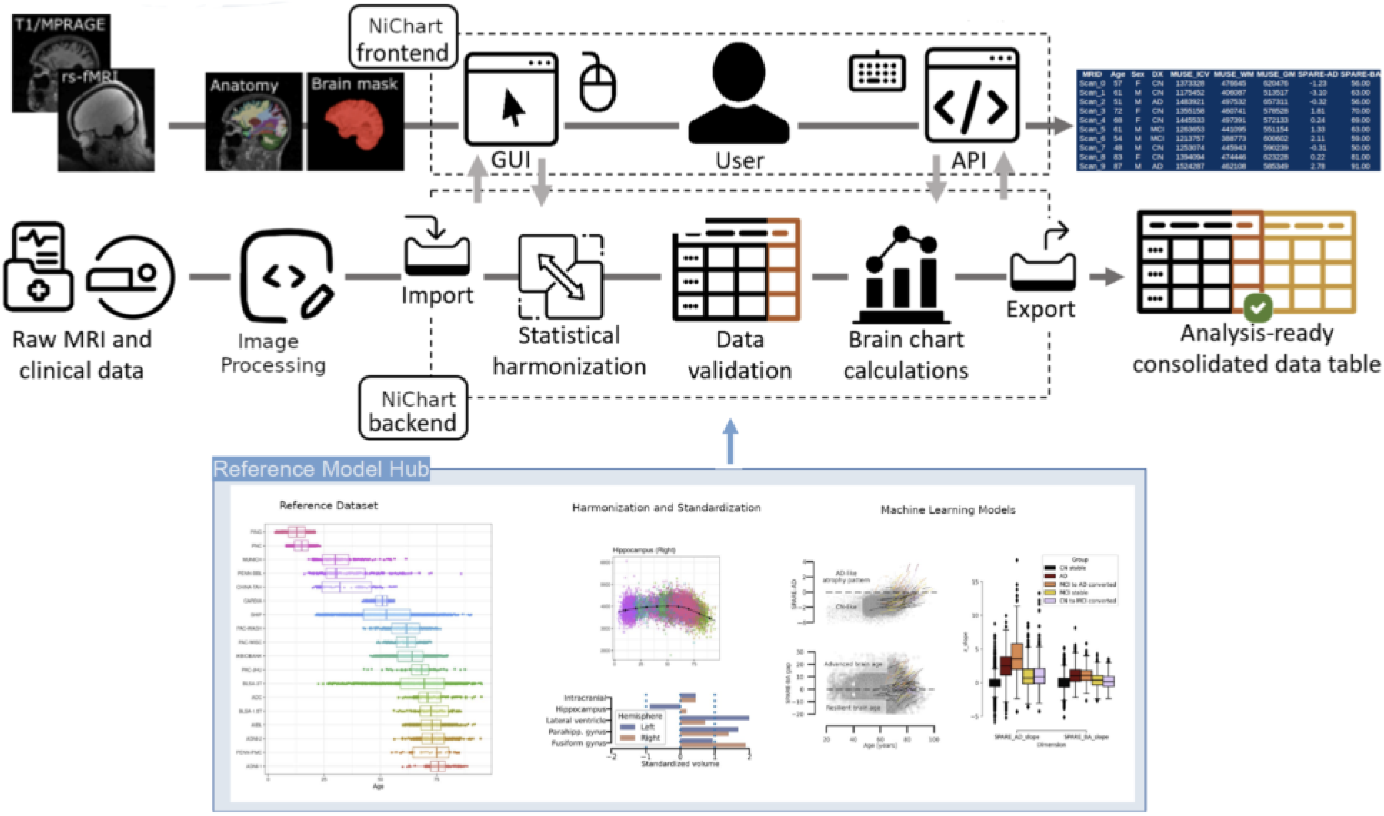
Keywords:

Aging
Data Organization
Degenerative Disease
Informatics
Machine Learning
MRI
Open Data
Open-Source Software
Statistical Methods
Workflows

[1|2]Indicates the priority used for review



·Visualization of niCHART integrated software platform, including mutually-compatible web-based processing and local container-based pipelines.



·Visualization of niCHART general analysis pipeline, post-processing data visualization, and ML-based dimensional representation system for biomarker discovery with inclusion of a reference data..

Abstract Information

My abstract is being submitted as a Software Demonstration.

No

Please indicate below if your study was a "resting state" or "task-activation” study.

Other

Healthy subjects only or patients (note that patient studies may also involve healthy subjects):

Patients

Are you Internal Review Board (IRB) certified? Please note: Failure to have IRB, if applicable will lead to automatic rejection of abstract.

Yes

Was any human subjects research approved by the relevant Institutional Review Board or ethics panel? NOTE: Any human subjects studies without IRB approval will be automatically rejected.

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Not applicable

Please indicate which methods were used in your research:

Functional MRI
Structural MRI
Diffusion MRI
Computational modeling

For human MRI, what field strength scanner do you use?

1.5T
3.0T

Which processing packages did you use for your study?

AFNI
SPM
FSL
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Provide references using author date format

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