ICT in healthcare: Radiomics as a tool to differentiate benign vs. malignant lesions in different imaging modalities

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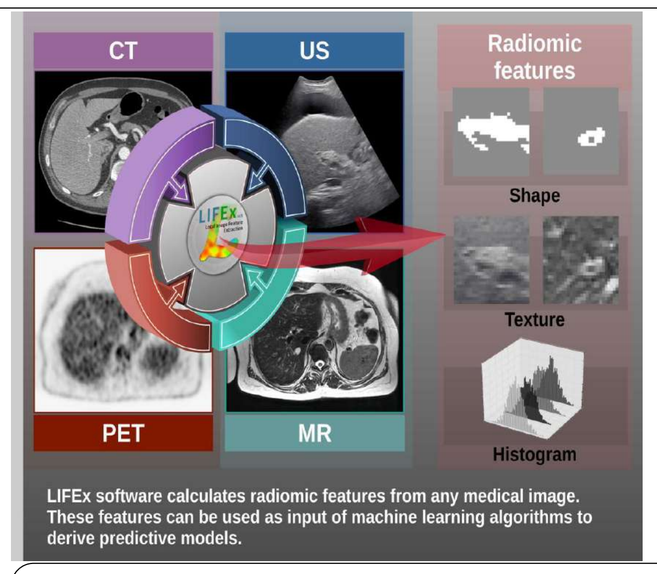
PROJECT MOTIVATION AND BACKGROUND

Motivation:

- Computer-assisted diagnosis can help improve the management of patients with suspicious lesions detected on CT, PET, MRI and/or US.
- Timely and correct diagnosis is crucial to improve the outcome in patients with oncological disorders.

•**Background**:

- Quantitative image analysis techniques (*radiomics*) aim to extract meaningful shape and/or textural *features* from medical images.
- Often invisible to the naked eye, such features can provide crucial insights into the biomedical properties of the underlying tissue.
- Radiomics holds great promises for personalised healthcare



AIMS AND OBJECTIVES

Aim:

- To develop and validate radiomics-based methods to differentiate between benign and malignant lesions on CT, PET US.

Objectives:

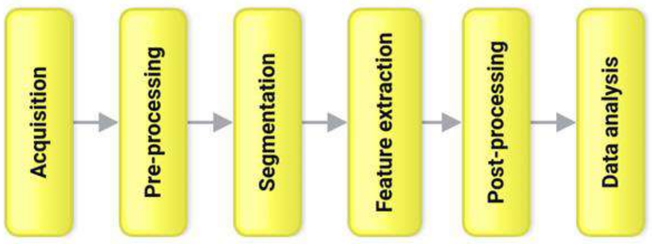
- To extract and analyse radiomic features from datasets of medical images such
- To apply machine learning algorithms to classify lesions based on their radiomic profiles.
- To compare the performance of different imaging modalities in distinguishing benign from malignant lesions

METHODOLOGY

There are 2 basic approaches of radiomics.

- Conventional radiomics
- Deep-learning radiomics

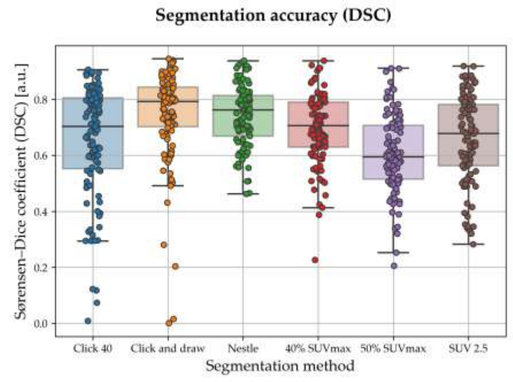
Conventional radiomics consists of six sequential steps shown in fig. below (Bianconi et al., 2020).

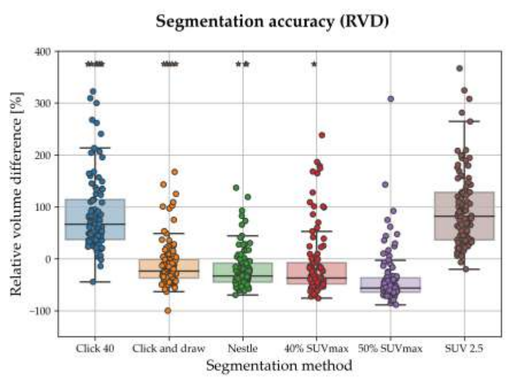


PROJECT IMPLEMENTATION

Performance analysis of six semi-automated tumour delineation methods on [18F]-FDG PET in patients with head & neck cancer

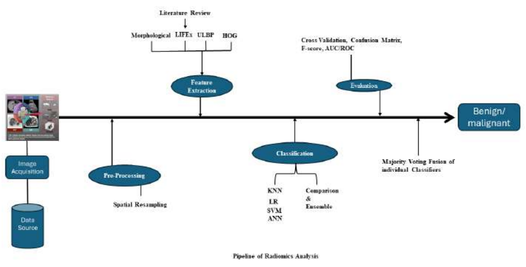
- We evaluated the performance of six hand-crafted, training-free methods (four threshold-based, two algorithm-based) for the semi-automated delineation of HNC lesions on FDG PET.
- The study was carried out on a population of n = 103 subjects, and the standard of reference was manual segmentation generated by nuclear medicine specialists. Figures of merit were Sørensen–Dice coefficient (DSC) and relative volume difference (RVD).





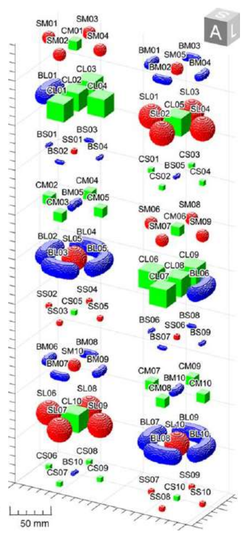
PROJECT IMPLEMENTATION

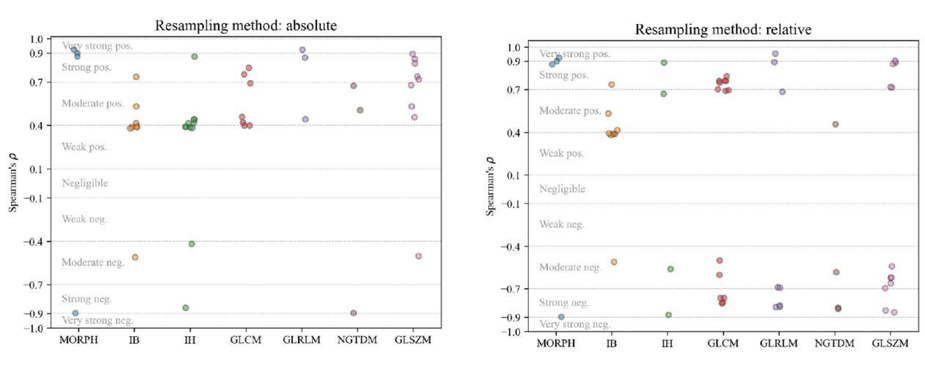
The basic pipeline of the project is to gather data from an authentic source and apply image processing techniques. Select the best method of machine learning and check its accuracy. For this purpose, first, we tested the dependency of radiomic features using CT phantoms.



Sensitivity of radiomics features to region volume

- We found that out of 103 features, 45 (54) were volume-dependent when absolute (relative) signal resampling was applied.
- Signal resampling scheme had a marked effect on the number and distribution of the volume-correlated features.
- Relative resampling resulted in more volume-correlated features than absolute resampling.
- ROI volume can be a potentially confounding factor in radiomics analysis.





PROJECT IMPLEMENTATION

Classification of lung nodules on CT via pseudo-colour images and deep features from pre-trained convolutional networks

- In this work we propose a pseudo-colouring scheme based on principal component analysis (PCA) as an alternative to GS and PCL for extracting deep features by pre-trained CNN from CT scans.
- We compared the effectiveness of the three methods for lung nodule classification by combining them with three pre-trained CNN models (ConvNeXT, ResNet50 and Swin V2), four classifiers (1-NN, Gaussian naïve Bayes, linear classifier and logistic regression) and three feature normalisation methods (none, min-max and Z-score).

Table: Results of cross validation (train set = LIDC-IDRI, test set = LUNGx). Boldface indicates the highest accuracy, italics the baseline value (conventional features).

Pseudo-colour method	Feature extraction	Background removal	Classifier	Normalisation method	Acc. (%)
GS	convnext	Yes	Linear Classifier	Z-score	62.3
GS	convnext	Yes	Logistic Regression	Z-score	62.3
GS	resnet50	Yes	GaussianNB	Z-score	62.3
GS	resnet50	Yes	GaussianNB	None	62.3
GS	resnet50	Yes	GaussianNB	Min-max	62.3
PCA	resnet50	No	GaussianNB	None	63.8
PCA	swinv2	No	Logistic Regression	Min-max	63.8
PCL	resnet50	Yes	GaussianNB	Min-max	**65.2**
PCL	resnet50	Yes	GaussianNB	Z-score	**65.2**
PCL	resnet50	No	Logistic Regression	Z-score	**65.2**
PCL	swinv2	Yes	Linear Classifier	None	**65.2**
–	conventional	–	Logistic Regression	None	*63.8*

National and international collaborations

- **CNIT** (National, Inter-University Consortium for Telecommunications, Perugia Research Unit – www.cnit.it)
- **The University of Buckingham**, TenD Innovations Centre, Buckingham, United Kingdom.

Ongoing work

- Differentiation between benign vs. malignant breast lesions on US images.