UNIVERSITÀ DEGLI STUDI DI MILANO
DIPARTIMENTO DI FISICA

IEO
Istituto Europeo
di Oncologia

Repeatability and robustness of radiomic features extracted from Magnetic Resonance images of pelvic district: a phantom study

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First-year students Workshop 2018
Università degli Studi di Milano, Dipartimento di Fisica, 9th October 2018

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Introducion
to Radiomics

Radiomics + MR:
need for phantom
studies

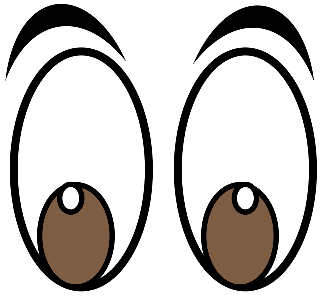
Data from
“standard
phantom”

Development of
“ad hoc phantom”

What is radiomics?

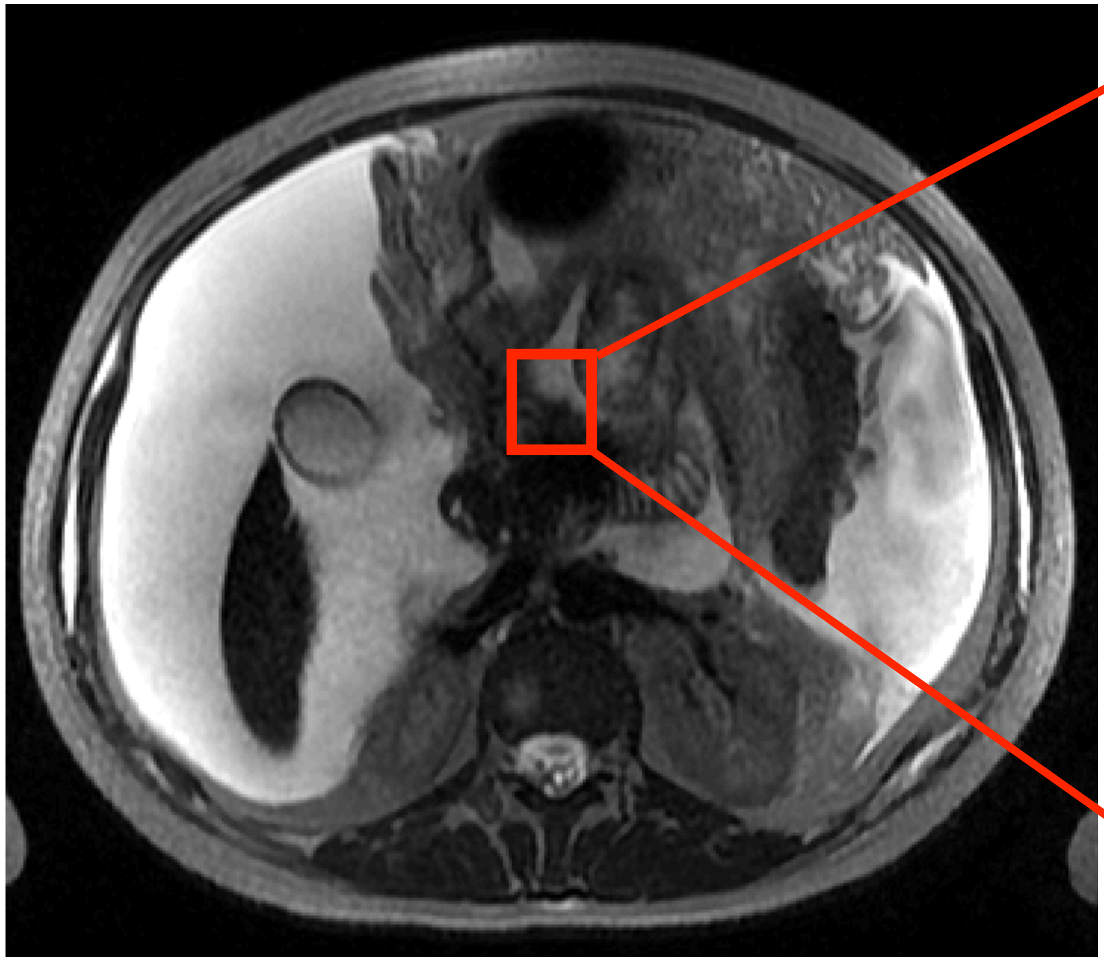
What is radiomics?

What is radiomics?

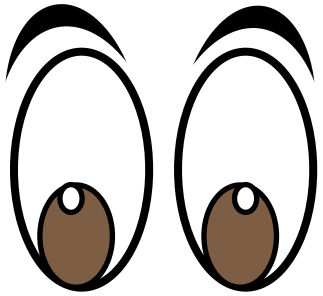


What is radiomics?

512 x 512 matrix



313	289	305	293	266	312	407
302	279	293	271	228	270	376
285	265	274	252	205	236	340
271	255	264	250	209	227	318
267	257	268	264	231	239	315
273	264	278	281	248	248	313
285	267	280	288	255	244	297
295	265	266	283	260	239	271
301	261	245	275	276	250	254
300	259	232	269	296	276	256
293	262	232	265	302	292	266
282	265	241	261	287	283	269
262	251	242	252	261	260	266
231	219	228	241	242	248	269
195	183	211	236	244	260	283
169	165	207	243	260	279	289
169	176	225	261	275	281	274
194	213	258	281	277	265	246
223	252	287	291	270	247	230
239	276	299	291	264	243	233
242	284	295	281	261	246	240



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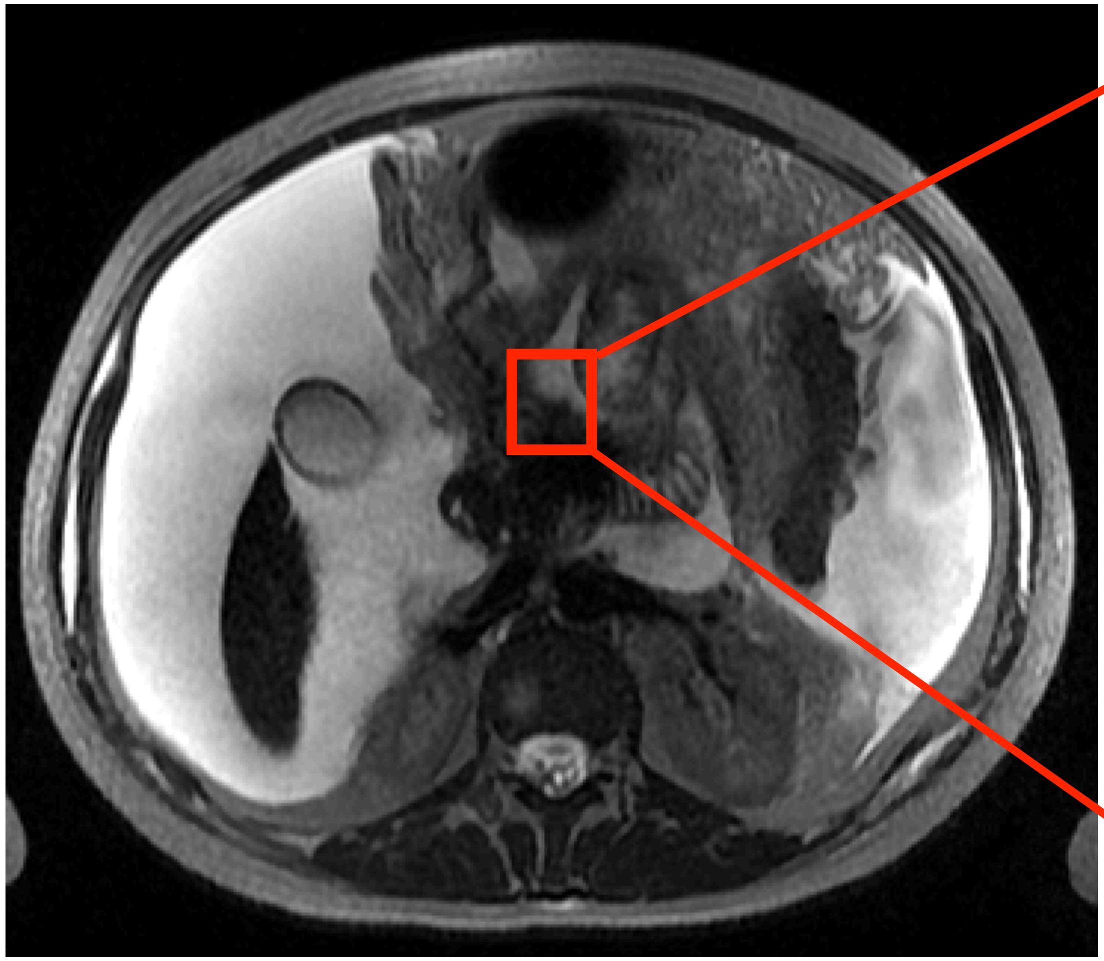

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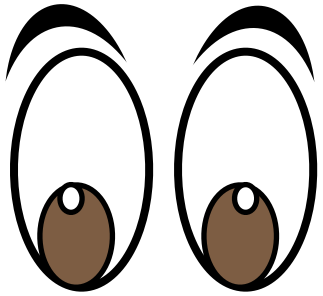

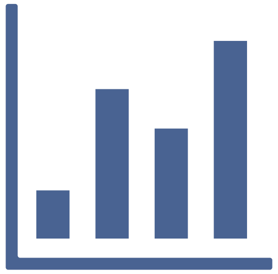

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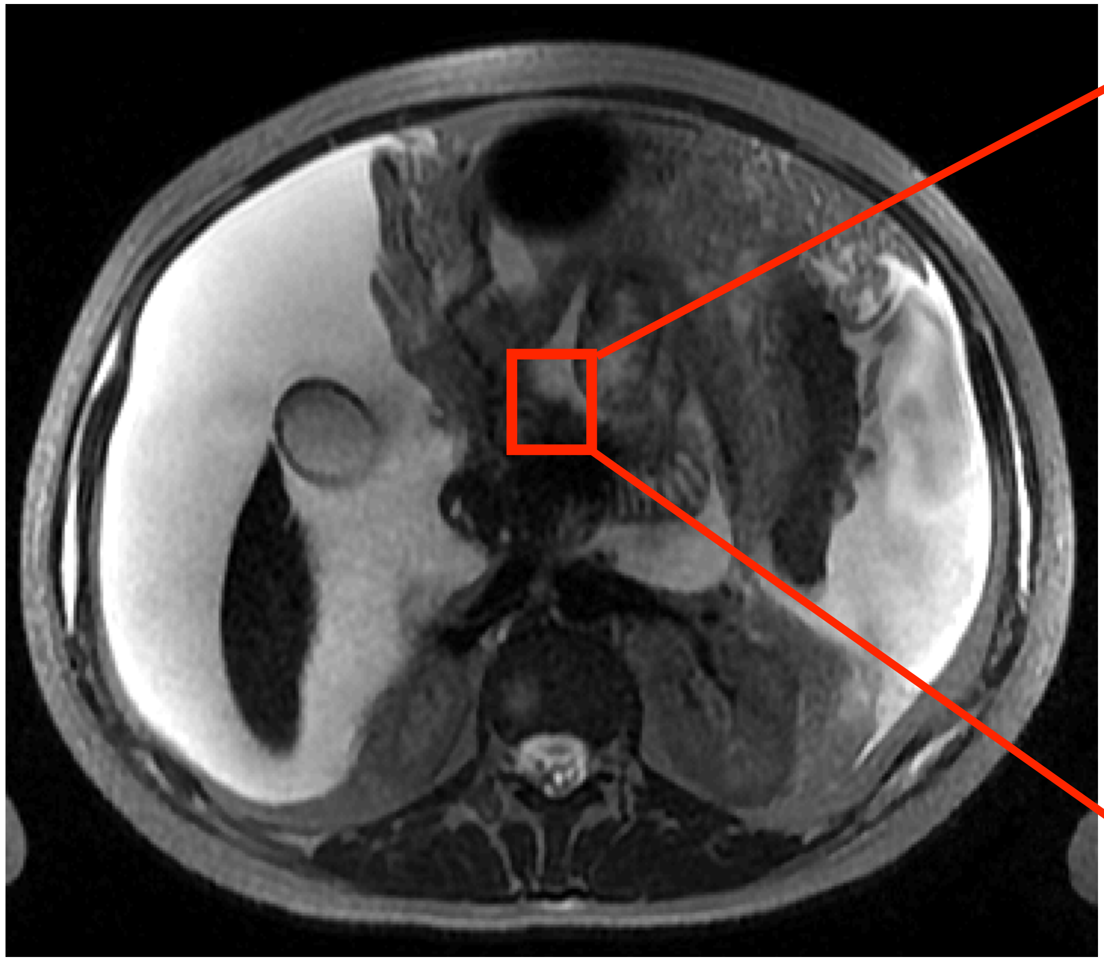
512 x 512 matrix



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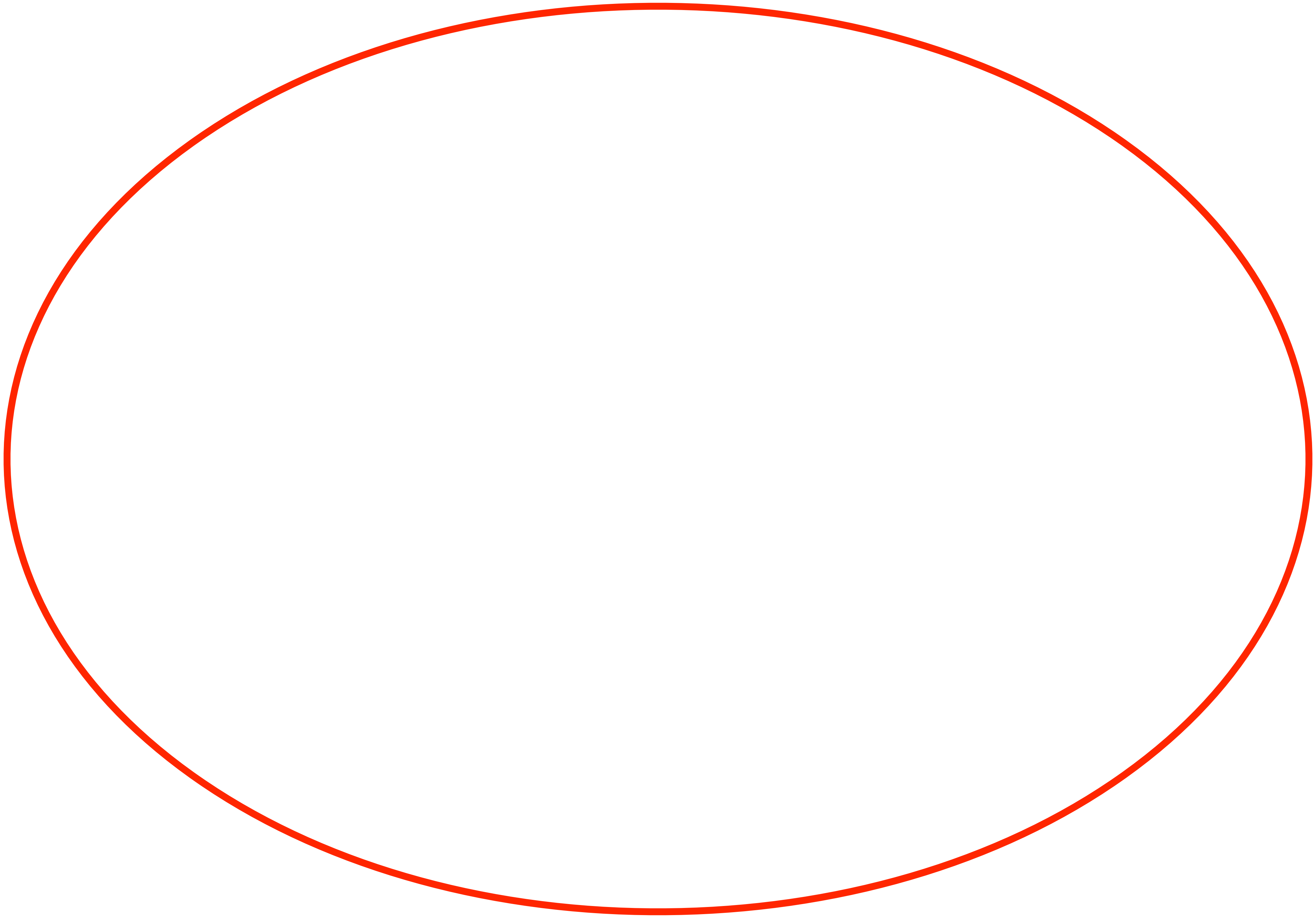
RADIOMICS

“Radiomics cycle”



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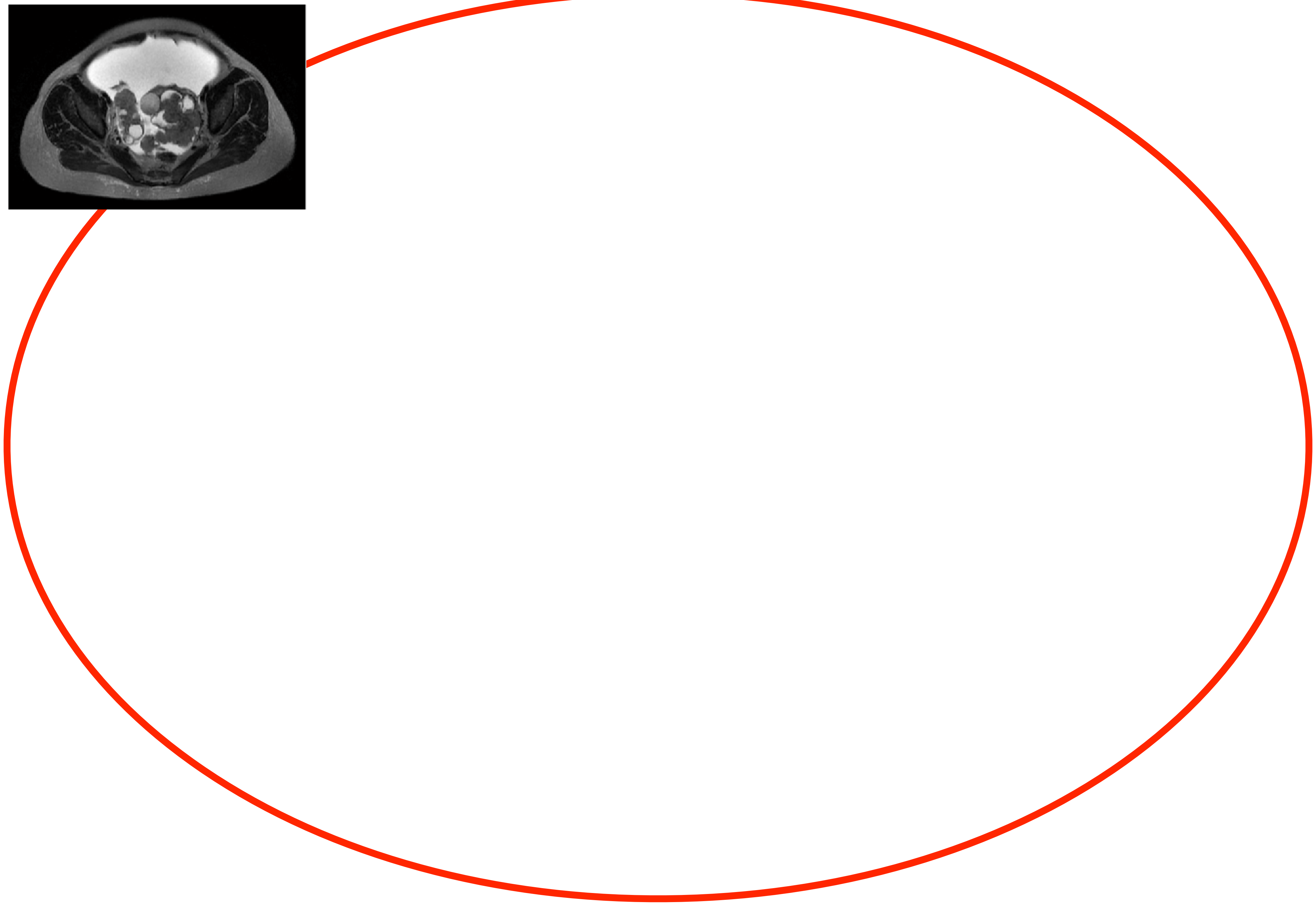
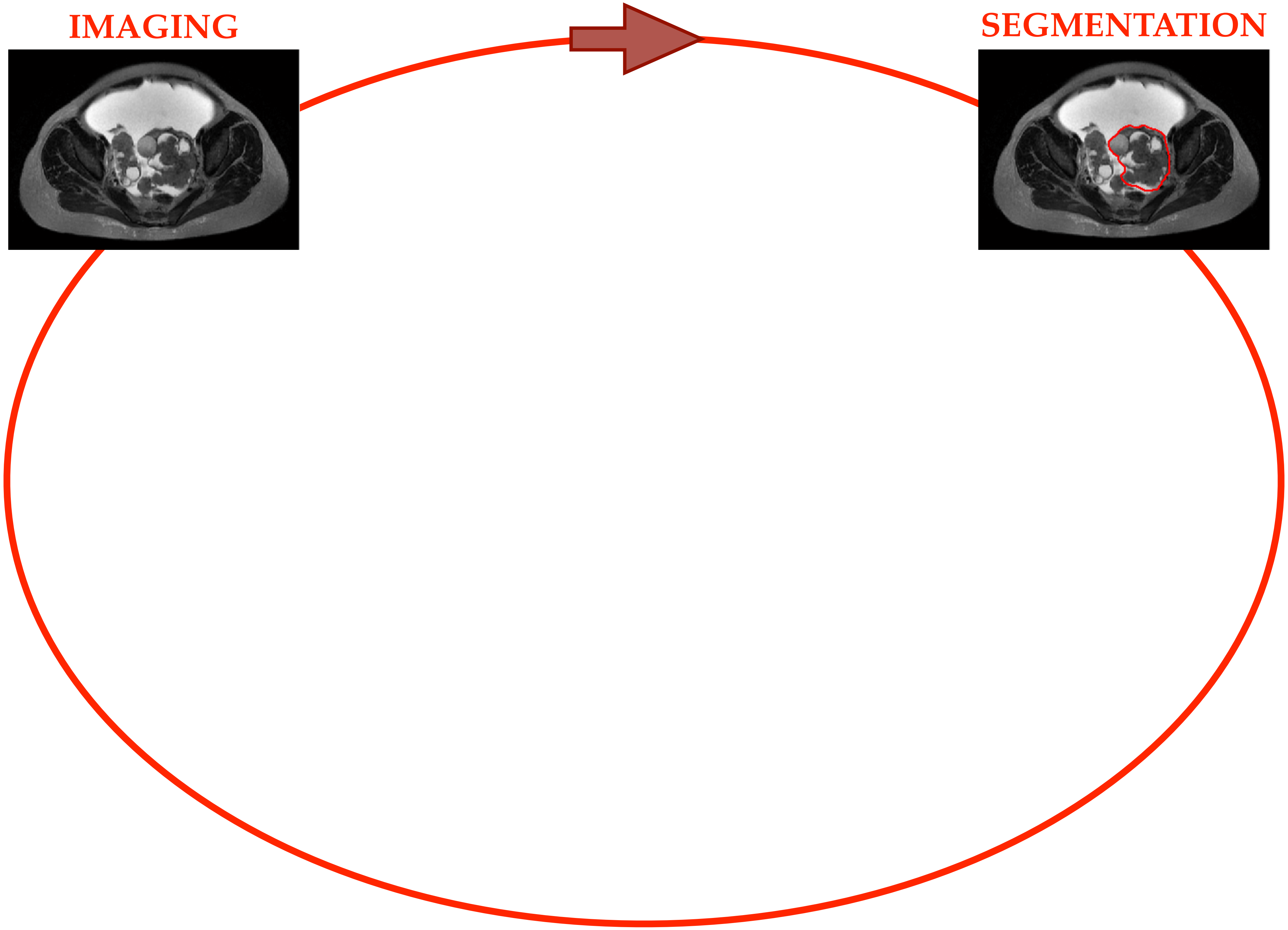


IMAGING

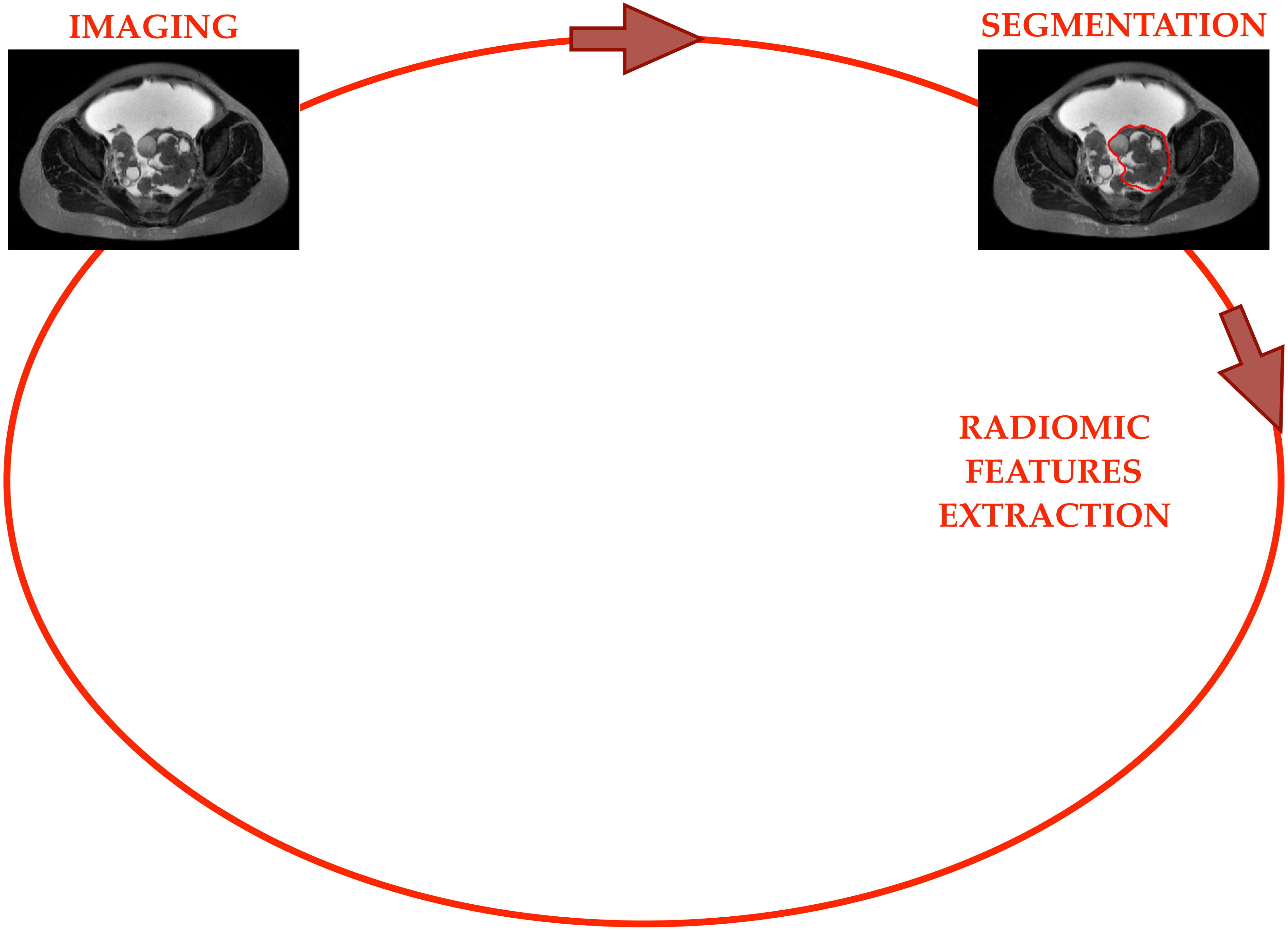
“Radiomics cycle”



IMAGING

SEGMENTATION

“Radiomics cycle”

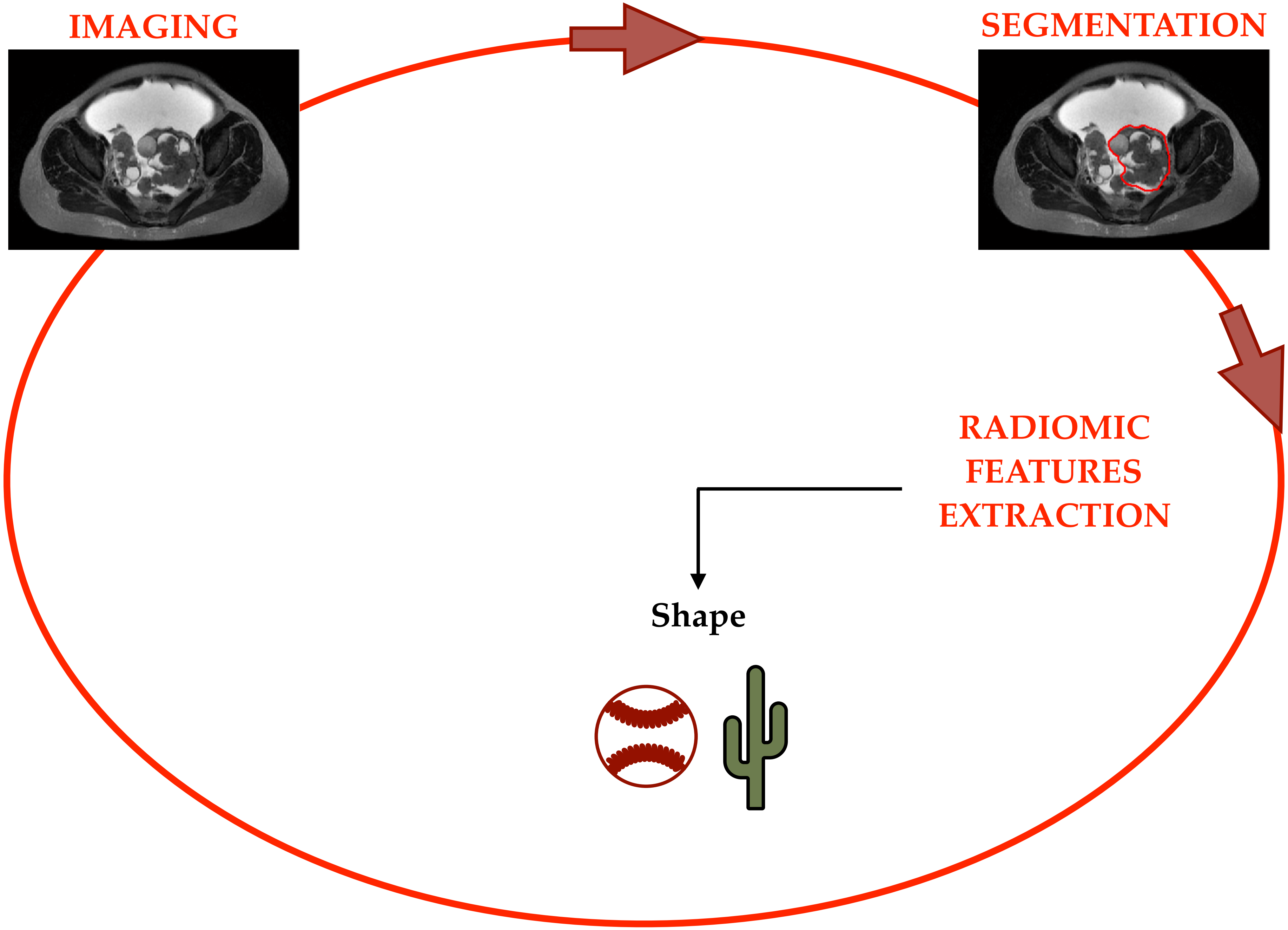


IMAGING

SEGMENTATION

RADIOMIC
FEATURES
EXTRACTION

“Radiomics cycle”



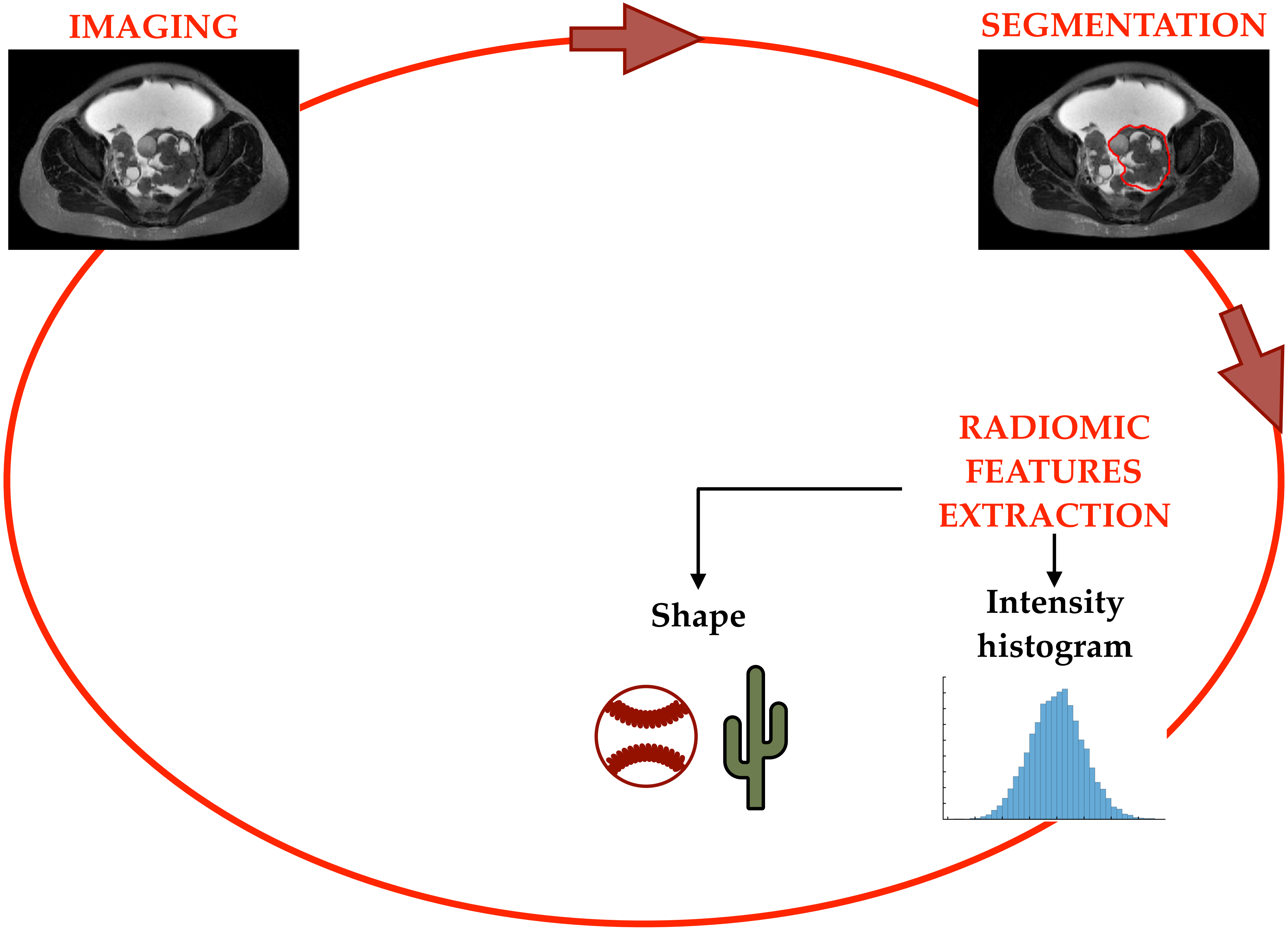
IMAGING

SEGMENTATION

RADIOMIC FEATURES EXTRACTION

Shape

“Radiomics cycle”



IMAGING

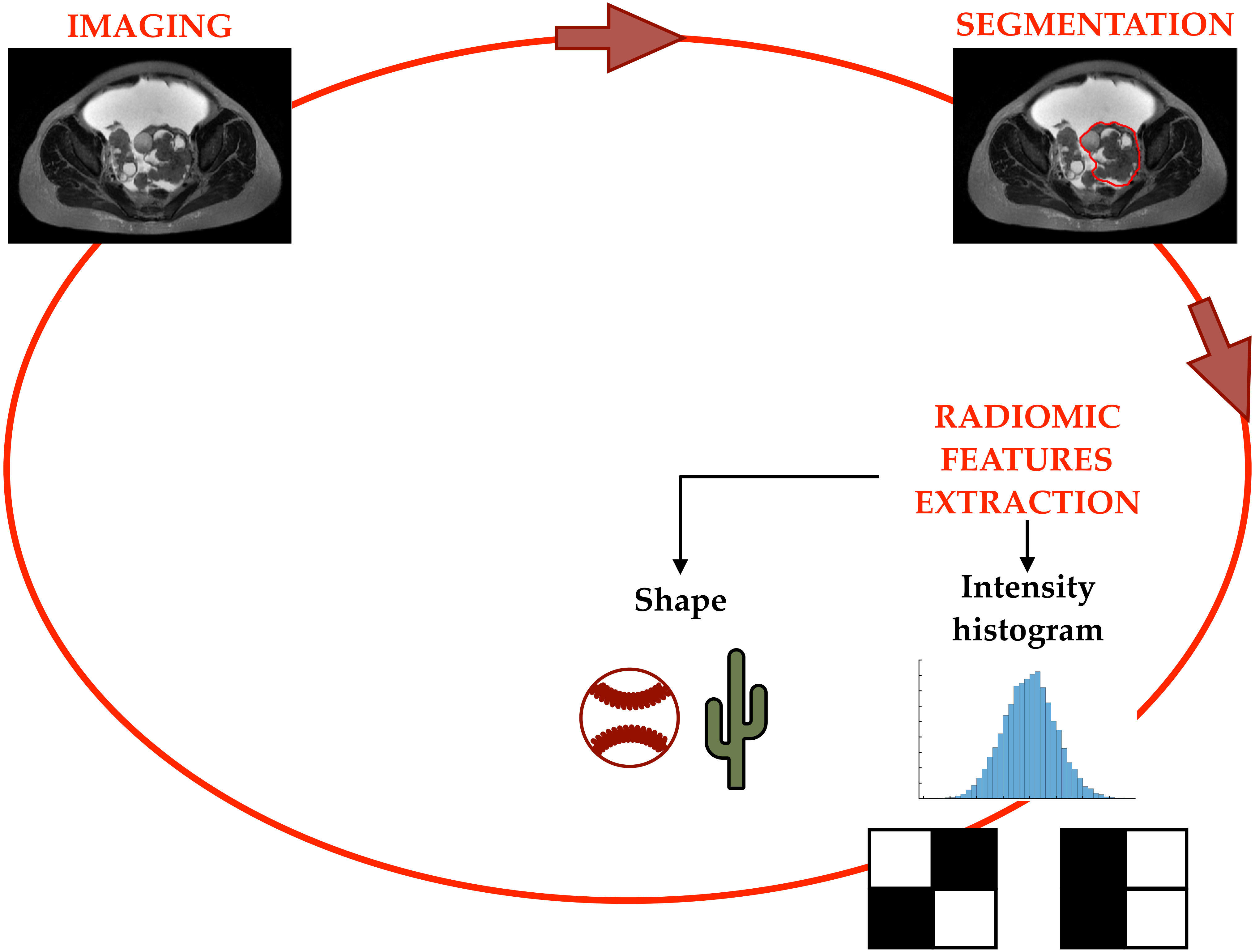
SEGMENTATION

RADIOMIC FEATURES EXTRACTION

Shape

Intensity histogram

“Radiomics cycle”



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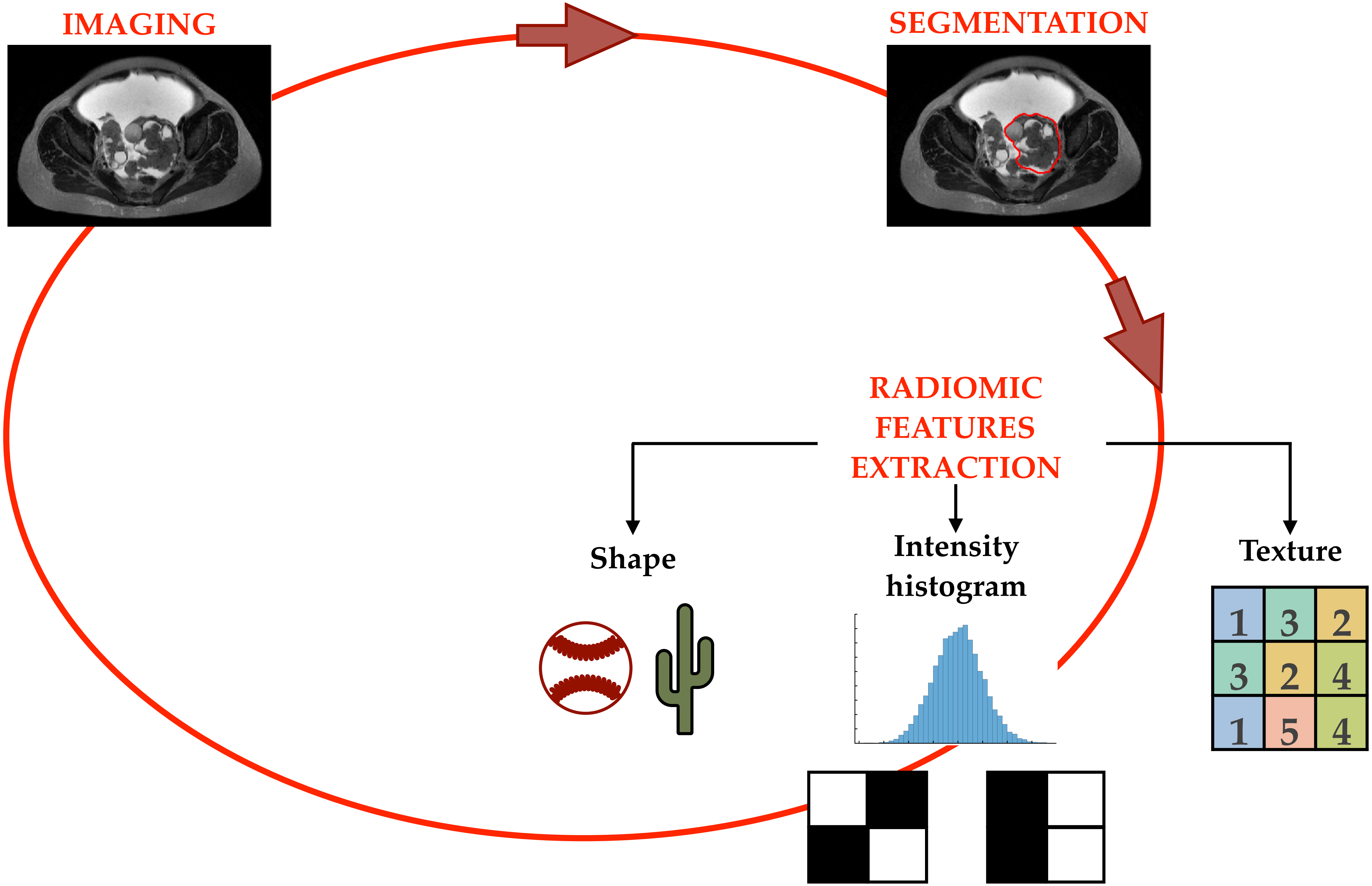
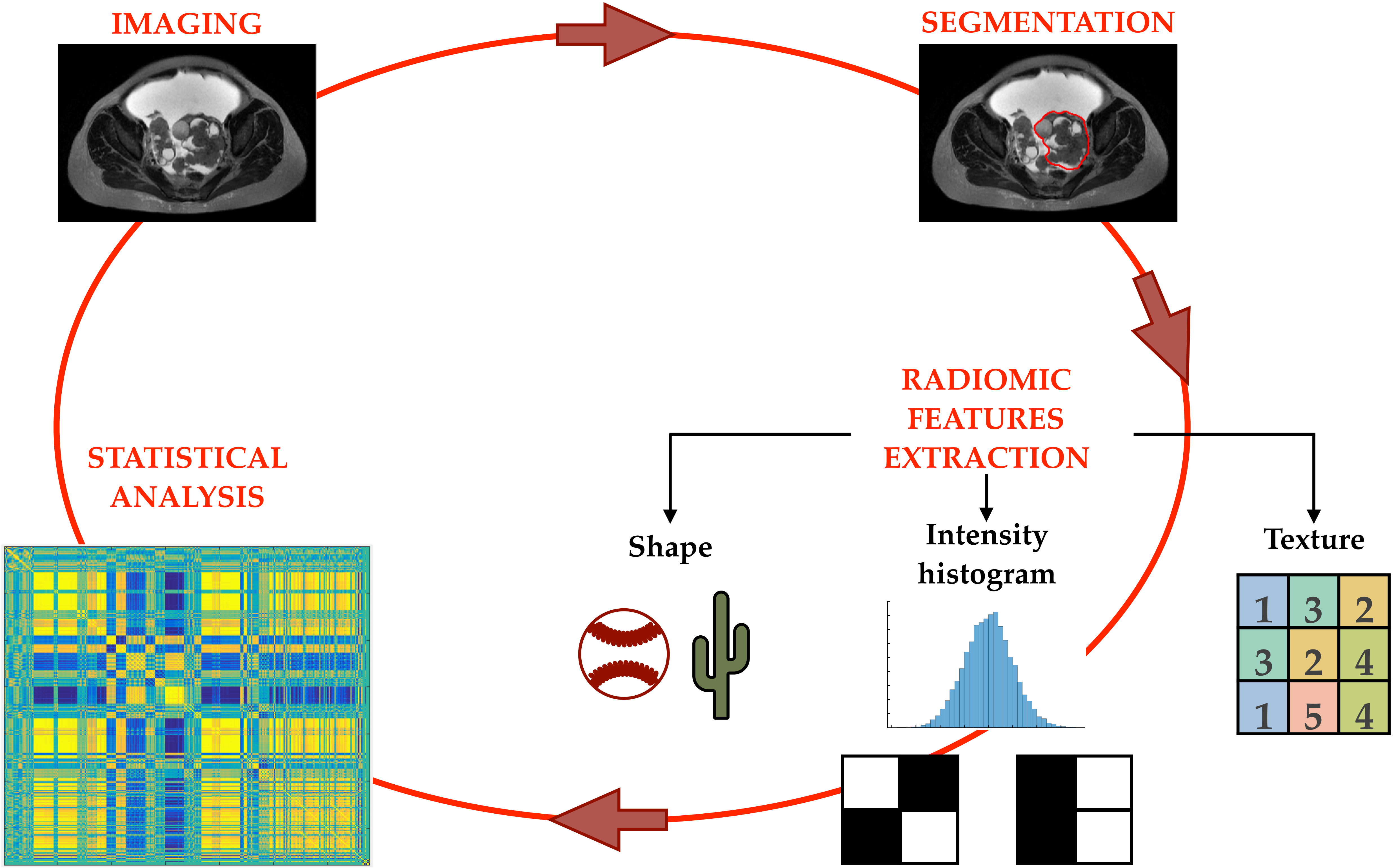


1	3	2
3	2	4
1	5	4

“Radiomics cycle”



IMAGING

SEGMENTATION

RADIOMIC FEATURES EXTRACTION

Shape

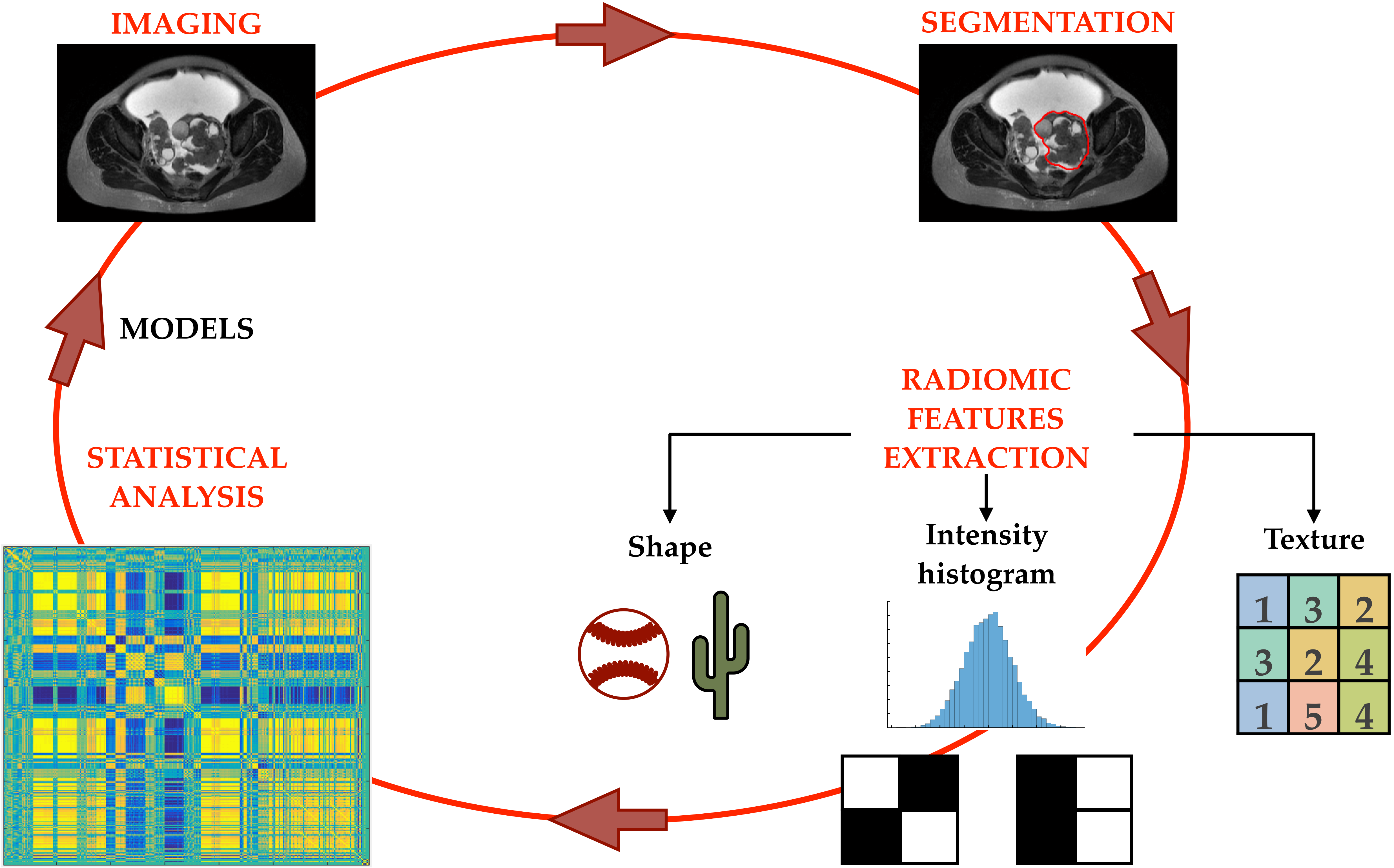
Intensity histogram

Texture

1	3	2
3	2	4
1	5	4

STATISTICAL ANALYSIS

“Radiomics cycle”



IMAGING

SEGMENTATION

RADIOMIC FEATURES EXTRACTION

Shape

Intensity histogram

Texture

1	3	2
3	2	4
1	5	4

STATISTICAL ANALYSIS

MODELS

My interest in radiomics

My interest in radiomics

support clinical decision
in oncology

My interest in radiomics

support clinical decision in oncology

personalized medicine

My interest in radiomics

support clinical decision in oncology

physician

physicist

interdisciplinary work

statistician

biologist

other scientists

personalized medicine

My interest in radiomics

support clinical decision in oncology

physician

physicist

interdisciplinary work

statistician

biologist

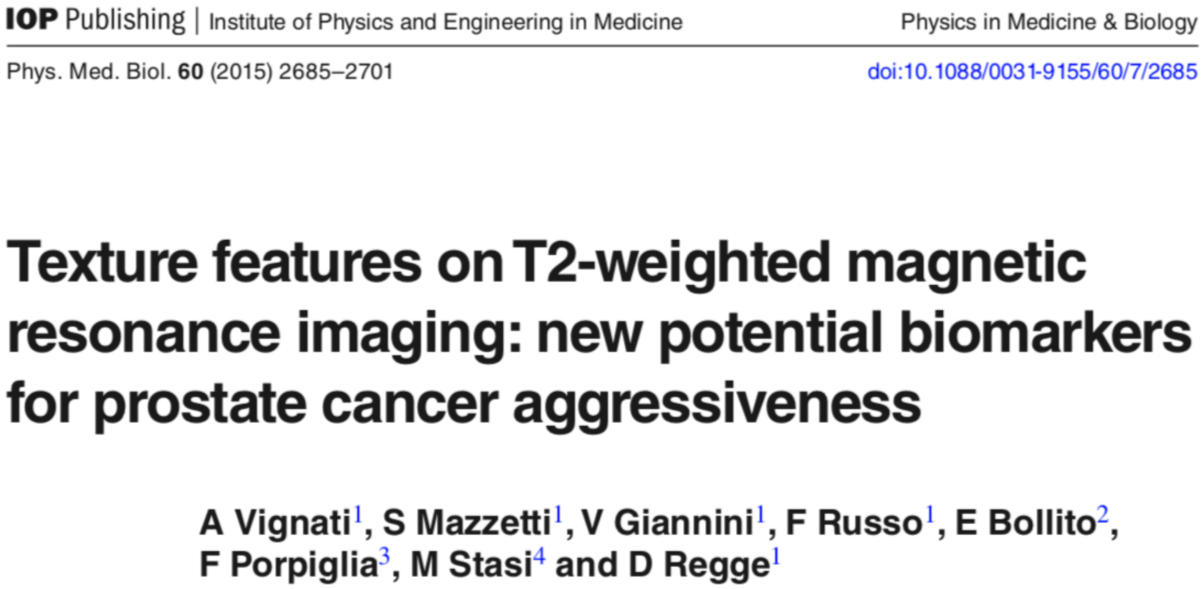
other scientists

personalized medicine

Machine Learning

Radiomics + Magnetic Resonance

Radiomics + Magnetic Resonance



IOP Publishing | Institute of Physics and Engineering in Medicine Physics in Medicine & Biology

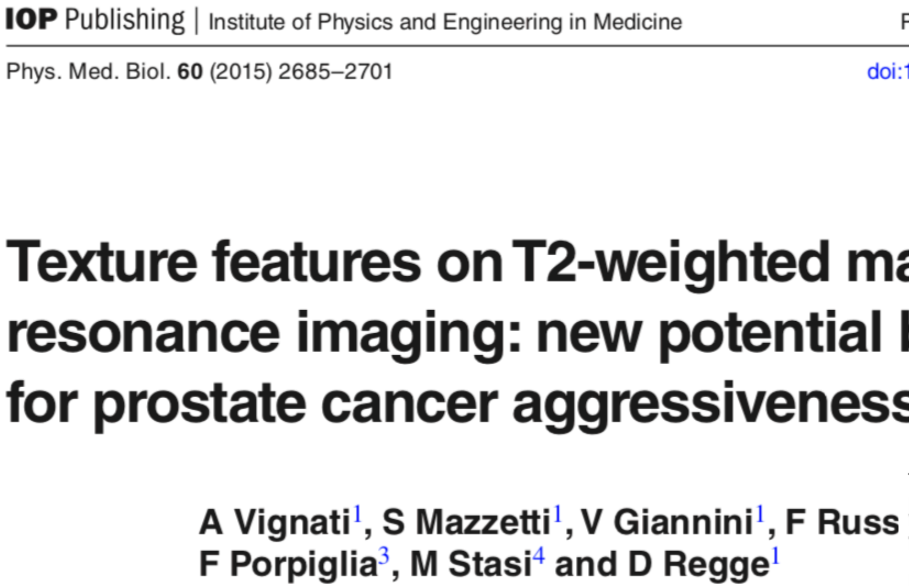
Phys. Med. Biol. **60** (2015) 2685–2701 doi:10.1088/0031-9155/60/7/2685

Texture features on T2-weighted magnetic resonance imaging: new potential biomarkers for prostate cancer aggressiveness

A Vignati[1], S Mazzetti[1], V Giannini[1], F Russo[1], E Bollito[2], F Porpiglia[3], M Stasi[4] and D Regge[1]

2015

Radiomics + Magnetic Resonance



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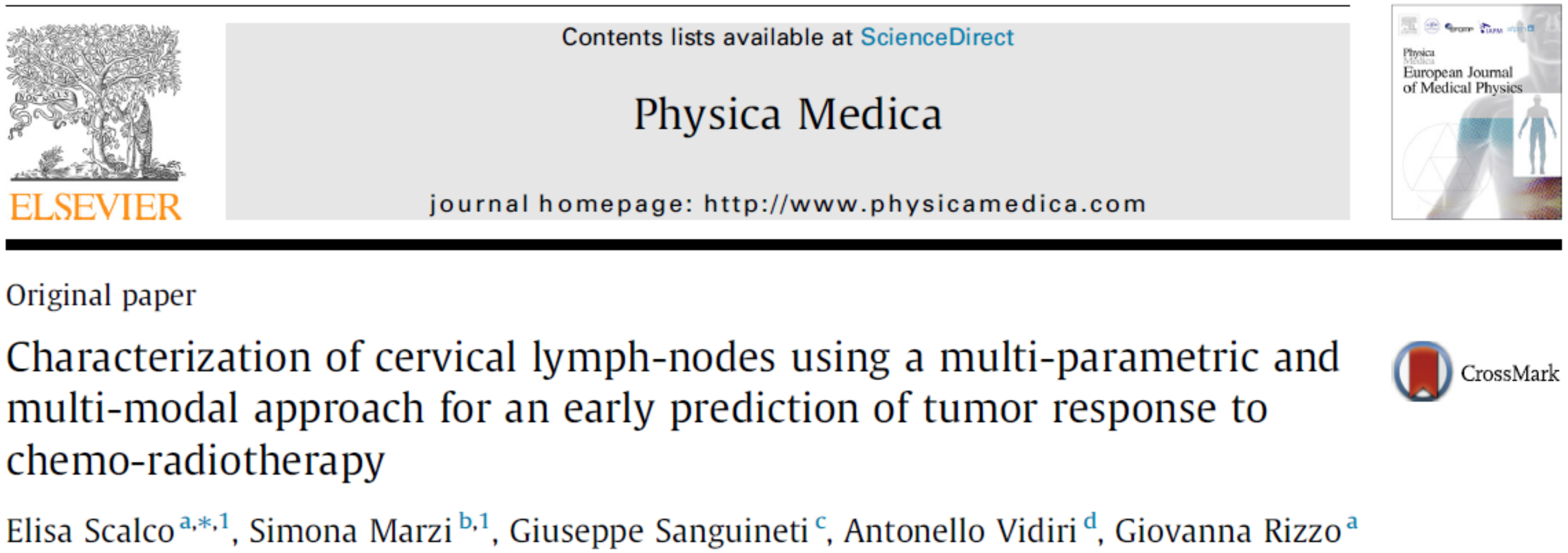
2016



Contents lists available at ScienceDirect

Physica Medica

journal homepage: http://www.physicamedica.com

Original paper

Characterization of cervical lymph-nodes using a multi-parametric and multi-modal approach for an early prediction of tumor response to chemo-radiotherapy

Elisa Scalco[a,*,1], Simona Marzi[b,1], Giuseppe Sanguineti[c], Antonello Vidiri[d], Giovanna Rizzo[a]

Radiomics + Magnetic Resonance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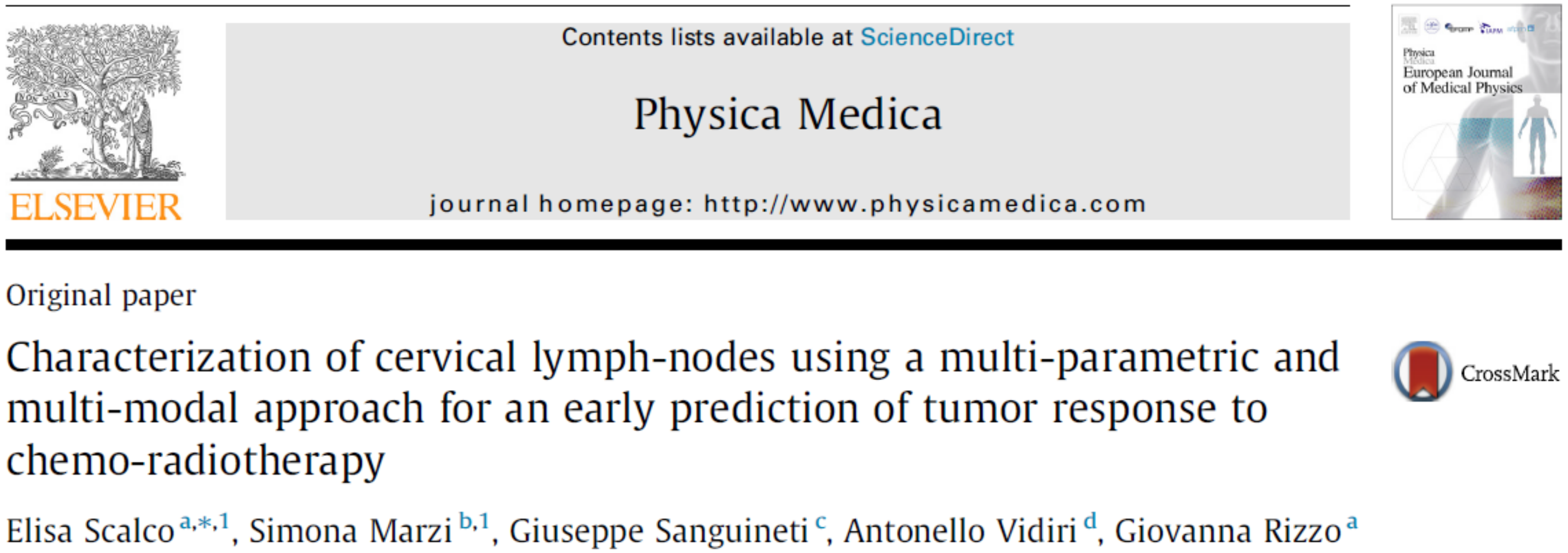
2016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development of a robust and validated protocol for the extraction of radiomic features from MR images

Radiomics + Magnetic Resonance

Radiomics + Magnetic Resonance

Retrospective data sets → **Quality and reliability of radiomic features:** **evaluation of variability**

Radiomics + Magnetic Resonance

Retrospective data sets → **Quality and reliability of radiomic features:**
evaluation of variability

	CT	PET	MRI	US
reproducibility	**LC**	**LC, OC**	❌	❌
image acquisition parameters	**LC, slice thickness**	**ADC, LC, EC, OC, 2D-3D mode, bed position**	❌	❌
scanners	**LC**	❌	❌	❌
reconstruction algorithm	**LC**	**ADC, LC, EC, OC**	❌	❌
respiratory motion	**LC**	**LC,OC**	❌	❌
dedicated phantom	❌	❌	❌	❌

*data based on

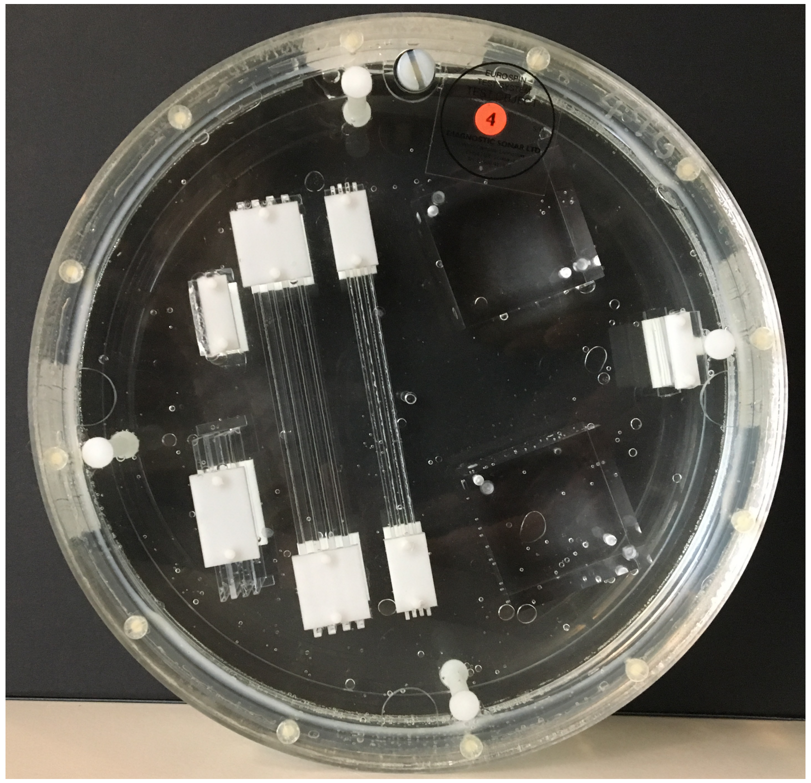
Larue RTHM, Defraene G, De Ruysscher D, Lambin P, Van Elmpt W. "Quantitative radiomics studies for tissue characterization: a review of technology and methodological procedures". *Br J Radiol* **2017**; 90: 20160665.

LC = Lung Cancer, OC = Oesophageal Cancer, AGC = Adrenal Gland Carcinoma, EC = Epiglottis Cancer

Phantom studies

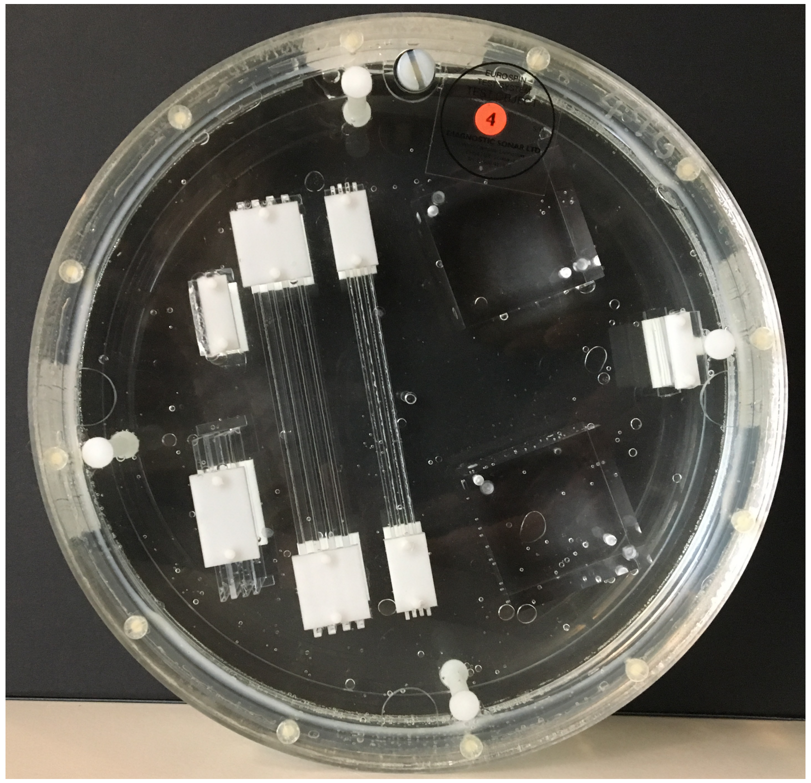
Phantom studies

QC phantom



Phantom studies

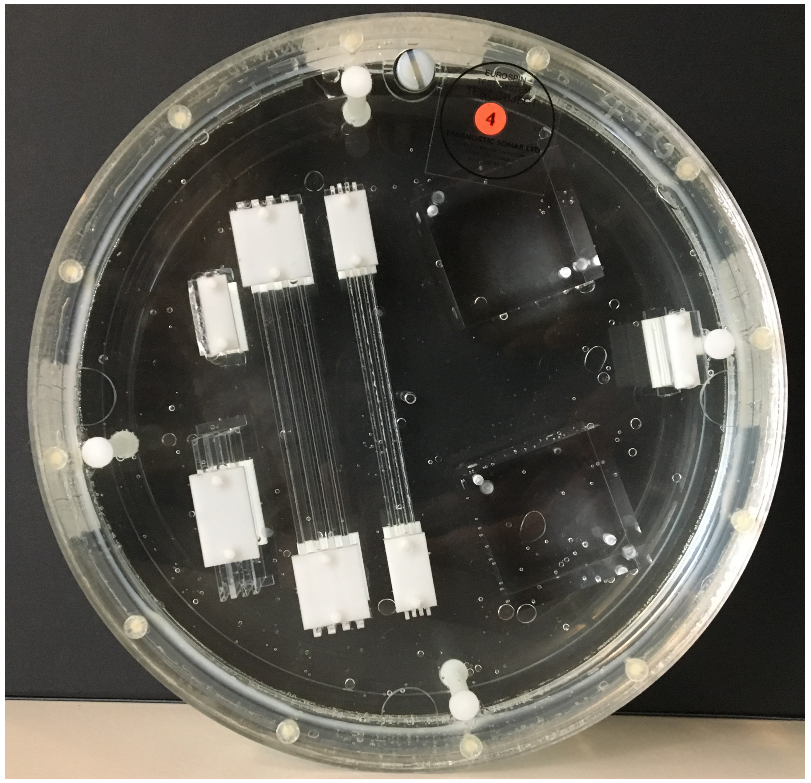
QC phantom



repeatability and robustness

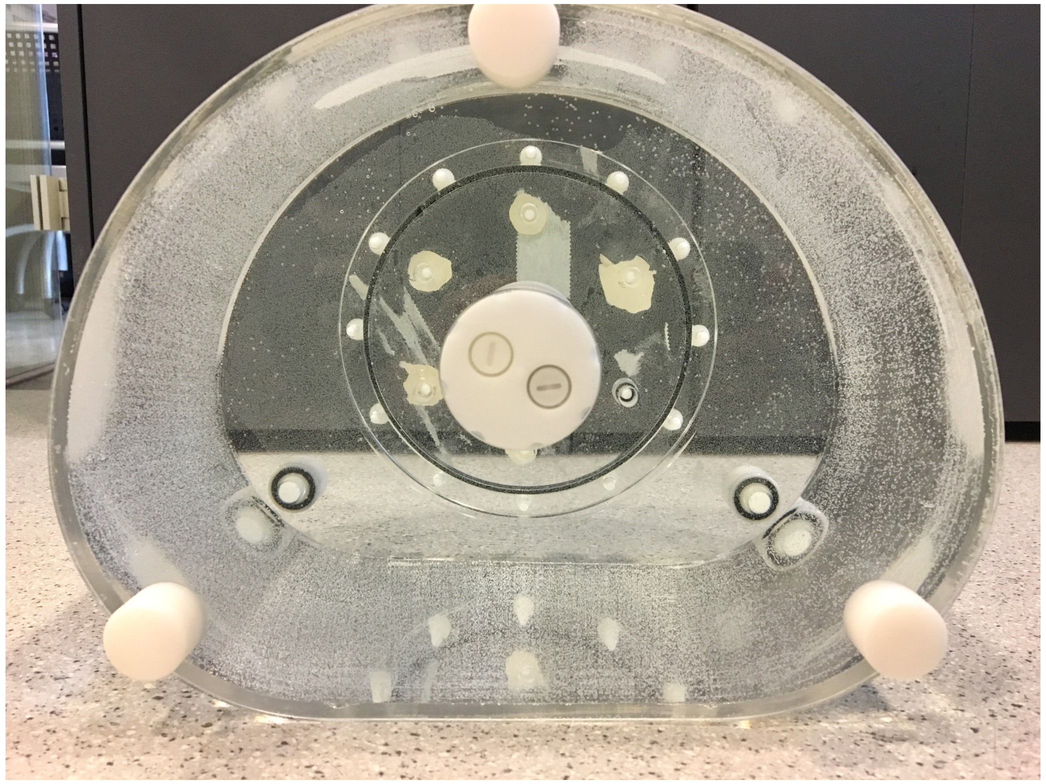
Phantom studies

QC phantom



under development

dedicated phantom



repeatability and robustness

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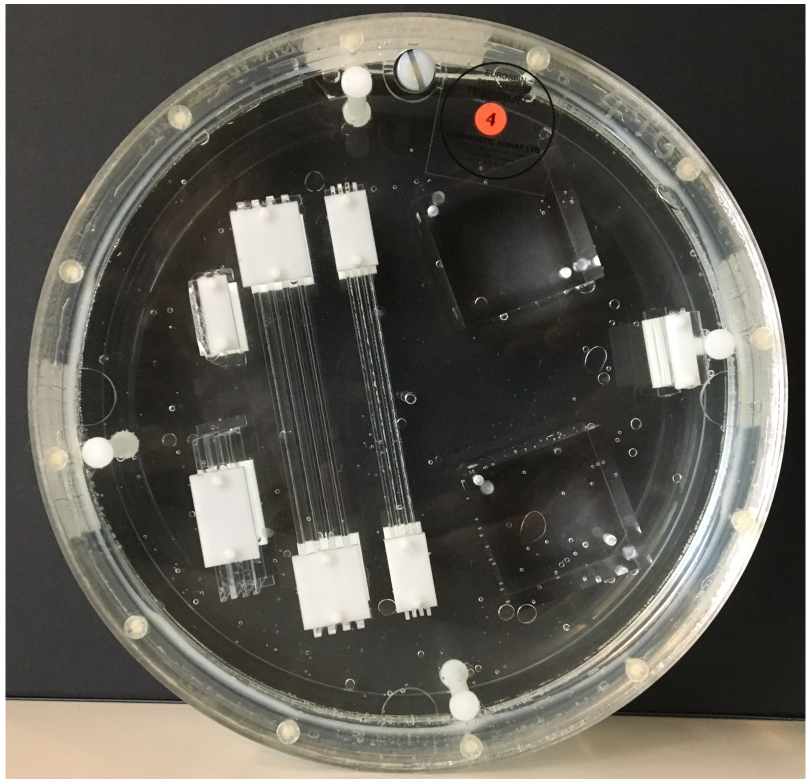

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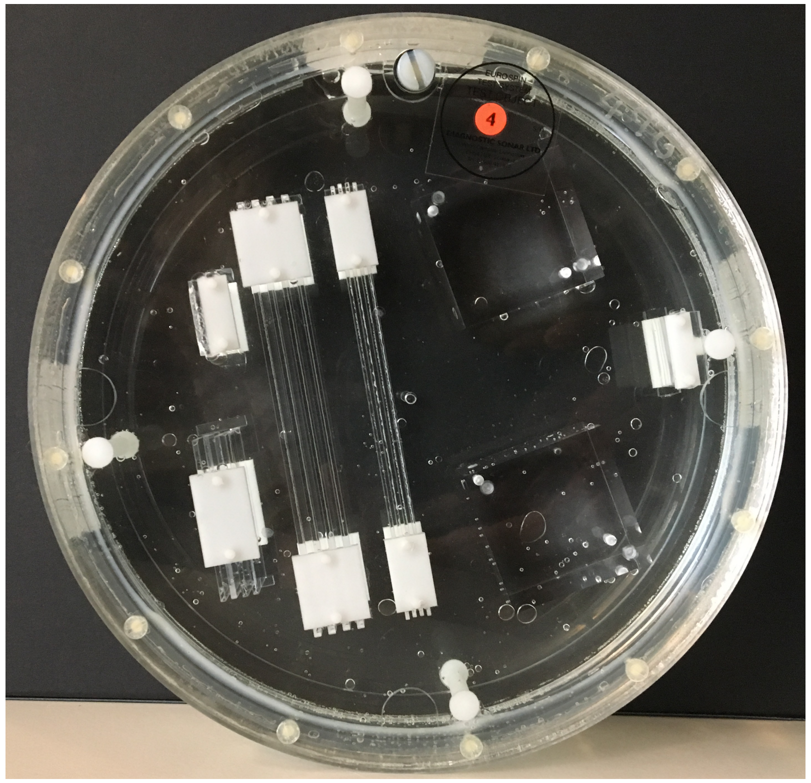
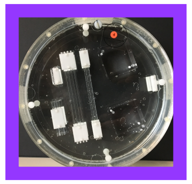


under development

repeatability and robustness

texture analysis

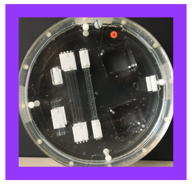


Materials & Methods

MR scanner @ IEO, Milano

1.5 T (63.86 MHz)

pelvic district:
- gynaecological cancer
- prostate cancer



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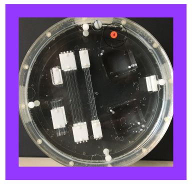

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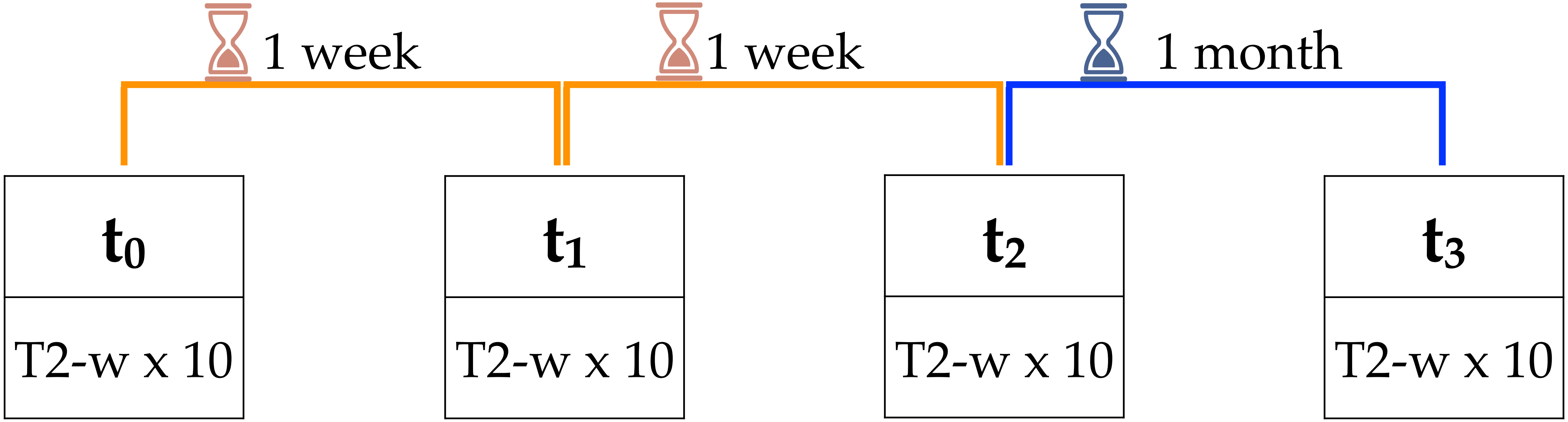
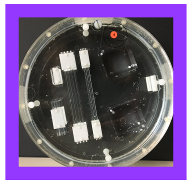


1 week

1 week

1 month

$\mathbf{t_0}$	$\mathbf{t_1}$	$\mathbf{t_2}$	$\mathbf{t_3}$
T2-w x 10	T2-w x 10	T2-w x 10	T2-w x 10



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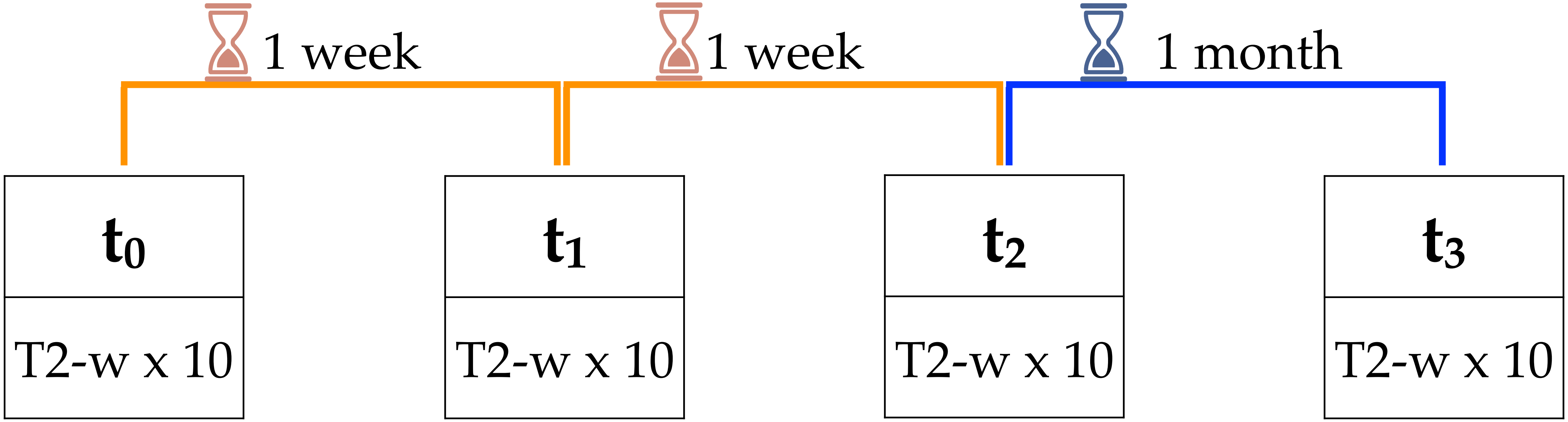
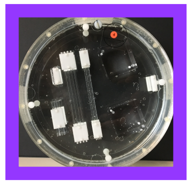


1 week
1 week
1 month

t_0	t_1	t_2	t_3
T2-w x 10	T2-w x 10	T2-w x 10	T2-w x 10

⚠ **NO change in setup/parameters!**

impact of the process of images acquisition on each feature



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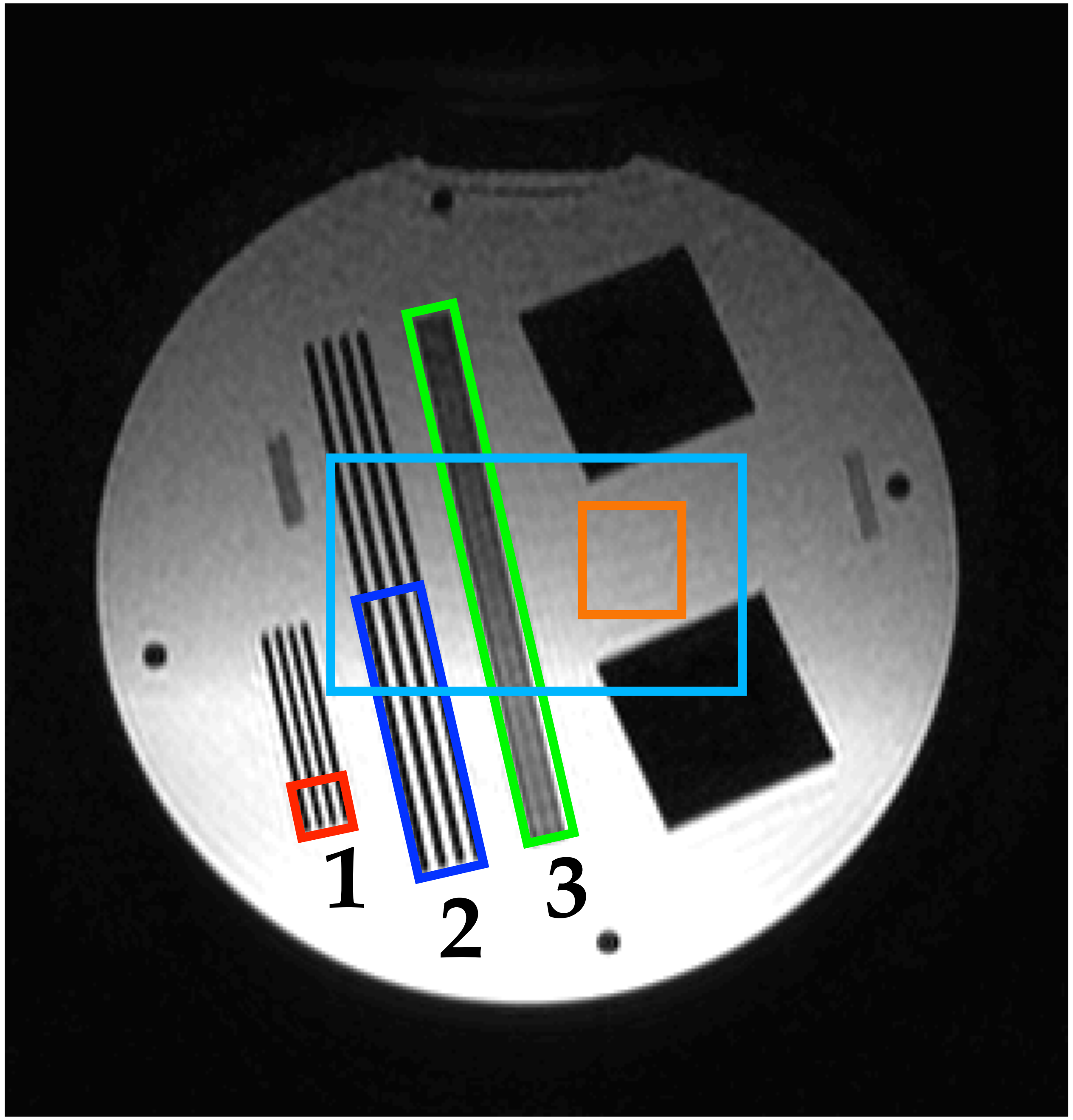
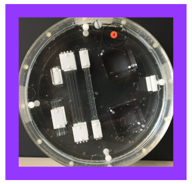
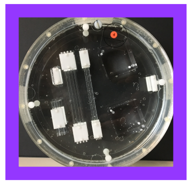


	Region Of Interest (ROI)
1	R1-Big
2	R1-Med
3	R1-Sma
4	R2-Big
5	R2-Med
6	R2-Sma
7	R3-Big
8	R3-Med
9	R3-Sma
10	R-All
11	R-Hom

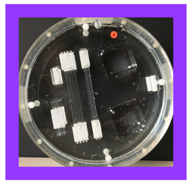


Materials & Methods



Materials & Methods

Data Analysis



Materials & Methods

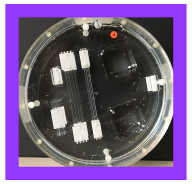
Data Analysis

<u>short-term repeatability</u>

<u>INTRA-comparison</u>

$$r = 1.96 \frac{\sigma}{|\mu|}$$

range of variability?



Materials & Methods

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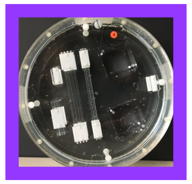
range of variability?

volume study



Materials & Methods

Data Analysis

short-term repeatability

INTRA-comparison

$$r = 1.96\,\frac{\sigma}{|\mu|}$$

range of variability?

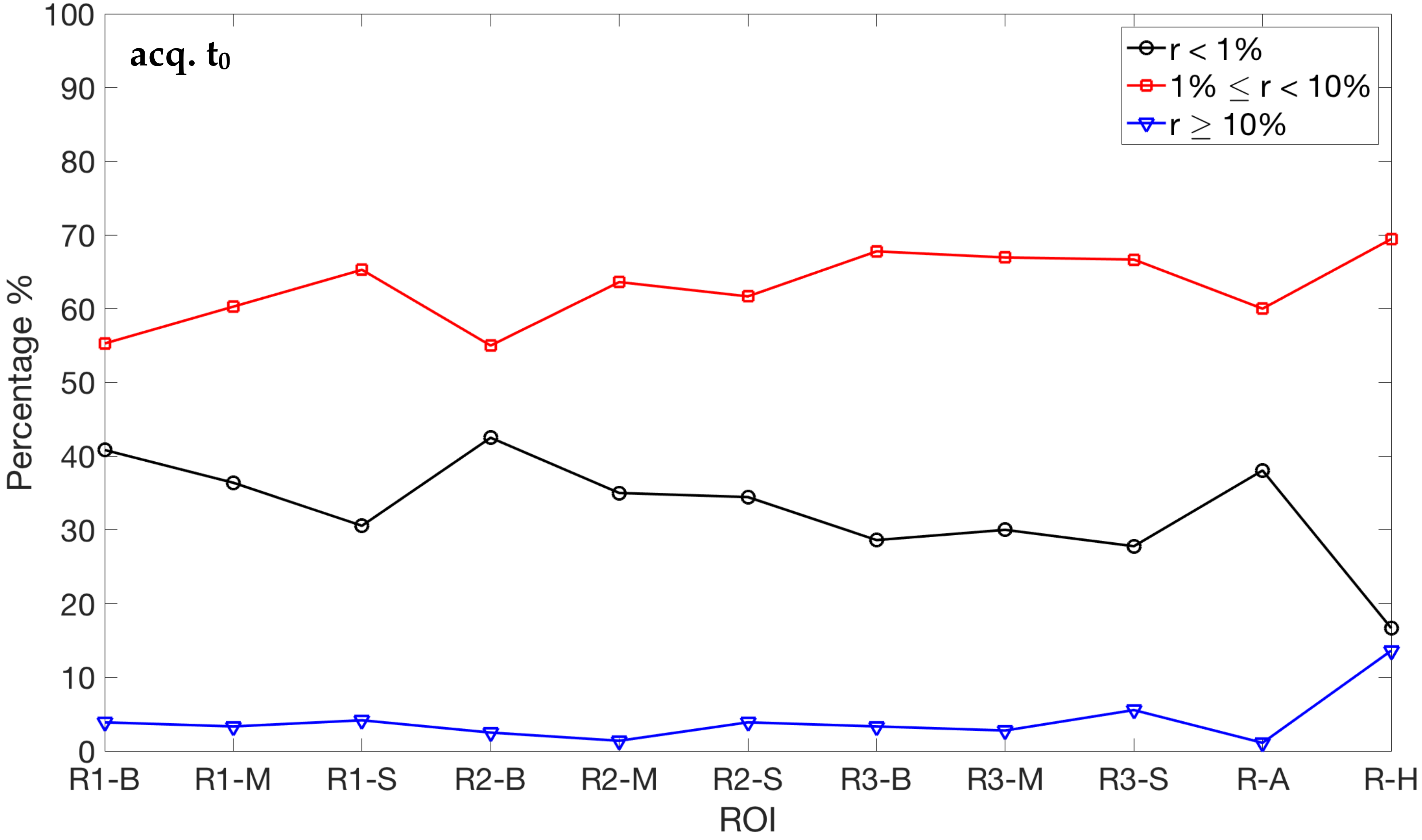
volume study

long-term repeatability

INTER-comparison

which features?

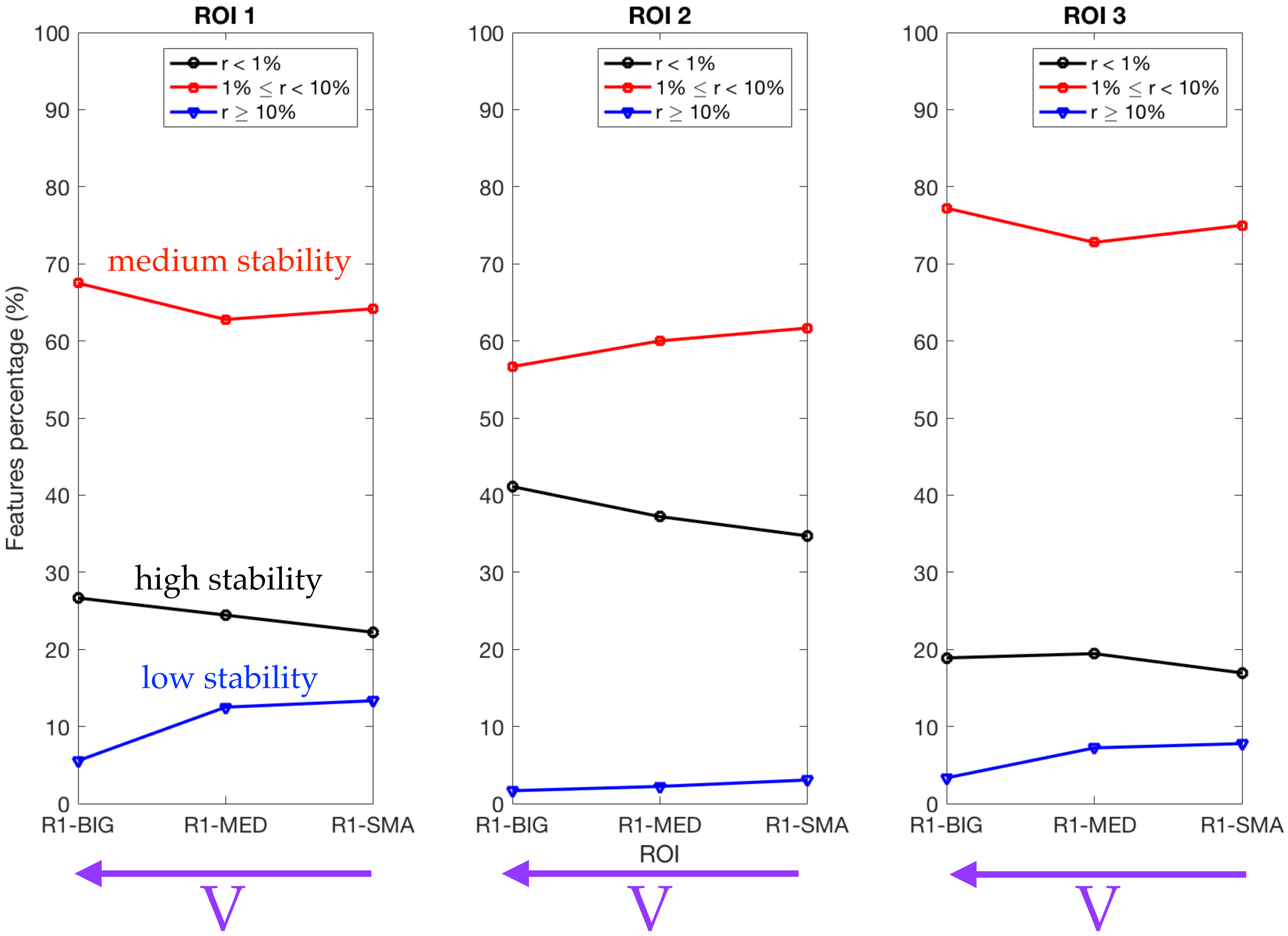
Results: short-term repeatability



$$r = 1.96 \frac{\sigma}{|\mu|}$$

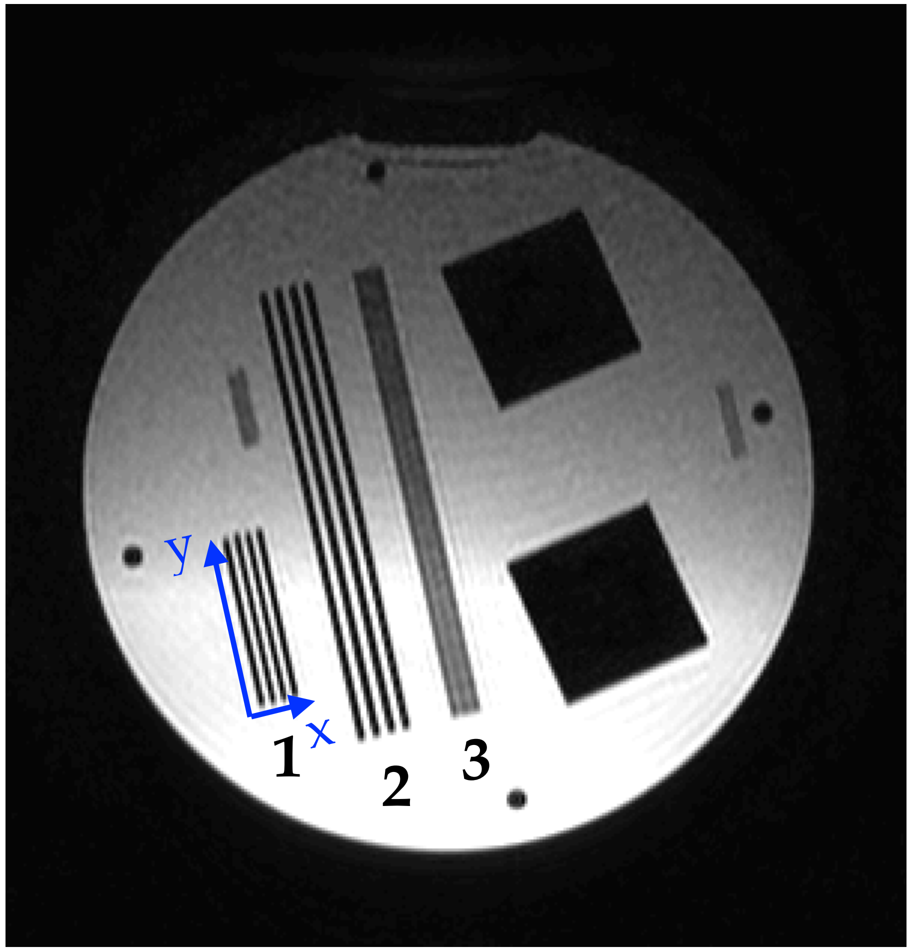
	t_0	t_1	t_2	t_3
$r < 1\,\%$	33%	31%	25%	22%
$1\,\% \leq r < 10\,\%$	63%	65%	66%	72%
$r \geq 10\,\%$	4%	5%	8%	6%

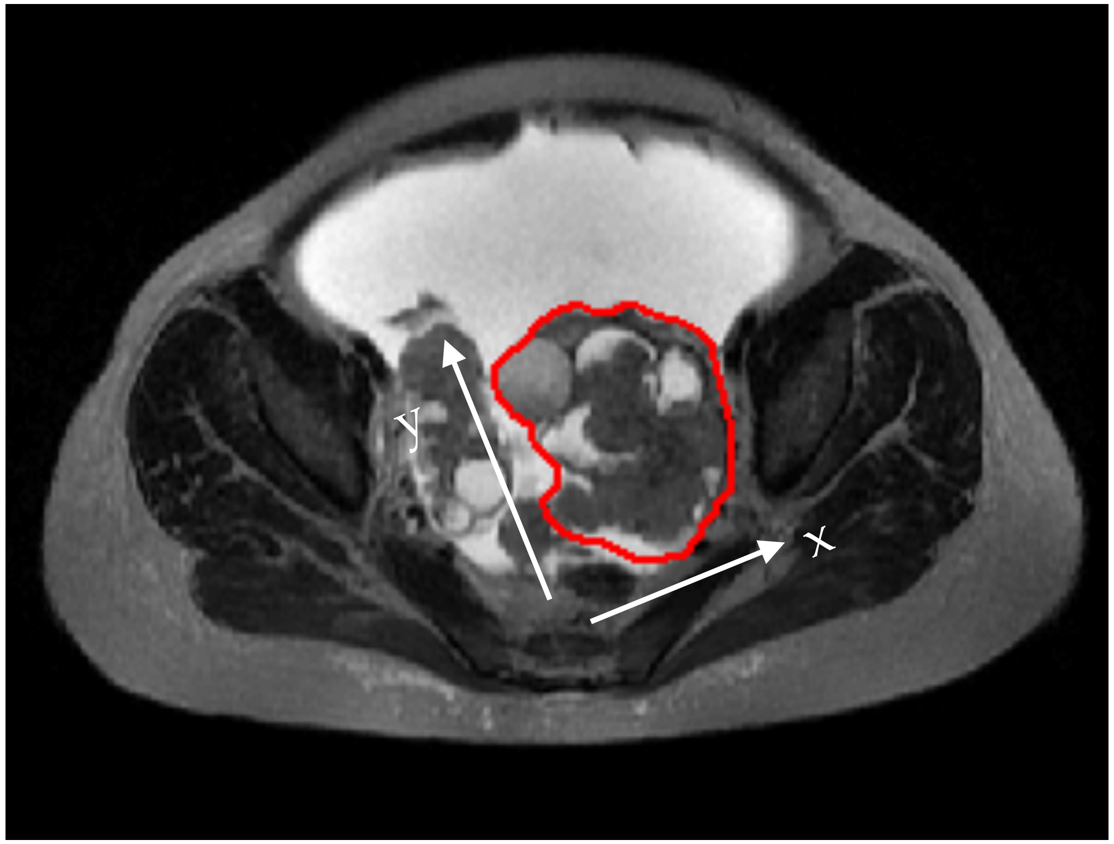
Results: volume study



Which volumes?

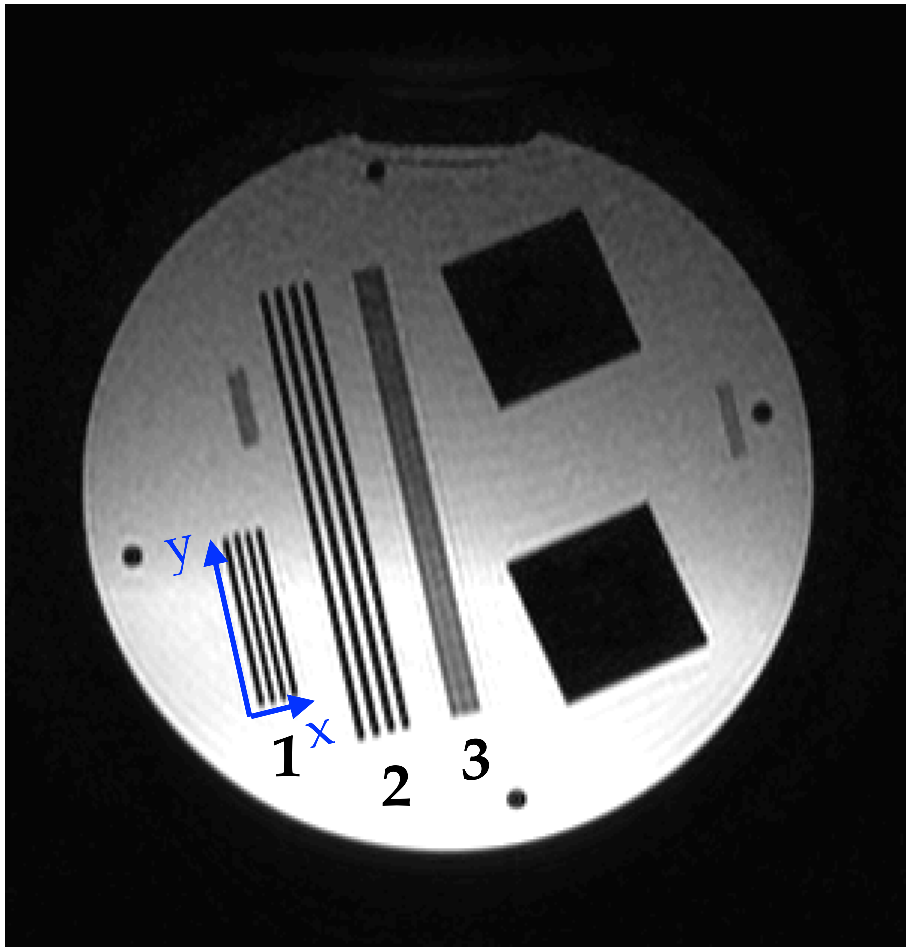
	R1-B	R1-M	R1-S	R2-B	R2-M	R2-S	R3-B	R3-M	R3-S	tumour
x (cm)	1.1	1.1	1.1	1.4	1.4	1.4	0.7	0.7	0.7	7.0
y (cm)	4.7	2.4	1.2	12.0	6.0	3.0	12.0	6.0	3.0	8.0
z (cm)	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5

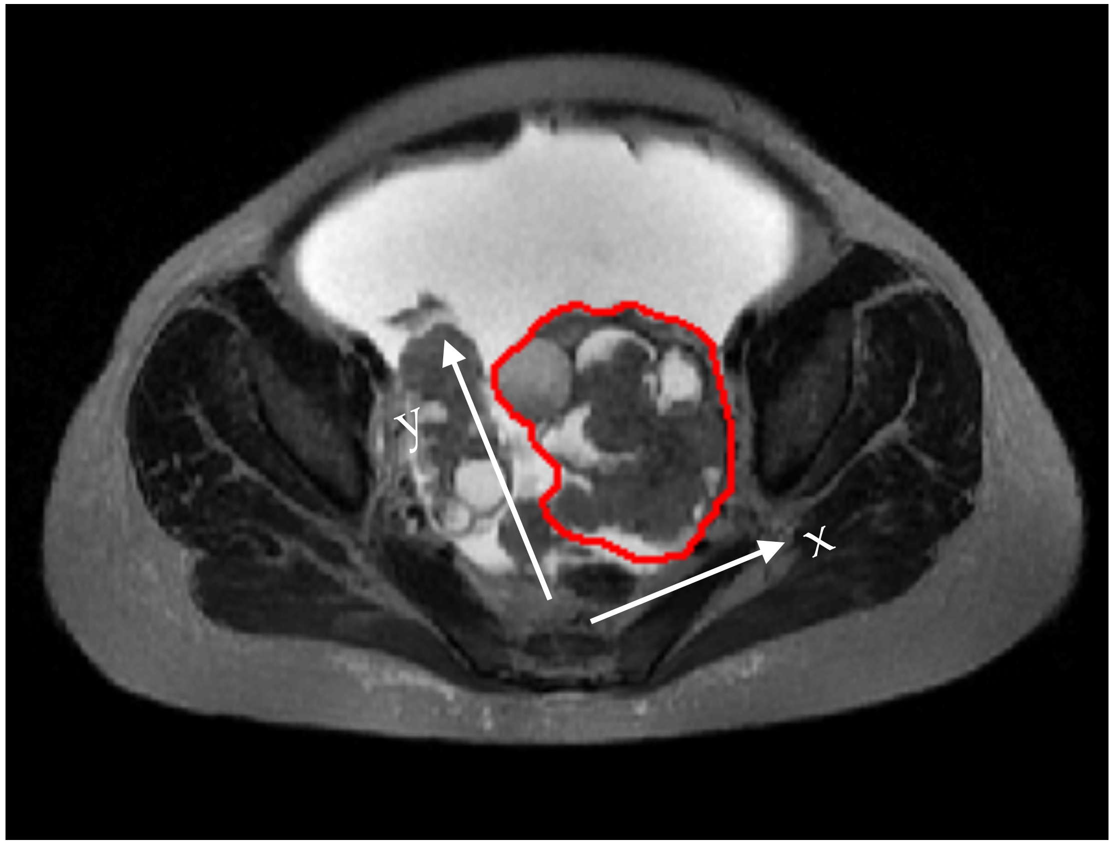




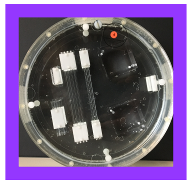
Which volumes?

	R1-B	R1-M	R1-S	R2-B	R2-M	R2-S	R3-B	R3-M	R3-S	tumour
x (cm)	1.1	1.1	1.1	1.4	1.4	1.4	0.7	0.7	0.7	7.0
y (cm)	4.7	2.4	1.2	12.0	6.0	3.0	12.0	6.0	3.0	8.0
z (cm)	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5

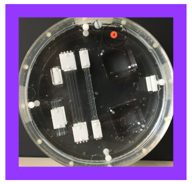




⚠ **SMALL TUMOUR VOLUMES**

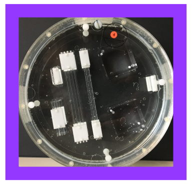


Results: long-term repeatability



Results: long-term repeatability

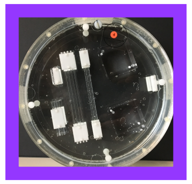
IN: **features with** $r < 10\% \ \forall \ t_i, \ ROI$



Results: long-term repeatability

IN: features with $r < 10\% \ \forall \ t_i$, *ROI*

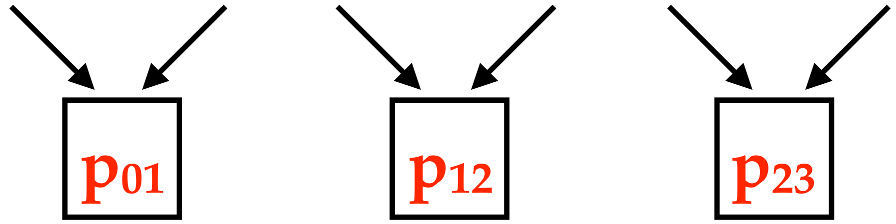
∀ feature	t_0	t_1	t_2	t_3
R1-B	$\mu_{(0,\text{R1-B})}$	$\mu_{(1,\text{R1-B})}$	$\mu_{(2,\text{R1-B})}$	$\mu_{(3,\text{R1-B})}$
R1-M	$\mu_{(0,\text{R1-M})}$	$\mu_{(1,\text{R1-M})}$	$\mu_{(2,\text{R1-M})}$	$\mu_{(3,\text{R1-M})}$
R1-S	$\mu_{(0,\text{R1-S})}$	$\mu_{(1,\text{R1-S})}$	$\mu_{(2,\text{R1-S})}$	$\mu_{(3,\text{R1-S})}$
…	…	…	…	…
R-A	$\mu_{(0,\text{R-A})}$	$\mu_{(1,\text{R-A})}$	$\mu_{(2,\text{R-A})}$	$\mu_{(3,\text{R-A})}$
R-H	$\mu_{(0,\text{R-H})}$	$\mu_{(1,\text{R-H})}$	$\mu_{(2,\text{R-H})}$	$\mu_{(3,\text{R-H})}$



Results: long-term repeatability

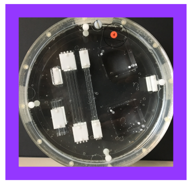
IN: features with $r < 10\% \ \forall \ t_i, ROI$

∀ feature	t_0	t_1	t_2	t_3
R1-B	$\mu_{(0,R1\text{-}B)}$	$\mu_{(1,R1\text{-}B)}$	$\mu_{(2,R1\text{-}B)}$	$\mu_{(3,R1\text{-}B)}$
R1-M	$\mu_{(0,R1\text{-}M)}$	$\mu_{(1,R1\text{-}M)}$	$\mu_{(2,R1\text{-}M)}$	$\mu_{(3,R1\text{-}M)}$
R1-S	$\mu_{(0,R1\text{-}S)}$	$\mu_{(1,R1\text{-}S)}$	$\mu_{(2,R1\text{-}S)}$	$\mu_{(3,R1\text{-}S)}$
…	…	…	…	…
R-A	$\mu_{(0,R\text{-}A)}$	$\mu_{(1,R\text{-}A)}$	$\mu_{(2,R\text{-}A)}$	$\mu_{(3,R\text{-}A)}$
R-H	$\mu_{(0,R\text{-}H)}$	$\mu_{(1,R\text{-}H)}$	$\mu_{(2,R\text{-}H)}$	$\mu_{(3,R\text{-}H)}$



paired-sample t-test

p_{01} p_{12} p_{23}



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∀ feature	t_0	t_1	t_2	t_3
R1-B	$\mu_{(0,R1\text{-}B)}$	$\mu_{(1,R1\text{-}B)}$	$\mu_{(2,R1\text{-}B)}$	$\mu_{(3,R1\text{-}B)}$
R1-M	$\mu_{(0,R1\text{-}M)}$	$\mu_{(1,R1\text{-}M)}$	$\mu_{(2,R1\text{-}M)}$	$\mu_{(3,R1\text{-}M)}$
R1-S	$\mu_{(0,R1\text{-}S)}$	$\mu_{(1,R1\text{-}S)}$	$\mu_{(2,R1\text{-}S)}$	$\mu_{(3,R1\text{-}S)}$
…	…	…	…	…
R-A	$\mu_{(0,R\text{-}A)}$	$\mu_{(1,R\text{-}A)}$	$\mu_{(2,R\text{-}A)}$	$\mu_{(3,R\text{-}A)}$
R-H	$\mu_{(0,R\text{-}H)}$	$\mu_{(1,R\text{-}H)}$	$\mu_{(2,R\text{-}H)}$	$\mu_{(3,R\text{-}H)}$

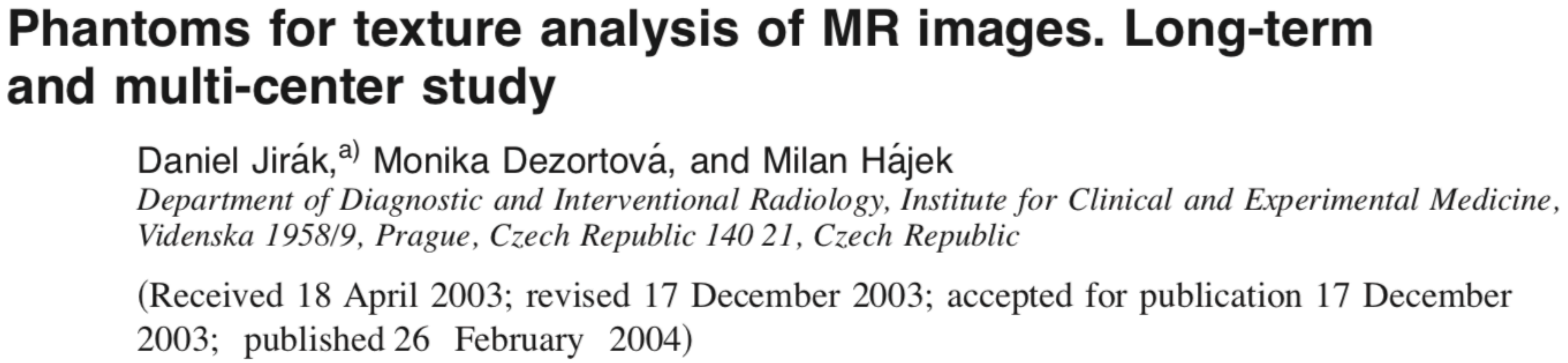
paired-sample t-test

p_{01} p_{12} p_{23}

OUT: features with long-term repeatability

Texture phantom

Texture phantom



Phantoms for texture analysis of MR images. Long-term and multi-center study

Daniel Jirák,[a] Monika Dezortová, and Milan Hájek

Department of Diagnostic and Interventional Radiology, Institute for Clinical and Experimental Medicine, Videnska 1958/9, Prague, Czech Republic 140 21, Czech Republic

(Received 18 April 2003; revised 17 December 2003; accepted for publication 17 December 2003; published 26 February 2004)

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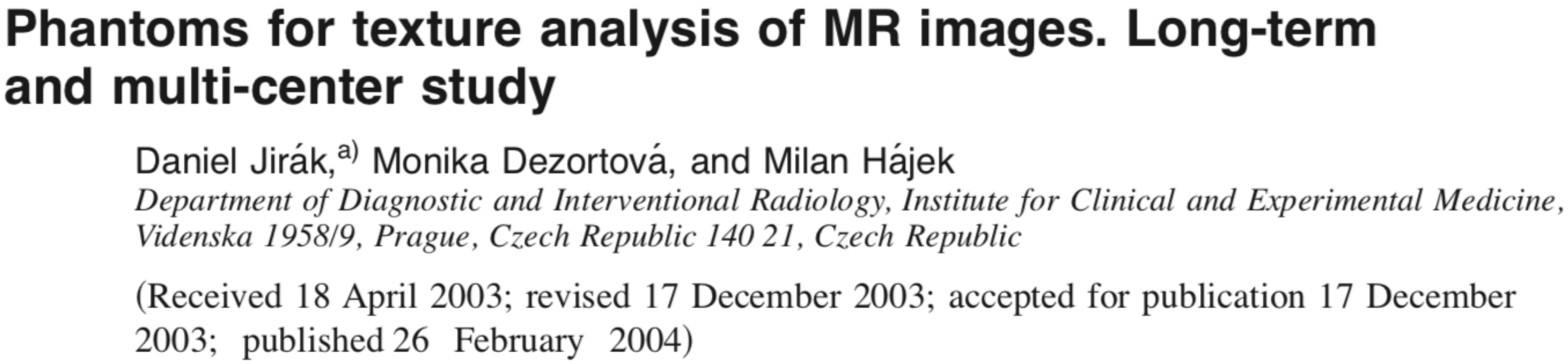

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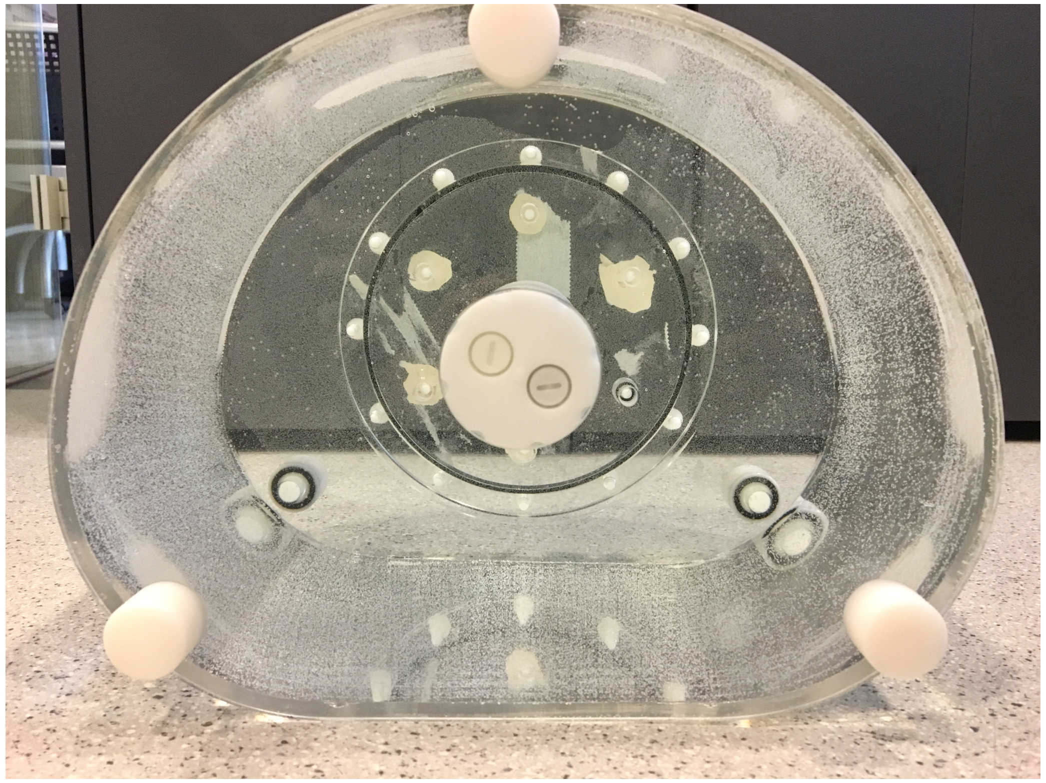
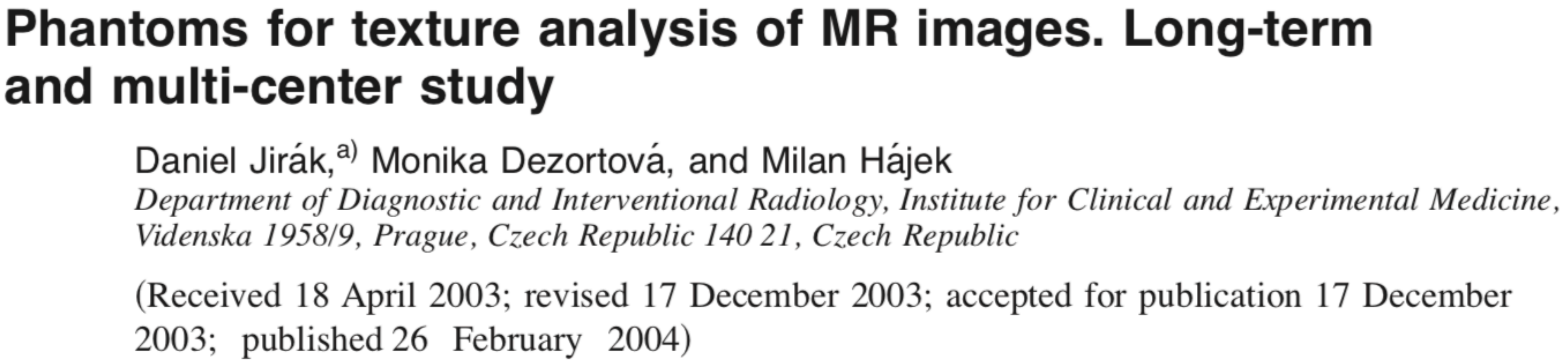
Simulation of human body (pelvis)



Texture phantom



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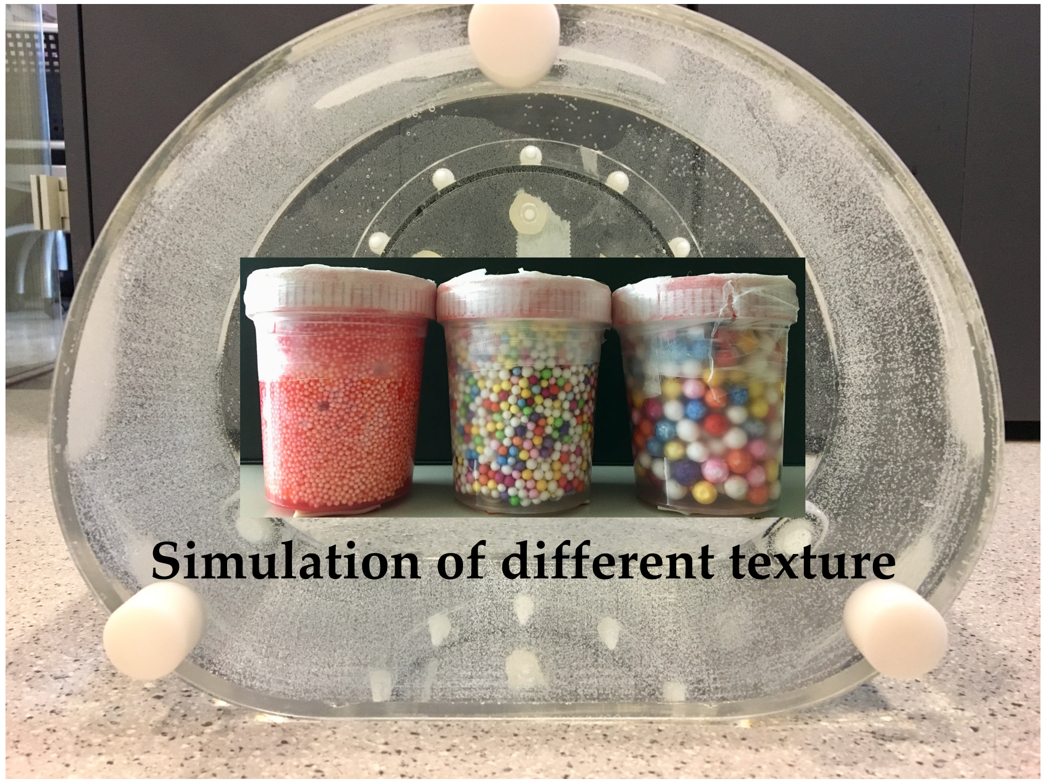
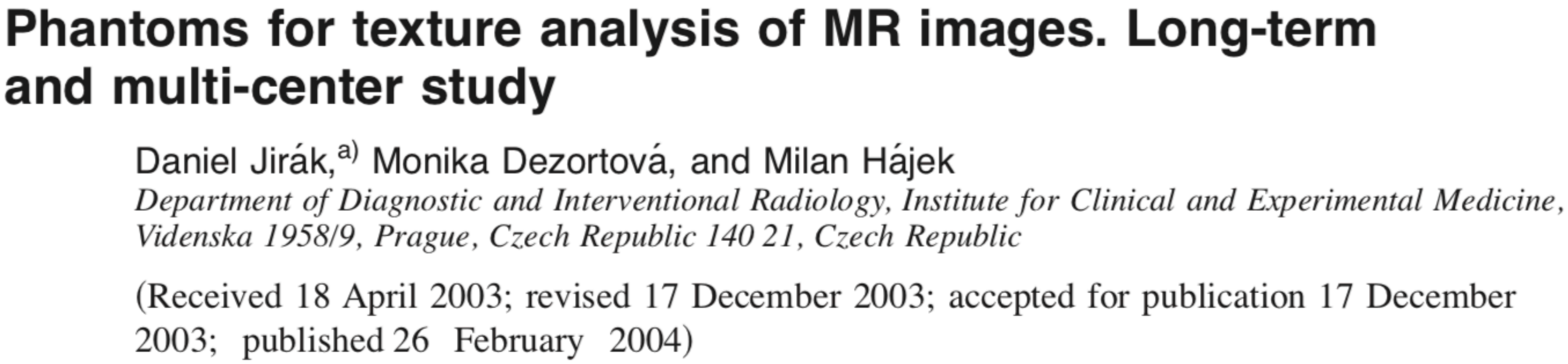


Simulation of different texture

Texture phantom



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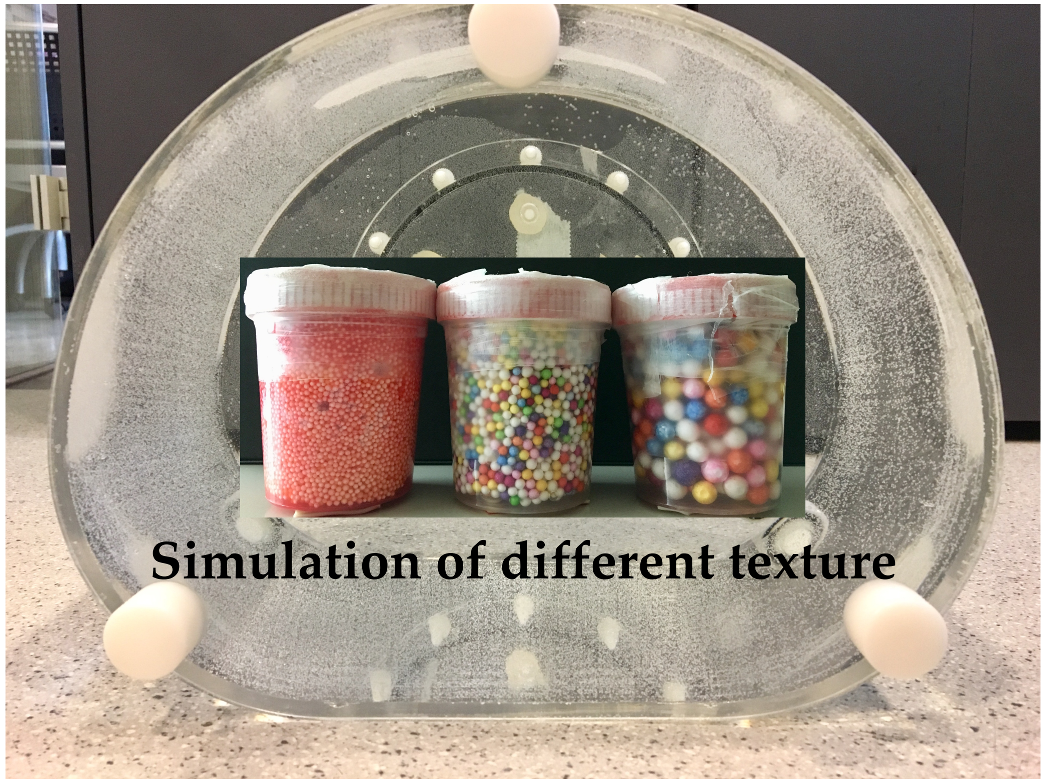
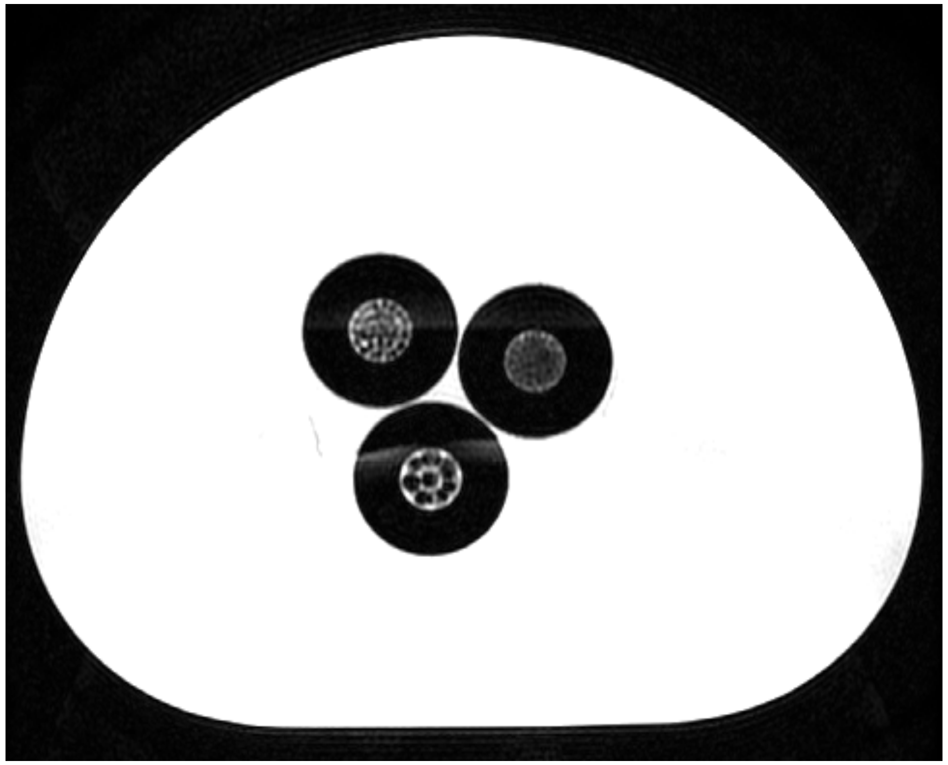
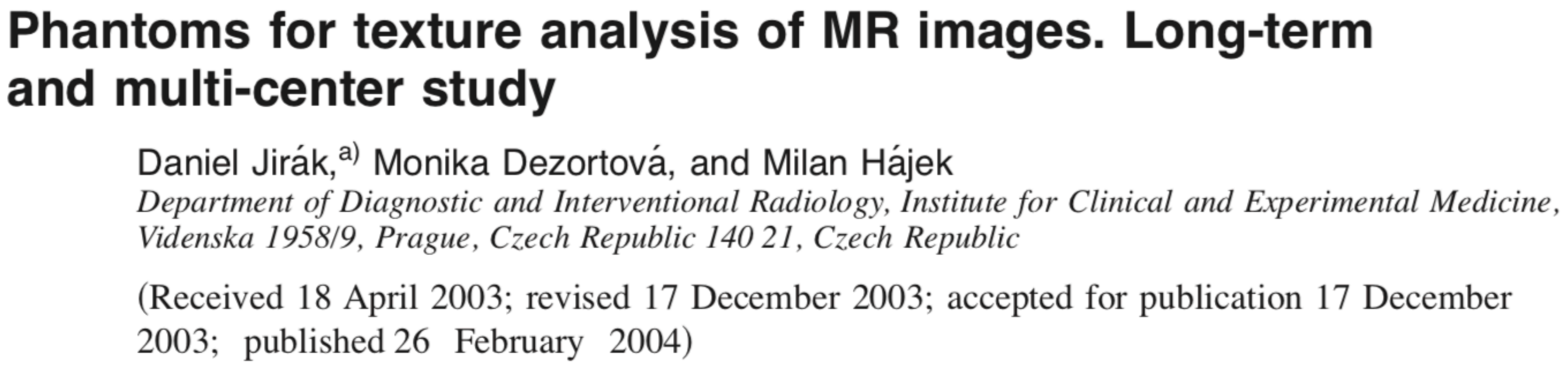


Simulation of different texture



Texture phantom



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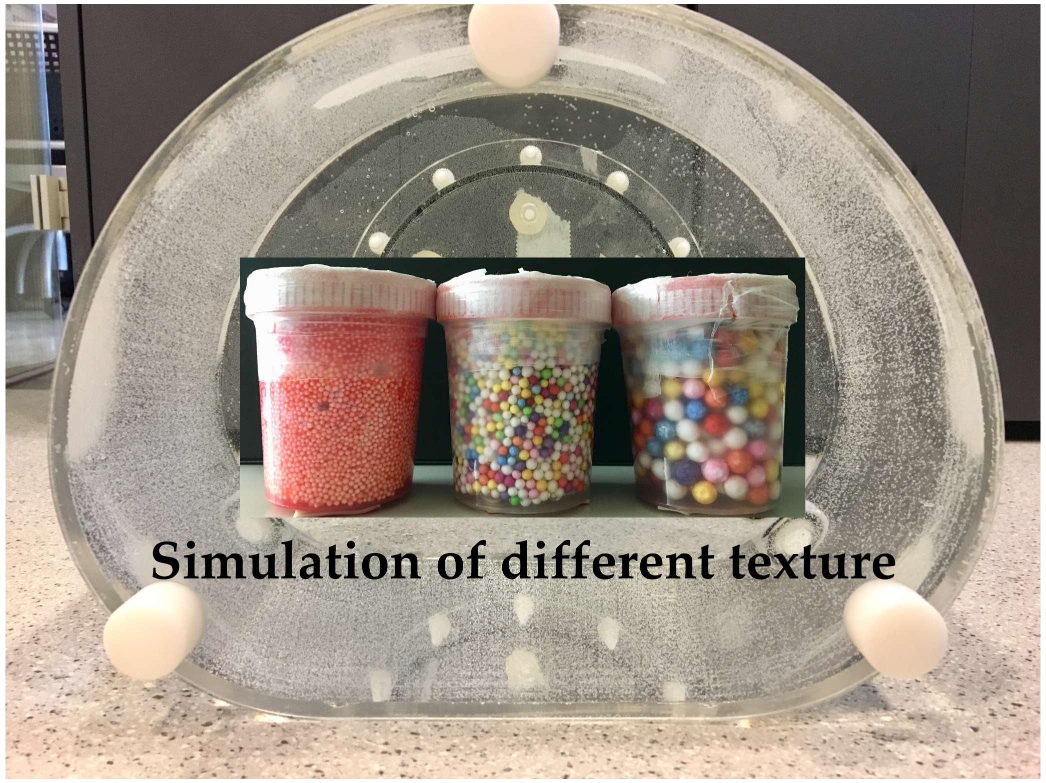
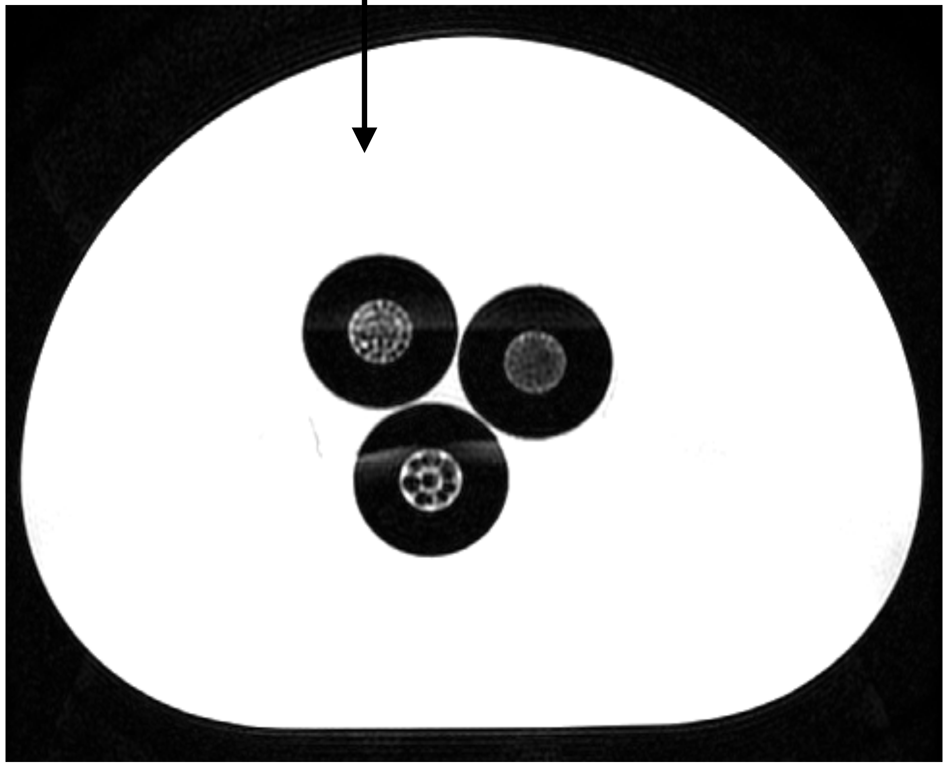


Simulation of different texture

next: $MnCl_2$



Calibration curves: T_1 and T_2 for $MnCl_2$

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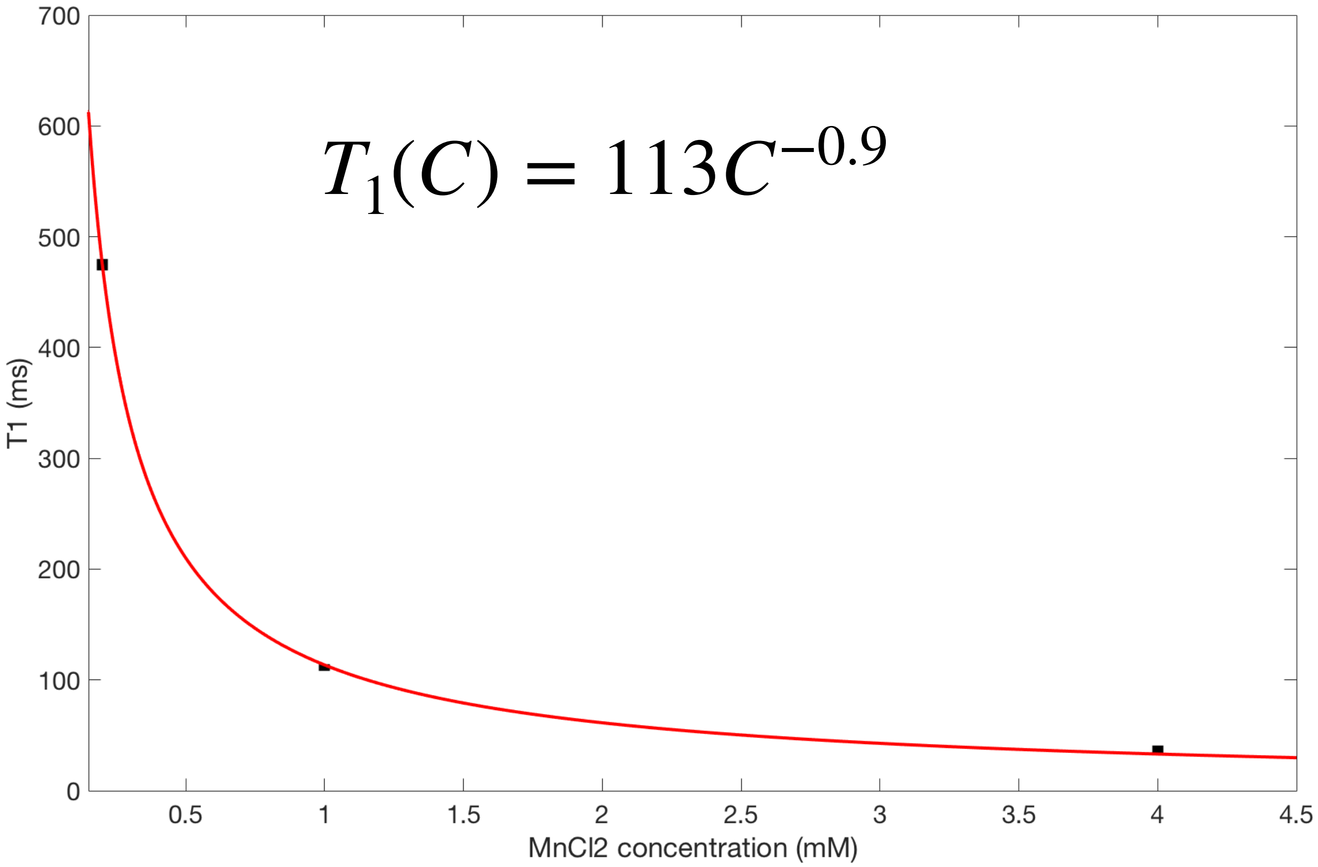
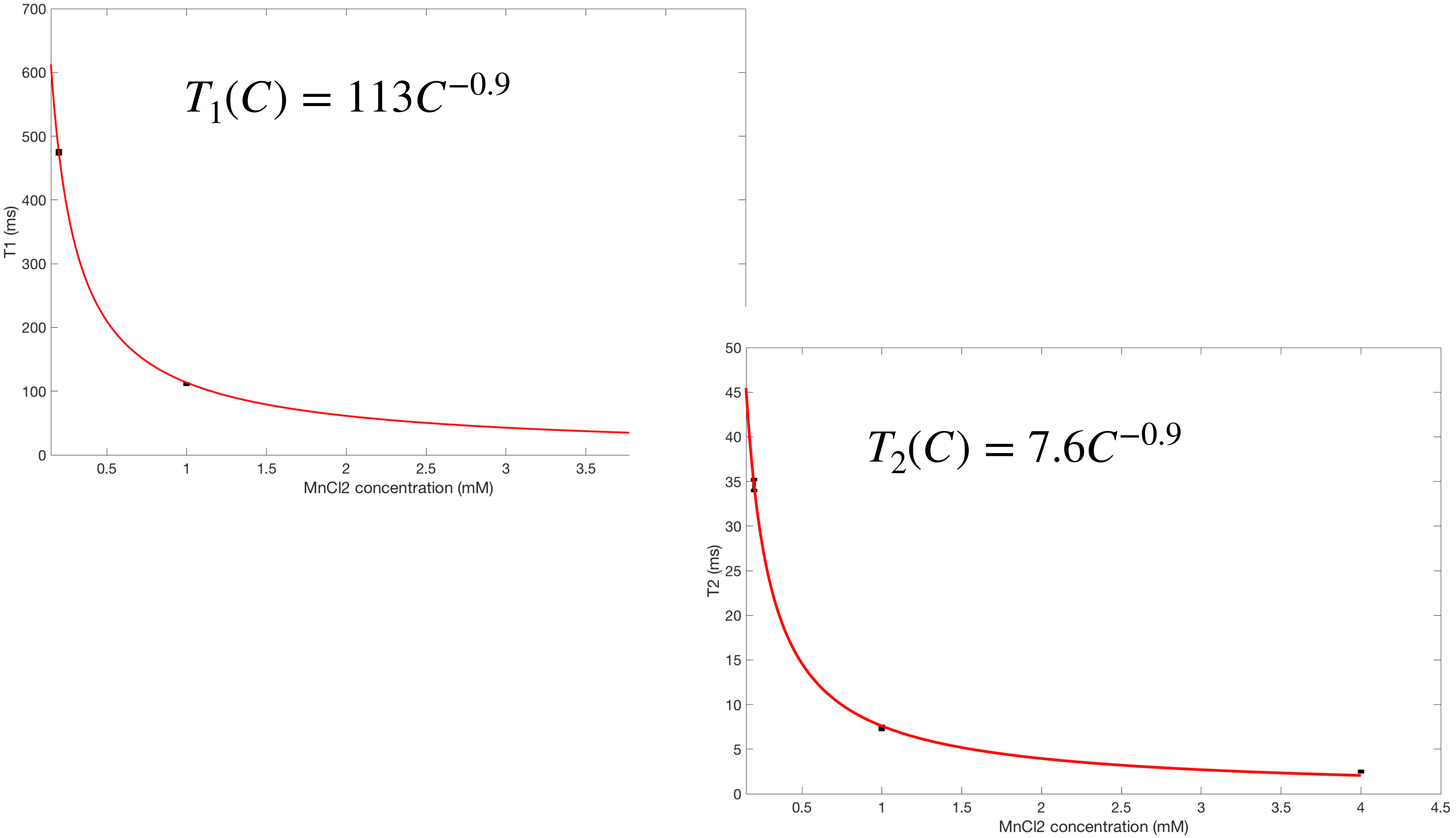
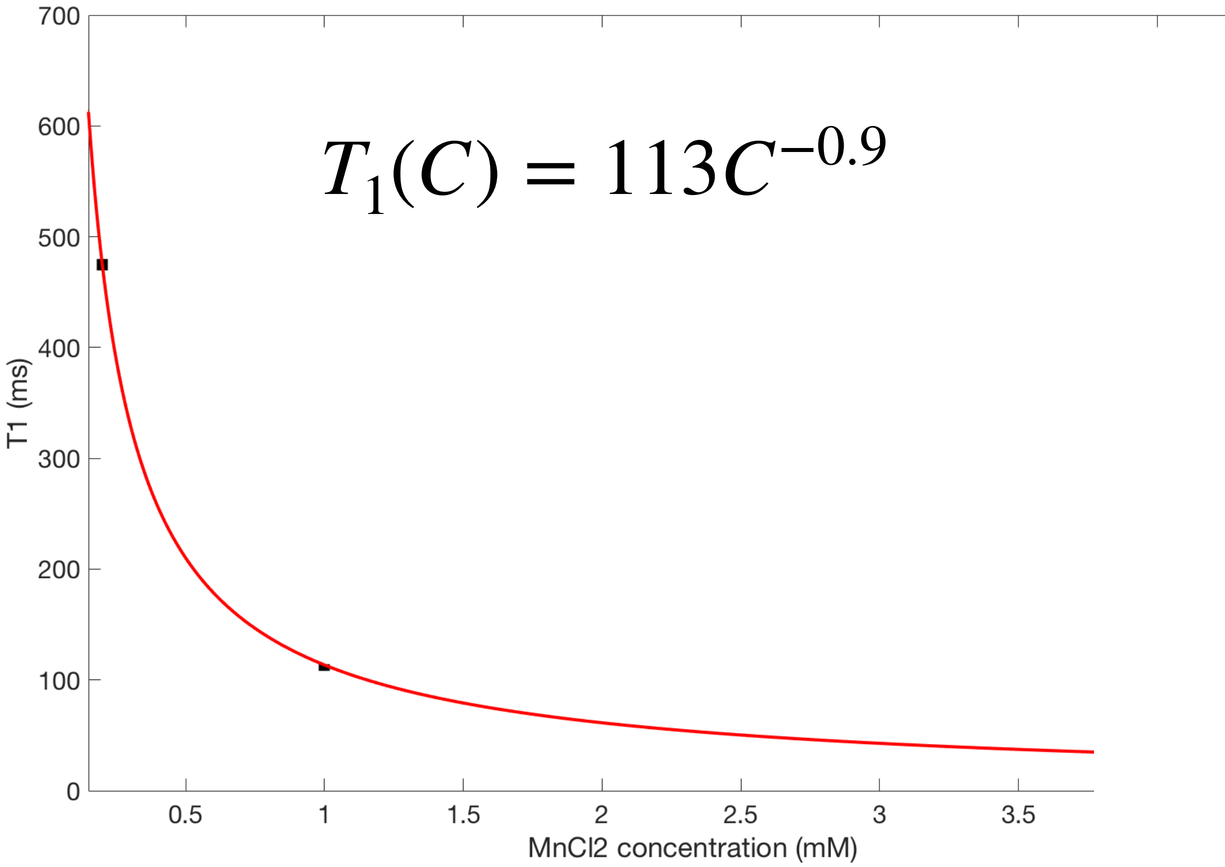


Calibration curves: T_1 and T_2 for $MnCl_2$



Calibration curves: T_1 and T_2 for $MnCl_2$

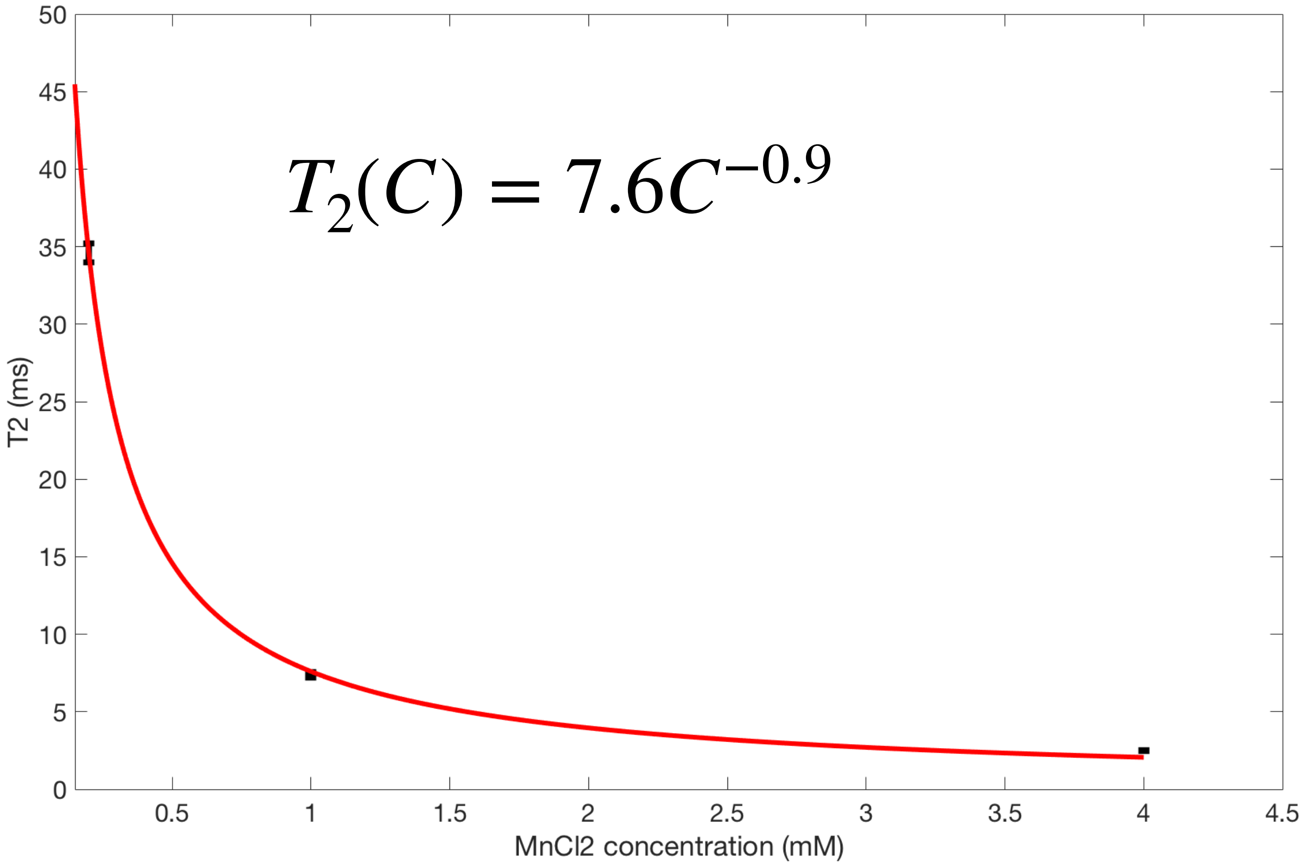


$$T_1(C) = 113C^{-0.9}$$

tissue of interest

↓

$MnCl_2$ concentration



$$T_2(C) = 7.6C^{-0.9}$$

Conclusion

Conclusion

🧗‍♀️ Challenge: can we “trust” the radiomic features extracted from MR images?

Conclusion

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🏔️ Preliminary results:

Conclusion

Challenge: can we “trust” the radiomic features extracted from MR images?

Preliminary results:

1. **A workflow to test the reliability of the features, both for short- and long-term repeatability in the same experimental condition, has been established.**

Conclusion

🧗‍♀️ Challenge: can we “trust” the radiomic features extracted from MR images?

🏔️ Preliminary results:

1. **A workflow to test the reliability of the features, both for short- and long-term repeatability in the same experimental condition, has been established.**

2. **The unstable radiomic features (i.e. with dependency on image acquisition process) has been identified.**

Conclusion

Challenge: can we “trust” the radiomic features extracted from MR images?

Preliminary results:

1. **A workflow to test the reliability of the features, both for short- and long-term repeatability in the same experimental condition, has been established.**
2. **The unstable radiomic features (i.e. with dependency on image acquisition process) has been identified.**
3. **A dedicated phantom has been designed to simulate *in vivo* conditions for further radiomic analyses.**

What's next?

What's next?

Final aim: protocol for application in clinics

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1. **Optimize and test the dedicated phantom**

What’s next?

Final aim: protocol for application in clinics

1. **Optimize and test the dedicated phantom**
2. **Study the dependency of the radiomic features on the MR sequence parameters**

What’s next?

Final aim: protocol for application in clinics

1. **Optimize and test the dedicated phantom**

2. **Study the dependency of the radiomic features on the MR sequence parameters**

3. **Test other sequences**

What's next?

Final aim: protocol for application in clinics

1. **Optimize and test the dedicated phantom**

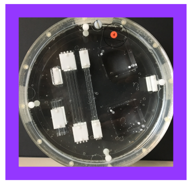
2. **Study the dependency of the radiomic features on the MR sequence parameters**

3. **Test other sequences**

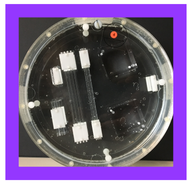
4. **Test other scanners (manufacturers, higher fields)**

Thank you!

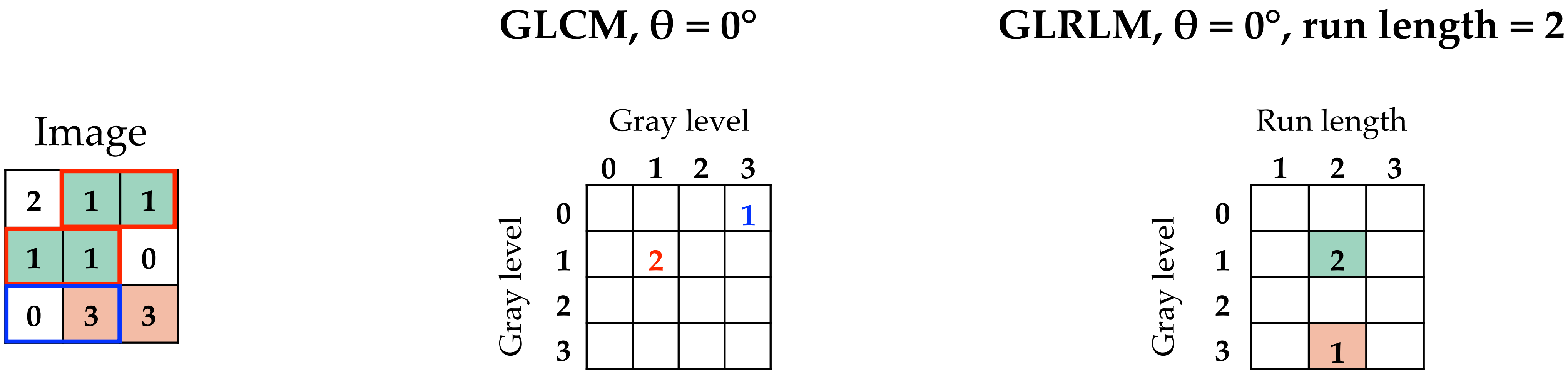
BACKUP



GLCM and GLRLM



GLCM and GLRLM



GLCM, θ = 0°

GLRLM, θ = 0°, run length = 2

Image

2	1	1
1	1	0
0	3	3

Gray level (columns) / Gray level (rows)

	0	1	2	3
0				1
1		2		
2				
3				

Run length (columns) / Gray level (rows)

	1	2	3
0			
1		2	
2			
3		1	

def. final features - GLCM25

$$autocorrelation = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} ij\mathbf{P}(i,j)$$

$p_x(i) = \sum_{j=1}^{N_g} \mathbf{P}(i,j)$ be the marginal row probabilities,

$p_y(i) = \sum_{i=1}^{N_g} \mathbf{P}(i,j)$ be the marginal column probabilities, ⟶ $IMC2 = \sqrt{1 - e^{-2(HXY2 - HXY)}}$

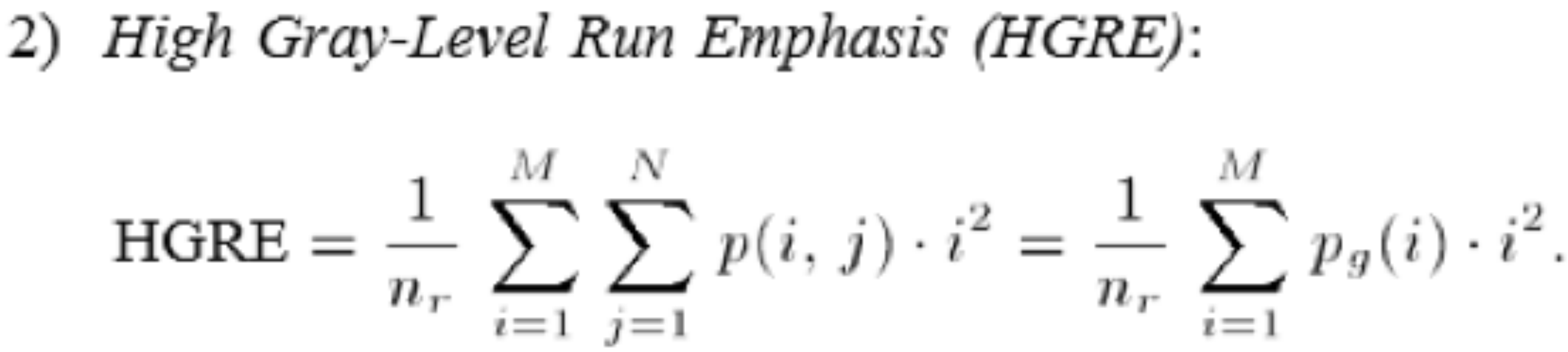
$$HXY = -\sum_{i}\sum_{j} p(i,j) \log(p(i,j))$$

$$sum\ average = \sum_{i=2}^{2N_g}\left[i\mathbf{P}_{x+y}(i)\right]$$

$$sum\ entropy = -\sum_{i=2}^{2N_g} \mathbf{P}_{x+y}(i)\log_2\left[\mathbf{P}_{x+y}(i)\right]$$

$$sum\ variance = \sum_{i=2}^{2N_g}(i - SE)^2\mathbf{P}_{x+y}(i)$$

def. final features - GLRLM25



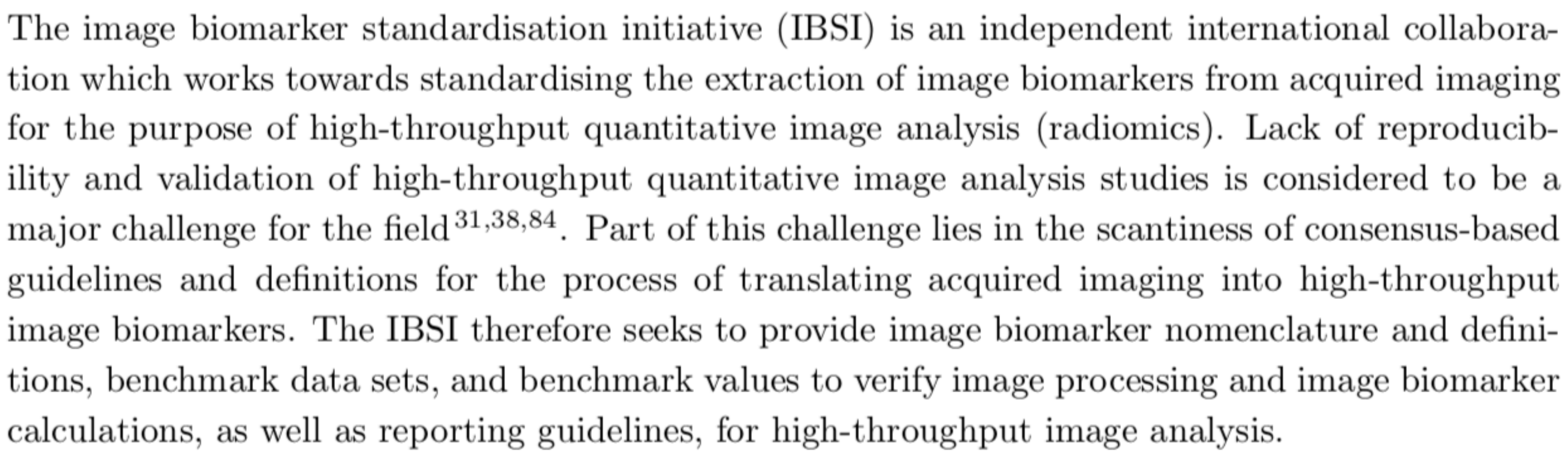
2) *High Gray-Level Run Emphasis (HGRE)*:

$$\mathrm{HGRE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i, j) \cdot i^2 = \frac{1}{n_r} \sum_{i=1}^{M} p_g(i) \cdot i^2.$$

Step 3: Features extraction

Image Biomarker Standardisation Initiative (IBSI)

Zwanenburg A, Leger S, Vallières M, Löck S. Image biomarker standardisation initiative. arXiv preprint arXiv:1612.07003



The image biomarker standardisation initiative (IBSI) is an independent international collaboration which works towards standardising the extraction of image biomarkers from acquired imaging for the purpose of high-throughput quantitative image analysis (radiomics). Lack of reproducibility and validation of high-throughput quantitative image analysis studies is considered to be a major challenge for the field[31,38,84]. Part of this challenge lies in the scantiness of consensus-based guidelines and definitions for the process of translating acquired imaging into high-throughput image biomarkers. The IBSI therefore seeks to provide image biomarker nomenclature and definitions, benchmark data sets, and benchmark values to verify image processing and image biomarker calculations, as well as reporting guidelines, for high-throughput image analysis.

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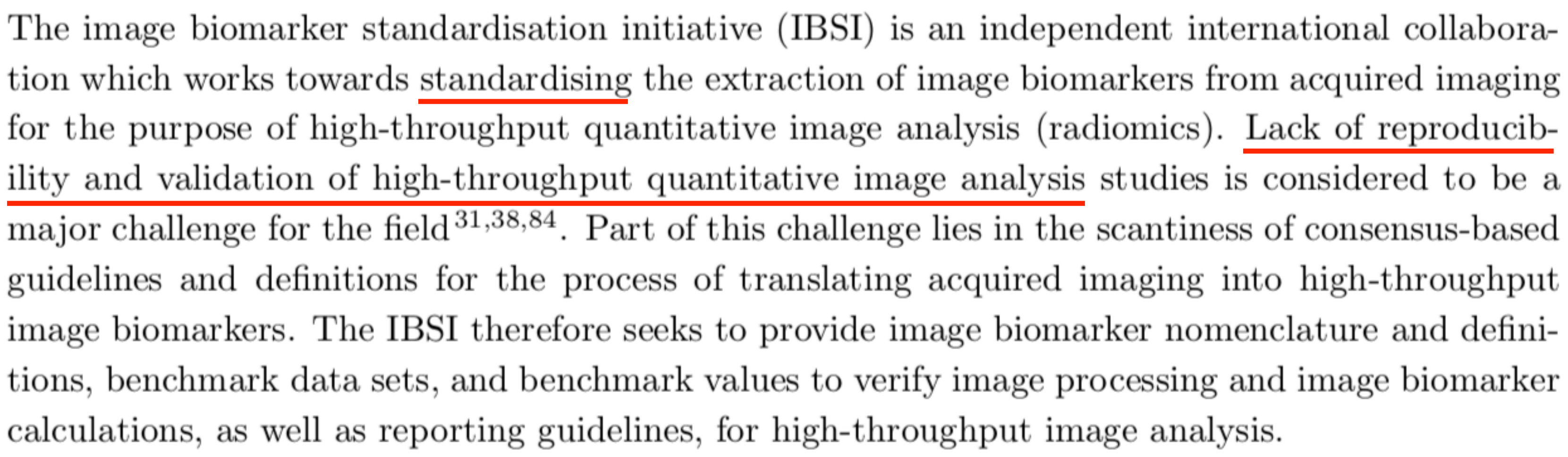
Aim



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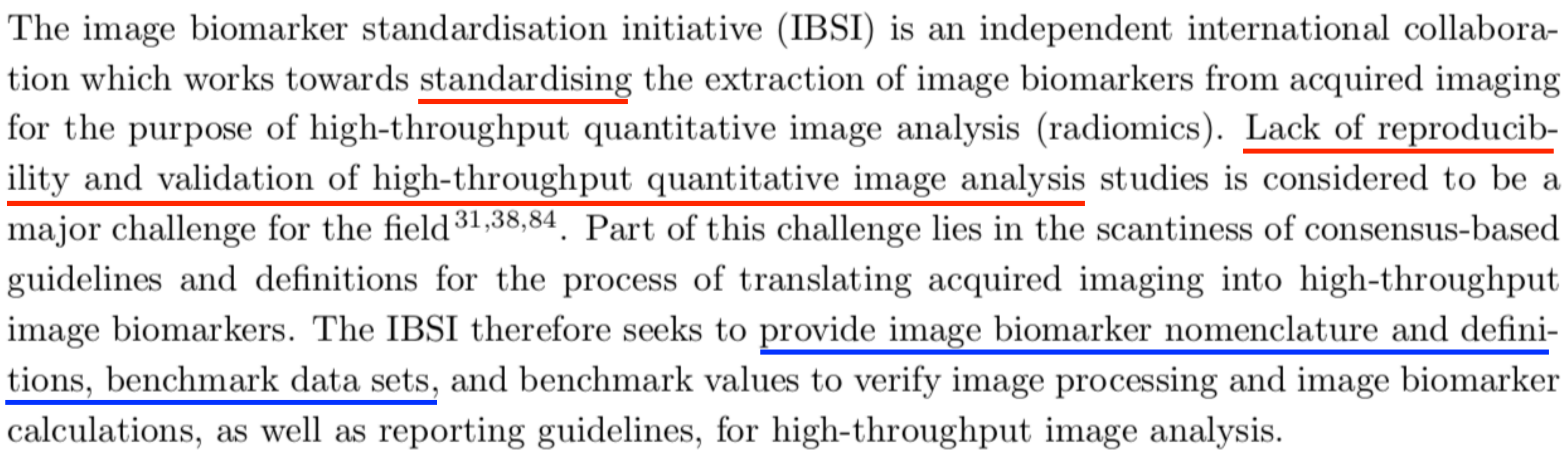
How?



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Aim

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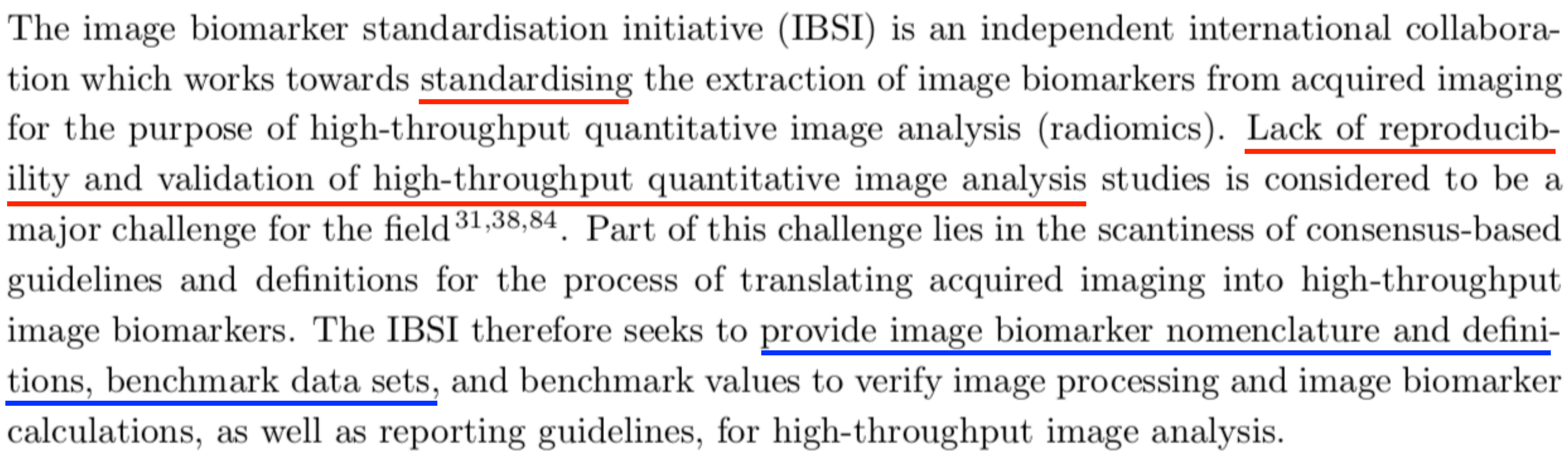

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Reference for features definition

Step 3: Features extraction

IBSI digital phantom

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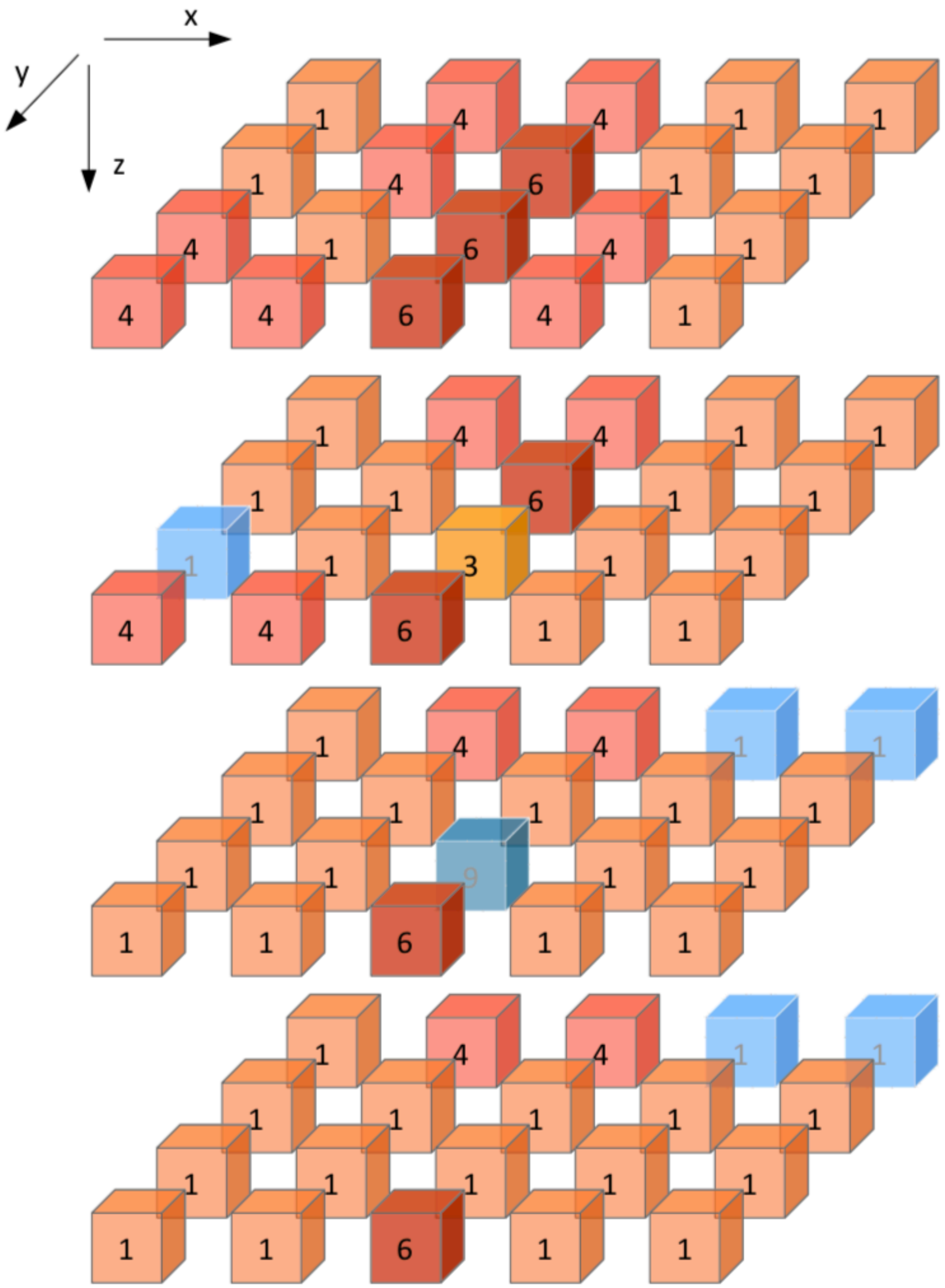


Step 4: Statistics and model building

Feature selection methods

Dimensionality reduction to reduce the risk of overfitting

↓

subset of relevant features

↓

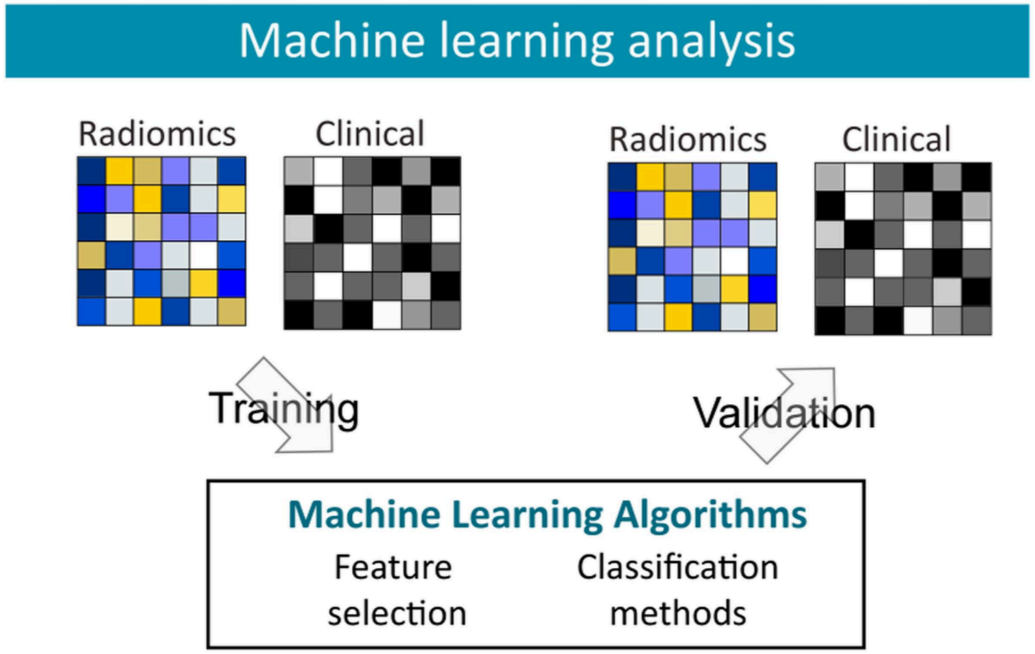
WILCOXON TEST (4)

Classification methods

ML classification procedures for building predictive model

↓

RANDOM FOREST (4)



*from (4)

Step 4: Statistics and model building

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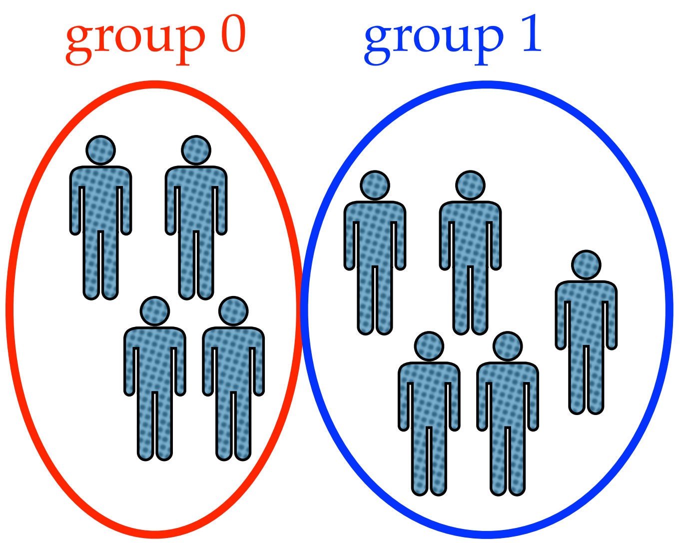
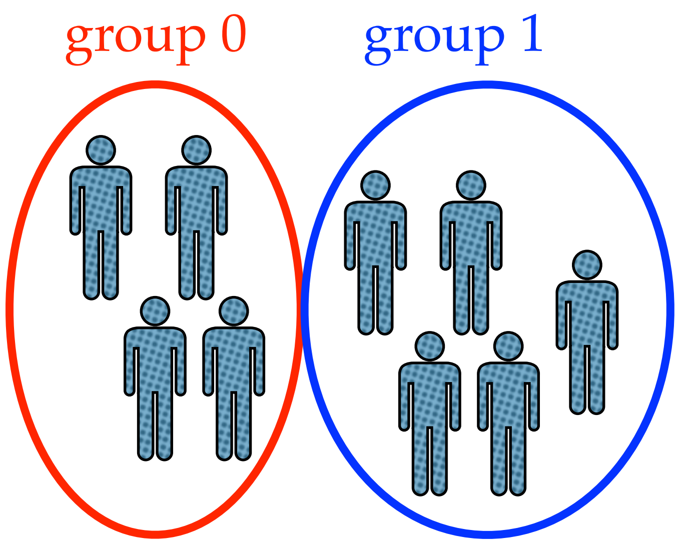
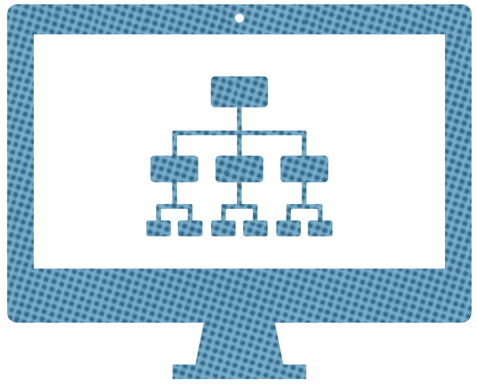


Training set

Step 4: Statistics and model building

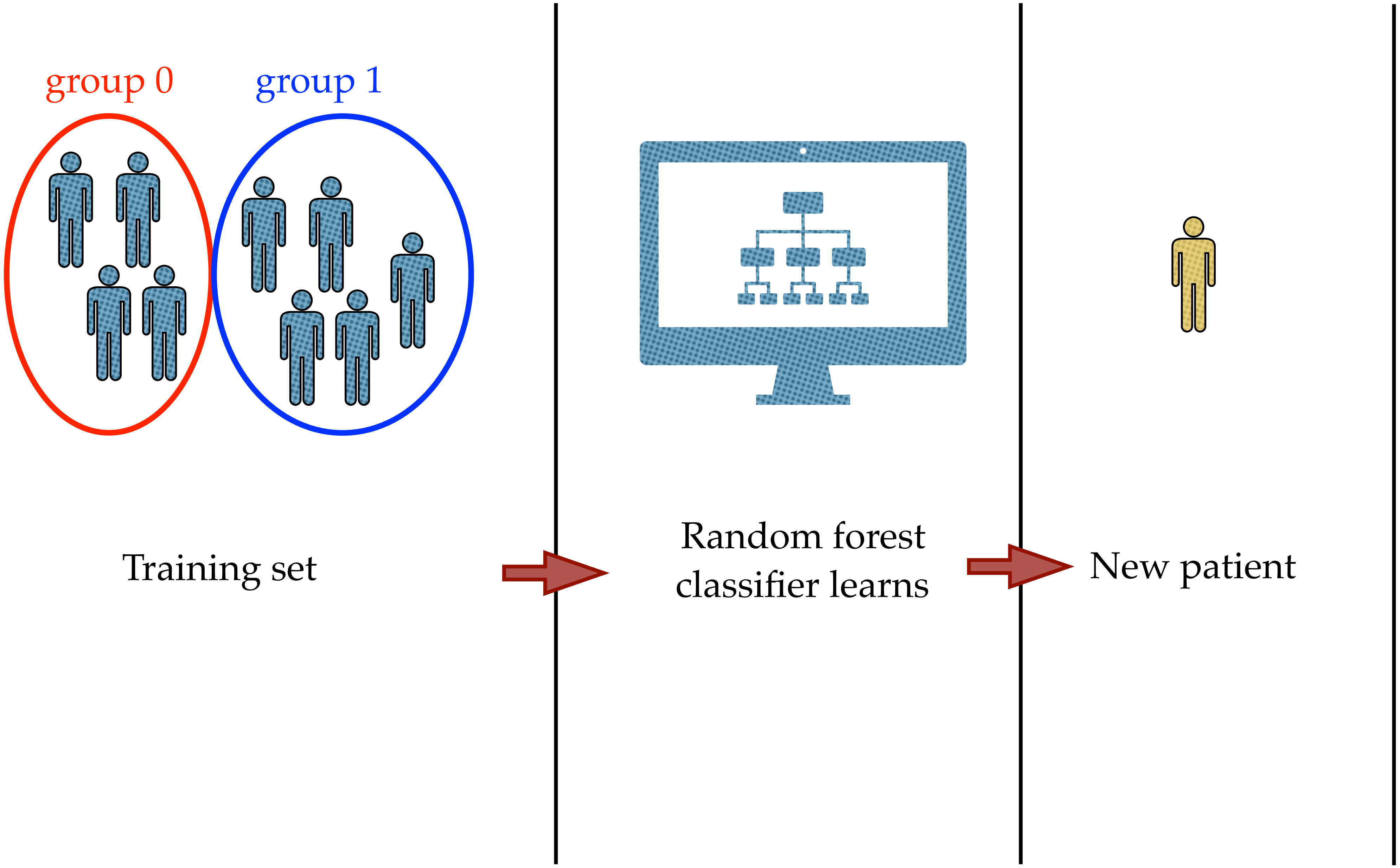


Training set



Random forest classifier learns

Step 4: Statistics and model building



group 0

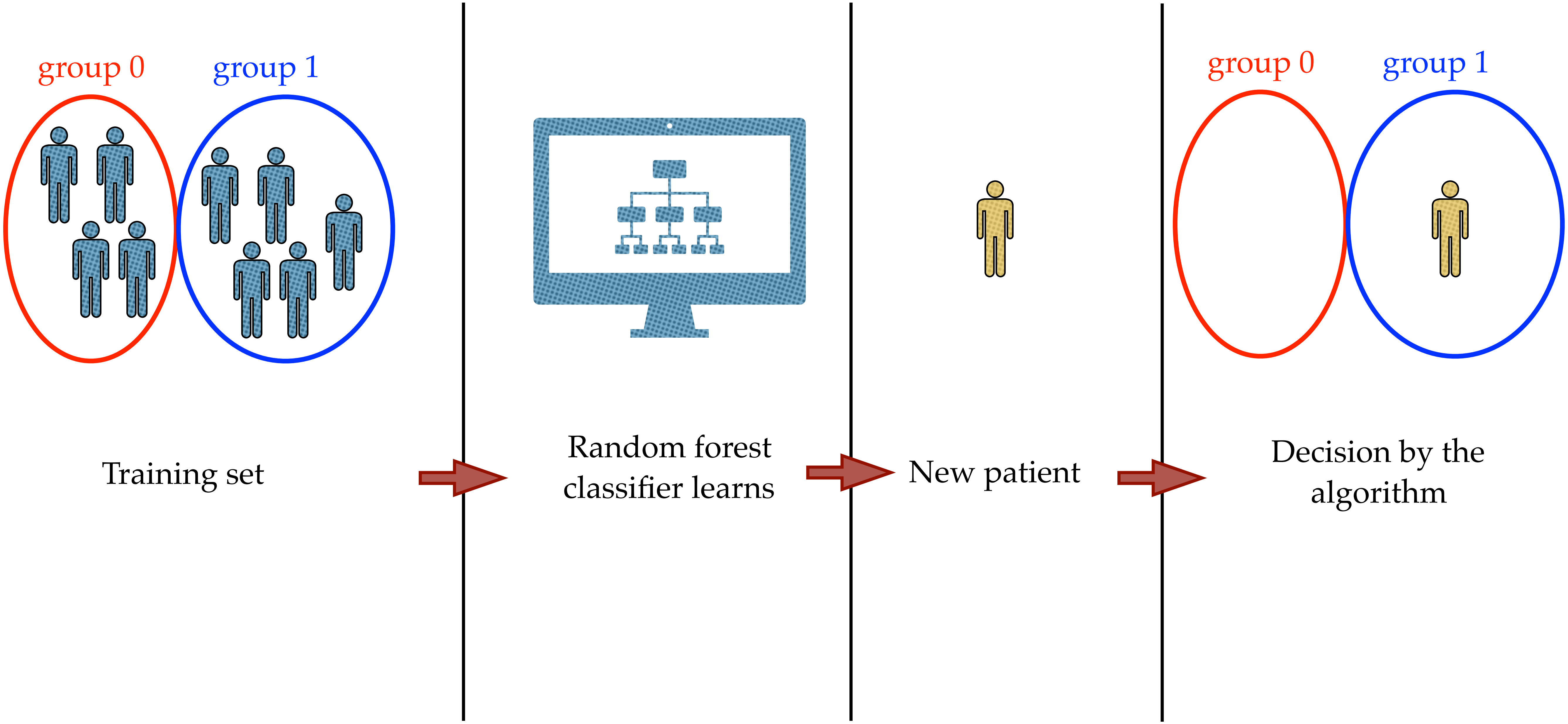
group 1

Training set

Random forest classifier learns

New patient

Step 4: Statistics and model building



group 0 group 1

Training set

Random forest classifier learns

New patient

group 0 group 1

Decision by the algorithm