

Cancer Imaging Phenomics Toolkit (CaPTk):

A Radio(geno)mics Platform for Quantitative Image Analytics



Christos Davatzikos, Despina Kontos, Paul Yushkevich, Russell Shinohara, Yong Fan, Ragini Verma Center for Biomedical Image Computing and Analytics (CBICA), University of Pennsylvania captk@cbica.upenn.edu FUNDING: NIH/NCI/ITCR U24CA189523

Primary Aim: To enable swift and efficient translation of cutting-edge academic research into clinically useful tools^[1].

Clinical experts: facilitating use of complex algorithms for Target Audience: • clinically relevant studies through a user-friendly interface.

Computational experts: allowing batch-processing of multiple subjects and integration of new algorithms.





www.cbica.upenn.edu/captk







Texture features 49 60 50 58 Grey-Leve 54 62 67 Matrices Patterns Original grav levels Difference











Specialized Applications

Organ-Specific Segmentation



GBM Recurrence Prediction ^[11, 12] (Predictive Maps of Peritumoral Infiltration)





Future Directions

Multiscale Feature Extraction Cohort-Based Interface | **Traditional Machine Learning Training Module** |

References	[10] Bakas et al., Advancing TCGA alioma MRI collections with expert segmentation labels and radiomic features. Nature Scientific Data,
[1] Davatzikos et al., Cancer imaging phenomics toolkit: quantitative imaging analytics for precision diagnostics and predictive modeling of	2017
clinical outcome, Journal of Medical Imaging , 2018	[11] Akbari et al., Imaging Surrogates of infiltration obtained via multiparametric imaging pattern analysis predict subsequent location of
[2] Shinohara et al., Statistical normalization techniques for magnetic resonance imaging, Neuroimage Clinical, 2014	recurrence of glioblastoma, Neurosurgery, 2016
[3] Gaonkar et al., Adaptive geodesic transform for segmentation of vertebrae on CT images, Medical Imaging, 2014	[12] Rathore et al., Radiomic signature of infiltration in peritumoral edema predicts subsequent recurrence in glioblastoma: Implications
[4] Yushkevich et al., ITK-SNAP: An interactive tool for semi-automatic segmentation of multi-modality biomedical images, IEEE Eng Med	for personalized radiotherapy planning, Journal of Medical Imaging , 2018
Biol Soc ., 2016	[13] Bakas et al., In vivo detection of EGFRvIII in glioblastoma via perfusion magnetic resonance imaging signature consistent with deep
[5] Bakas et al., GLISTRboost: Combining multimodal MRI segmentation, registration, and biophysical tumor growth modeling with	<i>peritumoral infiltration</i> , Clinical Cancer Research , 2017
gradient boosting machines for glioma segmentation, Springer, LNCS , 2016	[14] Tunc et al., Automated tract extraction via atlas based Adaptive Clustering, Neurolmage, 2014
[6] Kamnitsas et al, Efficient multi-Scale 3D CNN with fully connected CRF for accurate brain lesion segmentation, Med Image Anal, 2016	[15] Tunc et al., Individualized Map of white matter pathways: connectivity-based paradigm for neurosurgical planning, Neurosurgery,
[7] Keller et al., Estimation of breast percent density in raw and processed full field digital mammography images, Medical Physics, 2012	2016
[8] Keller et al., Preliminary evaluation of the publicly available Laboratory for Breast Radiodensity Assessment (LIBRA) software tool,	[16] Macyszyn et al., Imaging patterns predict patient survival and molecular subtype in glioblastoma via machine learning techniques,
Breast Cancer Research 2015	Neuro-Oncology, 2016
[9] Li et al., Predicting treatment response and survival of early-stage non-small cell lung cancer patients treated with stereotactic body	[17] Zheng et al. Parenchymal texture analysis in digital mammography: A fully automated pipeline for breast cancer risk assessment.
radiation therapy using unsupervised two-way clustering of radiomic features, Int. Workshop on Pulmonary Imaging, 2017	Medical Physics. 2015