OncoRay – National Center for Radiation Research in Oncology, Dresden

# **Radiomics** opportunities and challenges

Alex Zwanenburg





HELMHOLTZ ZENTRUM DRESDEN ROSSENDORF



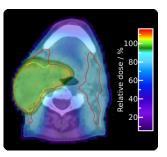


# Radiomics for personalised medicine

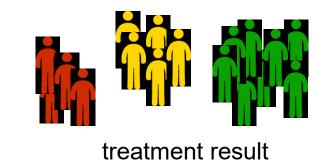




same cancer diagnosis



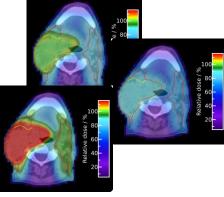
same treatment



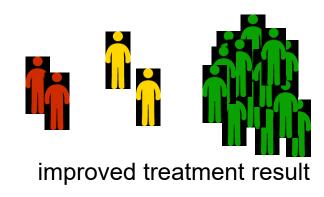
inter-patient heterogeneity



same cancer diagnosis

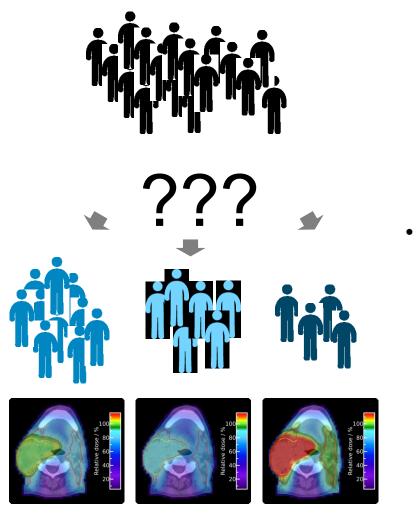


personalised treatment

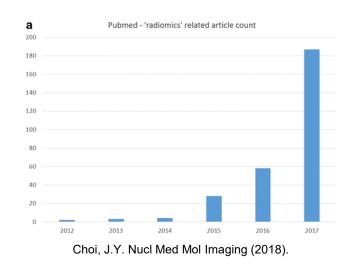


# Radiomics for personalised medicine





- Treatment personalisation based on:
  - Clinical data (staging)
  - Demographic data (smoking, age)
  - Tumour genetics (gene mutations, RNA expressions)
  - Imaging
- Radiomics: High-throughput analysis of medical imaging



### A spectrum of imaging



### amount of quantified information $\rightarrow$

**Visual assessment** 

no quantification

lung nodule detection, tumor localization, nodal involvement

#### **Quantitative analysis**

quantification of simple features

tumor staging, RT dose planning, treatment individualization Conventional radiomics quantification using handcrafted features

treatment individualization, differentiation of histological subtypes Deep learning radiomics convolutional neural networks

lung nodule detection, tumor localization & segmentation, treatment individualization

### Does radiomics work?





- Most radiomic studies are difficult to reproduce:
  - Important details are not reported
  - Bias in development and validation of radiomic models
  - Data may not provide the required heterogeneity:
    - Small data sets
    - Single center cohorts
- Addressing heterogeneity:
  - Use more data from different sources (*study-centric solution*)
  - Reduce sources of variability (*field-wide solution*)



#### Visual assessment

acquisition and reconstruction



### Sources of variability

• inter-observer variability

### Sources of variability

#### Visual assessment

acquisition and reconstruction

#### Quantitative analysis

acquisition and segmentation reconstruction



### Sources of variability

- inter-observer variability
- image acquisition
- image reconstruction
- segmentation
- software errors

### Sources of variability

#### Visual assessment

acquisition and reconstruction

#### Quantitative analysis

acquisition and segmentation reconstruction

#### Conventional radiomics

acquisition and reconstruction	segmentation	image processing	feature computation	modelling	



### Sources of variability

- inter-observer variability
- image acquisition
- image reconstruction
- segmentation
- software errors
- image processing
- feature computation
- modelling approaches
- modelling errors

# Sources of variability

#### Visual assessment

acquisition and reconstruction

#### Quantitative analysis

acquisition	
and	segmentation
reconstruction	

#### Conventional radiomics

acquisition and reconstruction	image processing	feature computation	modelling
--------------------------------------	---------------------	------------------------	-----------

#### Deep learning radiomics

acquisition and reconstruction	image processing	feature computation	modelling
--------------------------------------	---------------------	------------------------	-----------



### Sources of variability

- inter-observer variability
- image acquisition
- image reconstruction
- segmentation
- software errors
- image processing
- feature computation
- modelling approaches
- modelling errors
- deep learning architecture

# Can we reduce variability?



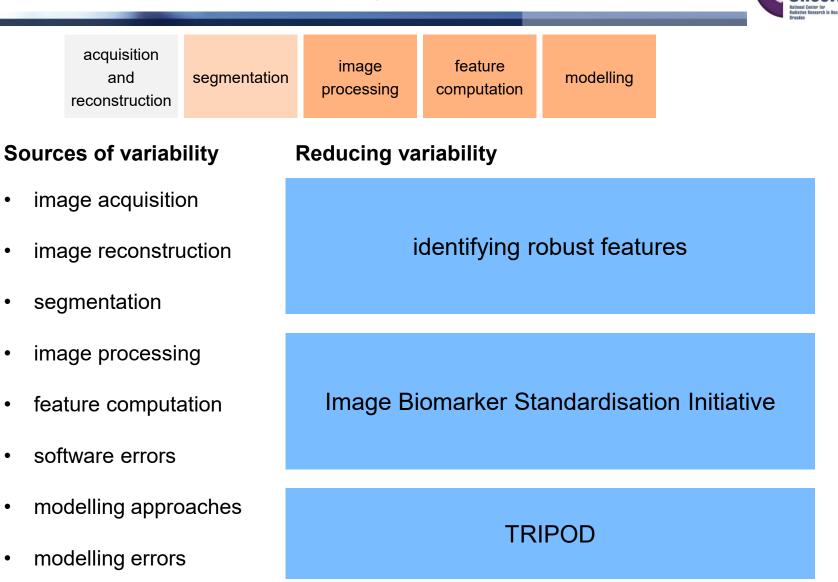
### Sources of variability

- image acquisition
- image reconstruction
- segmentation
- image processing
- feature computation
- software errors
- modelling approaches
- modelling errors

### **Reducing variability**

- $\rightarrow$  calibration, standard protocols
- $\rightarrow$  standard protocols & algorithms
- $\rightarrow$  standard protocols, (semi-)automated contouring
- $\rightarrow$  standard workflow, benchmarks
- $\rightarrow$  standard definitions, benchmarks
- $\rightarrow$  benchmarks
- $\rightarrow$  guidelines
- $\rightarrow$  guidelines, benchmarks

# Can we reduce variability?



### Finding robust features

• Conventional approach: test-retest imaging

acquisition and reconstruction

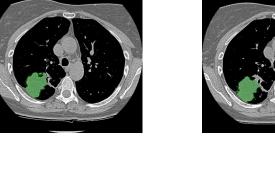
segmentation

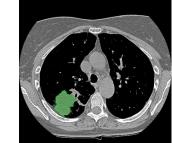
Tumour-phenotype specific!

• Proposed approach: *image perturbations* 

rotation noise addition translation shrinkage/ randomisation growth

Perturbations can identify robust features if no test-retest set is available.







### Image biomarker standardisation initiative

- Aims:
  - Establish nomenclature and definitions for 172 commonly used image biomarkers
  - Establish an image processing scheme for feature computation
  - Provide benchmark data sets and associated values for software verification
  - Provide a set of reporting guidelines



image processing

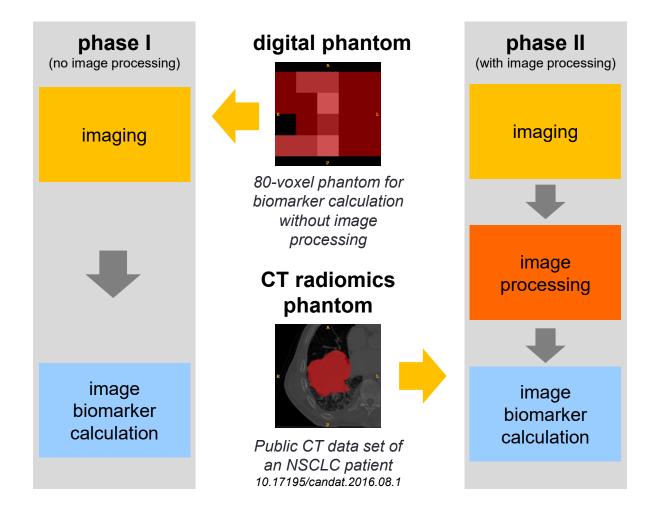


feature

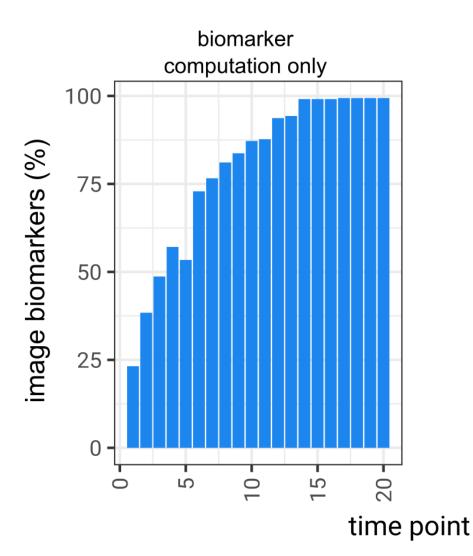
computation

# Image biomarker standardisation initiative





# Image biomarker standardisation initiative



OncoRay (IN) National Center for Rediction Research in Oncology

# Modelling



### Annals of Internal Medicine RESEARCH AND REPORTING METHODS

Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD): The TRIPOD Statement Gary S. Collins, PhD; Johannes B. Reitsma, MD, PhD; Douglas G. Altman, DSc; and Karel G.M. Moons, PhD

Annals of Internal Medicine RESEARCH AND REPORTING METHODS

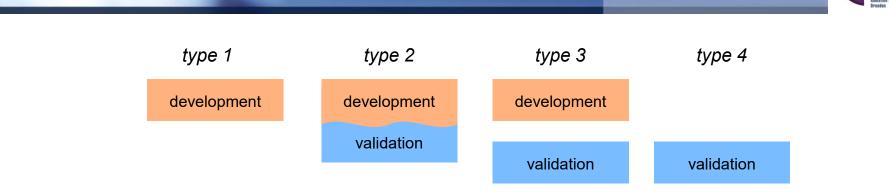
Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD): Explanation and Elaboration

Karel G.M. Moons, PhD; Douglas G. Altman, DSc; Johannes B. Reitsma, MD, PhD; John P.A. Ioannidis, MD, DSc; Petra Macaskill, PhD; Ewout W. Steyerberg, PhD; Andrew J. Vickers, PhD; David F. Ransohoff, MD; and Gary S. Collins, PhD

- The TRIPOD papers describe:
  - how to create **unbiased** diagnostic and prognostic models
  - how to report them
- Use TRIPOD to improve the quality of your research

modelling

# The importance of validation



- Example 1: type 1 with univariate feature selection
- Example 2: type 1 with LASSO feature selection (*less features in model*)
- Example 3: type 2 with LASSO and cross-validation
- Example 4: type 2 with feature selection <u>on all data</u>, and cross-validation
- Example 5: type 3 with external validation of 1-4

example	validation set	reported validation	external validation
1	development	0.71 (0.65-0.77)	0.53 (0.43-0.62)
2	development	0.68 (0.62-0.74)	0.55 (0.44-0.65)
3	validation folds	0.51 (0.38-0.64)	0.55 (0.43-0.65)
4	validation folds	0.63 (0.50-0.77)	0.55 (0.46-0.64)

### Conclusion



- Many radiomic studies are not reproducible
- Radiomics is susceptible to variability
- The influence of variability can be reduced, but requires:
  - technological development (e.g. auto-segmentation)
  - harmonisation
  - methodological rigour
  - effort and collaboration

### Questions





alexander.zwanenburg@nct-dresden.de