Radiomics

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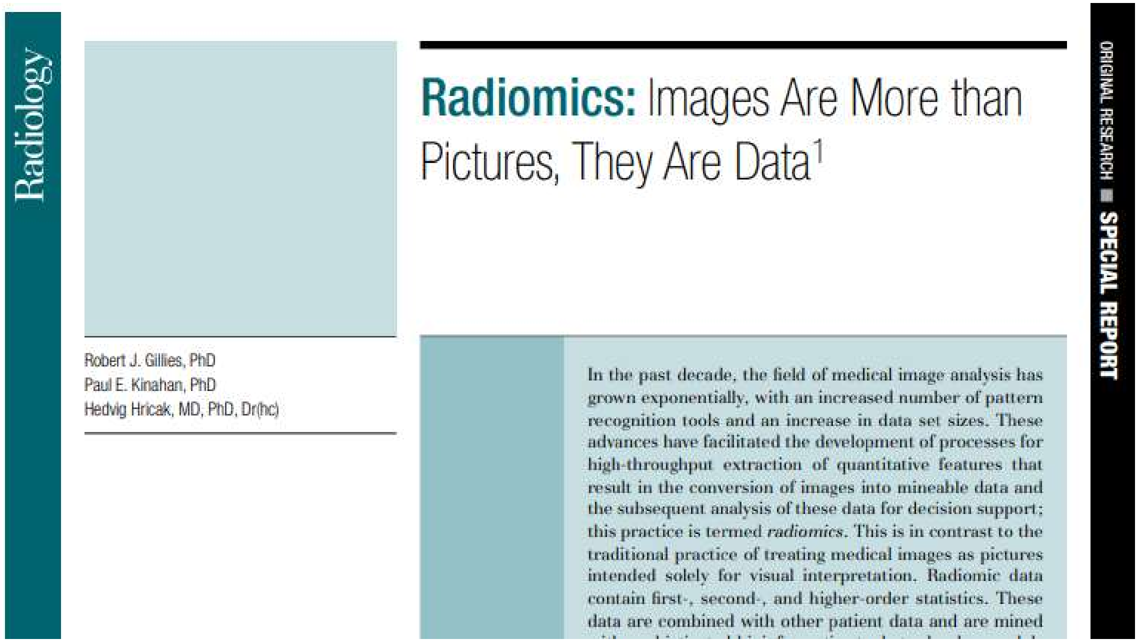
Radiomic hypotesis

Molecular heterogeneity of cancer lesions is cause of different clinical outcome.

Such heterogeneity can be captured, *in vivo*, on the entire lesion volume, by high-throughput quantitative radiomics descriptors from 3D image of cancer lesion.

Different expression level of a signature of radiomic features are able to predict different prognosis or treatment response of patients with similar cancer diagnosis (statistical analysis and predictive models).



Radiology

ORIGINAL RESEARCH ■ SPECIAL REPORT

Radiomics: Images Are More than Pictures, They Are Data[1]

Robert J. Gillies, PhD
Paul E. Kinahan, PhD
Hedvig Hricak, MD, PhD, Dr(hc)

In the past decade, the field of medical image analysis has grown exponentially, with an increased number of pattern recognition tools and an increase in data set sizes. These advances have facilitated the development of processes for high-throughput extraction of quantitative features that result in the conversion of images into mineable data and the subsequent analysis of these data for decision support; this practice is termed *radiomics*. This is in contrast to the traditional practice of treating medical images as pictures intended solely for visual interpretation. Radiomic data contain first-, second-, and higher-order statistics. These data are combined with other patient data and are mined

Radiomics: a new approach for the study of cancer

HHS Public Access

Author manuscript

Eur J Cancer. Author manuscript; available in PMC 2015 August 12.

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Radiomics: Extracting more information from medical images using advanced feature analysis

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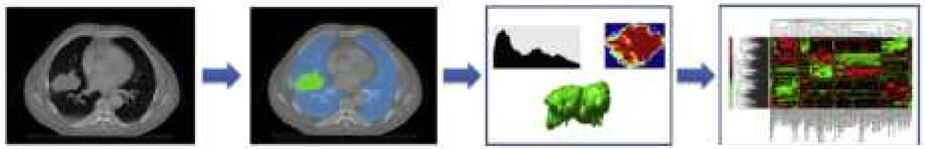


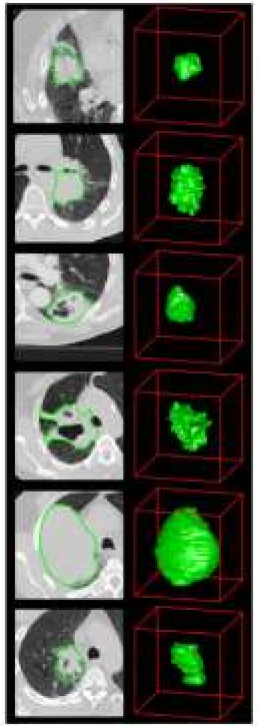
Imaging

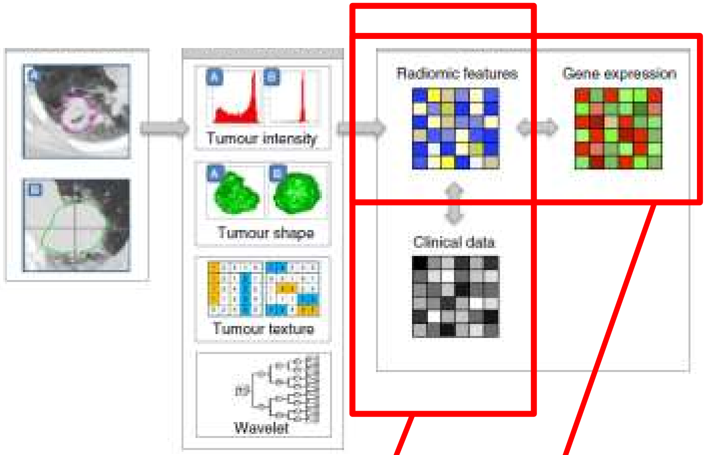
Volume

Feature

Statistical correlations

Comprehensive quantification of disease phenotypes by applying a large number of quantitative image features representing lesion heterogeneity and correlating with omics and clinical data



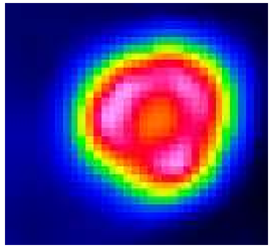
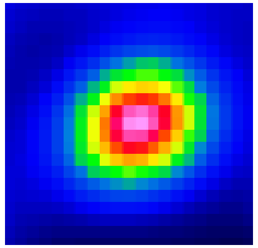
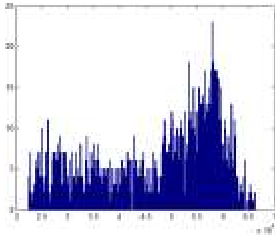
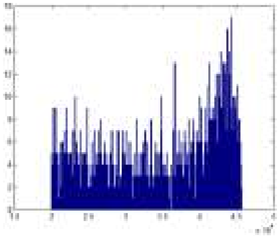
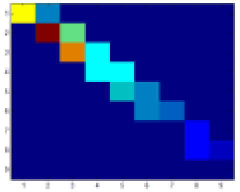
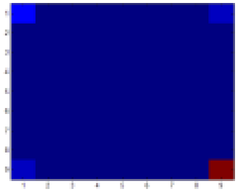


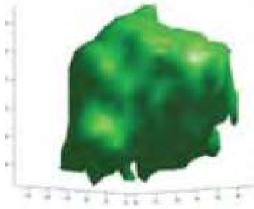
RADIOGENOMICS

RADIOMICS

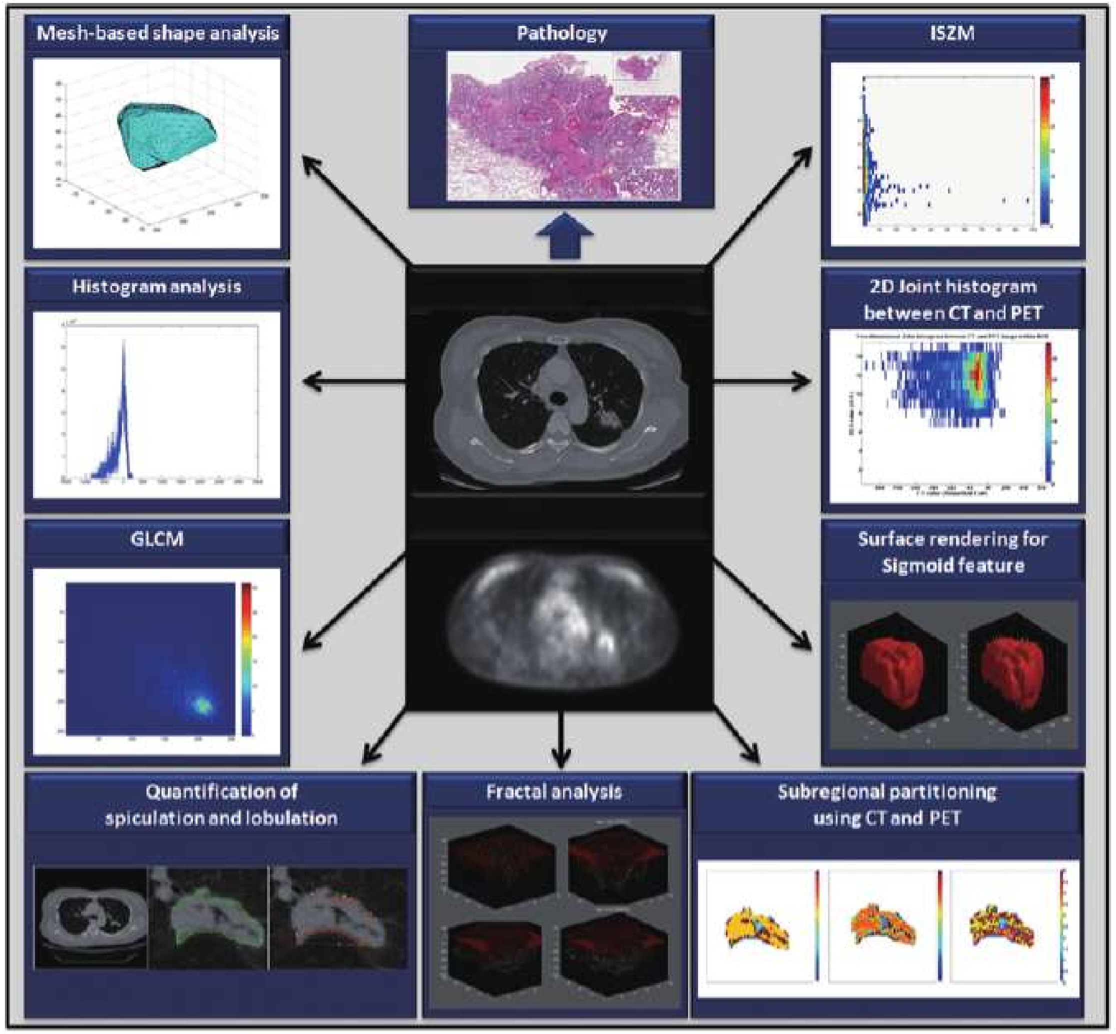
Texture and shape features

Feature	Description		Examples
Texture-First order	Grey level frequency distribution from histogram Analysis	Global	Minimum, mean and maximum intensity Standard deviation Skewness Kurtosis Percentile values Range of intensities
Texture-Second order	From spatial grey level dependence matrices (SGLDM) or co–occurrence matrices *They express how often a pixel of intensity i finds itself within a certain relationship to another pixel of intensity j*	Local	Entropy Energy Contrast Homogeneity Dissimilarity Uniformity Correlation
Texture-Third order	From neighbourhood grey-tone difference matrices (NGTDMs)	Local	Coarseness Contrast Busyness Complexity
	From voxel alignment matrices	Regional	Run-length and emphasis Run-length variability
	From grey level size zone matrices *They reflect regional intensity variations or the distribution of homogeneous regions*	Regional	Zone emphasis Size-zone variability
Shape and Size			Spericity Compactness Eccentricity Surface Area Sperical Disproportion Surface to Volume ratio Solidity



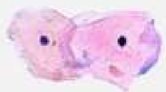
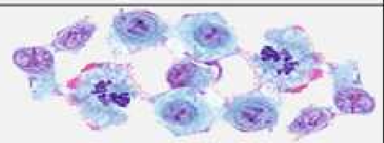
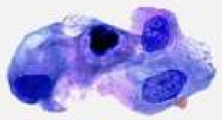
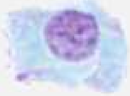
Radiomics



https://www.researchgate.net/figure/Various-radiomic-features-such-as-mesh-based-shape-histogram-gray-level-co-occurrence_fig3_315902486

Morphological features

1. Metabolic Target Volume (MTV)
2. Surface
3. Spherical disproportion
(ratio between measured surface of the lesion and surface of an equivalent-sphere in terms of volume)
4. Sphericity
5. Surface-to-volume ratio

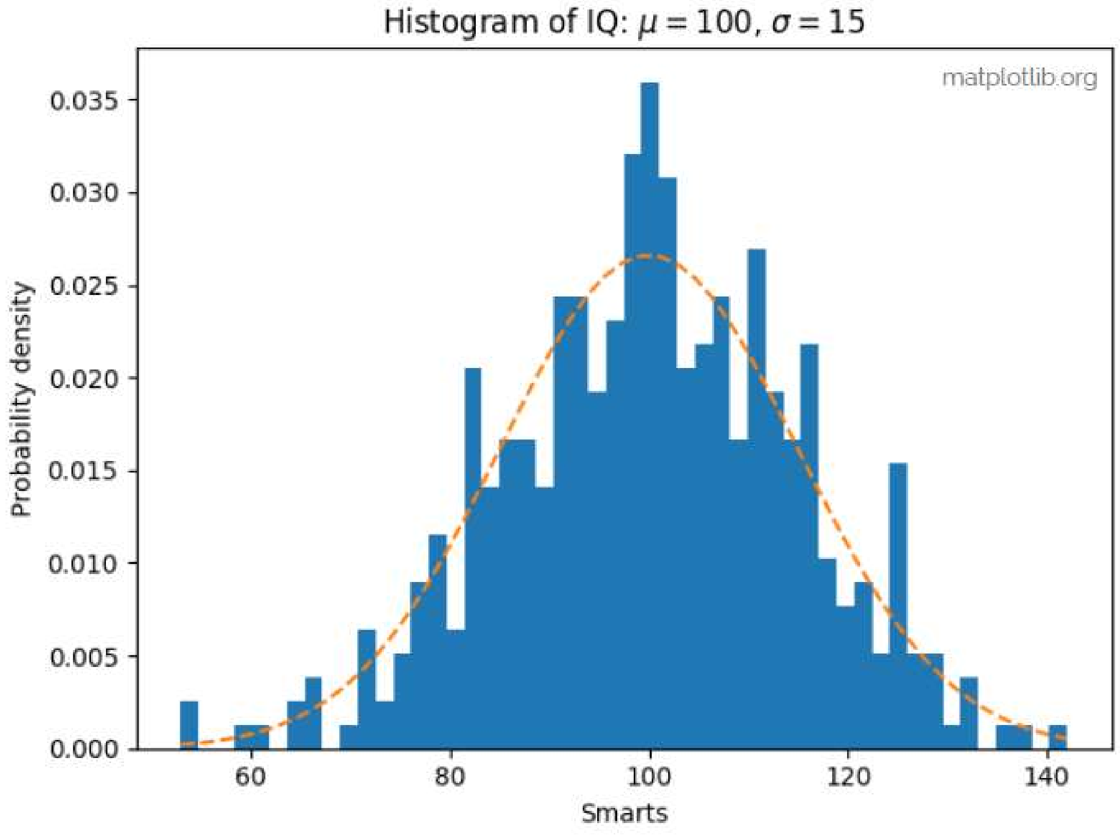
Normal	Cancer	
		Large, variably shaped nuclei
		Many dividing cells; Disorganized arrangement
		Variation in size and shape
		Loss of normal features

http://sphweb.bumc.bu.edu/otlt/MPH-Modules/PH/PH709_Cancer/PH709_Cancer7.html

Radiomics

Histogram-based features

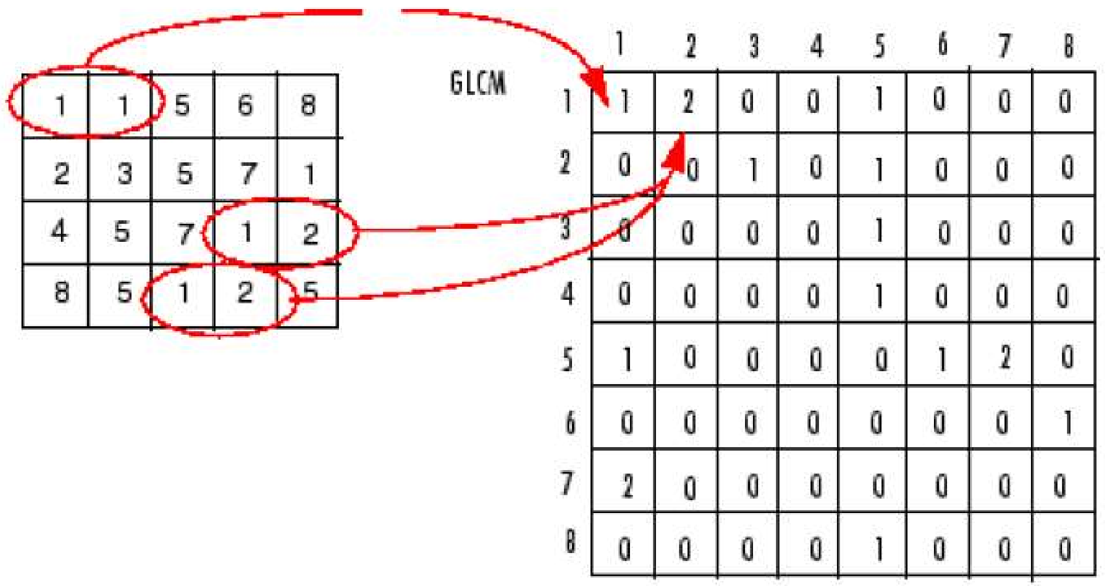
1. Maximum
2. Minimum
3. Mean
4. Median
5. Mean Absolute Deviation (MAD)
6. Root Mean Square (RMS)
7. Energy
8. Entropy
9. Kurtosis
10. Skewness
11. Standard Deviation
12. Uniformity
13. Variance



Texture descriptors
Gray-Level Co-occurrence Matrix (GLCM)*

1. Energy
2. Contrast
3. Entropy
4. Homogeneity
5. Correlation
6. Sum Average
7. Variance
8. Dissimilarity
9. Auto Correlation

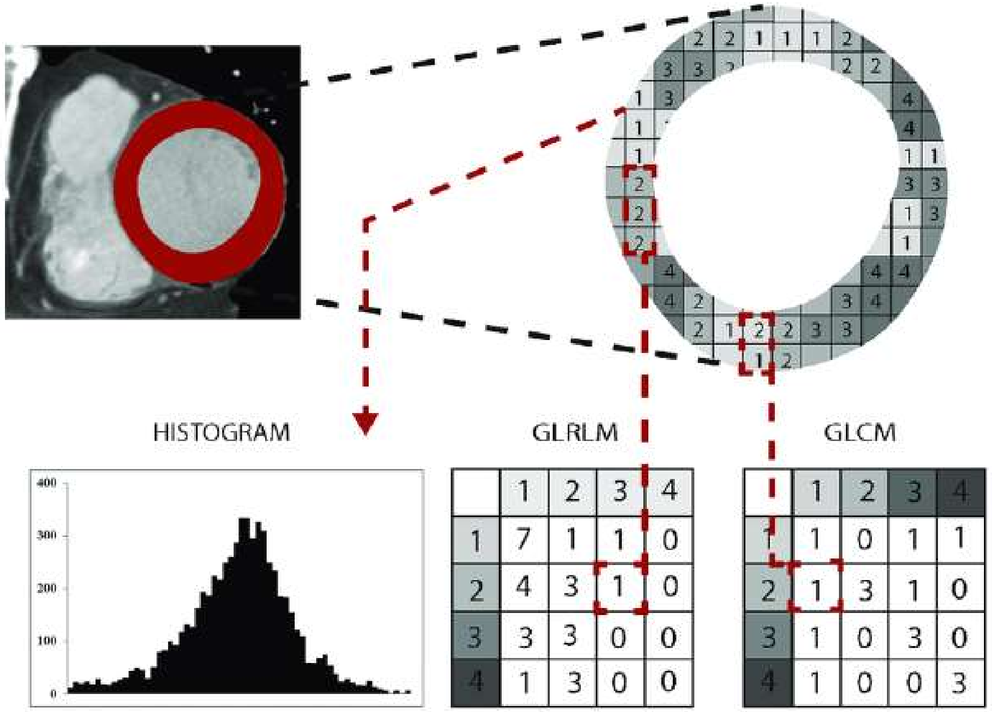
* A Gray Level Co-occurrence Matrix (GLCM) quantifies the number of times the combination of levels X and Y occur in two pixels in the image that are separated by a distance of D pixels along angle A.



mathworks.com

Radiomics

Texture descriptors
Gray-Level Run Length Matrix (GLRLM)*



GLRLM

	1	2	3	4
1	7	1	1	0
2	4	3	1	0
3	3	3	0	0
4	1	3	0	0

GLCM

	1	2	3	4
1	1	0	1	1
2	1	3	1	0
3	1	0	3	0
4	1	0	0	3

https://www.researchgate.net/figure/Principles-of-generating-texture-analysis-features-Principles-of-generating-the_fig2_320821651

*A Gray Level Run Length Matrix (GLRLM) quantifies gray level runs, which are defined as the length in number of pixels, of consecutive pixels that have the same gray level value.

It describes # runs with gray level G and length L that occur in the image along angle A.

Radiomics

Texture descriptors
Gray-Level Size Zone Matrix (GLSZM)

1	2	3	4
1	3	4	4
3	2	2	2
4	1	4	1

Level	*Size zone, s*		
g	1	2	3
1	2	1	0
2	1	0	1
3	0	0	1
4	2	0	1

http://thibault.biz/Research/ThibaultMatrices/GLSZM/GLSZM.html

* A gray level zone is defined as a the number of connected voxels that share the same gray level intensity.

Contrary to GLCM and GLRLM, the GLSZM is rotation independent, with only one matrix calculated for all directions in the ROI

Texture descriptors
Neighbouring Gray Tone Difference Matrix (NGTDM)*

$$\mathbf{I} = \begin{bmatrix} 1 & 2 & 5 & 2 \\ 3 & 5 & 1 & 3 \\ 1 & 3 & 5 & 5 \\ 3 & 1 & 1 & 1 \end{bmatrix}$$

i	n_i	p_i	s_i
1	6	0.375	13.35
2	2	0.125	2.00
3	4	0.25	2.63
4	0	0.00	0.00
5	4	0.25	10.075

https://pyradiomics.readthedocs.io/en/latest/features.html

* A Neighbouring Gray Tone Difference Matrix quantifies the difference between a gray value and the average gray value of its neighbours within distance D

Radiomics

PREPROCESSING | FEATURE EXTRACTION | FEATURE SELECTION | TRAINING AND INTERNAL TESTING

EXTRACT THE FOLLOWING FEATURE FAMILIES

MORPHOLOGICAL FEATURES

- [x] Morphology (25 features 3D or 10 features 2D)

INTENSITY-BASED FEATURES

- [x] Intensity-based statistic (18 features)
- [x] Intensity histogram features (16 features)

TEXTURE-BASED FEATURES

- [x] Grey-level co-occurrence matrix (25 features)
- [x] Grey-level run length matrix (16 features)
- [x] Grey-level size zone matrix (15 features)
- [x] Neighbourhood grey tone difference matrix (5 features)
- [x] Neighbouring grey level dependence matrix (16 features)

APPLY THE FOLLOWING TRANSFORMATION FILTERS FOR FILTER-BASED FEATURES (111 features for each filter)

- [ ] Wavelet - not recommended for 2D modalities, it will greatly increase the required time (minutes instead of seconds for each image)
- [ ] Square
- [ ] Squareroot
- [ ] Logarithm
- [ ] Exponential
- [ ] Gradient
- [ ] Laplacian of gaussian (LoG)
- [ ] Local binary patterns (LBP) - the use of this filter will greatly increase the required time (minutes instead of seconds for each image)

Textures in cancer by PET

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Exploring feature-based approaches in PET images for predicting cancer treatment outcomes

I. El Naqa, Ph.D.[a], P. Grigsby, M.D.[a], A. Apte, M.Sc[a], E. Kidd, M.D.[a], E. Donnelly, M.D.[a], D. Khullar, M.Sc[a], S. Chaudhari, B.Sc[a], D. Yang, Ph.D.[a], M. Schmitt, B.Sc[b], Richard Laforest, Ph.D.[b], W. Thorstad, M.D.[a], and J. O. Deasy, Ph.D.[a]

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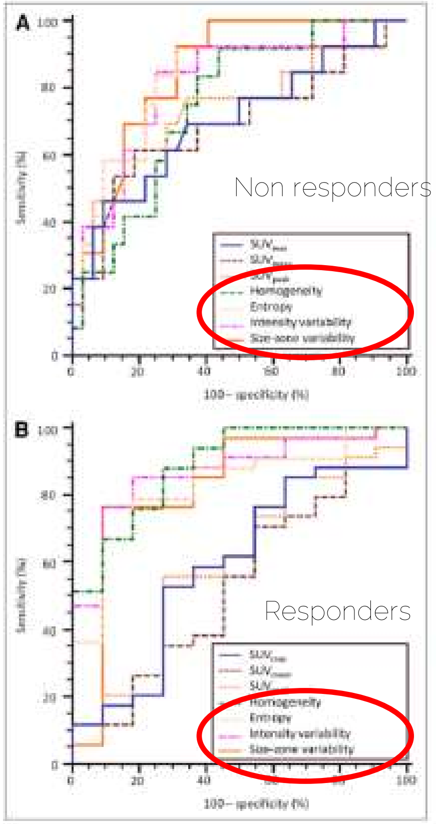

Table 2

Association between different extracted features and overall survival in a cohort of 9 head and neck patients measured by Spearman's rank correlation (rs) and the area under the ROC curve (AUC).

Variable		Spearman (rs)	AUC
Tumor volume		*0.6928*	*0.8750*
SUV Measurements	Maximum	0.3464	0.7000
	Minimum	-0.2642	0.6000
	Mean	0.1732	0.6500
	Standard deviation	0.3464	0.6750
IVH Intensity-volume metrics	I_{10}	0.1732	0.7000
	I_{90}	0.0	0.5000
	$I_{10\text{-}90}$	0.2598	0.6750
	V_{10}	-0.1732	0.5750
	V_{90}	*-0.7794*	*0.9500*
	$V_{10\text{-}90}$	0.0866	0.5000
Texture-based features	Energy	0.0866	0.5000
	Contrast	-0.5196	0.8000
	Local homogeneity	0.5196	0.8250
	Entropy	-0.1732	0.5250
Shape-based features	Eccentricity	0.2598	0.6500
	Euler Number	*0.6166*	*0.8500*
	Solidity	*-0.6088*	*0.8500*
	Extent	*-0.6062*	*0.8500*

J Nucl Med 2011; 52:369–378

Intratumor Heterogeneity Characterized by Textural Features on Baseline ^{18}F-FDG PET Images Predicts Response to Concomitant Radiochemotherapy in Esophageal Cancer

Florent Tixier[1], Catherine Cheze Le Rest[1,2], Mathieu Hatt[1], Nidal Albarghach[1,3], Olivier Pradier[1,3], Jean-Philippe Metges[3,4], Laurent Corcos[4], and Dimitris Visvikis[1]

[1]INSERM U650 LaTIM, CHU Morvan, Brest, France; [2]Department of Nuclear Medicine, CHU Morvan, Brest, France; [3]Institute of

A study in which we hope not to be cited…

PLOS ONE

RESEARCH ARTICLE

False Discovery Rates in PET and CT Studies with Texture Features: A Systematic Review

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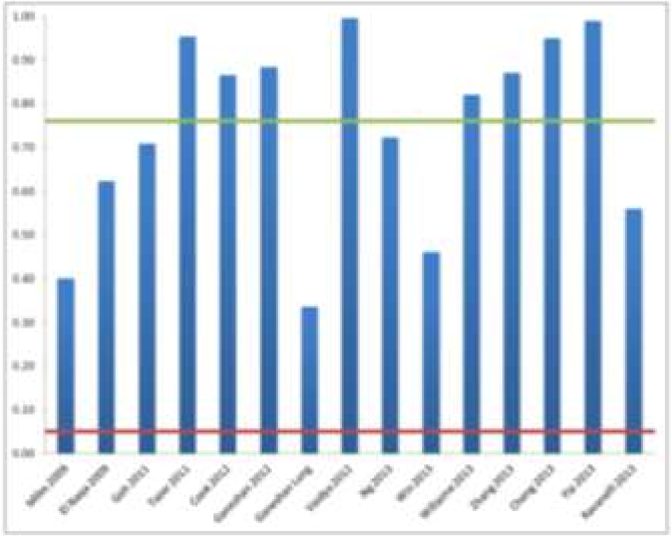

Fig 2. Probability of a false positive result based on number of hypotheses tested per study (blue columns) for all study categories. 5% type-I error probability = red line, average type-I error probability (76%) over all studies = green line (Note—additional inflation of the type-I error probability due to the use of the optimum cut-off approach is not included here).

doi:10.1371/journal.pone.0124165.g002

Key methodological issues

- Repeatability, the closeness of the agreement between the results of successive radiomic measurements under the same conditions of measurement

- Riproducibility, the closensess of the agreement between the results of radiomic measurement under similar conditions of measurements

- Significance, the ability of radiomic in effectively characterizing cancer lesion heterogeneity

Stability