Artificial Intelligence in Medicine

Explainable Artificial Intelligence for sarcoma patients

Speaker:
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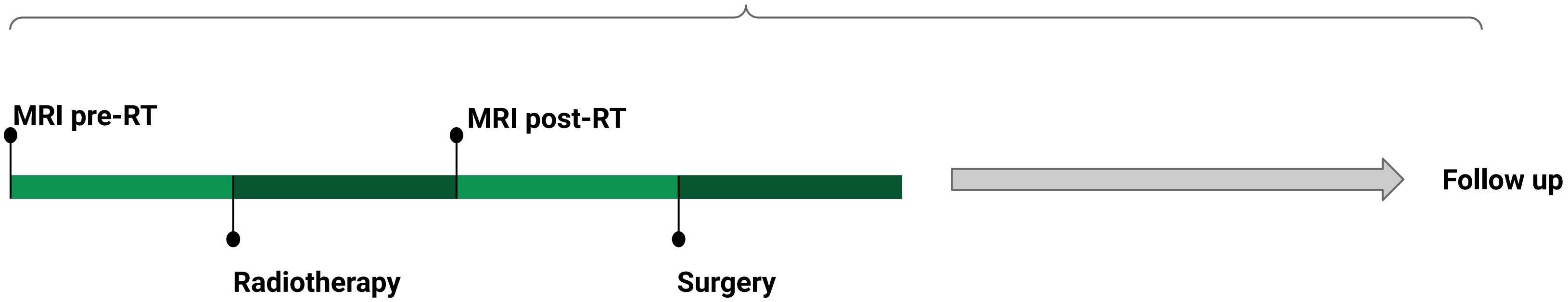
Soft-tissue-sarcomas (STS)

Soft-tissue-sarcomas (STS) represent a **rare** and heterogeneous group of tumors, with more than **100 histological subtypes** and account for **1% of solid cancers in adults. Limbs are the most common primary site.**
Their clinical management is particularly challenging.



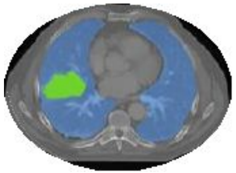
Task

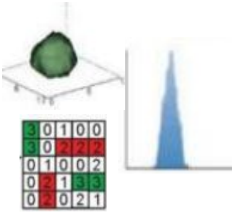
The goal of this study **is to predict** STS patients outcome to radiotherapy, in terms of **distant metastasis development**

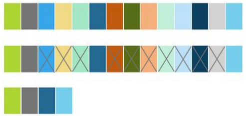
To address this task we consider an approach based on **Radiomics, Dosiomics and Machine Learning**

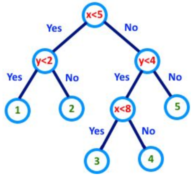
Radiomics: workflow

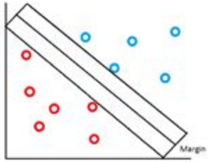
Imaging → Segmentation → Feature extraction → Feature selection → ML algorithms











→ **PREDICTIONS** + **EXPLAINABILITY**

Dataset Careggi

Images

CT

Dose distribution

T1mdc

T2

Structures

✓

✗

+ **Label**

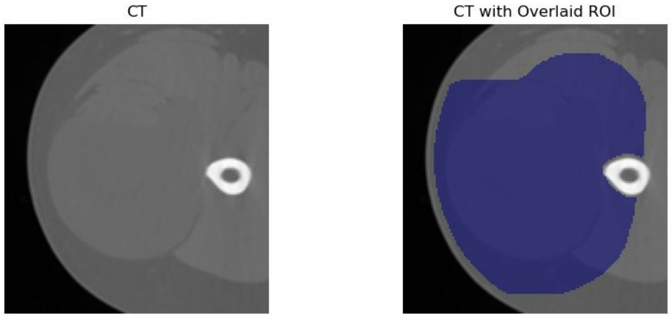
46 patients

- 25 metastasis
- 21 no metastasis

Dataset Careggi: ROI

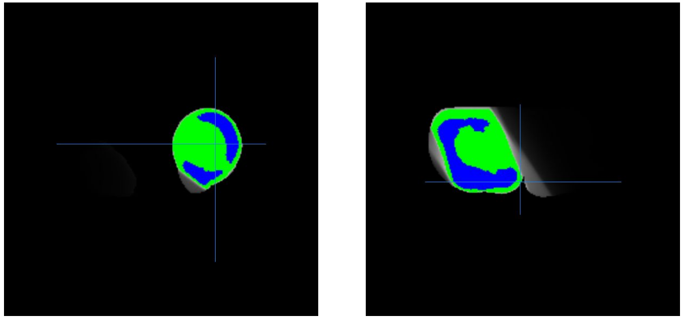
Radiomic approach → CT

- PTV, GTV, CTV



Dosiomic approach: which ROI?

- PTV, GTV, CTV
- Isodose volume of the 50%, 70%, 90%, 95%, 98% of the maximum value.



Dataset TCIA

- https://www.cancerimagingarchive.net/collection/soft-tissue-sarcoma/

Images	Structures
CT	✓
PET	✓
T1mdc	✗
T2	✗

+ **Label**

50 patients

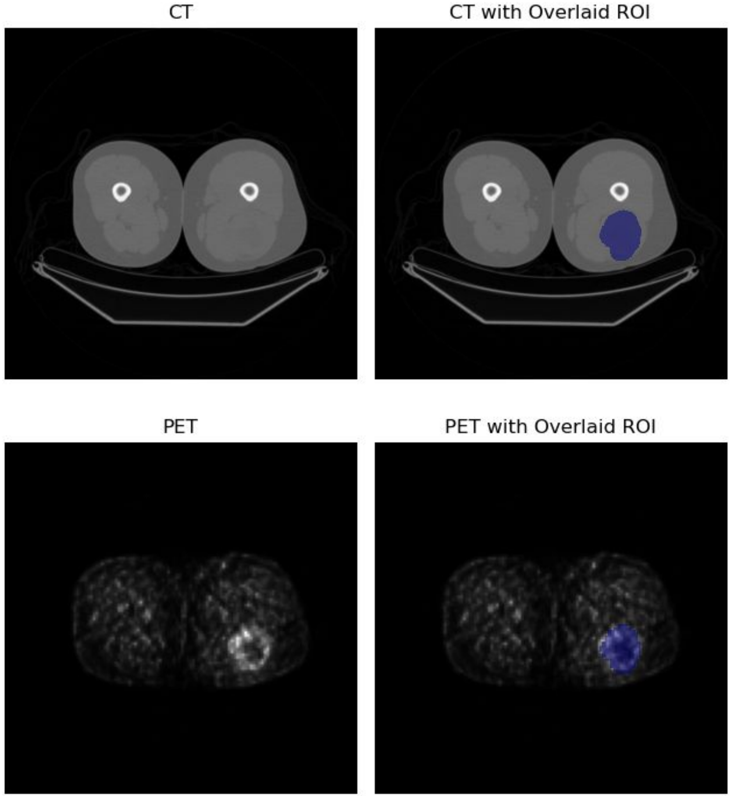
- 26 metastasis
- 24 no metastasis

TCIA Dataset: ROI

ROI → Tumor Mass

CT

PET



Features extraction

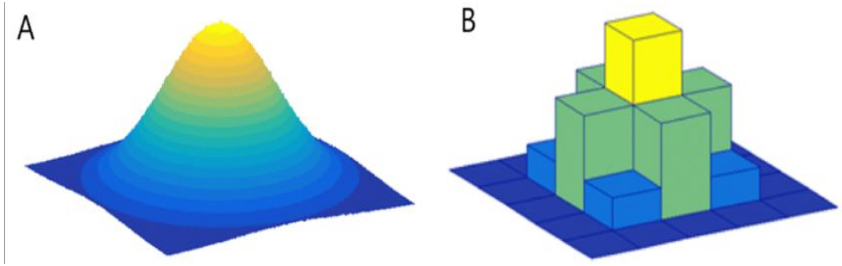
python
+
RADIOMICS

107 Features:

- Size- and Shape-based Features
- First Order Statistics Features
- Texture Features

Image intensity discretization (bin count)

Bin count = 32, 50



The computation of the **texture-based and some of the intensity features**, as defined in the PyRadiomics package, requires **binning the intensity histogram**. It specifies the number of bins to create when making a histogram and for discretization of the image gray level.

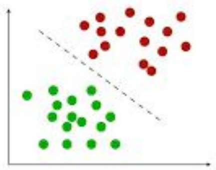
Machine Learning Classifiers

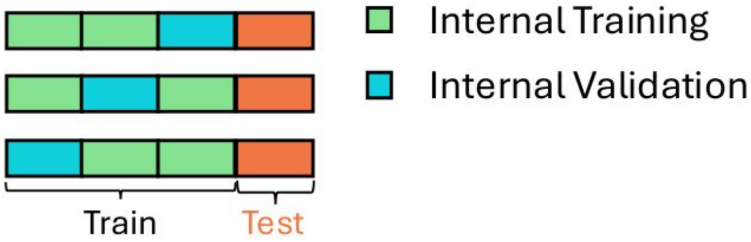
Classification

Adaboost

Random Forest

GradientBoostingClassifier





- Trained and tested using a **3-fold Nested Cross-Validation**, which allowed us to perform hyperparameter optimization through a **grid search.**

- This strategy allows us to have stable and reliable performance even if we are working with a small dataset

- The experiment was repeated using all possible combinations of the available features (combination set). **Separately for each dataset.**

Results: Random Forest

Careggi Dataset

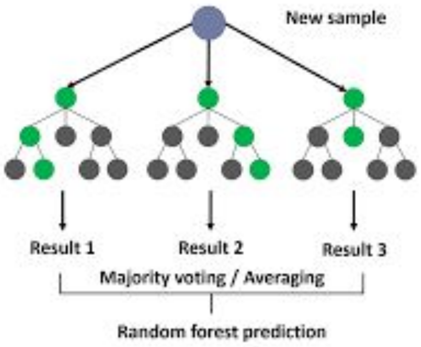
Features Combination	Test AUC-ROC Mean	Test AUC-ROC Std
CT	0,48	0,12
DOSE_iso_70_bc_32	0,67	0,07
CT + DOSE_iso_70_bc_32	0,58	0,04

Dataset TCIA

Features Combination	Test AUC-ROC	Test AUC-ROC Std
CT	0,69	0,14
PET	0,80	0,10
CT+PET	0,75	0,11

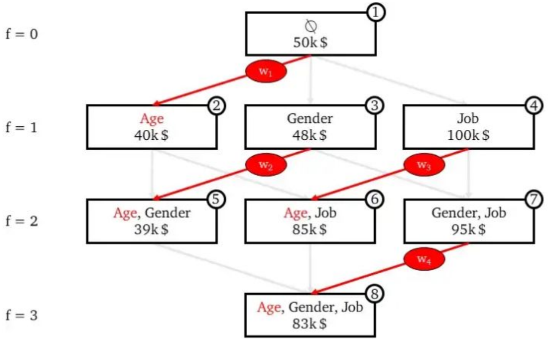
Explainability

Random Forest



In a random forest, a ranking of feature importance can be performed by calculating **the average depth** at which each feature appears in the trees of the forest.

SHAP



SHAP (SHapley Additive exPlanations) method computes the contribution of each feature to the prediction by **considering all possible combinations of feature inputs.**

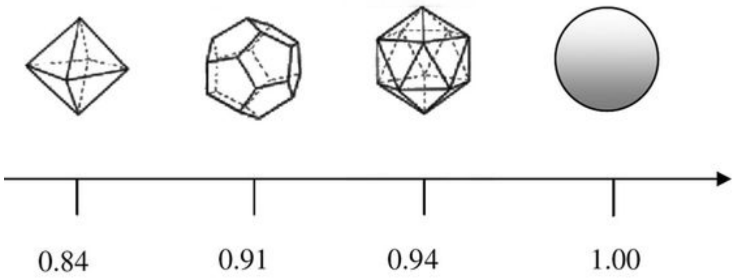
Explainability: Careggi Dataset

RF features importance

- **Maximum_DOSE**_iso_70_bc_32
- **Sphericity_DOSE**_iso_70_bc_32

SHAP

Sphericity is a measure of the roundness of the shape of the tumor region relative to a sphere.



Explainability: TCIA Dataset

RF features importance

- **glrlm_RunPercentage_PET**_mass
- **Maximum_PET**_mass

→ **SHAP**

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

$$\begin{bmatrix} 5 & 2 & 5 & 4 & 4 \\ 3 & 3 & 3 & 1 & 3 \\ 2 & 1 & 1 & 1 & 3 \\ 4 & 2 & 2 & 2 & 3 \\ 3 & 5 & 3 & 3 & 2 \end{bmatrix} \xrightarrow{\quad\theta = 0^\circ\quad} \begin{bmatrix} 1 & 0 & 1 & 0 & 0 \\ 3 & 0 & 1 & 0 & 0 \\ 4 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 3 & 0 & 0 & 0 & 0 \end{bmatrix}$$

MATRIX

GLRLM MATRIX

Conclusions

Work by FI and PI groups

Challenges:

- Difficulty to collect large datasets in the field of medical imaging.
- **Small and high-dimensional datasets** (instability, overfitting).

Principal results:

- Radiomic features extracted from **Dose distribution** and **PET** showed encouraging results in predicting distant metastasis development

Next Steps:

- Provide medical interpretation of radiomic features
- We would like to introduce **clinical data** and **radiomic features from MRI** into the model

Thank you for your attention!

Explainability: Cohen's d

$$d = \frac{M_1 - M_2}{s}$$

	Cohen's d sign	Probability of belonging to the metastasis class	
Maximum_DOSE	−	↑	↑
Sphericity_DOSE	+	↑	↓
Maximum_PET	−	↑	↑
GLRLM_RunPercentage_PET	+	↑	↓

Cose interessanti

https://github.com/ncaptier/radshap

TABNET rete che consente di capire la features importance