University of Torino
Graduate Program in Physics

XXXV Cycle

Medical Physics Ph D

Evaluation of the impact of acquisition and preprocessing parameters on radiomic features

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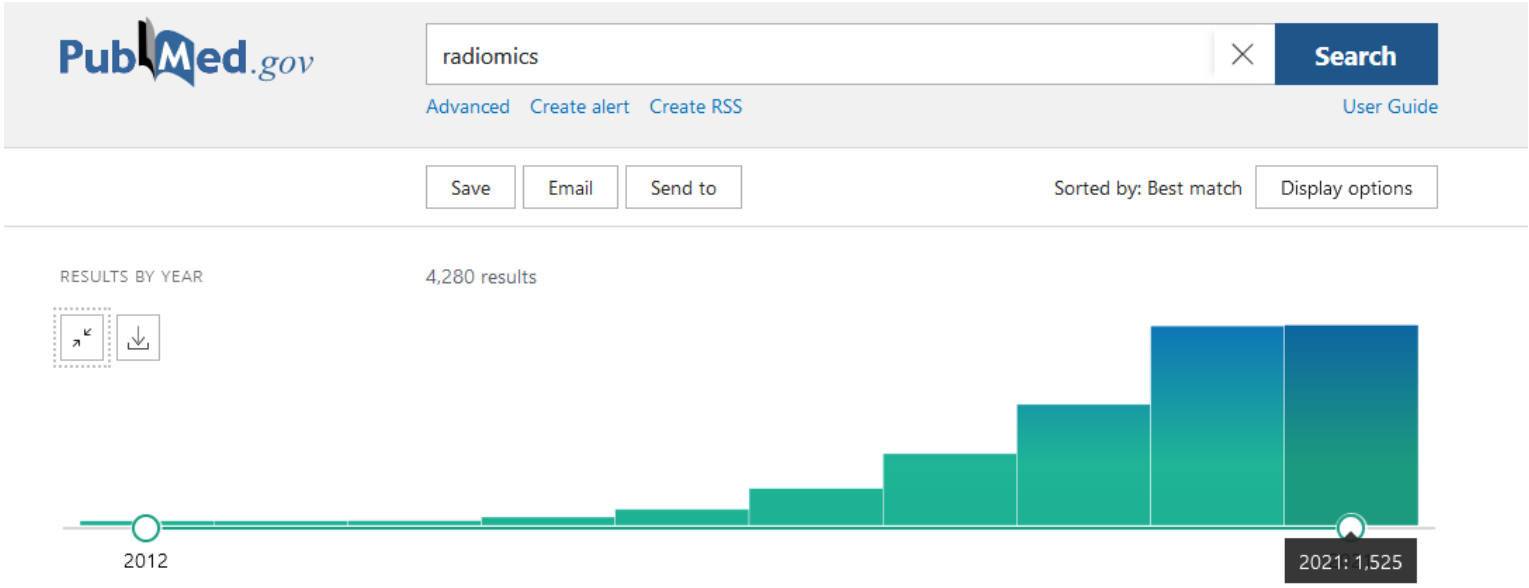
Osvaldo Rampado

Tutor: Prof. Vincenzo Monaco

What is radiomics?

Radiomics is a new discipline that aims to quantify the phenotypes of a disease by considering his radiological images and by calculating a large number of quantitative characteristics, and correlating the results with clinical data.



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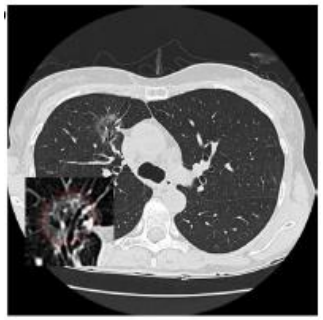
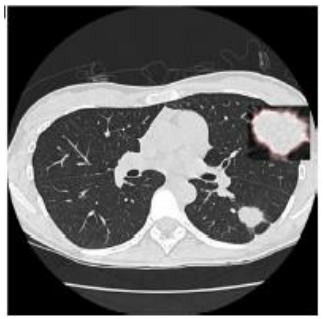
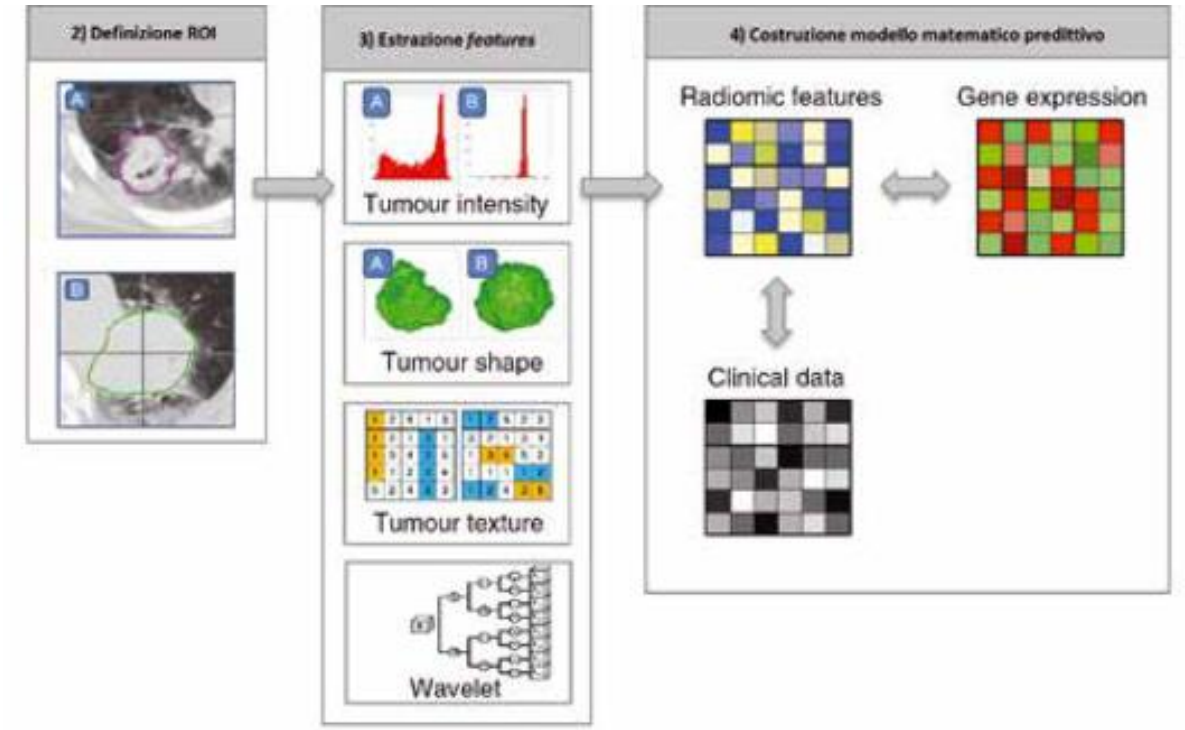
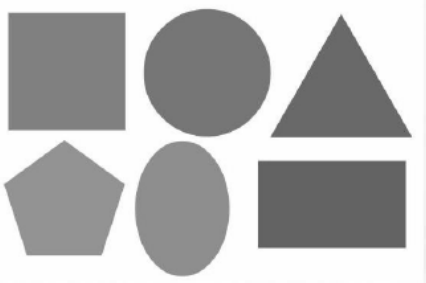






Radiomics features examples

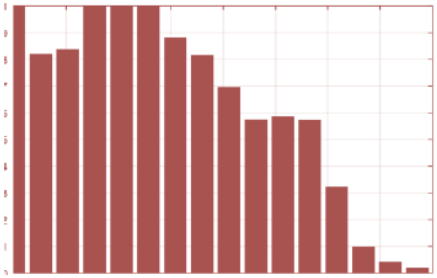
Shape



Sphericity

$$F_{morph.sphericity} = \frac{(36\pi V^2)^{1/3}}{A}$$

Intensity



$$kurtosis = \frac{\frac{1}{N}\sum_i (X(i)-\bar{X})^4}{\left(\frac{1}{N}\sum_i (X(i)-\bar{X})^2\right)^2}$$

$$entropy = \sum_i (P(i)\log_2 P(i))$$

Texture

$$autocorrelation = \sum_{i,j} i * j * P(i,j)$$

Gray level co-occurrence features

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

(a) Grey levels

		j			
		0	3	0	0
	i	0	1	3	1
		0	0	1	0
		2	1	0	0

(b) $\mathbf{M}_{m_{+=\rightarrow}}$

		j			
		0	0	0	2
	i	3	1	0	1
		0	3	1	0
		0	1	0	0

(c) $\mathbf{M}_{m_{-=\leftarrow}}$

https://arxiv.org/abs/1612.07003

IBSI: Image Biomarker Standardization Inititative

Radiomics Quality Score

However, radiomics analysis faces several important challenges, which are mainly caused by the various technical factors influencing the extracted radiomic features.

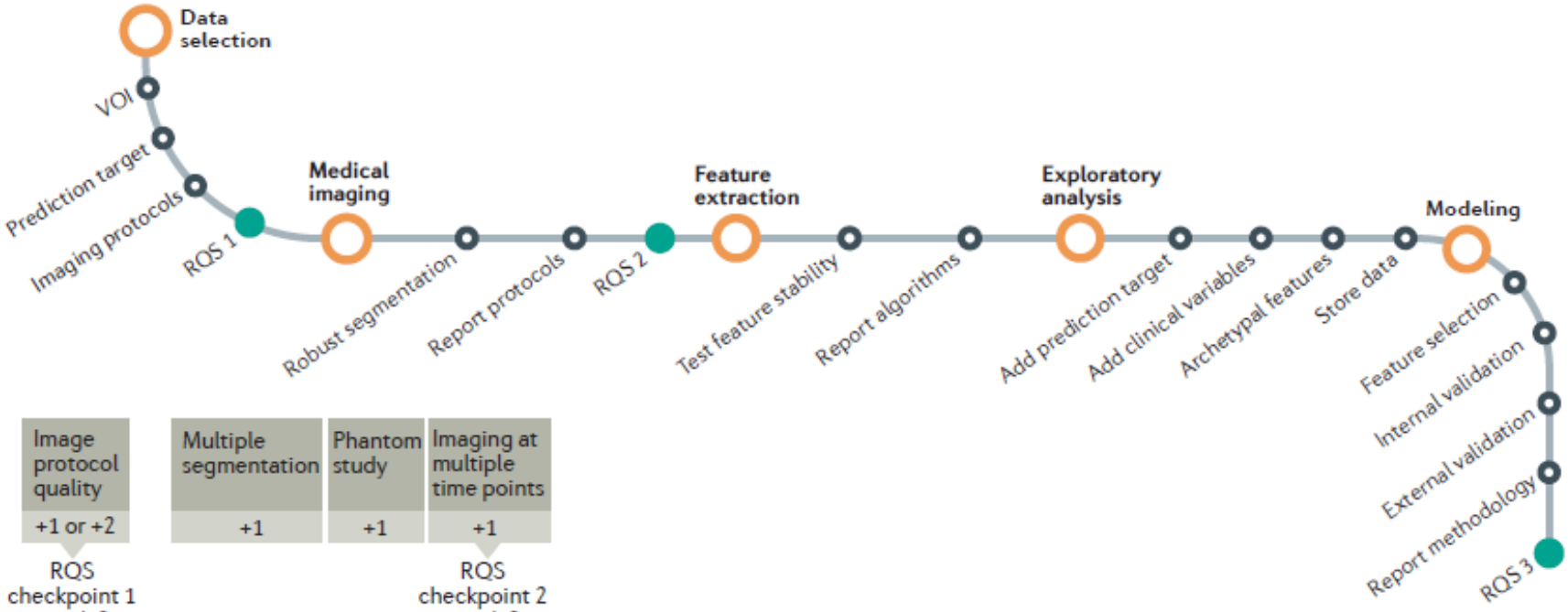


Image protocol quality	Multiple segmentation	Phantom study	Imaging at multiple time points
+1 or +2	+1	+1	+1
RQS checkpoint 1 total: 2			RQS checkpoint 2 total: 3

Feature reduction or adjustment for multiple testing	Multivariable analysis	Biological correlates	Cut-off analysis	Discrimination statistics	Calibration statistics	Prospective study	Validation	Comparison to 'gold standard'	Potential clinical applications	Cost-effectiveness analysis	Open science and data
-3 or +3	+1	+1	+1	+1 or +2	+1 or +2	+7	-5 to +5	+2	+2	+1	+1 to +4
											RQS checkpoint 3 total: 31

RQS Total	36

Lambin et al. 2017 Dec;14(12):749-762.

My research activity

In the field of radiomics applied to nuclear medicine PET images (^{68}Ga and ^{18}F):

- Influence of different reconstruction methods
- Impact of different segmentations on neuroendocrine tumours
- Investigation of the consequences of different pre processing parameters (discretization)
- Preliminary assessment of predictive value of radiomics in PRRT patients
- Development of a test phantom with 3D simulated lesions

In the field of radiomics applied to lung CT images (Covid patients)

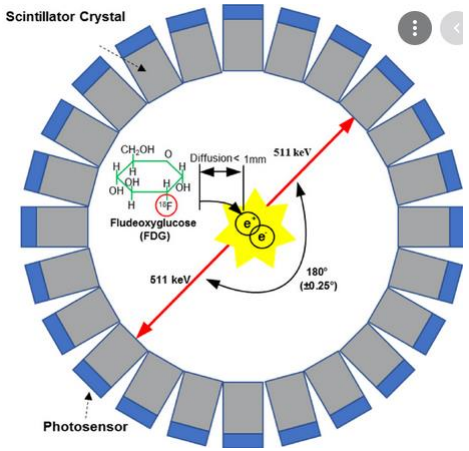
- Evaluation of the impact of different image reconstruction methods

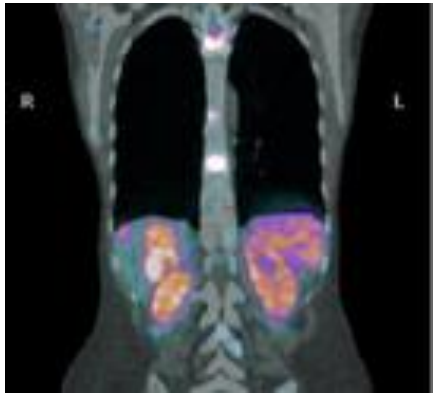
In the field of radiomics applied to breast MRI images

- Preliminary investigation of predictive values of therapy response

Radiomics applied to nuclear medicine PET images

- → In the last 4 years, hundreds of studies investigating PET/CT uptake heterogeneity published.
- → Contradictory results and controversies as a consequence of the number of required preprocessing steps
- → The vast majority of studies to date have been carried out using FDG (and static SUVimages), with only a few examples ofthe use of other radiotracers.





a

Conventional PET/CT analysis approach

PET/CT imaging

Image acquisition & Reconstruction

Preprocessing

Tumor segmentation (Recognition & Delineation)

Quantification

Feature extraction (SUV, MTV and TLG)

Analysis

Statistical analysis (and rarely machine learning)

b

Radiomics PET/CT analysis approach

PET/CT imaging

Image acquisition & Reconstruction

Preprocessing

Tumor segmentation (Recognition & Delineation)

Intensity quantization (Absolute or relative)

Quantification

Histogram generation (First order)

Texture matrix design (Second & higher order)

Texture feature extraction

Analysis

Statistical analysis and/or Machine learning

Impact of segmentation and discretization

Liberini *et al. EJNMMI Physics* (2021) 8:21
https://doi.org/10.1186/s40658-021-00367-6

EJNMMI Physics

ORIGINAL RESEARCH Open Access

Impact of segmentation and discretization on radiomic features in ^{68}Ga-DOTA-TOC PET/CT images of neuroendocrine tumor

Virginia Liberini[1*], Bruno De Santi[2], Osvaldo Rampado[3], Elena Gallio[3], Beatrice Dionisi[1], Francesco Ceci[1], Giulia Polverari[1], Philippe Thuillier[1,4], Filippo Molinari[2] and Désirée Deandreis[1]

- Neuroendocrine tumors (NET): heterogeneous group of malignancies represented by different histological subtypes and different primary locations

- Only one study evaluating the robustness of RFs in function of image acquisition and reconstruction parameters for ^{68}Ga-DOTA-peptides PET/CT (without considering the consequences of different segmentation approaches).

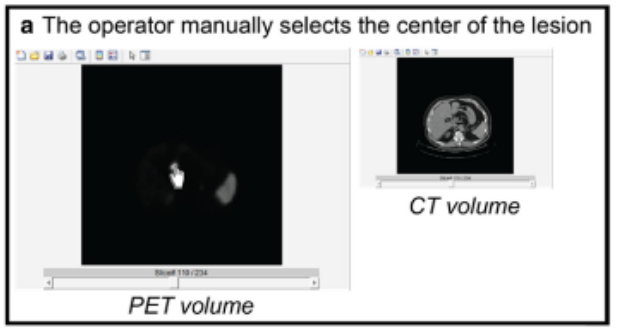
- Several reasons to evaluate the RFs robustness specifically in ^{68}Ga-DOTA-peptide tracers.

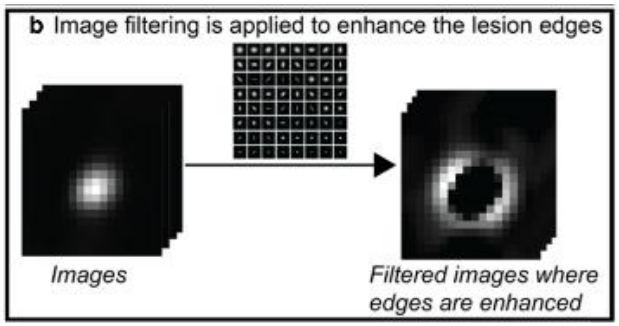
The objective of this study was to evaluate the robustness of RFs in function of segmentation methods and discretization settings in ^{68}Ga-DOTATOC PET/CT images.

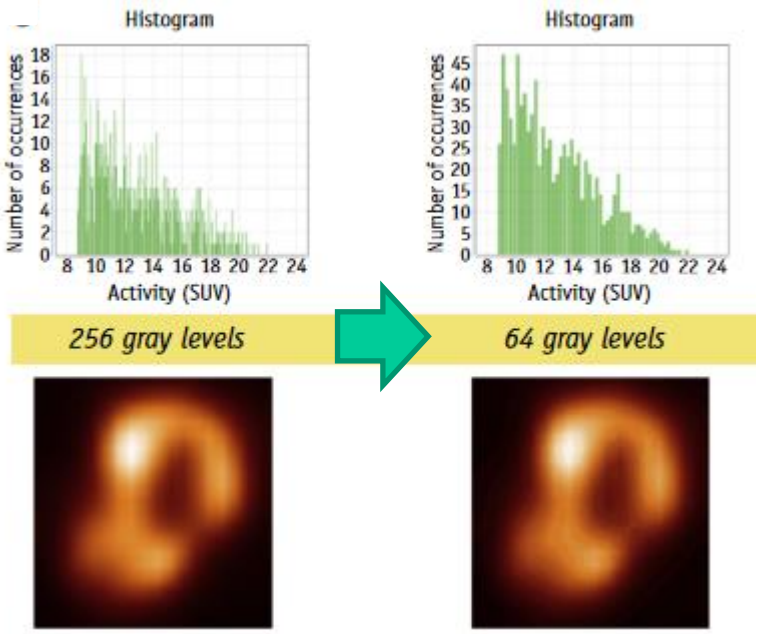
Impact of segmentation and discretization: methods

49 patients were retrospectively analyzed.

Tumor contouring: manually by 4 different operators and with a semi-automatic edge-based segmentation (SAEB) algorithm. Three SUV_{max} fixed thresholds (20, 30, 40%) were applied.







51 RFs were extracted applying two different intensity rescale factors for gray-level discretization: one absolute (AR60 = SUV from 0 to 60) and one relative (RR = min-max of the VOI SUV).

Impact of segmentation and discretization: analysis

Quantitative comparisons between VOI_m and VOI_{SAEB} were evaluated through the Dice similarity coefficient (DSC), which measures spatial overlap between two different segmentations of the same lesion:

$$DSC(V_1, V_2) = 2\frac{|V_1 \cap V_2|}{|V_1| + |V_2|}$$

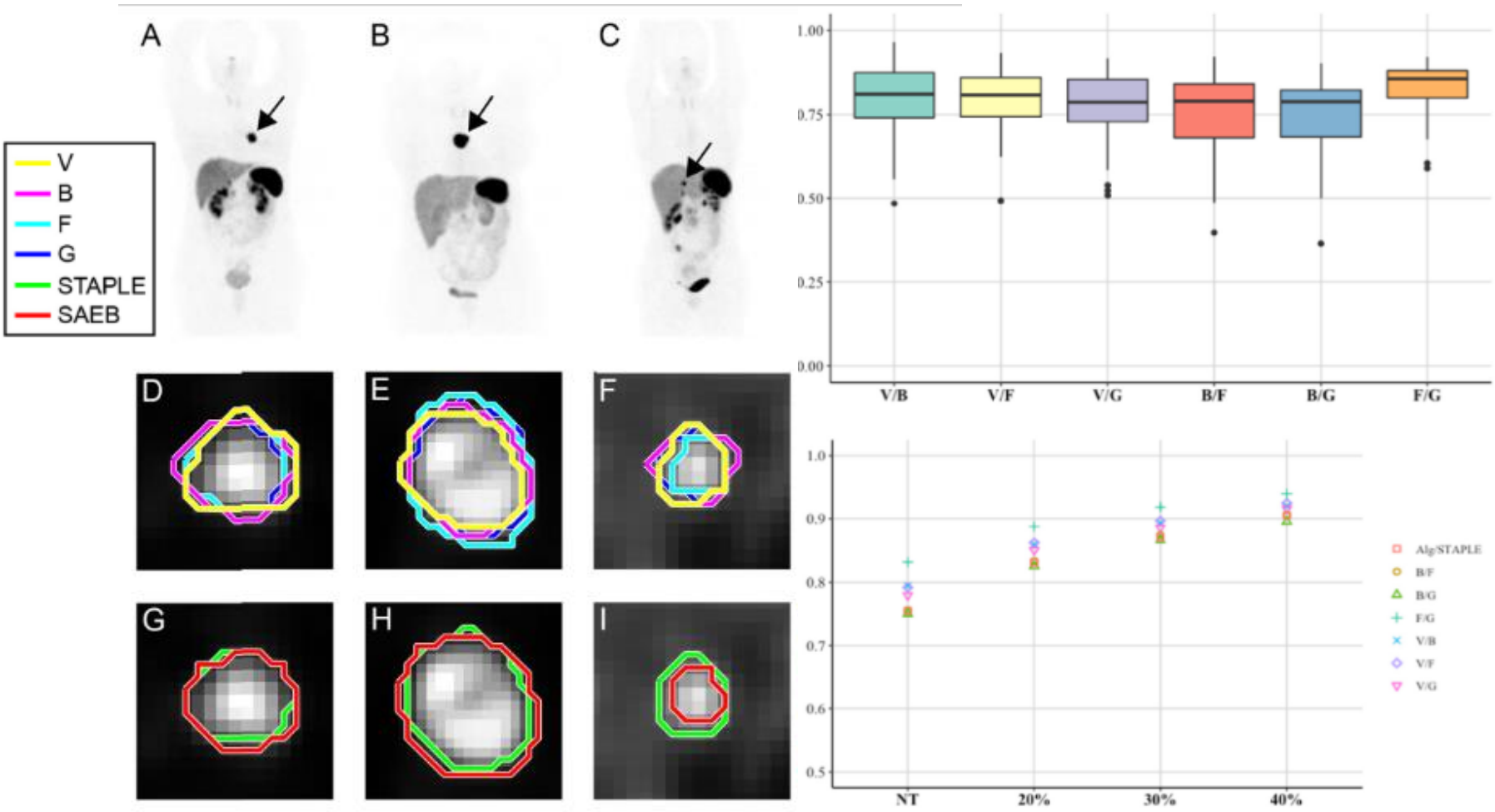
Robustness of RFs was assessed by two-way mixed effects intra-class correlation coefficients (ICC) to evaluate consistency and coefficient of variance for each lesion (COV^L) to evaluate agreement in the various settings.

$$ICC = \frac{BMS - RMS}{BMS + (N-1) \times RMS}$$

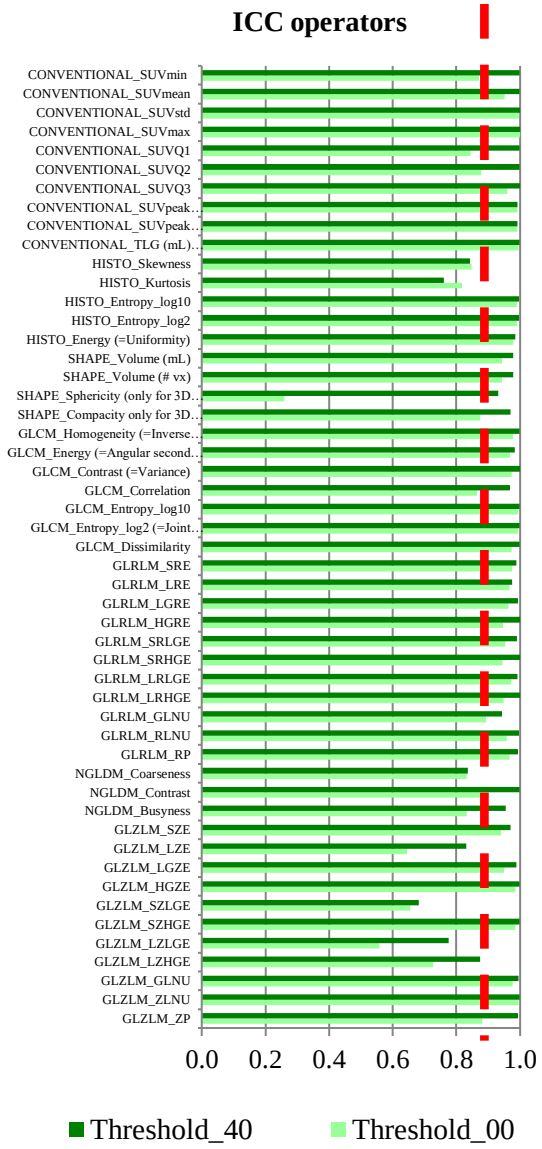
$$COV^L = 100 \times \frac{\sqrt{\frac{1}{N-1}\sum_{k=1}^{N}\left(m_k^L - \underline{m}^L\right)^2}}{\underline{m}^L}$$

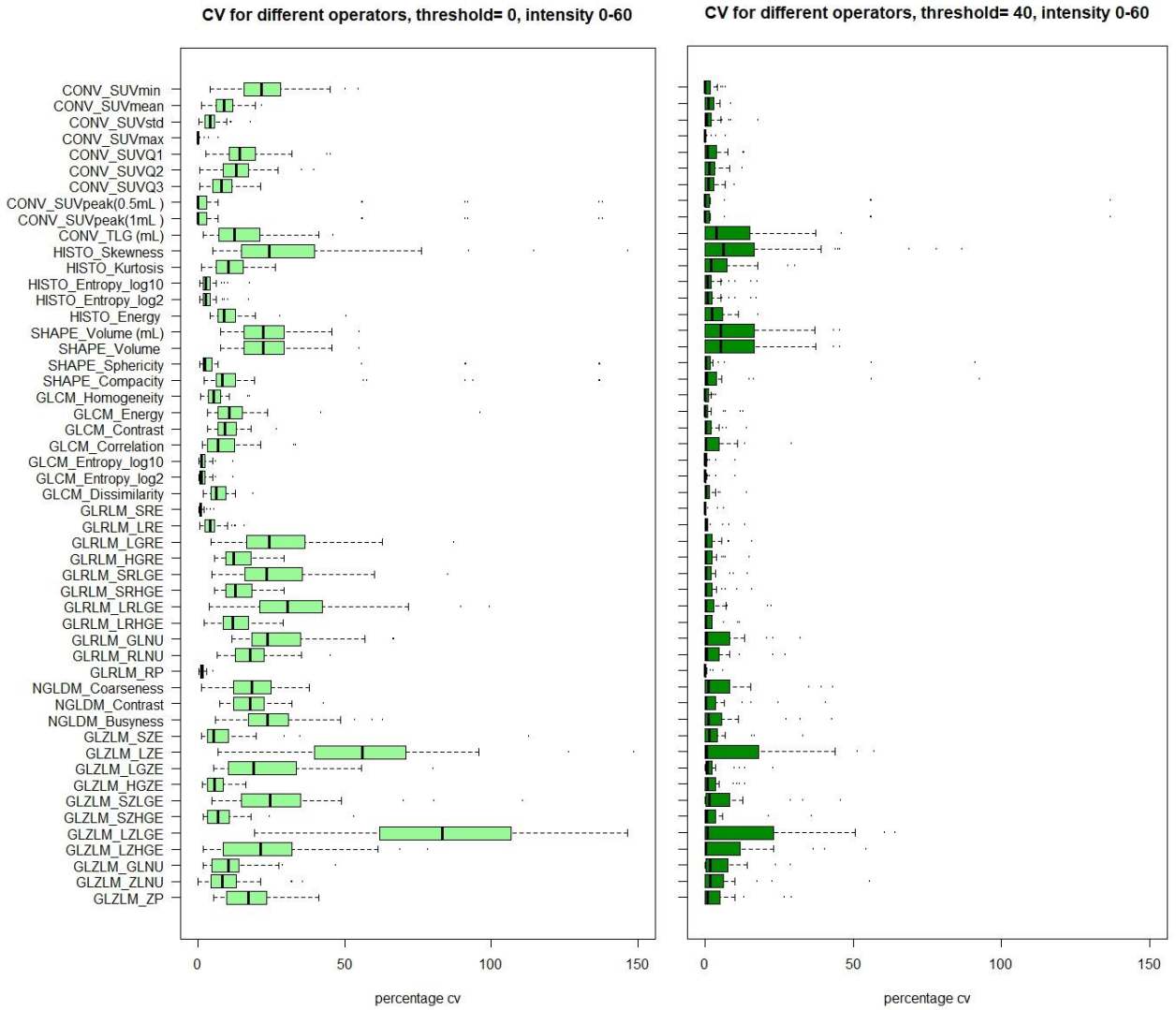
The RFs' correlation with volume and SUV_{max} was analyzed by calculating Pearson's correlation coefficients.

Comparison of different segmentation methods

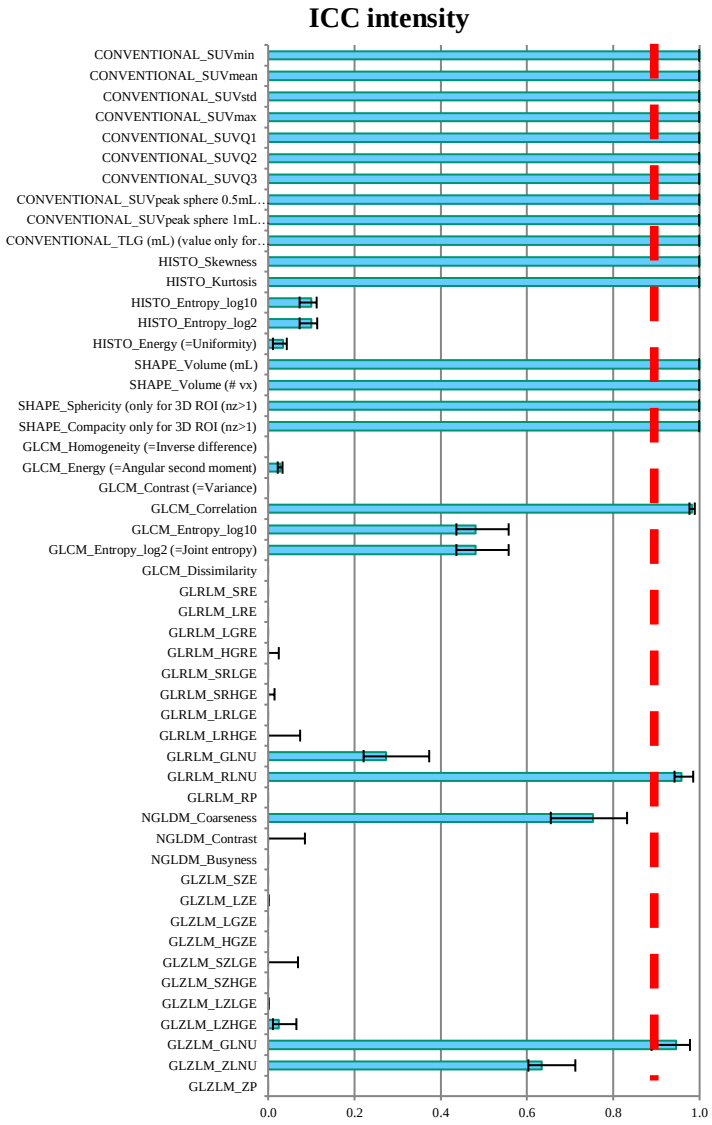


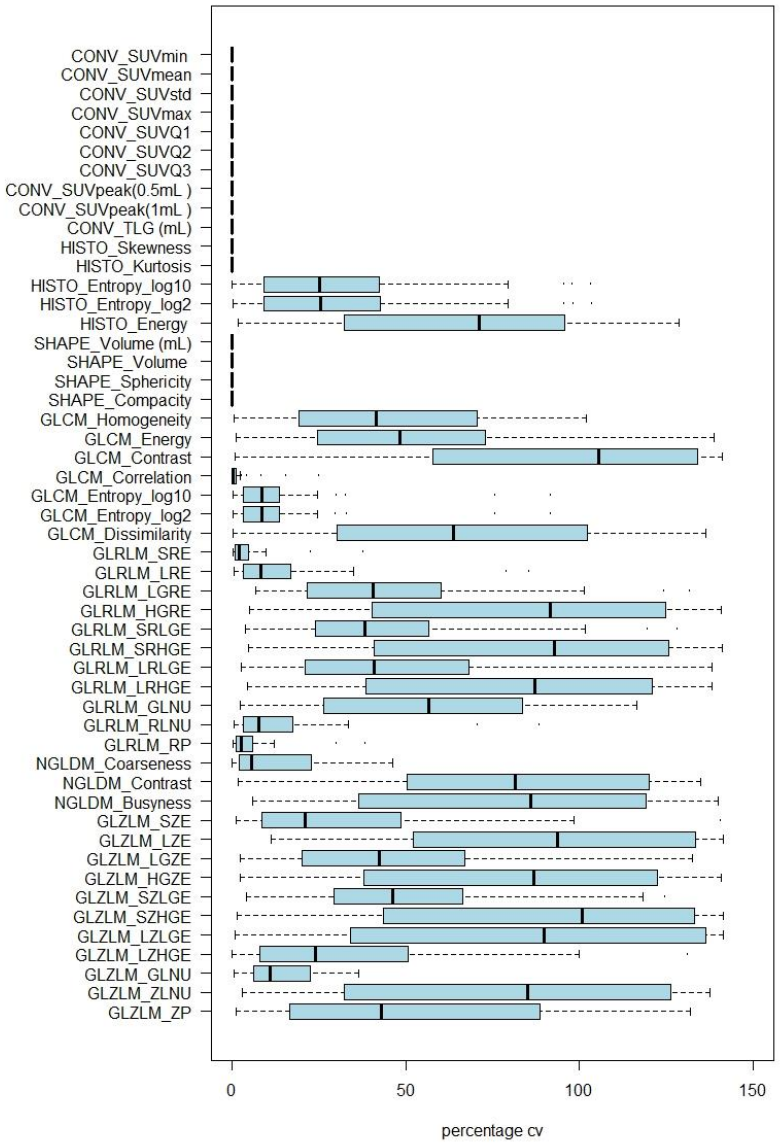
Different segmentation methods: impact on radiomic features





Different discretization methods: impact on radiomic features





Conclusions of this study

The manual delineation of VOI had an impact on RFs values dependent on RF type, preserving the correlation with high ICC values in most cases despite some relatively high COV^{L} values.

The 40% SUV_{max} threshold increased the RFs robustness, but with a potential loss of information and analyzable lesions.

A semi-automatic segmentation algorithm might be helpful to solve both the impact of different manual segmentations on RFs robustness and the loss of valuable information due to SUV_{max} threshold segmentation method.

Finally, the gray-level discretization influences the robustness of RFs, which vary depending on the use of relative or absolute resampling. In our opinion, an absolute resampling better suited to the evaluation of NETs with functional imaging (^{68}Ga-DOTA-TOC PET/CT).

These results underline the needing to standardize the methodology used in the radiomic PET studies in ^{68}Ga-DOTA-TOC PET/CT.

My research activity

In the field of radiomics applied to nuclear medicine PET images (^{68}Ga and ^{18}F):

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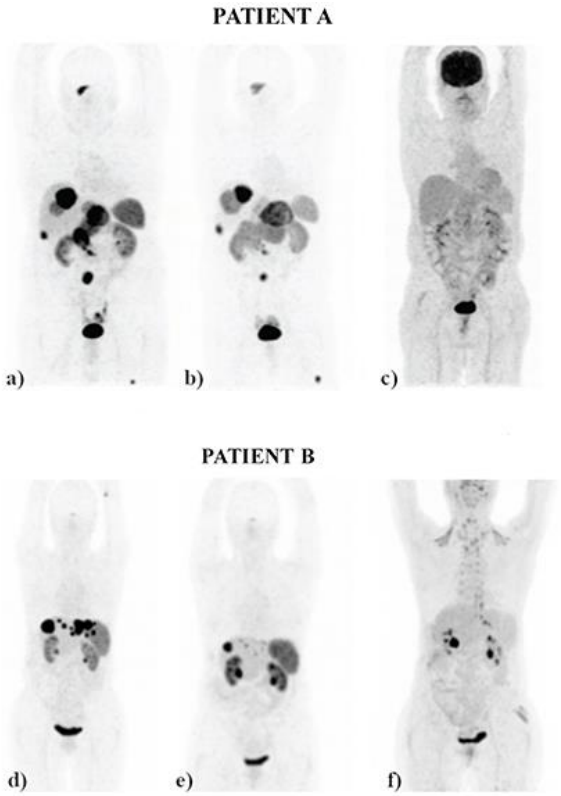
In the field of radiomics applied to breast MRI images

- Preliminary investigation of predictive values of therapy response

Potential predictive value of radiomics for a radiometabolic therapy

frontiers in Medicine

BRIEF RESEARCH REPORT
published: 26 January 2021
doi: 10.3389/fmed.2020.601853



^{68}Ga-DOTATOC PET/CT-Based Radiomic Analysis and PRRT Outcome: A Preliminary Evaluation Based on an Exploratory Radiomic Analysis on Two Patients

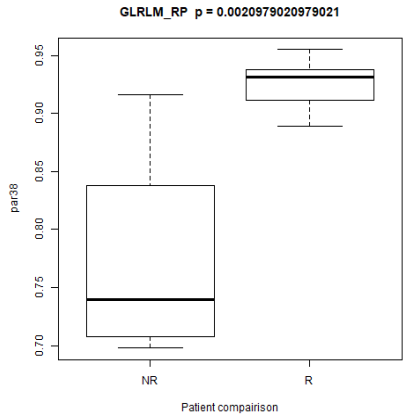
Virginia Liberini[1], Osvaldo Rampado[2], Elena Gallio[2], Bruno De Santi[3], Francesco Ceci[1], Beatrice Dionisi[1], Philippe Thuillier[1,4], Libero Ciuffreda[5], Alessandro Piovesan[6], Federica Fioroni[7], Annibale Versari[8], Filippo Molinari[3] and Désirée Deandreis[1]*

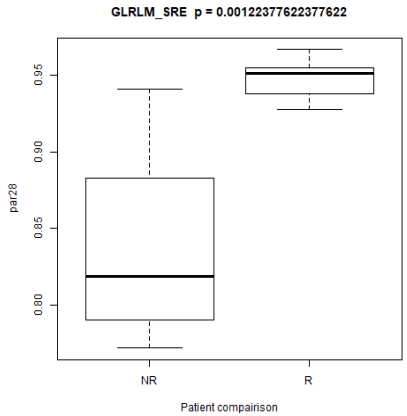
Aim: This work aims to evaluate whether the radiomic features extracted by 68Ga-DOTATOC-PET/CT of two patients are associated with the response to peptide receptor radionuclide therapy (PRRT) in patients affected by neuroendocrine tumor (NET).

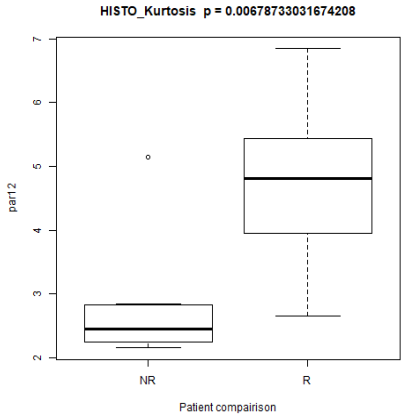
Methods: This is a pilot report in two NET patients who experienced a discordant response to PRRT (responder vs. non-responder) according to RECIST1.1. A total of eight liver metastases in patient A and 10 liver metastases in patient B were considered for inter-patient RF comparison. Radiomic analysis was performed, extracting 38 radiomic features (RFs) from the patients' lesions.

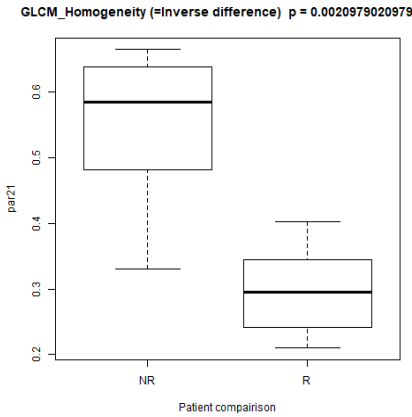
Potential predictive value of RF in PRRT: responder vs non responder

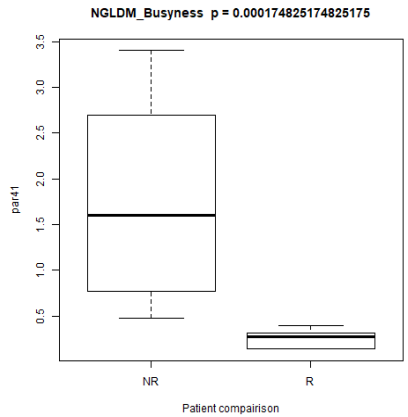
Comparing the liver metastases of pre-PRRT scan, 28 RFs resulted significantly different between patients A and B in the Mann–Whitney test.

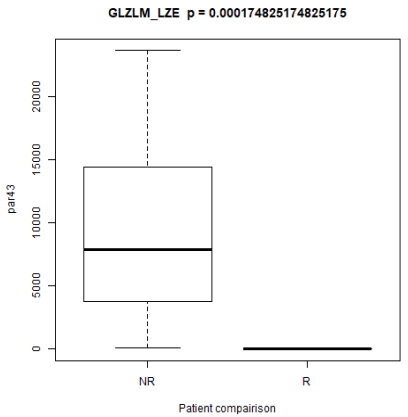


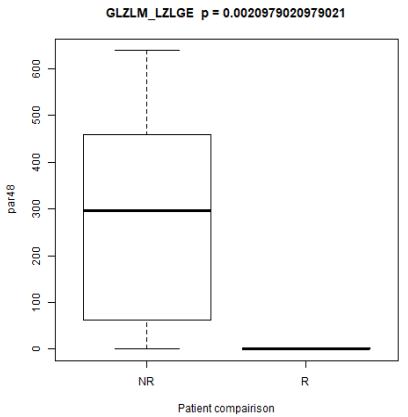


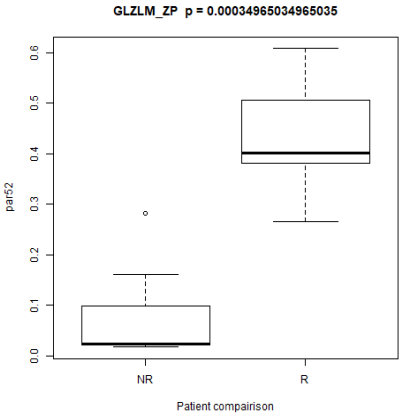






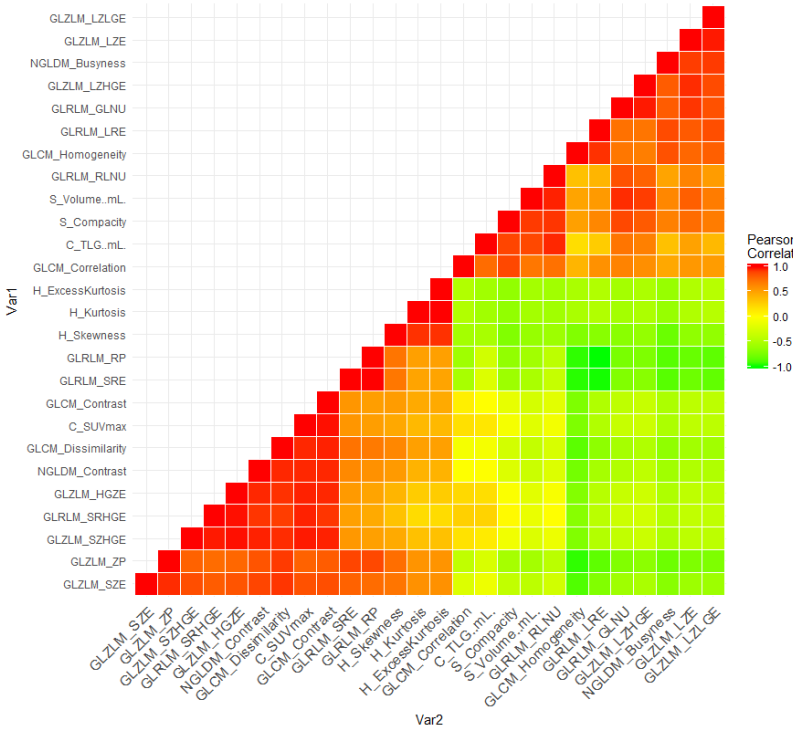


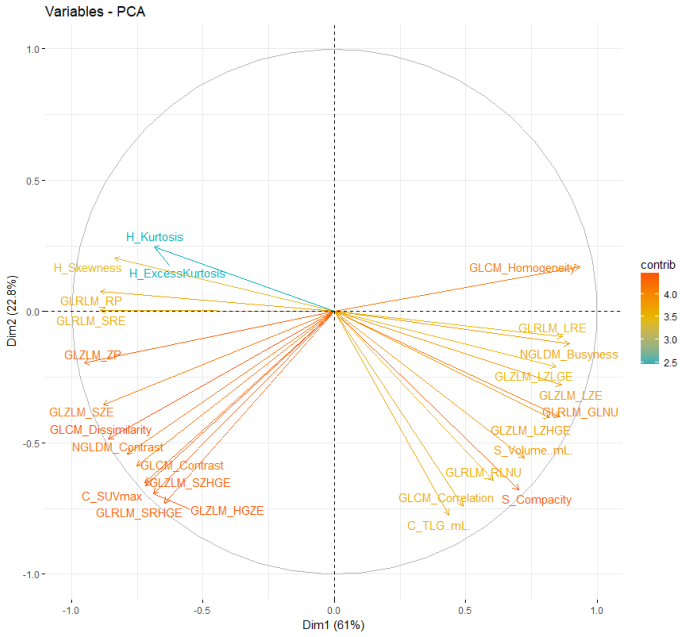




Potential predictive value of RF in PRRT: correlation and independence

Pearson correlation and principal component analysis (PCA) were used to evaluate the correlation and independence of the different RFs.





Conclusion: This preliminary analysis suggests the use of RFs as parameters to evaluate response to PRRT in NET patients. Moreover, pre-therapy RFs and RF changes observed from pre- to post-therapy scan might help to predict and to assess response to PRRT, leading to optimization in the management of NET patients.

Potential diagnostic value of RF in lung NET

biomedicines MDPI

Biomedicines. 2021 Mar; 9(3): 281.
Published online 2021 Mar 10. doi: 10.3390/biomedicines9030281

PMCID: PMC8001140
PMID: 33801987

Diagnostic Value of Conventional PET Parameters and Radiomic Features Extracted from 18F-FDG-PET/CT for Histologic Subtype Classification and Characterization of Lung Neuroendocrine Neoplasms

Philippe Thuillier,[1,2,*] Virginia Liberini,[1] Osvaldo Rampado,[3] Elena Gallio,[3] Bruno De Santi,[4] Francesco Ceci,[1] Jasna Metovic,[5] Mauro Papotti,[5] Marco Volante,[6] Filippo Molinari,[4] and Désirée Deandreis[1]

Aim: To evaluate if conventional Positron emission tomography (PET) parameters and radiomic features (RFs) extracted by 18F-FDG-PET/CT can differentiate among different histological subtypes of lung neuroendocrine neoplasms (Lu-NENs).

Conclusion: In our study, conventional PET parameters were able to distinguish Lu-NECs from Lu-NETs, but not TC from AC. RFs did not provide additional information.

My research activity

In the field of radiomics applied to nuclear medicine PET images (^{68}Ga and ^{18}F):

- Impact of different reconstruction methods
- Evaluation of the impact of different segmentations on neuroendocrine tumours
- Evaluation of the impact of different pre processing parameters (discretization)
- Preliminary assessment of predictive value of radiomics in PRRT patients
- Development of a test phantom with 3D simulated lesions

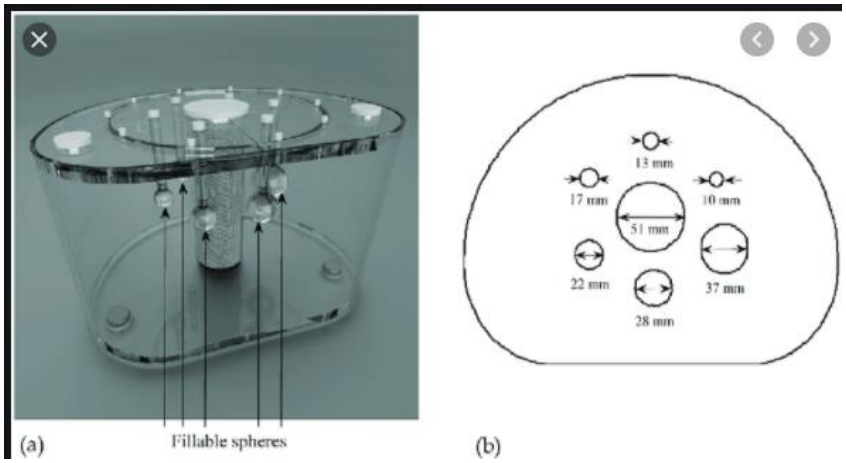
In the field of radiomics applied to lung CT images (Covid patients)

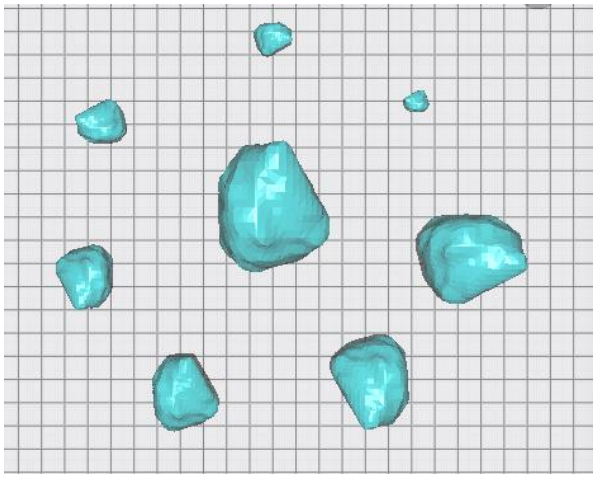
- Evaluation of the impact of different image reconstruction methods

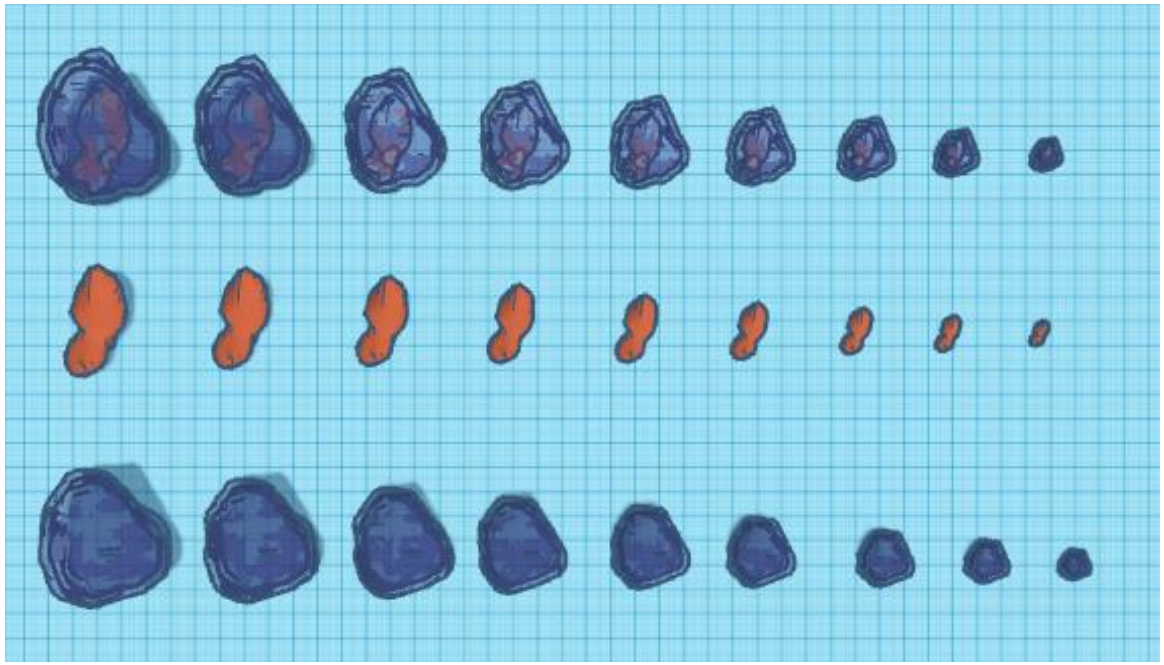
In the field of radiomics applied to breast MRI images

- Preliminary investigation of predictive values of therapy response

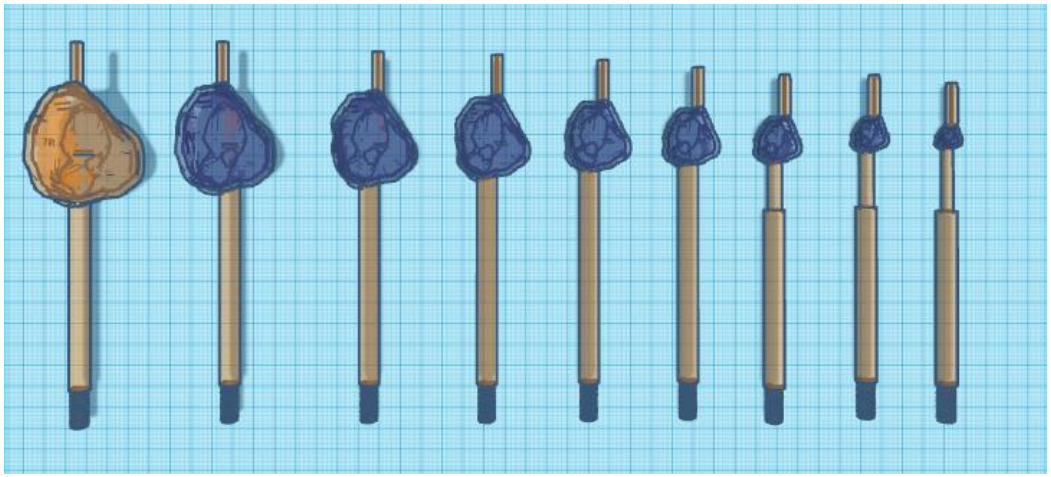
Development of a test phantom with 3D simulated lesions





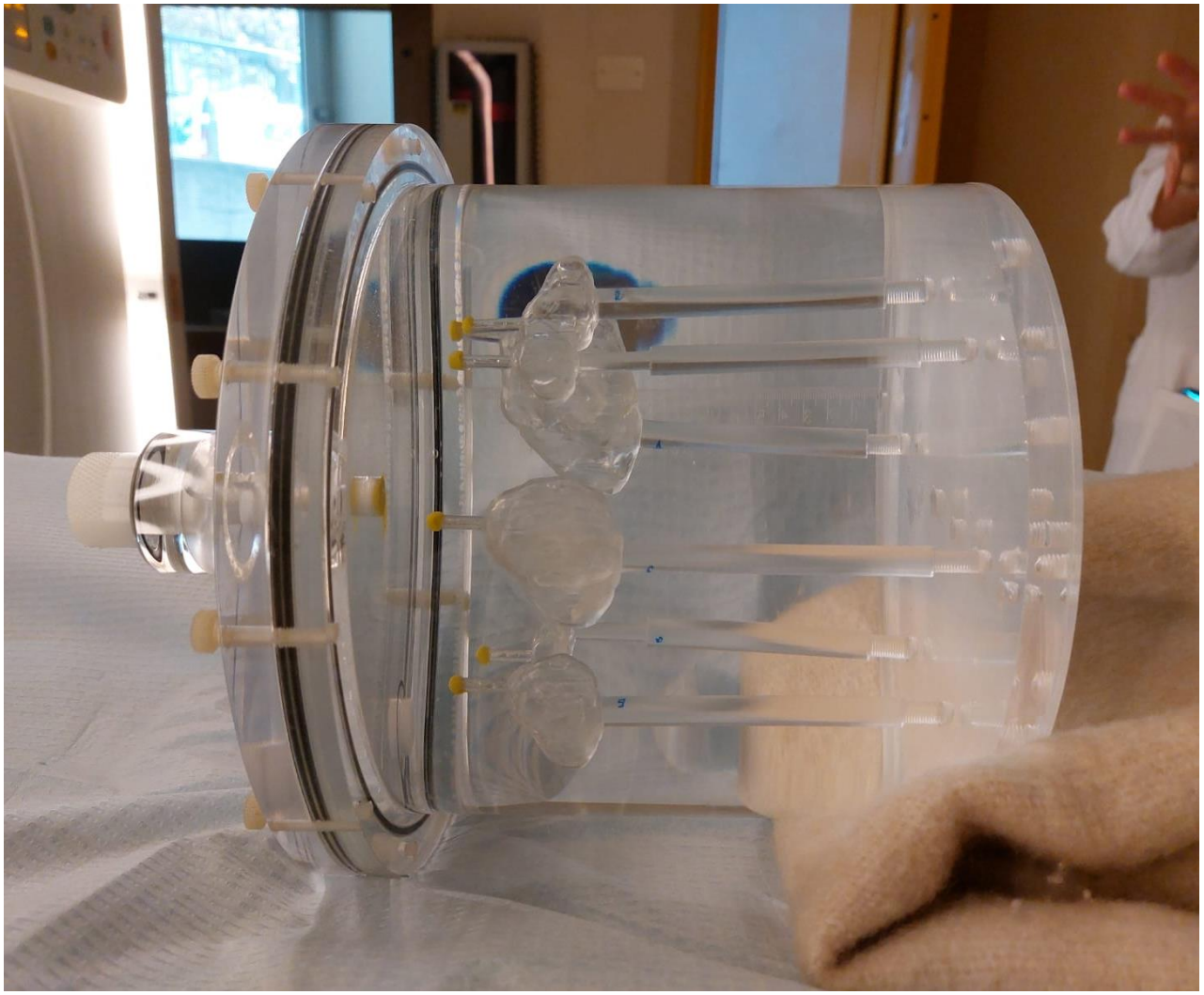


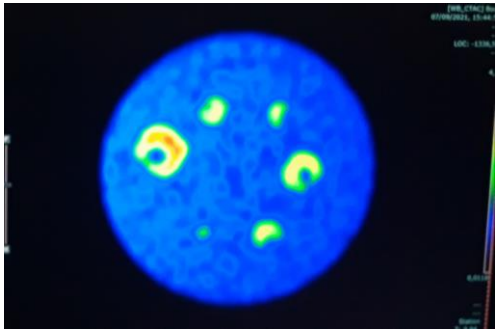
Development of a test phantom with 3D simulated lesions

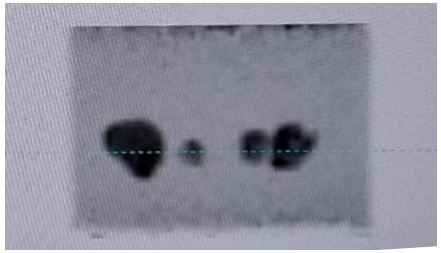


Part	X	Y	Z
Lesion maximum size	47,39	54,38	45,21
Necrotic core m. size	23,67	42,38	25,63

Development of a test phantom with 3D simulated lesions







Next steps…

Main results expected from phantom study in PET/CT:

- robustness of the main radiomic features with respect to different image acquisition protocols

- investigation of the optimal acquisition and reconstruction parameters to correctly assess the radiomic features.

- definition of models that allow us to predict the effect on the radiomic characteristics of changes in acquisition parameters.

- evaluate the actual possibility of carrying out multicentric radiomic studies exempt from confounding elements linked to the different technologies and methods of image production.

CORSO FAD SINCRONO AIFM

SCUOLA SUPERIORE
DI FISICA IN MEDICINA
PIERO CALDIROLA

Radiomica per fisici medici: istruzioni per l'uso

Responsabili Scientifici:
Michele Avanzo, Osvaldo Rampado

Corso FAD teorico pratico
Modalità sincrona • **3 incontri**
22-23-24 settembre 2021

aifm FAD

Evento Formativo in fase di accreditamento
Professioni: Fisico
Obiettivo formativo: contenuti tecnico-professionali (conoscenze e competenze) specifici di ciascuna professione, specializzazione e attività ultraspecialistiche

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Responsabili Scientifici:

Michele Avanzo, *Torino*

Osvaldo Rampado, *Torino*

Coordinatori Scientifici:

Francesca Botta, *Milano*

Veronica Rossetti, *Torino*

Finalità del Corso

La radiomica è una disciplina che si è sviluppata nell'ultimo decennio nell'ambito della diagnostica per immagini quantitativa. In particolare le caratteristiche radiomiche di un elemento di un'immagine medica sono il risultato di un calcolo applicato ai valori numerici dei pixel, il cui risultato può essere correlato alla forma, al volume e alla distribuzione statistica e spaziale di tali valori. L'interesse crescente per le caratteristiche radiomiche è dato dal significato che esse possono avere nei percorsi clinici diagnostici e terapeutici.
Il flusso di lavoro di uno studio radiomico prevede diversi compiti che appartengono comunemente alle conoscenze e competenze dello specialista in fisica medica: dall'assicurazione di qualità delle immagini acquisite al ricampionamento dei dati, dalle tecniche di segmentazione dei volumi alle elaborazioni statistiche dei risultati.

CORSO AIFM

Giovedì 23 settembre 2021

9.00 Il preprocessing dei dati.
Marco Bertolini, Giacomo Feliciani

10.00 Studi su fantoccio per valutare la stabilità dei risultati.
Francesca Botta, Osvaldo Rampado

10.50 *Coffee break*

11.10 Il quality assurance dei dati a disposizione.
Cristina de Mattia

12.00 Data standardization and methods for multi center dataset harmonization.
Mathieu Hatt

13.00 *Pausa pranzo*

14.00 Esercitazione 2 • Valutazione dell'impatto di apparecchiature e parametri di acquisizione non omogenei.
Osvaldo Rampado, Elena Gallio

16.00 Confronto docenti discenti.

Venerdì 24 settembre 2021

9.00 La scelta delle variabili cliniche di interesse.
Nicola Dinapoli

10.00 La selezione delle features e lo sviluppo di un modello.
Michele Avanzo

10.50 *Coffee break*

11.10 La validazione interna ed esterna.
Tiziana Rancati

12.00 Sessione non accreditata ECM.

13.00 *Pausa pranzo*

14.00 Esercitazione 3 • Selezione features di interesse per un dataset e sviluppo di una signature radiomica.
Michele Avanzo

16.00 Confronto docenti discenti.

Backup slides

My research activity

In the field of radiomics applied to nuclear medicine PET images (^{68}Ga and ^{18}F):

- Impact of different reconstruction methods
- Evaluation of the impact of different segmentations on neuroendocrine tumours
- Evaluation of the impact of different pre processing parameters (discretization)
- Preliminary assessment of predictive value of radiomics in PRRT patients
- Development of a test phantom with 3D simulated lesions

In the field of radiomics applied to lung CT images (Covid patients)

- Evaluation of the impact of different image reconstruction methods

In the field of radiomics applied to breast MRI images

- Preliminary investigation of predictive values of therapy response

Impact of iterative reconstruction in CT

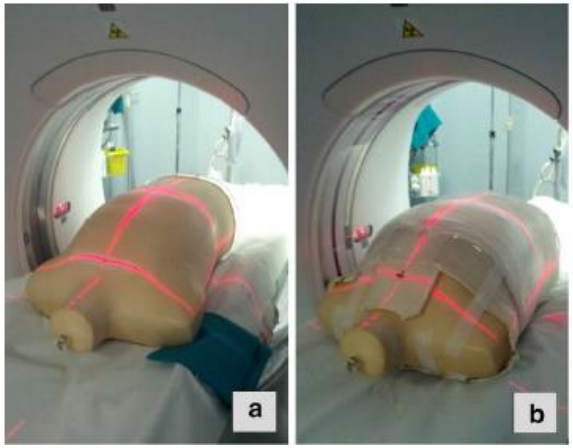
Effects of different levels of CT iterative reconstruction on low-contrast detectability and radiation dose in patients of different sizes: an anthropomorphic phantom study

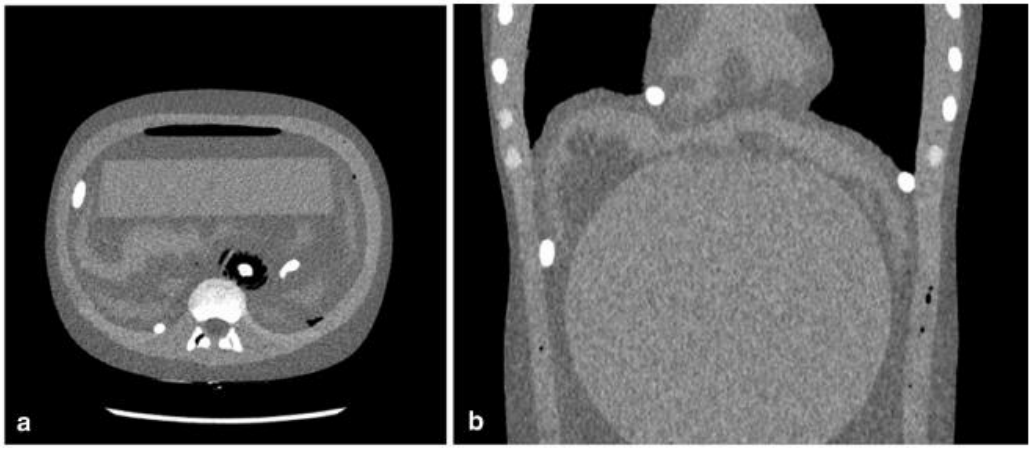
Osvaldo Rampado, Alessandro Depaoli, Filippo Marchisio, Marco Gatti, Damien Racine, Valeria Ruggeri, Irene Ruggirello, Fatemeh Darvizeh, Paolo Fonio & Roberto Ropolo

La radiologia medica **126**, 55–62 (2021) | Cite this article

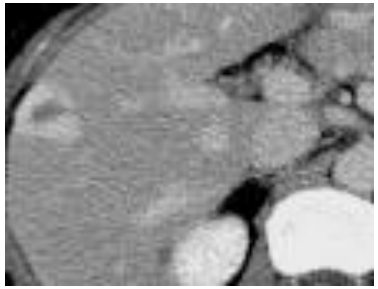
La radiologia medica
https://doi.org/10.1007/s11547-020-01228-5

COMPUTED TOMOGRAPHY

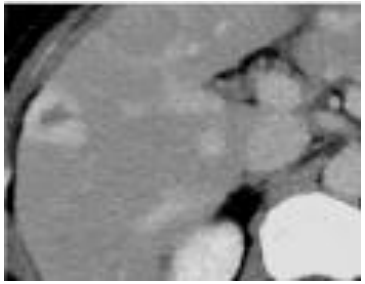




FBP

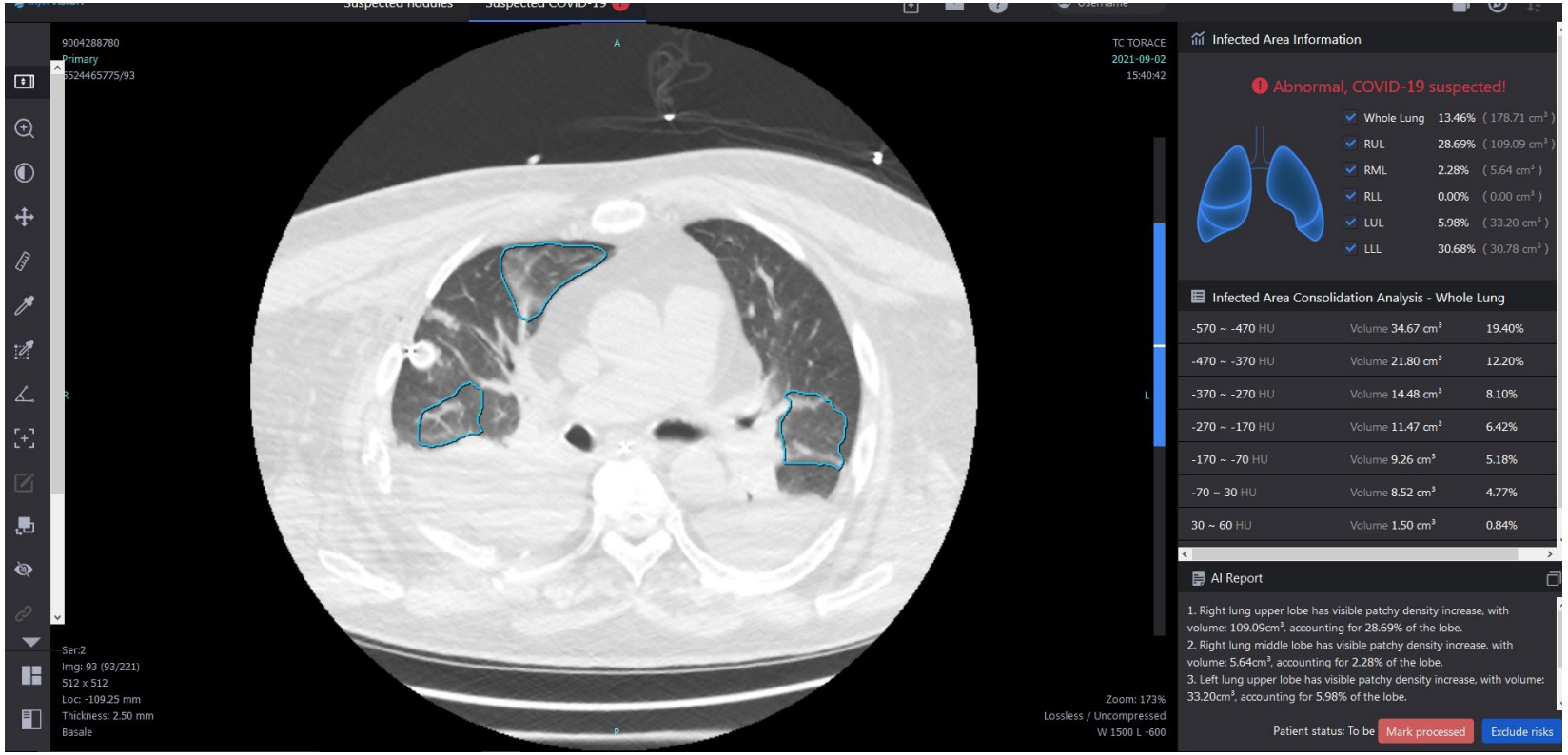


Iterative reconstruction



The iterative algorithm maintained the low-contrast detectability up to a dose reduction of about 70%, following application of a 50% ASIR-V combined with automatic tube current modulation, regardless of the phantom size. At further dose reductions using greater iterative percentages, a significant decrease in detectability was observed.

Lung CT radiomics



30 patients with COVID pneumonia (swab positive), including 15 with CT with ASIR and 15 with CT without ASIR 30 patients with non-COVID pneumonia (swab negative), including 15 with CT with ASIR and 15 with CT without ASIR

29 mm spherical ROI for each patient.

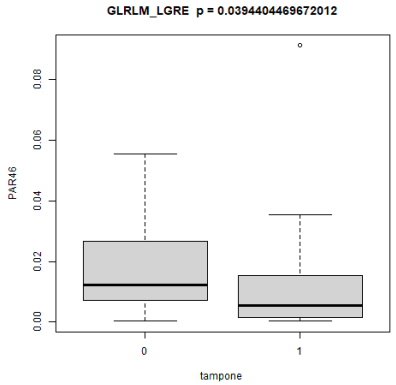
Lung CT radiomics

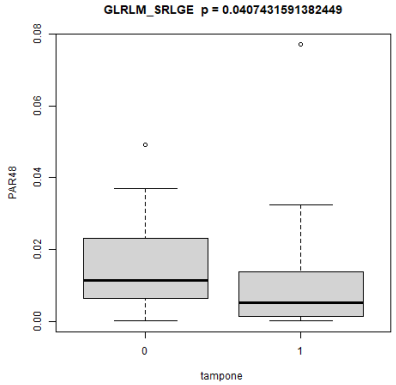
The most interesting results are related to the texture features. There are 9 features that show significant differences between the presence or absence of ASIR, and 4 other features that highlight the differences between positive and negative patients (with single AUC values between 0.64 and 0.67).

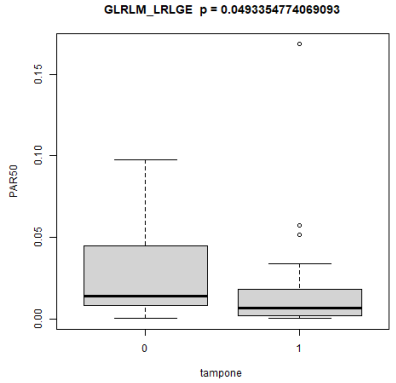
Two other features have p values of 0.06 and 0.07 with respect to the buffer and AUC> 0.63, therefore potentially interesting for the model.

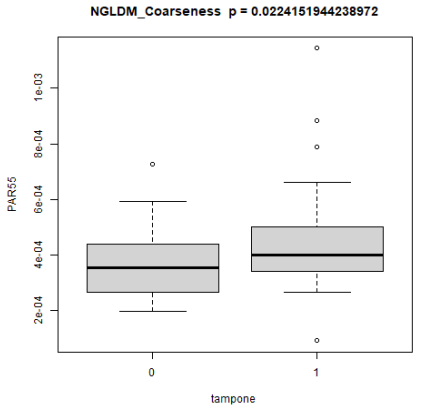
	Confronto tra ASIR presente e assente			Confronto tampone positivo e negativo			Scheirer–Ray–Hare test (analogo non parametrico di ANOVA a due vie)			
Confronto tra ASIR presente e assente	Tutti	Tamp 0	Tamp 1	Tutti	ASIR 0	ASIR 1	ASIR	tampone	interdipendenza tampone e	AUC singole
GLCM_Homogeneity[=InverseDifference]	0.04	0.21	0.08	1.00	0.91	0.92	0.04	1.00	0.87	0.50
GLCM_Energy[=AngularSecondMoment]	0.07	0.15	0.23	0.89	0.78	0.95	0.07	0.89	0.81	0.51
GLCM_Contrast[=Variance]	0.11	0.36	0.19	0.62	0.78	0.85	0.12	0.61	0.91	0.54
GLCM_Correlation	0.29	0.81	0.31	0.82	0.71	0.82	0.28	0.81	0.63	0.52
GLCM_Entropy_log10	0.06	0.25	0.17	0.69	0.73	0.95	0.06	0.68	0.98	0.53
GLCM_Entropy_log2[=JointEntropy]	0.06	0.25	0.17	0.69	0.73	0.95	0.06	0.68	0.98	0.53
GLCM_Dissimilarity	0.10	0.40	0.17	0.78	0.94	0.98	0.10	0.77	0.89	0.52
GLRLM_SRE	0.05	0.17	0.11	0.92	0.99	0.98	0.05	0.92	0.95	0.51
GLRLM_LRE	0.04	0.18	0.11	0.95	0.88	0.95	0.04	0.95	0.86	0.50
GLRLM_LGRE	0.83	0.90	0.96	0.04	0.13	0.18	0.90	0.04	0.92	0.65
GLRLM_HGRE	0.12	0.67	0.11	0.68	0.30	0.67	0.12	0.67	0.35	0.53
GLRLM_SRLGE	0.79	0.84	0.99	0.04	0.13	0.19	0.86	0.04	0.90	0.65
GLRLM_SRHGE	0.11	0.67	0.09	0.70	0.30	0.61	0.11	0.69	0.32	0.53
GLRLM_LRLGE	0.98	0.99	0.87	0.05	0.13	0.21	0.95	0.05	0.89	0.64
GLRLM_LRHGE	0.17	0.75	0.12	0.59	0.24	0.67	0.15	0.58	0.31	0.54
GLRLM_GLNU	0.12	0.69	0.09	0.60	0.32	0.85	0.11	0.59	0.38	0.54
GLRLM_RLNU	0.56	0.12	0.44	0.14	0.02	0.73	0.60	0.14	0.08	0.61
GLRLM_RP	0.05	0.17	0.12	0.95	0.94	0.98	0.05	0.95	0.92	0.50
NGLDM_Coarseness	0.25	0.18	0.93	0.02	0.02	0.55	0.29	0.02	0.28	0.67
NGLDM_Contrast	0.04	0.17	0.11	0.62	0.71	0.73	0.05	0.61	0.95	0.54
NGLDM_Busyness	0.93	0.36	0.40	0.19	0.07	0.89	0.98	0.19	0.19	0.60
GLZLM_SZE	0.04	0.28	0.09	0.80	0.99	0.82	0.04	0.79	0.75	0.52
GLZLM_LZE	0.04	0.27	0.09	0.98	0.76	0.82	0.04	0.98	0.69	0.50
GLZLM_LGZE	0.70	0.90	0.90	0.07	0.18	0.31	0.76	0.07	0.94	0.63
GLZLM_HGZE	0.15	0.67	0.11	0.67	0.29	0.67	0.14	0.67	0.34	0.53
GLZLM_SZLGE	0.76	0.99	0.90	0.06	0.16	0.24	0.82	0.06	1.00	0.64
GLZLM_SZHGE	0.08	0.46	0.12	0.96	0.55	0.70	0.08	0.96	0.51	0.50
GLZLM_LZLGE	0.66	0.99	0.40	0.09	0.06	0.52	0.60	0.09	0.47	0.62
GLZLM_LZHGE	0.89	0.75	0.99	0.11	0.33	0.21	0.83	0.11	0.80	0.38
GLZLM_GLNU	0.62	0.78	0.28	0.17	0.09	0.85	0.57	0.16	0.31	0.60
GLZLM_ZLNU	0.02	0.02	0.34	0.20	0.17	0.89	0.03	0.19	0.38	0.59
GLZLM_ZP	0.05	0.24	0.13	0.92	1.00	0.98	0.05	0.91	0.92	0.51

Lung CT radiomics: preliminary model





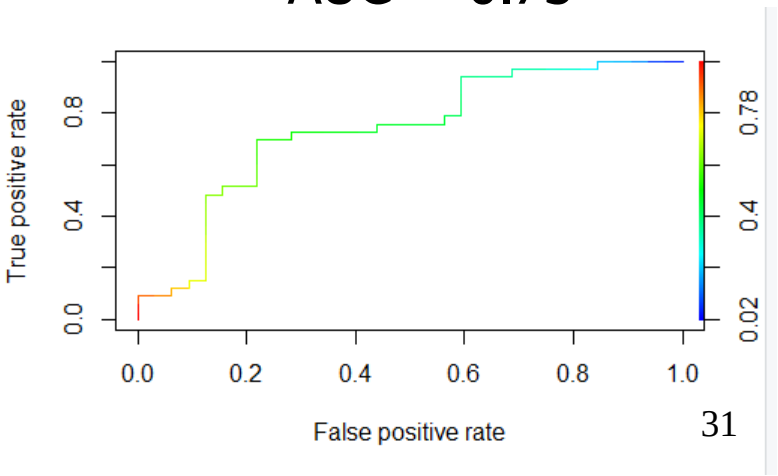





```
par1<-scale(my_data$GLRLM_LGRE)
par2<-scale(my_data$GLRLM_SRLGE)
par4<-scale(my_data$NGLDM_Coarseness)
par5<-scale(my_data$GLZLM_LGZE)

radiom_all <- glm(t ~ par1+par2+par4+par5,family=binomial(link=logit))
```

```
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.01475    0.27764   0.053   0.9576
par1        -12.07986    7.64917  -1.579   0.1143
par2         13.58766    8.18397   1.660   0.0969 .
par4          0.59097    0.39897   1.481   0.1385
par5         -2.05173    0.91394  -2.245   0.0248 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 90.094  on 64  degrees of freedom
Residual deviance: 78.410  on 60  degrees of freedom
AIC: 88.41
```

AUC = 0.73



My research activity

In the field of radiomics applied to nuclear medicine PET images (^{68}Ga and ^{18}F):

- Impact of different reconstruction methods
- Evaluation of the impact of different segmentations on neuroendocrine tumours
- Evaluation of the impact of different pre processing parameters (discretization)
- Preliminary assessment of predictive value of radiomics in PRRT patients
- Development of a test phantom with 3D simulated lesions

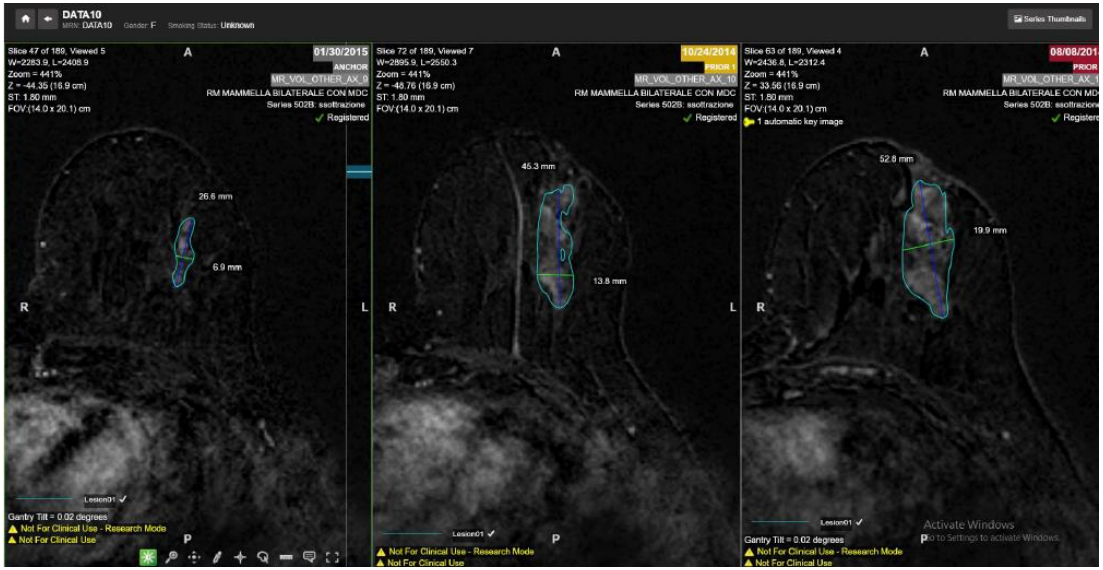
In the field of radiomics applied to lung CT images (Covid patients)

- Evaluation of the impact of different image reconstruction methods

In the field of radiomics applied to breast MRI images

- Preliminary investigation of predictive values of therapy response

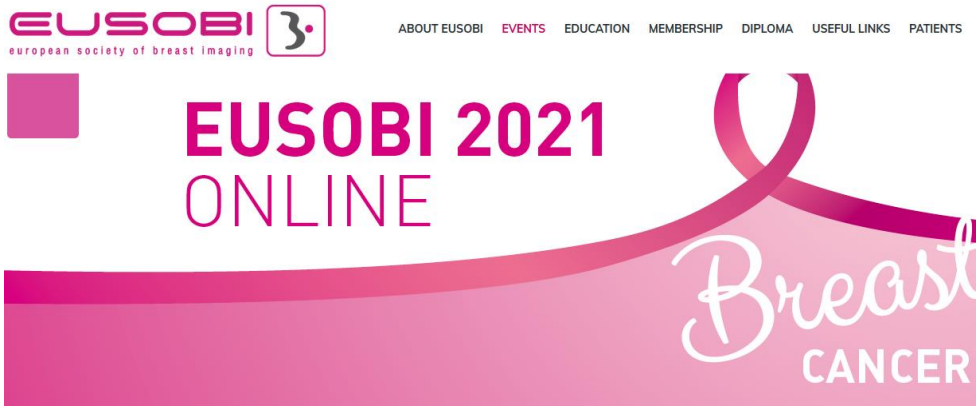
Radiomics applied to breast MRI



Purpose To investigate the potential correlation between radiomic features and pathological complete response (pCR) to neoadjuvant chemotherapy (NAC) of triple negative breast cancer (TNBC) at early, middle and end treatment breast MRI.

Methods We conducted a retrospective analysis including 13 patients with newly diagnosed TNBC, morphologically described as mass and mass-non-mass lesions, who underwent breast Dynamic Contrast Enhanced (DCE) MRI and DWI before, during and post-NAC, seven of whom experienced pCR. Using a commercial software (HealthMyne platform), each lesion was segmented on MRI images at early, middle and end treatment, extracting 38 morphological features,14 intensity-based statistical features and 138 GLCM-based texture feature values computed by means of five different feature aggregation methods. Radiomic metrics were evaluated in the first and the fifth DCE sequence and then in the highest b-value (b:1000) DWI sequence, avoiding the necrotic component, if present. A delta-radiomics approach was used to investigate the potential meaning of the variation of features between the early and the middle treatment MRI.

Radiomics applied to breast MRI



Results In the three stages of the treatment, radiomic features with statistically significant differences between pCR and no-pCR group were respectively: in pretreatment MRI, 1 feature in DCE sequences and 26 features in DWI sequences; in end treatment MRI, 4 features in DCE sequences and 6 features in DWI sequences; in the delta-radiomics analysis, 3 features in DCE sequences.

Conclusion Despite the small sample analyzed, our preliminary study suggests that MRI radiomic features could be helpful for predicting pCR to NAC in TNBC. However, large prospective studies will be required to confirm the statistical significance of these findings.

Summary statement

Radiomics is a new tool with immense potential for obtaining meanable data to customize each patient's treatment, with promising applications also on the response to NAC in TNBC patients.