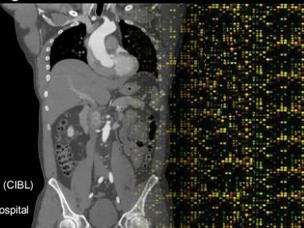


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**Radiomics:
The Promise of Imaging for Precision Medicine**



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Disclosure Information
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Dr. Hugo Aerts

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Objectives

- Describe the motivation and methodology for Computational Imaging & Radiomics
- Describe biomarker quantification studies in Radiomics and Imaging-Genomics (Radiogenomics)

Imaging for precision medicine

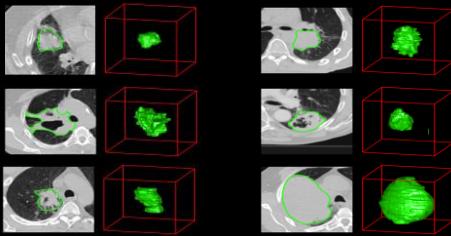
Advantages of Imaging:

- Performed non-invasively
- Provides 3D picture of the entire cancer
- Already performed in clinical practice
- Multiple times during treatment for diagnosis, staging, radiation oncology planning, response assessment
- Captures a cancer's appearance over time and space

Disadvantages of Imaging:

- Probes the cancer at the macroscopic level
- Often qualitative not quantitative
- Very heterogeneous acquisition protocols:
 - comparisons between patients difficult
 - comparisons same patient in time difficult
- Storage of only reconstructed images (not the raw data)

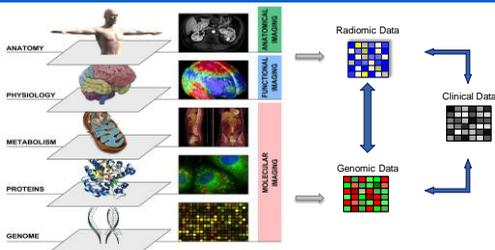
Representative CT images of lung cancer



Tumors are different

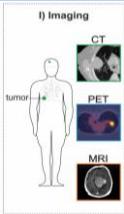
Medical imaging can capture these phenotypic differences

Multi-level patient data



*Lambin et al. Eur J Cancer 2012

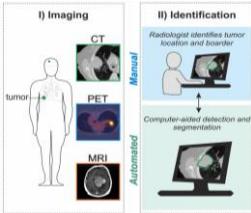
Image-based Phenotyping



Important Challenges:
Image Acquisition, reconstruction, standardization, storage

*accepted Aerts HJ, JAMA Oncology 2016

Image-based Phenotyping



Automatic detection of tumors and other abnormalities (CADe):

- 1) Improve diagnostic accuracy.
- 2) Improve speed of diagnostic reads.

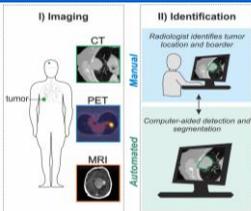
(Semi) automatic segmentation:

- 1) Method for high throughput analysis of images.
- 2) Reducing the **high intra- and inter-observer variability** observed for target definition.

Tumor Identification
Identifying tumor presence, location, and extend using visual assessment and/or using automated detection (CADe) and segmentation.

*accepted Aerts HJ, JAMA Oncology 2016

Image-based Phenotyping

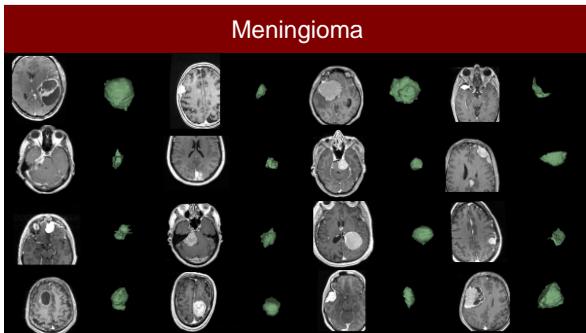


Semantic Quantification
Image-based phenotyping by visual assessment of expert radiologists

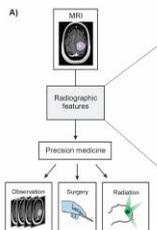
*accepted Aerts HJ, JAMA Oncology 2016

Image-based Phenotyping

(Radiomics and Imaging-Genomics examples)



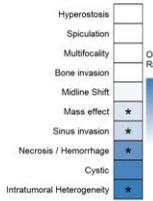
Study Design



*Coroller et al. submitted

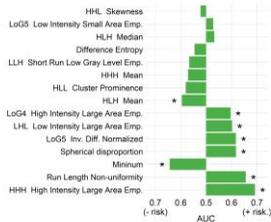
Univariate prediction (n=175)

A) Semantic features



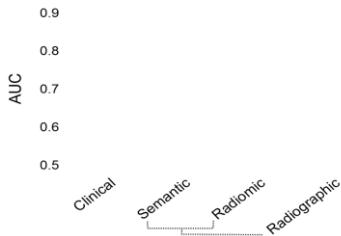
* Fisher exact test

B) Radiomic features



* Noether test

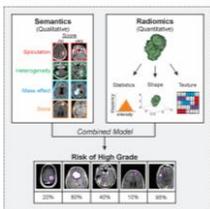
Random Forest Classifiers



*training dataset (n=131), validation dataset (n=44)

*Coroller et al. submitted

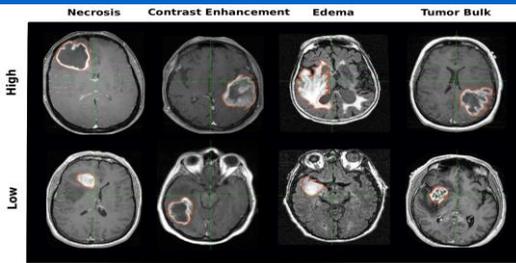
Conclusions meningioma



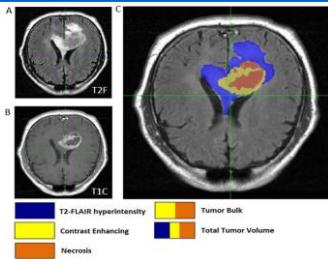
- Clinical model **could not predicted grade**
- Radiographic features **did predicted grade**
 - Semantic (simple, intuitive)
 - Radiomic (reproducible, high throughout)
- Combined model (sem. + rad.) **significantly improved grade classification**

*Coroller et al. submitted

Imaging-Genomics in GBM

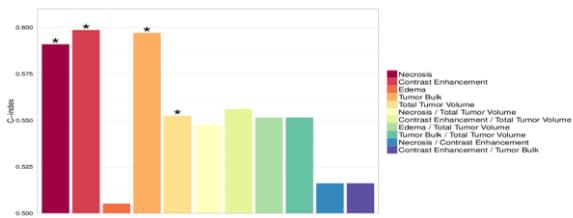


Methods: Manual delineations



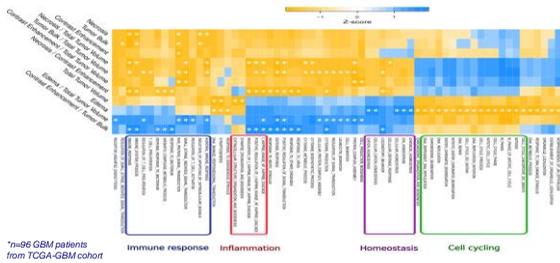
*Grossmann accepted BMC Cancer

Prognostic value of volumetric features

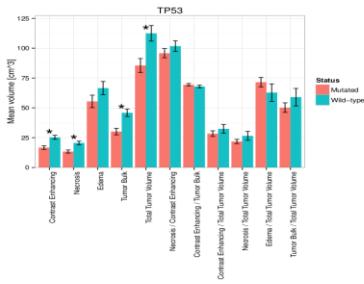


*Grossmann accepted BMC Cancer

Imaging-Genomics Pathway Analysis of MRI Derived Volumetric Tumor Phenotype Features in Glioblastoma



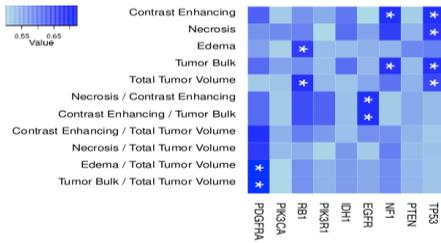
TP53 positive/negative



TP53 mutated tumors had significantly smaller CE and necrotic volumes ($p=0.012$ and 0.017 , respectively) compared to wild-type.

*Gutman et al. Neuro-Radiology 2015

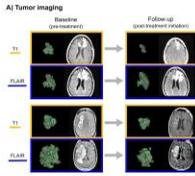
Volumetric features predict mutational status in GBM patients



n=76 GBM patients from TCGA-GBM cohort

*Gutman et al. Neuro-Radiology 2015

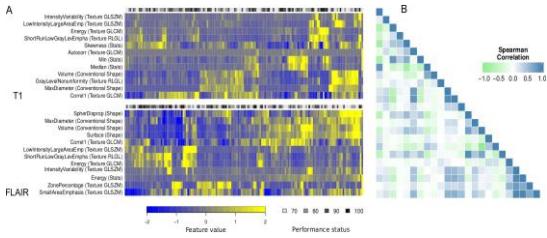
Recurrent Glioblastoma Treated with Bevacizumab



*165 patients enrolled in the phase II BRAIN trial

*Grossman et al. submitted

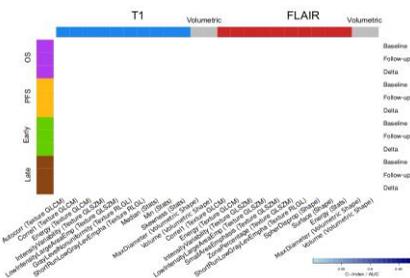
T1 and FLAIR radiomic data



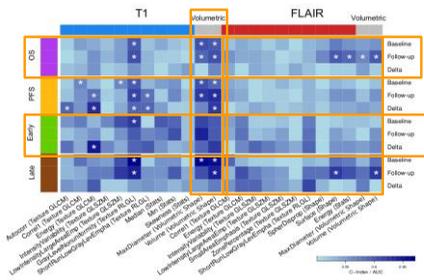
*165 patients enrolled in the phase II BRAIN trial

*Grossman et al. submitted

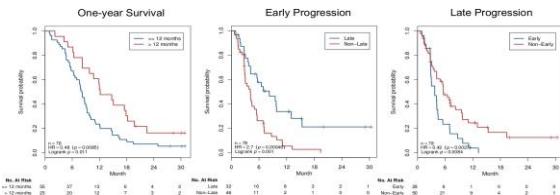
Prognostic value of T1 and FLAIR features



Prognostic value of T1 and FLAIR features



Multivariable survival and progression models derived from T1-weighted baseline imaging



These markers showed strong stratification power in independent validation data (hazard-ratio > 2; log-rank $p \leq 0.001$) after adjusting for age, sex, and baseline Karnofsky performance status.

*Grossman et al. submitted

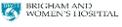
Radiomics: Current Status

- Imaging moves towards a computational data science (bioinformatics)
- Due to advances in imaging, quantitative imaging is currently possible
- Large retrospective and prospective potential
- Large number of imaging features defined & successfully implemented
- Feature extraction pipelines implemented in 3D-Slicer (Python / Matlab)
- Radiomics signatures are prognostic across cancer types
- Radiomics are strongly connected with genomic patterns
- Integration of multiple datasets to improve performance

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- Stephen Yip, PhD
- Elizabeth Huynh, PhD
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