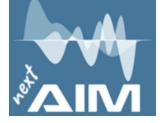
# **NEXT\_AIM** [INFN-CSN5, 2022-2024]

Artificial Intelligence in Medicine (AIM): **NEXt** steps focus on **N**o-so-big data and **EX**plainable techniques





Laboratori Nazionali del Sud

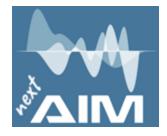


Consiglio Nazionale delle Ricerche Istituto di Bioimmagini e Sistemi Biologici Complessi

> Alessandro Stefano Software Engineer, PhD Consiglio Nazionale delle Ricerche



# Exploring the Challenges of Radiomics Signatures: A case study



# The question that I pose at the heart of my research project in next\_AIM is: What is radiomics used for?

Most of you will answer: Radiomics will one day replace biopsy or predict a patient's response to treatment.



MDPI

Article Phenotyping the Histopathological Subtypes of Non-Small-Cell Lung Carcinoma: How Beneficial Is Radiomics?

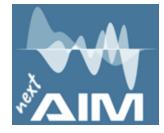
Giovanni Pasini <sup>1,2</sup>, Alessandro Stefano <sup>2,\*</sup>, Giorgio Russo <sup>2</sup>, Albert Comelli <sup>2,3</sup>, Franco Marinozzi <sup>1</sup> and Fabiano Bini <sup>1</sup>

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# Challenges and limitations in applying radiomics to PET imaging: Possible opportunities and avenues for research

#### Alessandro Stefano

Institute of Molecular Bioimaging and Physiology, National Research Council (IBFM-CNR), Cefalù, Italy

#### ARTICLE INFO

#### ABSTRACT

Keywords: Radiomics PET imaging Robustness Reproducibility

Radiomics, the high-throughput extraction of quantitative imaging features from medical images, holds immense potential for advancing precision medicine in oncology and beyond. While radiomics applied to positron emission tomography (PET) imaging offers unique insights into tumor biology and treatment response, it is imperative to elucidate the challenges and constraints inherent in this domain to facilitate their translation into clinical practice. This review examines the challenges and limitations of applying radiomics to PET imaging, synthesizing findings from the last five years (2019-2023) and highlights the significance of addressing these challenges to realize the full clinical potential of radiomics in oncology and molecular imaging. A comprehensive search was conducted across multiple electronic databases, including PubMed, Scopus, and Web of Science, using keywords relevant to radiomics issues in PET imaging. Only studies published in peer-reviewed journals were eligible for inclusion in this review. Although many studies have highlighted the potential of radiomics in predicting treatment response, assessing tumor heterogeneity, enabling risk stratification, and personalized therapy selection, various challenges regarding the practical implementation of the proposed models still need to be addressed. This review illustrates the challenges and limitations of radiomics in PET imaging across various cancer types, encompassing both phantom and clinical investigations. The analyzed studies highlight the importance of reproducible segmentation methods, standardized pre-processing and post-processing methodologies, and the need to create large multicenter studies registered in a centralized database to promote the continuous validation and clinical integration of radiomics into PET imaging.



## **Quartiles: Q1**

- Computer Science Applications
- Health Informatics

## *IF: 7.0*

#### I have highlighted the problems rather than the strengths of the use of radiomics in PET.



MDPI

Article

#### matRadiomics: A Novel and Complete Radiomics Framework, from Image Visualization to Predictive Model

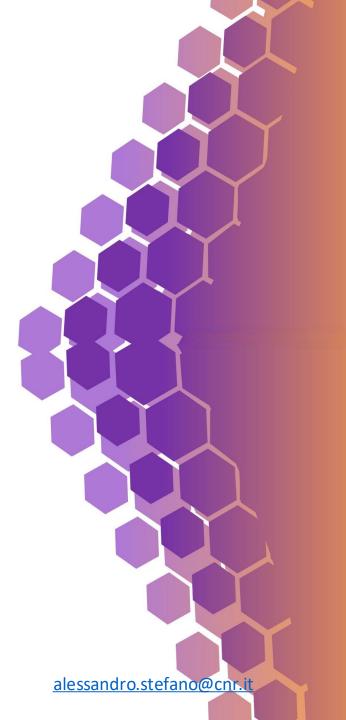
Giovanni Pasini <sup>1</sup><sup>(0)</sup>, Fabiano Bini <sup>2</sup><sup>(0)</sup>, Giorgio Russo <sup>1,\*</sup><sup>(0)</sup>, Albert Comelli <sup>1,3</sup><sup>(0)</sup>, Franco Marinozzi <sup>2</sup> and Alessandro Stefano <sup>1</sup><sup>(0)</sup>

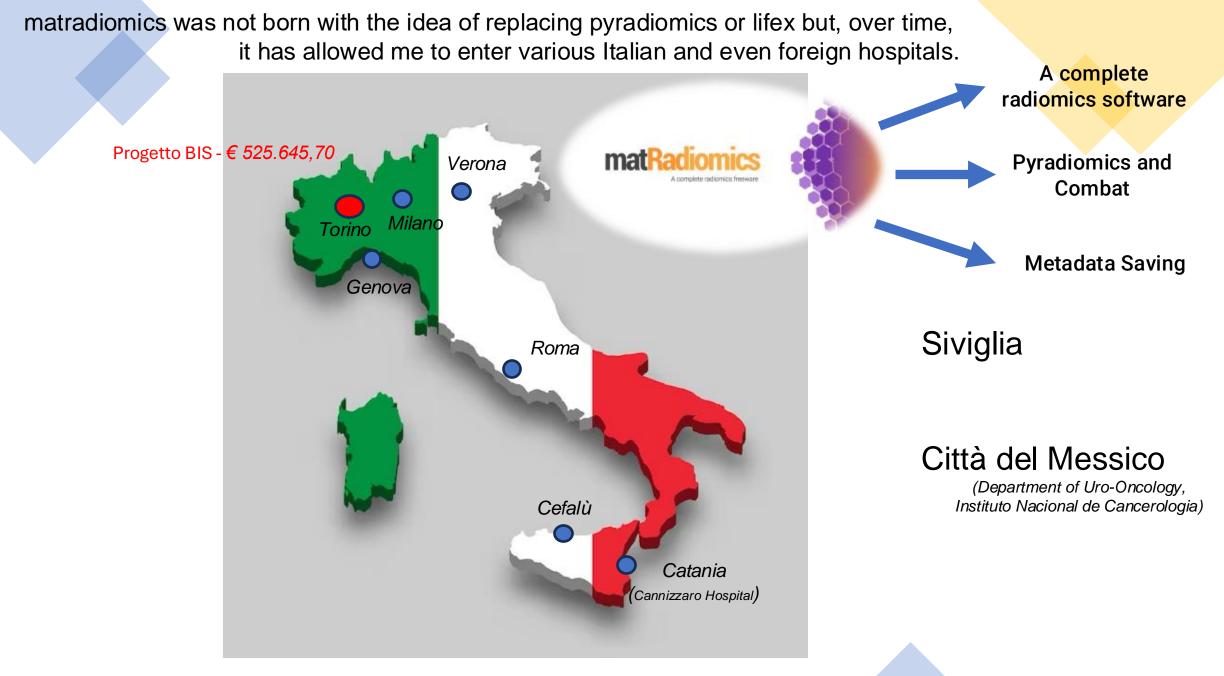
- <sup>1</sup> Institute of Molecular Bioimaging and Physiology, National Research Council (IBFM-CNR), Contrada Pietrapollastra-Pisciotto, 90015 Cefalò, Italy
- <sup>2</sup> Department of Mechanical and Aerospace Engineering, Sapienza University of Rome, Eudossiana 18, 00184 Rome, Italy
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# **matRadiomics**

A complete radiomics freeware

It is a tool that was born with the idea of making a radiomics study replicable.





AIMN: GRUPPO DI STUDIO «INTELLIGENZA ARTIFICIALE E RADIOMICA»

# **NEXT\_AIM: LNS activities**



#### Article

## A Critical Analysis of the Robustness of Radiomics to Variations in Segmentation Methods in <sup>18</sup>F-PSMA-1007 PET Images of Patients Affected by Prostate Cancer

Giovanni Pasini <sup>1,2,+</sup>, Giorgio Russo <sup>3,4</sup>, Cristina Mantarro <sup>4</sup>, Fabiano Bini <sup>1,\*</sup>, Selene Richiusa <sup>2</sup>, Lucrezia Morgante <sup>1</sup>, Albert Comelli <sup>2,5</sup>, Giorgio Ivan Russo <sup>6</sup>, Maria Gabriella Sabini <sup>7</sup>, Sebastiano Cosentino <sup>4</sup>, Franco Marinozzi <sup>1</sup>, Massimo Ippolito <sup>4,+</sup> and Alessandro Stefano <sup>2,3,+</sup>

		INÌ
Manual	Threshold	Region Growing
	•	•
FOR EACH SEGMENTATION MET	HOD FEATURE EXTRACTION FOR EAC	H SEGMENTATION METHOD
Original Image Type (107)	LoG Image Type (930)	Wavelet Image Type (744)
Shape Features	First Order Statistics Features	First Order Statistics Feature
First Order Statistics Features Texture Features GLCM GLDM GLRLM GLSZM NGTDM	Texture Features GLOM GLDM GLRLM GLSZM NGTDM	Texture Features GLCM GLDM GLRLM GLSZM NGTDM
L	3 DATASETS OF 1781 FEATURES MANUAL DATASET, THRESHOLDING DATASET,	

#### AIM:

1. The impact of 3 segmentation methods on radiomics features extracted from 18F-PSMA-1007 PET of 78 patients with prostate cancer.

MDP

2. The performance of KNN, SVM, DA, RF, AdaBoost and NN in discriminating between low- and high-risk patients.

#### **RESULTS**:

1. Shape feature class demonstrated the least robustness, while the GLCM feature class exhibited the highest robustness.

Furthermore, segmentation methods significantly impacted feature selection.

2. High performance was achieved using region growing and DA to discriminate between low-risk and high-risk prostate patients.

# **NEXT\_AIM: LNS activities**

### **SPRINGER LINK**

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Home > Journal of Imaging Informatics in Medicine > Article

## A Robust [<sup>18</sup>F]-PSMA-1007 Radiomics Ensemble Model for Prostate Cancer Risk Stratification

Original Paper | <u>Open access</u> | Published: 30 September 2024 (2024) <u>Cite this article</u>

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Giovanni Pasini Alessandro Stefano Cristina Mantarro, Selene Richiusa, Albert Comelli, Giorgio Ivan Russo, Maria Gabriella Sabini, Sebastiano Cosentino, Massimo Ippolito & Giorgio Russo

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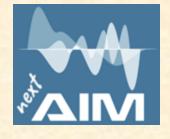
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<u>Journal of Imaging Informatics in</u> Medicine

Aims and scope ightarrow

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## **Quartiles: Q1**

 Radiology, Nuclear Medicine and Imaging

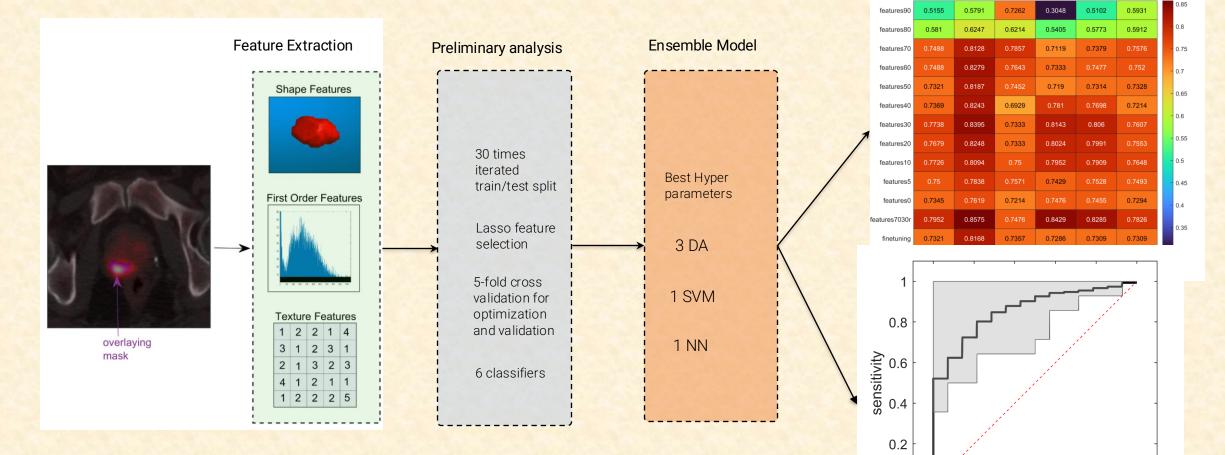
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Society for Imaging Informatics in Medicine

The name of the Journal of Digital Imaging (JDI) has been changed in Journal of Imaging Informatics in Medicine

# Summary



The aim of this study is to investigate the role of [18F]-PSMA-1007 PET in differentiating high- and low-risk prostate cancer (PCa) through a robust radiomics ensemble model.

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features7030r: AUC = 0.8575

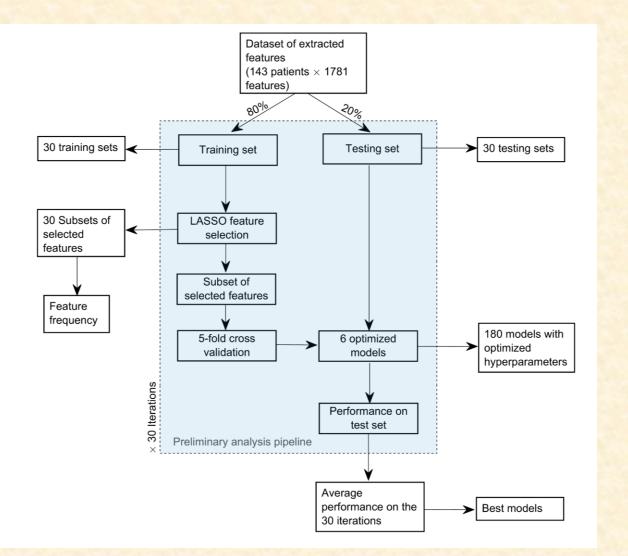
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0.6

This retrospective study included 143 PCa patients.

# **Preliminary Analysis**



A preliminary analysis is conducted to identify subsets of selected features, establish a pool of model hyperparameters, and determine the most effective classifiers among DA, SVM, KNN, NN, RF, and Boost.

It is used to measure stability of selected features.

Small datasets: dataset splitting has an impact on selected features and on the pool of hyperparameters

# **Subset of selected features**

Dataset name	Feature frequency	Subset size
features90	≥90%	1
features80	≥80%	2
features70	≥70%	4
features60	≥60%	5
features50	≥50%	8
features40	$\geq \! 40\%$	12
features30	≥30%	16
features20	≥20%	23
features10	$\geq 10\%$	34
features5	≥5%	52
features0	All 79 features	79
features7030r	Union between finetuning and features70 subsets	11
finetuning	fine-tuning subset	7

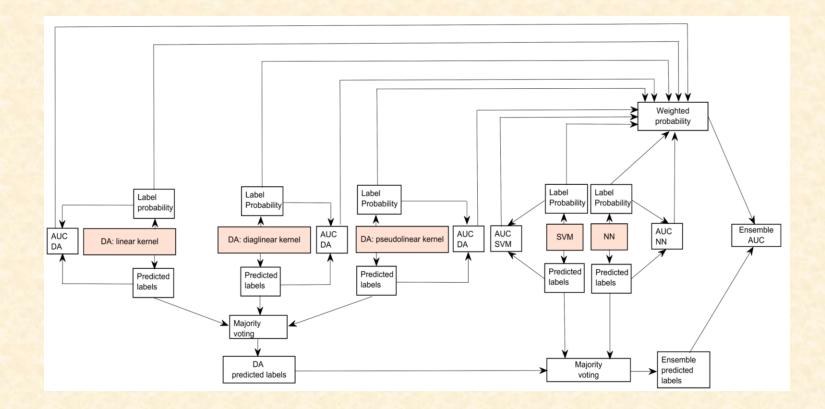
We created 11 datasets of features based on their frequency of appearance (from 0% to 90%) according to the feature frequency value

$$feature_{frequency} = rac{n}{rep} imes 100$$

In addition, the "finetuning" subset is obtained by considering the features with a feature frequency between 30 and 70.

The "features7030r" subset is the union between the "finetuning" and "features70.

# **Ensemble model**



Best hyperparameters chosen from the total pool of hyperparameters considering the median values

- DA: linear kernel, diaglinear kernel, pseudolinear kernel

- SVM

- NN

Majority voting

# Results

features90	0.5155	0.5791	0.7262	0.3048	0.5102	0.5931		0.85
features80	0.581	0.6247	0.6214	0.5405	0.5773	0.5912		0.8
features70	0.7488	0.8128	0.7857	0.7119	0.7379	0.7576	-	0.75
features60	0.7488	0.8279	0.7643	0.7333	0.7477	0.752	_	0.7
features50	0.7321	0.8187	0.7452	0.719	0.7314	0.7328		0.65
features40	0.7369	0.8243	0.6929	0.781	0.7698	0.7214		
features30	0.7738	0.8395	0.7333	0.8143	0.806	0.7607		0.6
features20	0.7679	0.8248	0.7333	0.8024	0.7991	0.7553	-	0.55
features10	0.7726	0.8094	0.75	0.7952	0.7909	0.7648	-	0.5
features5	0.75	0.7838	0.7571	0.7429	0.7528	0.7493	-	0.45
features0	0.7345	0.7619	0.7214	0.7476	0.7455	0.7294		0.4
features7030r	0.7952	0.8575	0.7476	0.8429	0.8285	0.7826		•
finetuning	0.7321	0.8168	0.7357	0.7286	0.7309	0.7309		0.35
	accuracy	auc	sensitivity	specificity	precision	f-score		

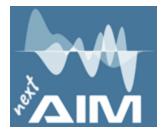
- ← Feature frequency > 90%
- ← Feature frequency > 80%
- ← Feature frequency > 70%
- ← Feature frequency > 60%
- ← Feature frequency > 50%
- Feature frequency > 40%
- ← Feature frequency > 30%
- ← Feature frequency > 20%
- ← Feature frequency > 10%
- ← Feature frequency > 5%
- ← Feature frequency > 0%

- Optimal subset

# **NEXT\_AIM: LNS activities**

The repository of the next\_AIM project is on baltig: <u>https://baltig.infn.it/nextaim</u>

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	Subgr	oups	and projects Shared projects Archived projects
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	0	R	Radiomics_matlab_CNRINFN $\oplus$
	0	F	func_ABIDE ①
	0	L	LungQuantUI 合
	0	D	DragonflAls
	0	Ν	NLP_notebooks
	0	L	LungQuant 合



#### Package: Radiomics\_matlab\_CNRINFN

This function allows importing an xlsx file containing the features of a **radiomics study**, selecting the most significant features, and implementing a predictive model based on Discriminant Analysis.

**INPUT**: a xlsx file, e.g. 'next\_AIM.xlsx';

**OUTPUT:** performance metrics including accuracy, and AUC ROC