# Radiomics
# A bridge between medical imaging and personalized medicine

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# Disclosures

**Research collaborations incl. funding, consultancy and speaker honoraria**

Pharma: Roche, Johnson & Johnson, Bristol-Myers Squibb

MedTech: Varian Medical Systems, Siemens, Philips, Sohard, Mirada Medical, ptTheragnostics, OncoRadiomics

Health insurance: CZ Health Insurance

**Spin-offs and commercial ventures**

MAASTRO Innovations B.V.

Medical Data Works B.V.

Various patents on medical machine learning & Radiomics

Public research funding

**Public research funding**

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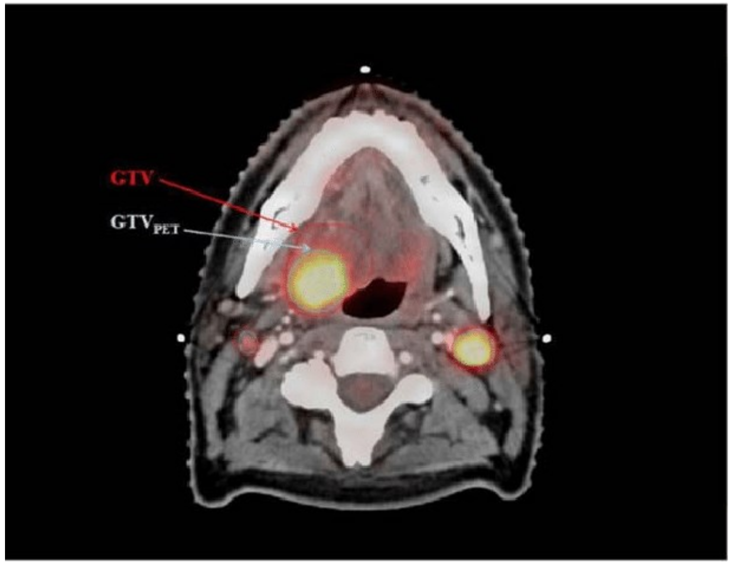
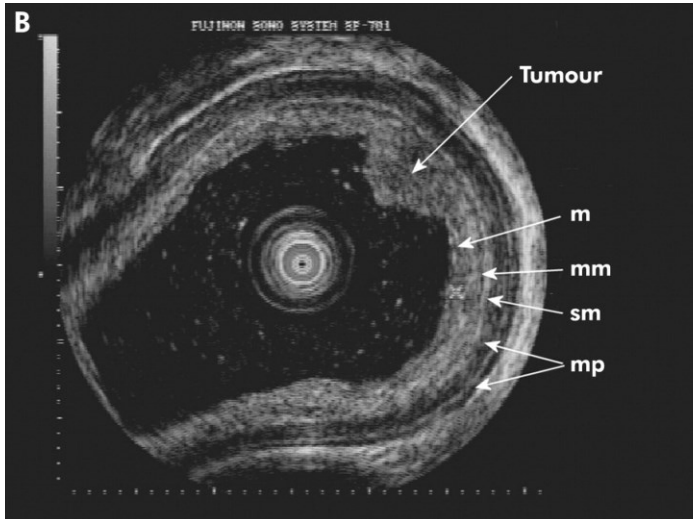
PROTRAIT, TraIT2HealthRI (NL-KWF)

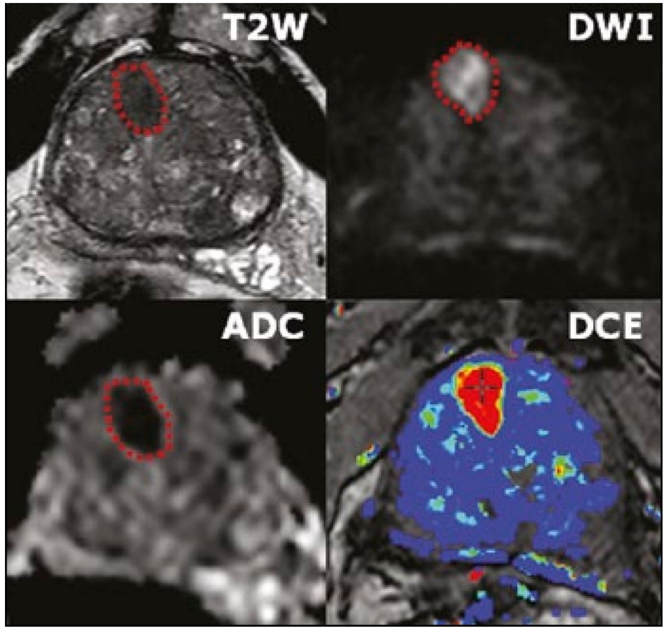
Data4LifeSciences (NL-NFU)

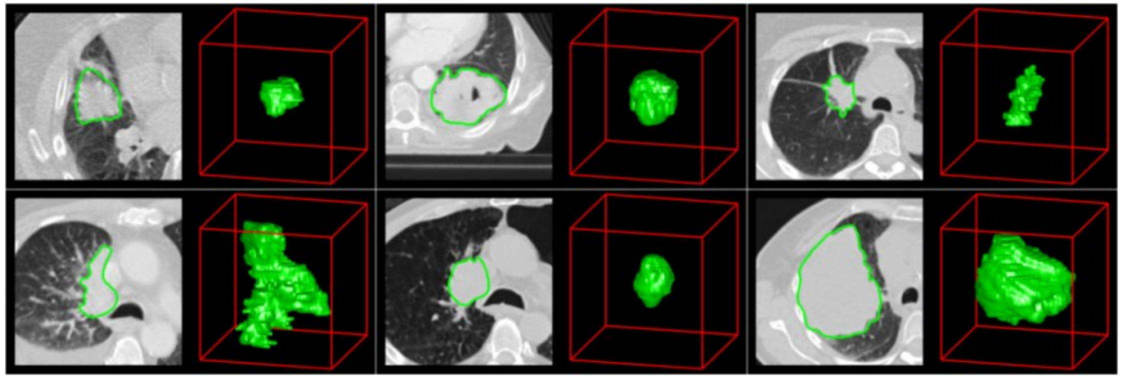
Digital Society Agenda – Health&Well-Being (NL-VSNU)

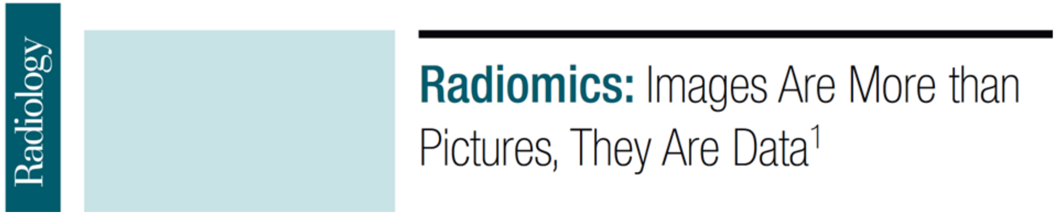
# Medical imaging






R Gillies, Radiology (2015) 48: 441-446.

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# Bridges

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# Bridges

Sint Servaasbrug, NL
Photo by Gilbert Kuhnert

# Bridges

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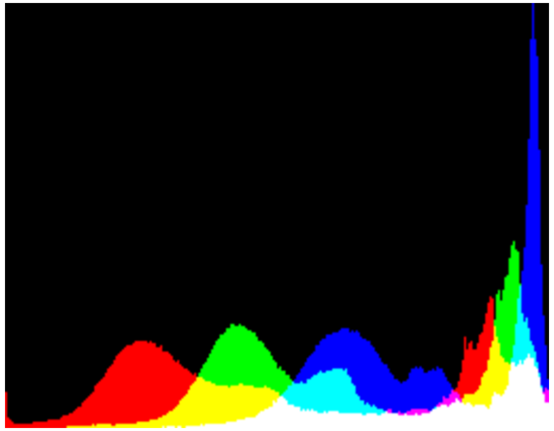
Sydney Harbour Bridge, AU

# Bridges

Millennium Bridge, UK

# Bridges



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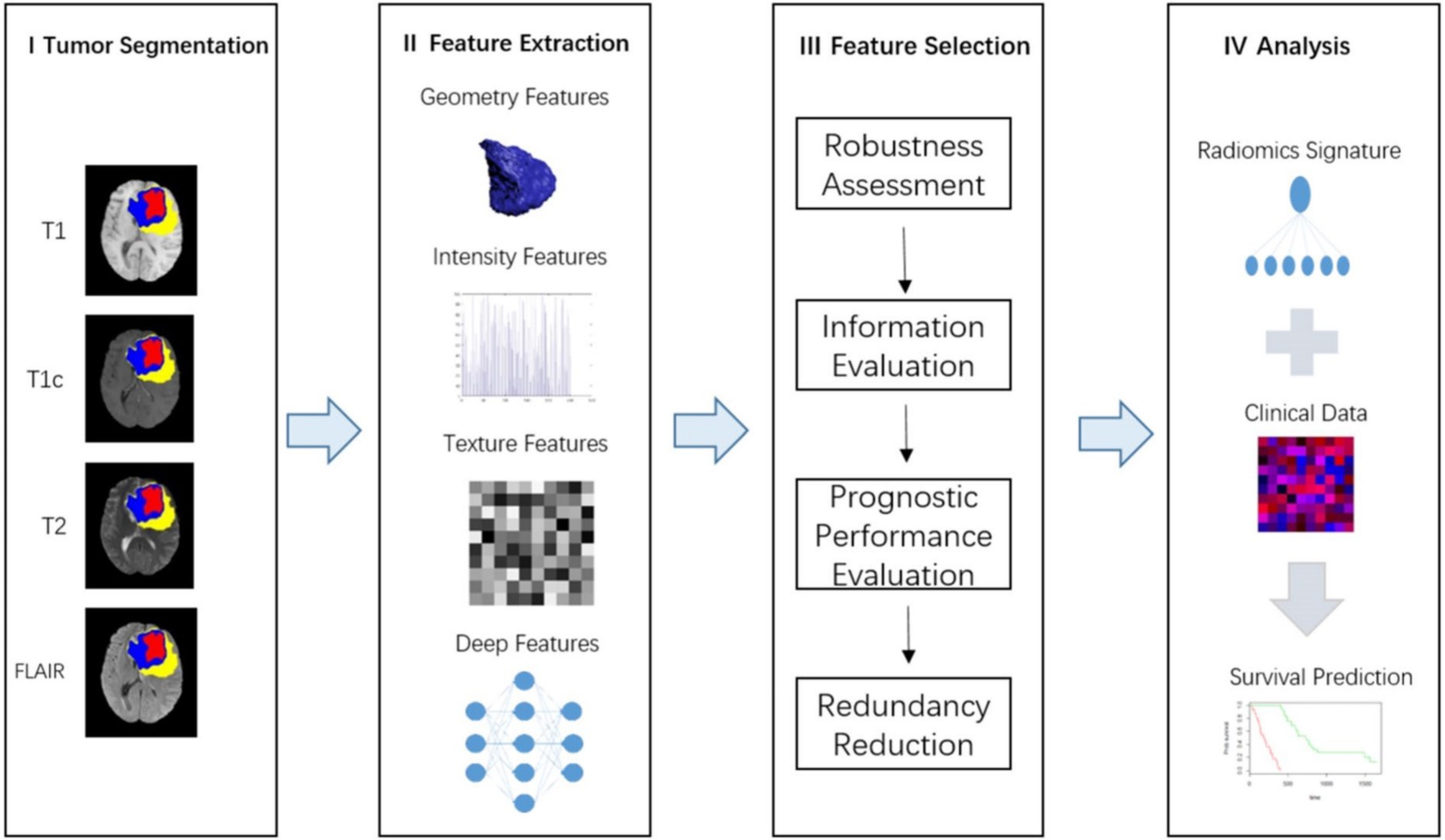
Øresundsbroen, DK
Photo by Daniel Karlsson

# Radiomics : from segmentation to prediction

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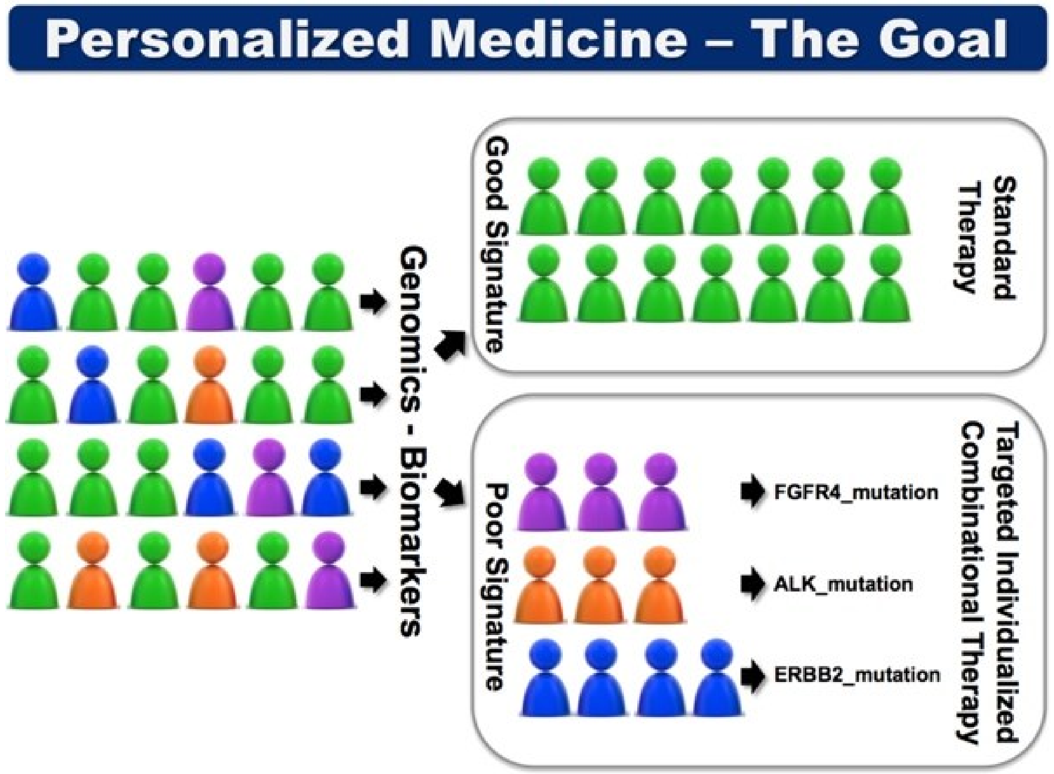
# From prediction to personalized medicine




***https://www.pennside.com/biomarker-companion-diagnostics-primer***

**Prognostic markers give information about :**

- Likely course of the disease in an untreated individual, or
- Likely course of disease regardless of treatment.

*Identify patients who would <u>not</u> <u>benefit</u> from excessive treatment.*

**Predictive markers give information about :**

- The expected benefit of a specific treatment, or
- The comparative benefits among two or more treatments.

*Identify patients <u>suited</u> <u>for</u> <u>a</u> <u>specific</u> <u>treatment</u>, or help identify <u>which</u> <u>treatment</u> <u>option</u> <u>might</u> <u>be</u> <u>best</u> for a specific patient.*

# Applications of radiomics

**Diagnostic / Characterization studies**

Benign vs malignant lung nodules

Non-invasive lung cancer histology

Oropharynx cancer HPV positivity

Associations with genetic mutation (EGFR, KRAS)

Tumour grade classification

**Prognostic / Predictive investigations**

Pathological complete response

Overall survival

Progression or metastases

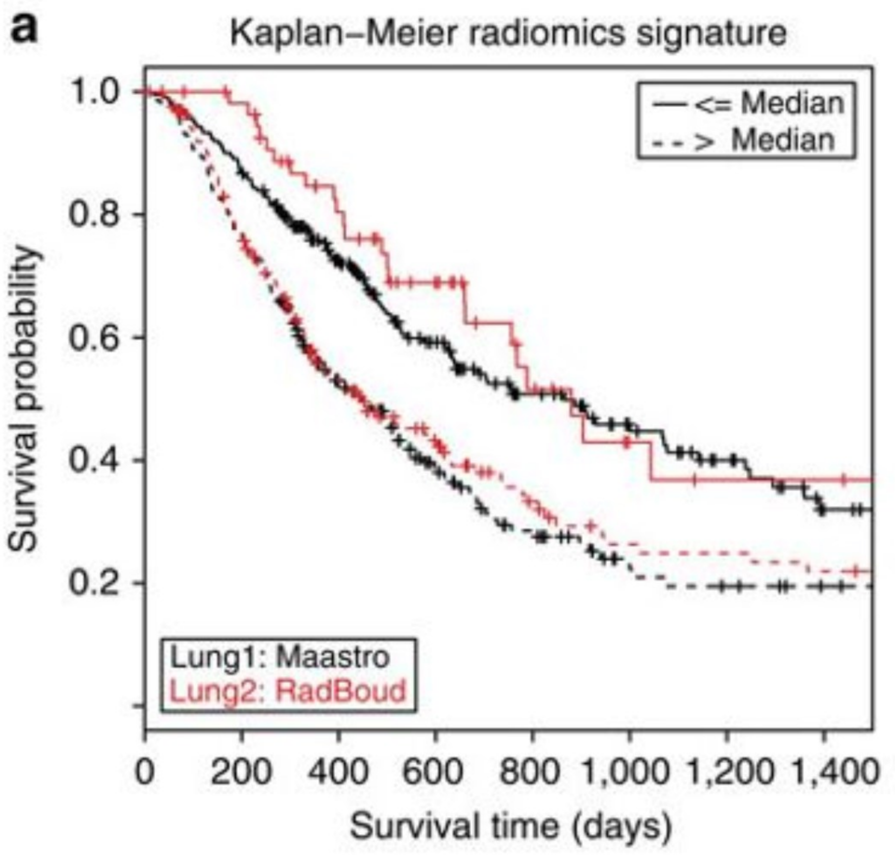
Local and nodal recurrences

Pathological lymph node metastases

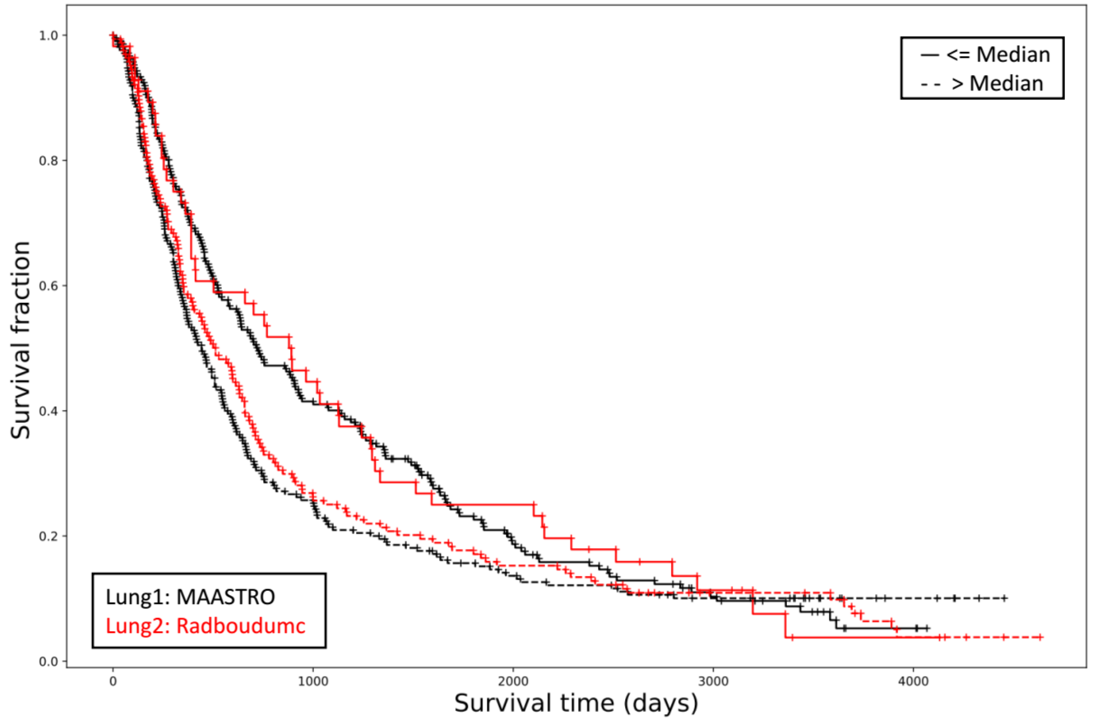
Numerous recent reviews available, e.g. :

Liu et al., “The Applications of Radiomics in Precision Diagnosis and Treatment of Oncology: Opportunities and Challenges”, Theranostics 9 (2019) 1303.

# Overall survival in NSCLC




**"Distributed Radiomics" follow-up study**




**$HCI_{Lung2}$ = 0.65**

H. Aerts et al., Nature Comms (2014) 5:4006.

**$HCI_{Lung2}$ = 0.58 (95% conf int : 0.51 to 0.65)**

Shi et al., Nature Data Science (2018) under review.

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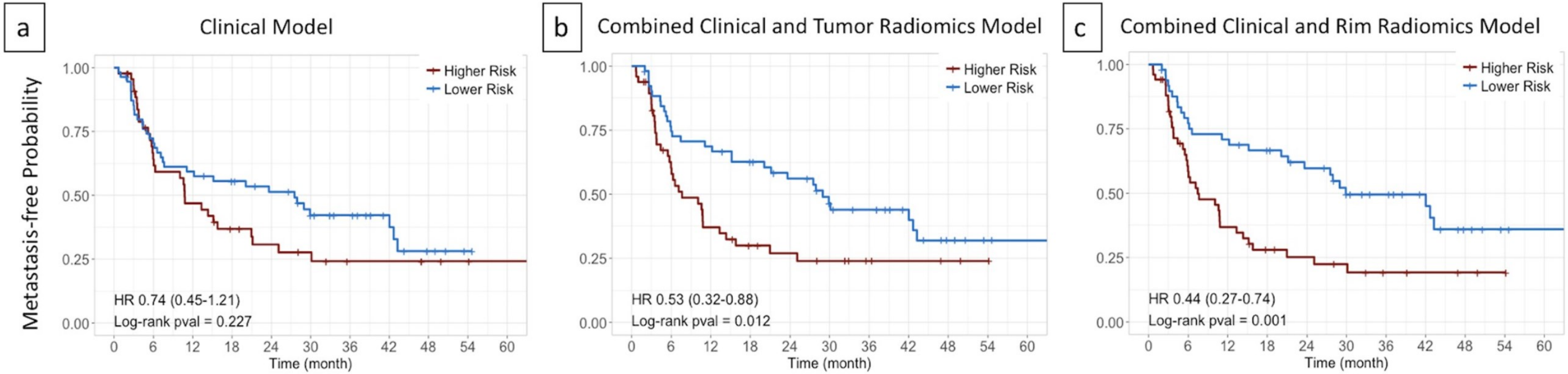
# Information from the tumour-parenchyma interface



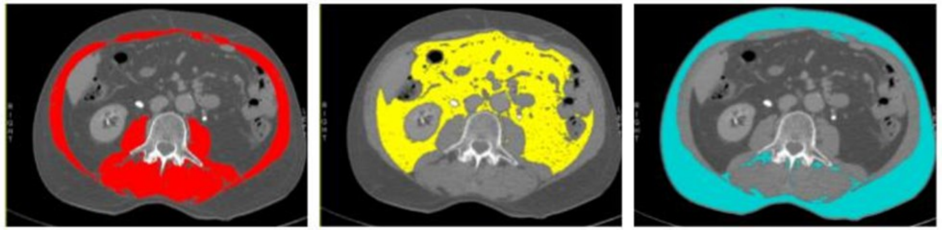

| | 0 | 6 | 12 | 18 | 24 | 30 | 36 | 42 | 48 | 54 | 60 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| a Higher Risk | 45 | 26 | 19 | 13 | 10 | 8 | 5 | 5 | 3 | 2 | 1 |
| a Lower Risk | 55 | 38 | 32 | 28 | 24 | 17 | 14 | 9 | 4 | 1 | 0 |
| b Higher Risk | 48 | 26 | 16 | 11 | 9 | 7 | 4 | 3 | 2 | 1 | 0 |
| b Lower Risk | 52 | 38 | 35 | 30 | 25 | 18 | 15 | 11 | 5 | 2 | 1 |
| c Higher Risk | 51 | 27 | 17 | 11 | 9 | 7 | 4 | 3 | 2 | 1 | 0 |
| c Lower Risk | 49 | 37 | 34 | 30 | 25 | 18 | 15 | 11 | 5 | 2 | 1 |

**Dou et al., "Peritumoral radiomics features predict distant metastasis in LA-NSCLC", (2018) PLoSONE 13:e0206108. https://doi.org/10.1371/journal.pone.0206108**

# Correlates in automated body composition analysis

**Conventional manual body composition segmentation**

| Skeletal muscle area | Visceral adipose Tissue | Subcutaneous adipose tissue |
|---|---|---|



**Radiomics feature extraction: three compartments**

113 features extracted per compartment (339 total)

**Feature selection**

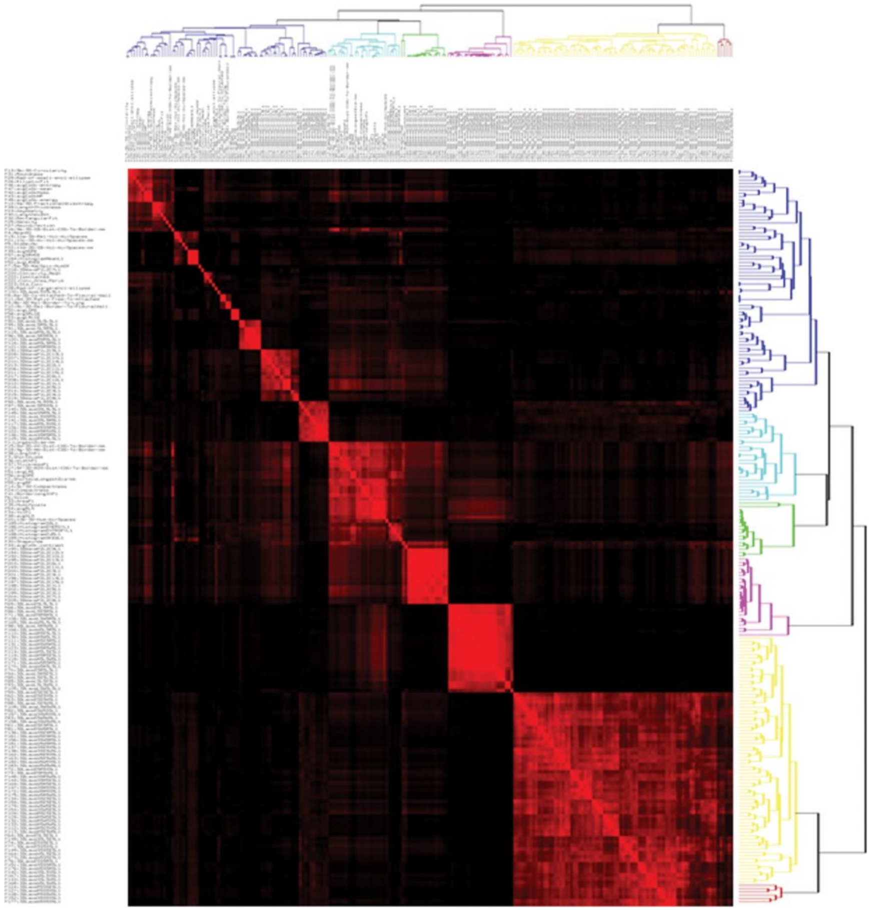
| Features highly correlated to mean skeletal muscle radio attenuation (SM-RA), N=18 | Feature elimination through minimization of pair-wise correlation, N=48 |
|---|---|

**Cohort split, 75% training - 25% test set**

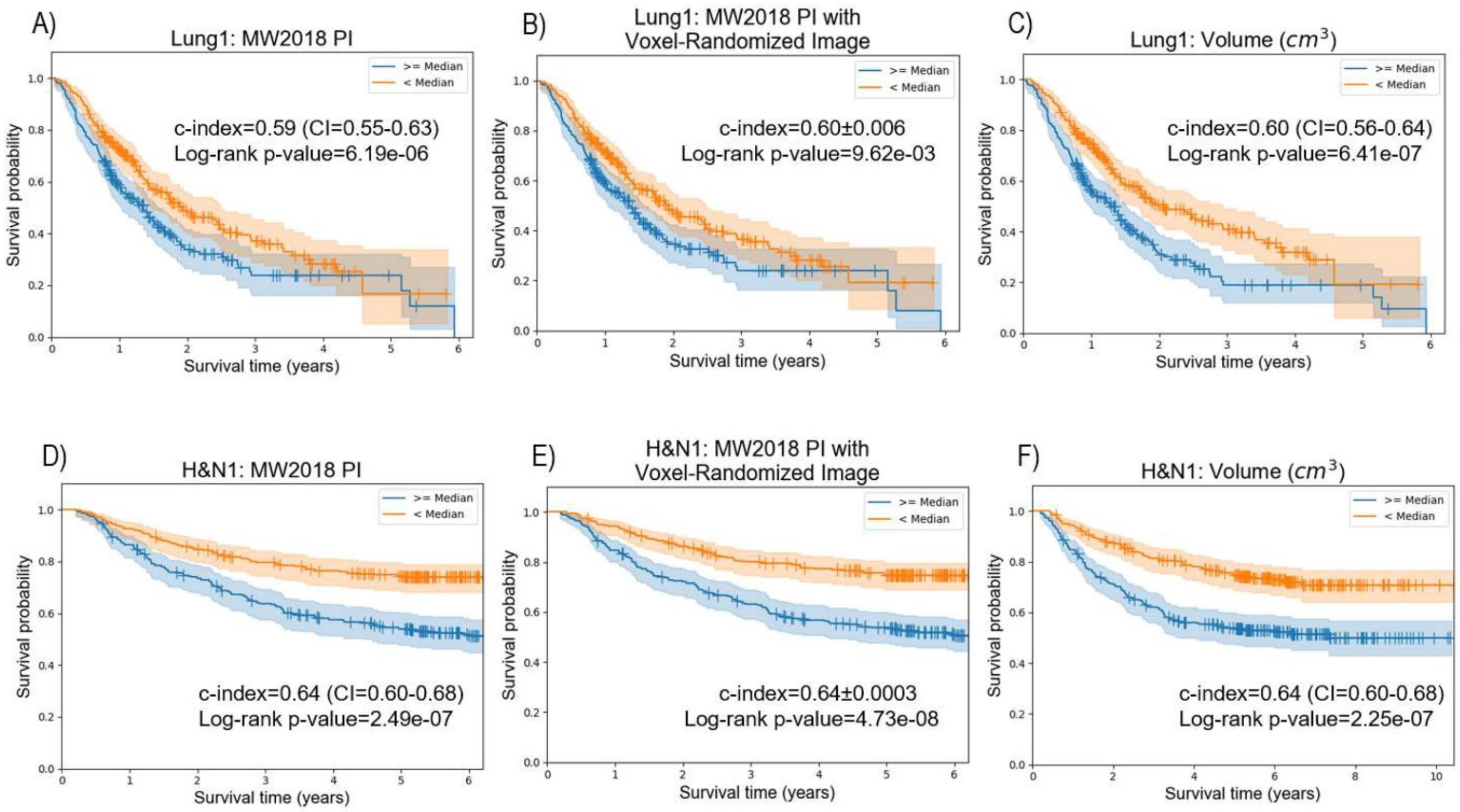
**Creating 4 prediction models for 90-day and 2-year mortality**

| Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|
| Clinical variables | Clinical variables | Clinical variables | Clinical variables |
| | SM-RA | SM-RA | SM-RA |
| | | Radiomics features correlated to SM-RA | Radiomics features remaining after minimization of pair-wise correlation |

# Feature clusters and signature equivalences

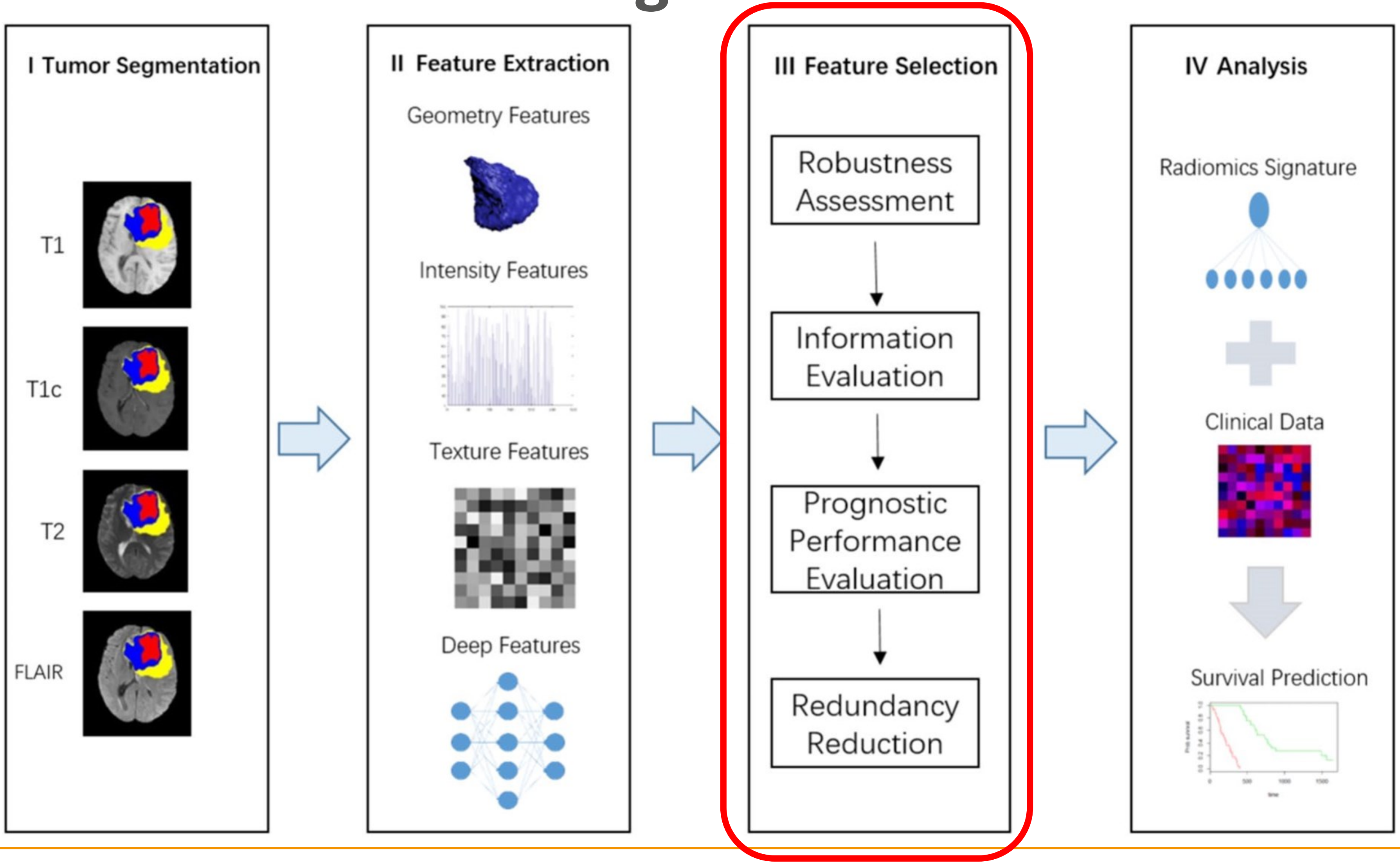


(Image from Y. Balagurunathan et al.)

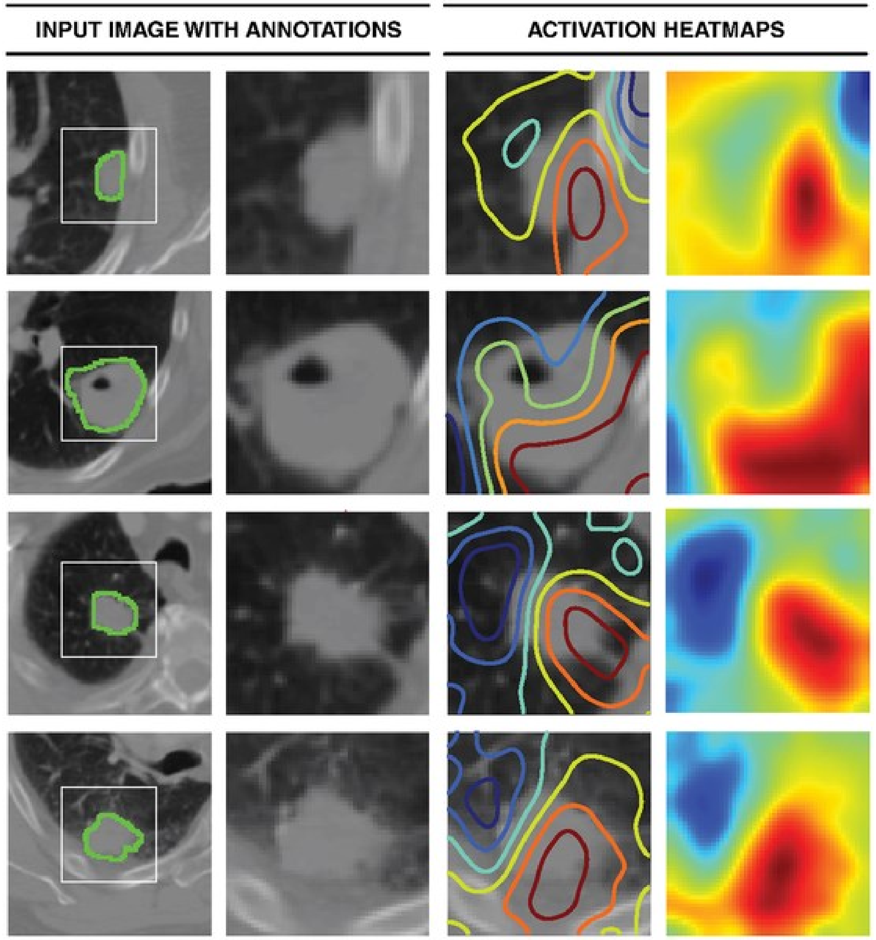



(Image courtesy of M. Welch)

# Clinical value comes from good feature selection



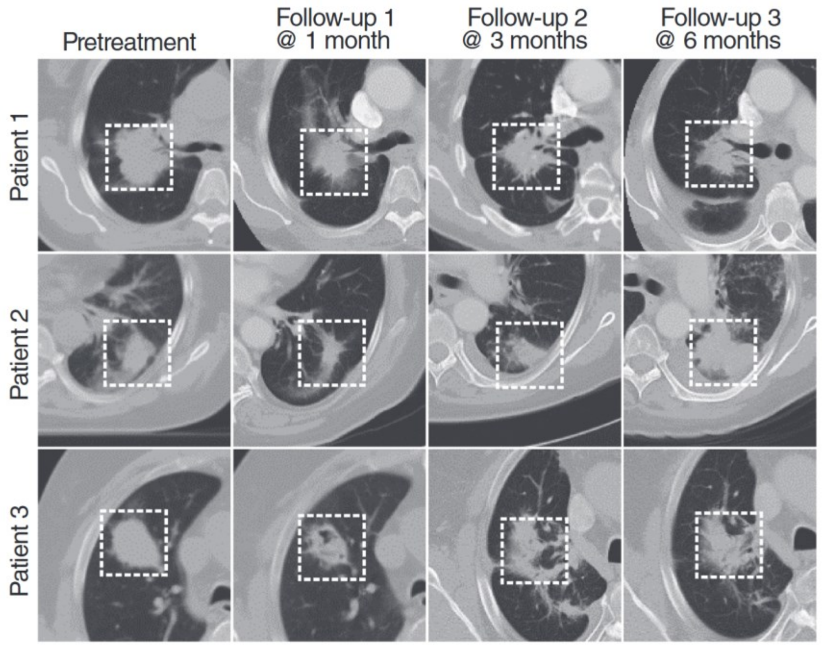
# Switching to deep learning neural networks




Hosny et al., Deep learning for lung cancer prognostication: A retrospective multi-cohort radiomics study. PLOS Medicine 15(2018): e1002711. https://doi.org/10.1371/journal.pmed.1002711

# Switching to deep learning neural networks

**Figure 1.**
Serial patient scans. Representative CT images of patients with stage III nonsurgical NSCLC before radiation therapy and 1, 3, and 6 months following radiation therapy. A single click seed point identifies the input image patch of the neural network (defined by the dotted white line).




Pre-treat CT + 1m + 3m + 6m re-scans

Pre-treat CT only
AUC = 0.58

Precision Medicine and Imaging

Clinical Cancer Research

**Deep Learning Predicts Lung Cancer Treatment Response from Serial Medical Imaging**

Yiwen Xu[1], Ahmed Hosny[1,2], Roman Zeleznik[1,2], Chintan Parmar[1], Thibaud Coroller[1], Idalid Franco[1], Raymond H. Mak[1], and Hugo J.W.L. Aerts[1,2,3]



**Results:** Deep learning models using time series scans were significantly predictive of survival and cancer-specific outcomes (progression, distant metastases, and local-regional recurrence). Model performance was enhanced with each additional follow-up scan into the CNN model (e.g., 2-year overall survival: $\boxed{AUC = 0.74}$, $P < 0.05$). The models stratified

**DOI:** 10.1158/1078-0432.CCR-18-2495

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# Summary

- Medical images can be quantitatively analysed with machine algorithms and AI that help us search for potential outcome markers.
- Radiomic prognostic and predictive markers need to be robustly tested and watchfully used (i.e. repeatability, reproducibility & generalizability).
- Radiomics models need to be independently verified and then repeatedly validated across multiple clinics.
- “Distributed methods” are potentially helpful to overcome concerns about sharing of patients’ clinical data and images.
- “Deep learning” could lead radiomics into some added clinical value; but we need more images, better follow-ups, robust method and relevant clinical questions.

# THANK YOU

* Countries where I lived in and worked as a medical physicist, before choosing NL as my home.

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