

# Artificial Intelligence in Medicine



Predictive models for Radiation Therapy  
treatments

Part 1

16/10/2020 - Leonardo Ubaldi

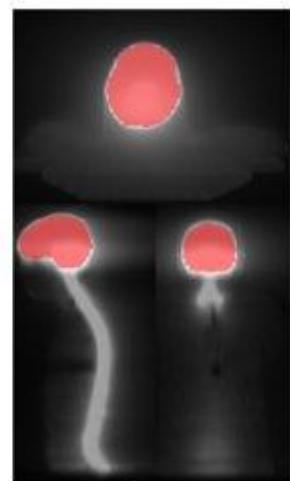
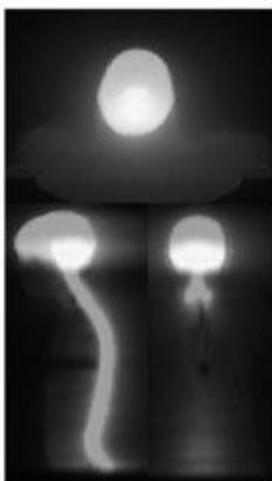
# Recap

Radiomics and dosiomic approach to build predictive models based on ML techniques, in order to determine the therapeutic response and clinical outcomes in paediatric patients affected by medulloblastoma.

AOU Meyer for clinical data and MRI  
(1 MR scanner)



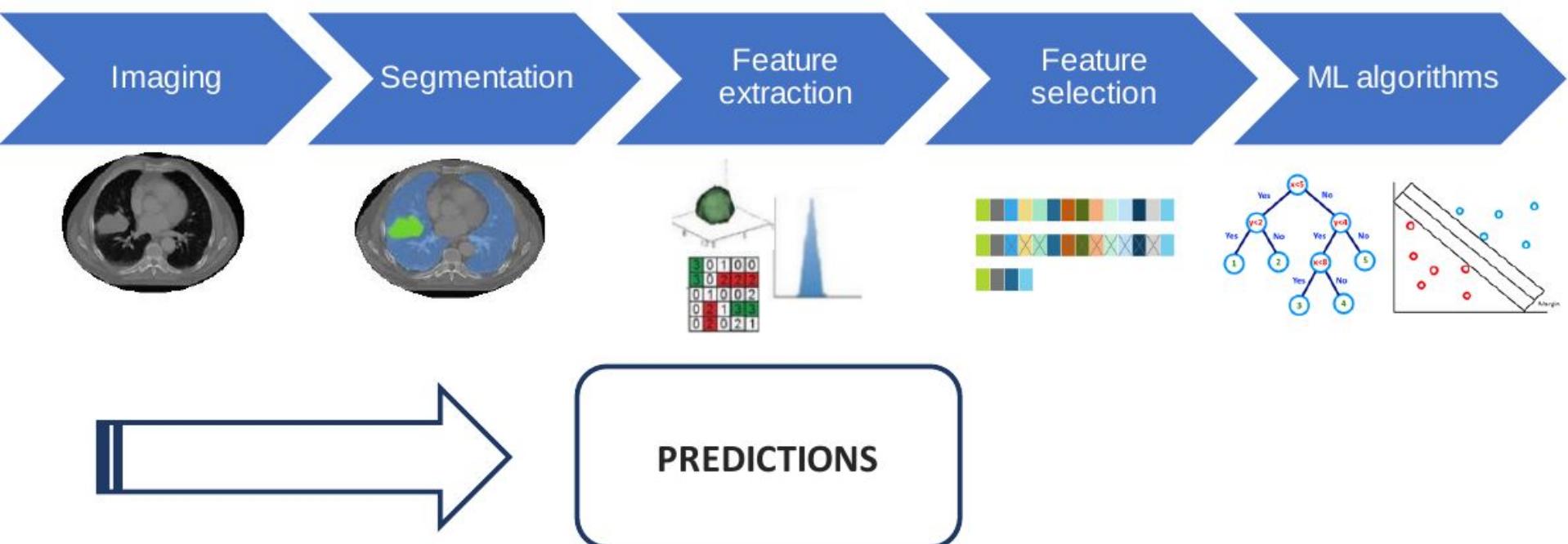
AOU Careggi for radiotherapy  
(1 CT scanner & 1 machine for RT)



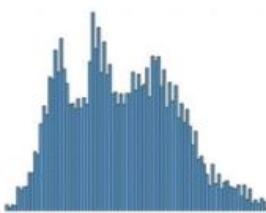
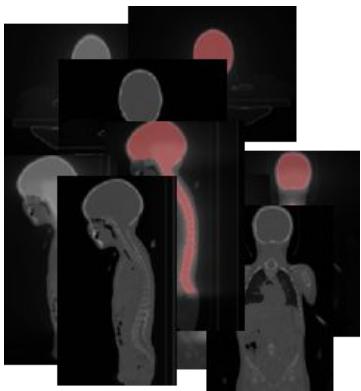
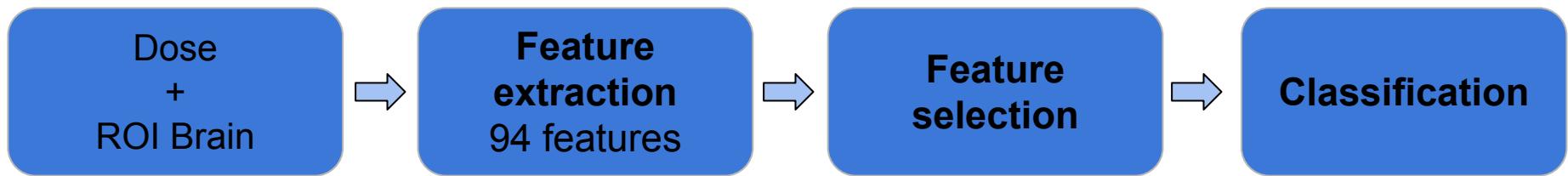
# Study Population

- Up to now 55 patients
- For each of them:
  - Imaging data (MRI & CT)
  - Radiotherapy data (dose distribution; prescription dose; fractionations; boost; machine parameters; structures)
  - Clinical data (histology; risk class; drugs; motor, cognitive and sensory deficits; possible radio-induced toxicity; metastasis; relapse; end state)

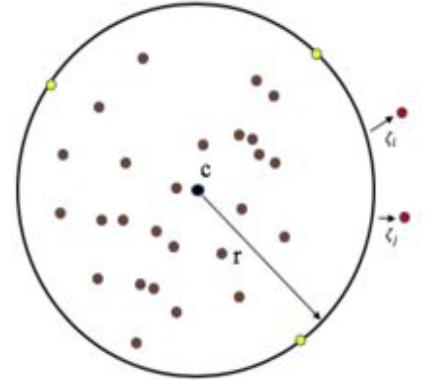
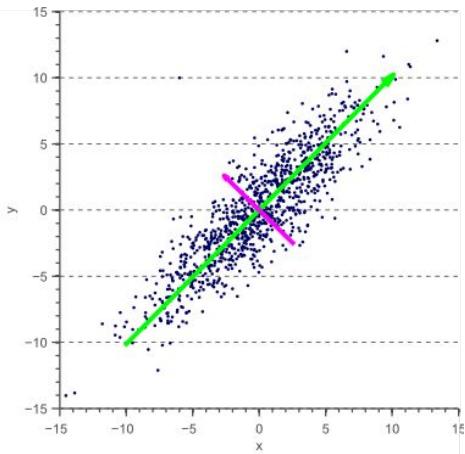
# Radiomics: typical workflow



# Workflow



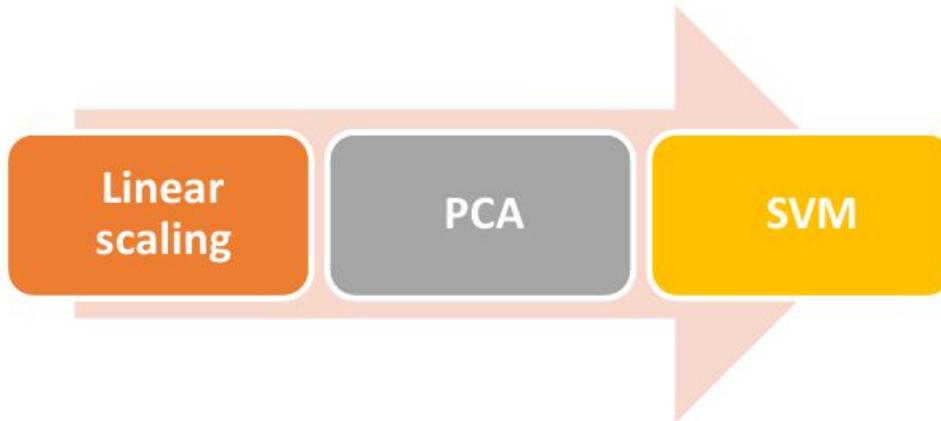
**pyradiomics**  
python  
+  
 $\infty$  RADIOMICS



# Radiological evidence of neuro damage

- ‘Radiological evidence of neuro damage’ → 38 subject
  - Outcome 0 → 6 subject
  - Outcome 1 → 32 subject
- Confusion matrix obtained with **One-Class SVM** (Novelty Detection) using features extracted from dose distribution

**Training set:**  
26 subjects  
with **label 1**

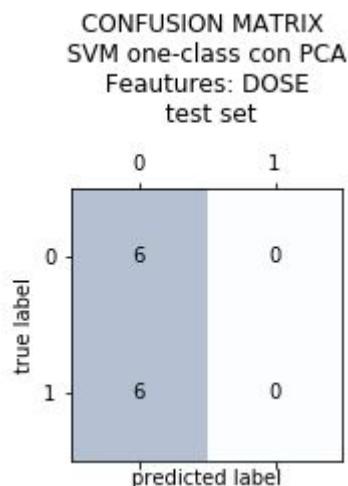
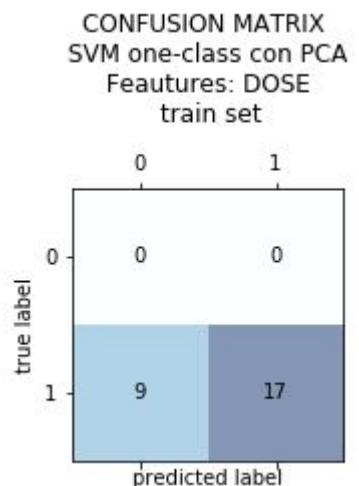
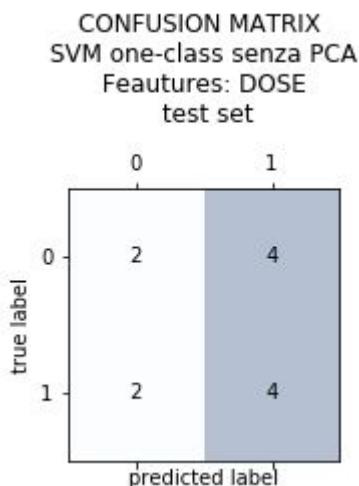
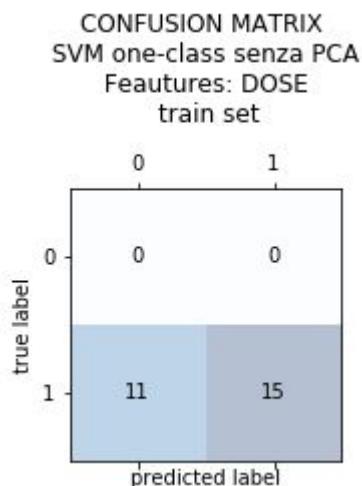


**Test set:**

- 6 subjects with **label 0**
- 6 subjects with **label 1**

# Radiological evidence of neuro damage

Confusion matrices obtained with **One-Class SVM** (Novelty Detection) using features extracted from the dose distribution



# New label: Relapse TOT

- The “**Radiological evidence of neuro damage**” label is not robust



- “**Relapse TOT**” (binary classification) → 45 subjects
  - label 0 → 21 subjects
  - label 1 → 24 subjects
- Features extracted from **dose distributions** within the brain ROI
- Classifiers: SVM, Random Forest, Adaboost and Nearest Neighbors**
  - 5 fold Cross-Validation**
  - No hyper-parameters optimization** → default hyper-parameters

# Results

CLASSIFIERS	Mean accuracy ± standard deviation
Adaboost	<b>0.47 ± 0.16</b>
SVM linear	<b>0.47 ± 0.11</b>
SVM rbf	<b>0.42 ± 0.19</b>
RandomForest	<b>0.49 ± 0.19</b>
NearestNeighbors	<b>0.51 ± 0.19</b>

Results obtained using only features extracted from the dose distributions

# Next steps

- Consider features extracted from MRI post-surgery and pre-treatment
- Introduction of other clinical outputs
- Introduction of more specific ROI for the features extraction step (smaller than the whole brain)

# Artificial Intelligence in Medicine



# AIM

## Part 2

Leonardo Ubaldi

# Recap

Radiomics approach to build predictive models based on ML techniques, in order to investigate the possibility to predict the:

- **Tumor stage**
- **Tumor histology**
- **Patients' survival time**

by considering the radiomic **features extracted from the thoracic CT** of patients with **Non Small Cell Lung Cancer (NSCLC)**.

# Datasets

## L-RT dataset:

- Composed by **47 non-small cell lung cancer (NSCLC) patients**
- Ospedale Civico Di Cristina Benfratelli, Università degli Studi di Palermo and INFN Catania.
- Available to our research group within the INFN AIM collaboration.

## Lung1 dataset:

Subset of **130 subjects** selected from the public dataset **Lung1 Maastro NSCLC**, which contains data of **non-small cell lung cancer (NSCLC) patients**.

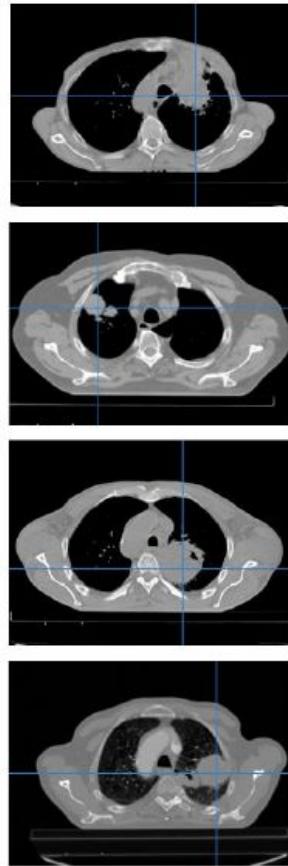
For each patient **108 features** extracted within the Gross Tumor Volume (GTV) from thoracic **CT images**, are available.

# Histology and stage

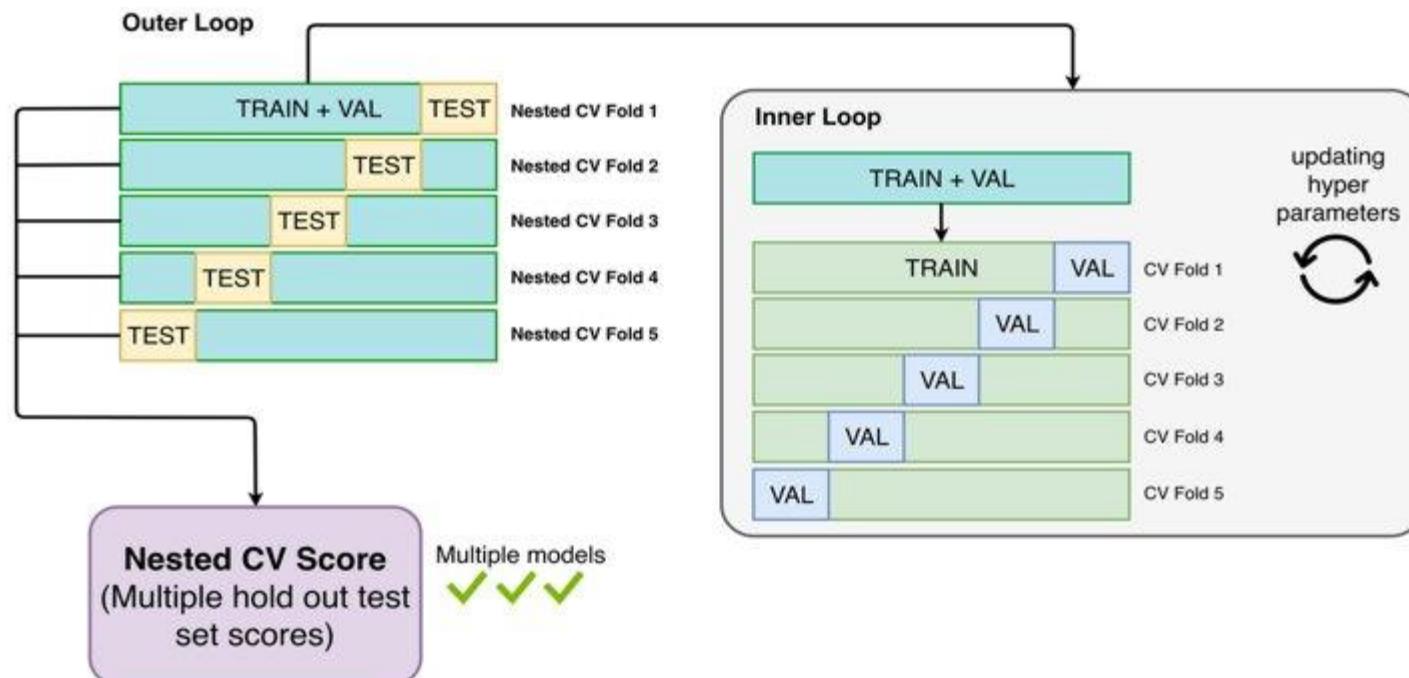
Histology	Lung1 (130)	L-RT (47)
Adenocarcinoma	16	20
Large Cell Carcinoma	60	10
Squamous Cell Carcinoma	54	4
Not Available	0	13

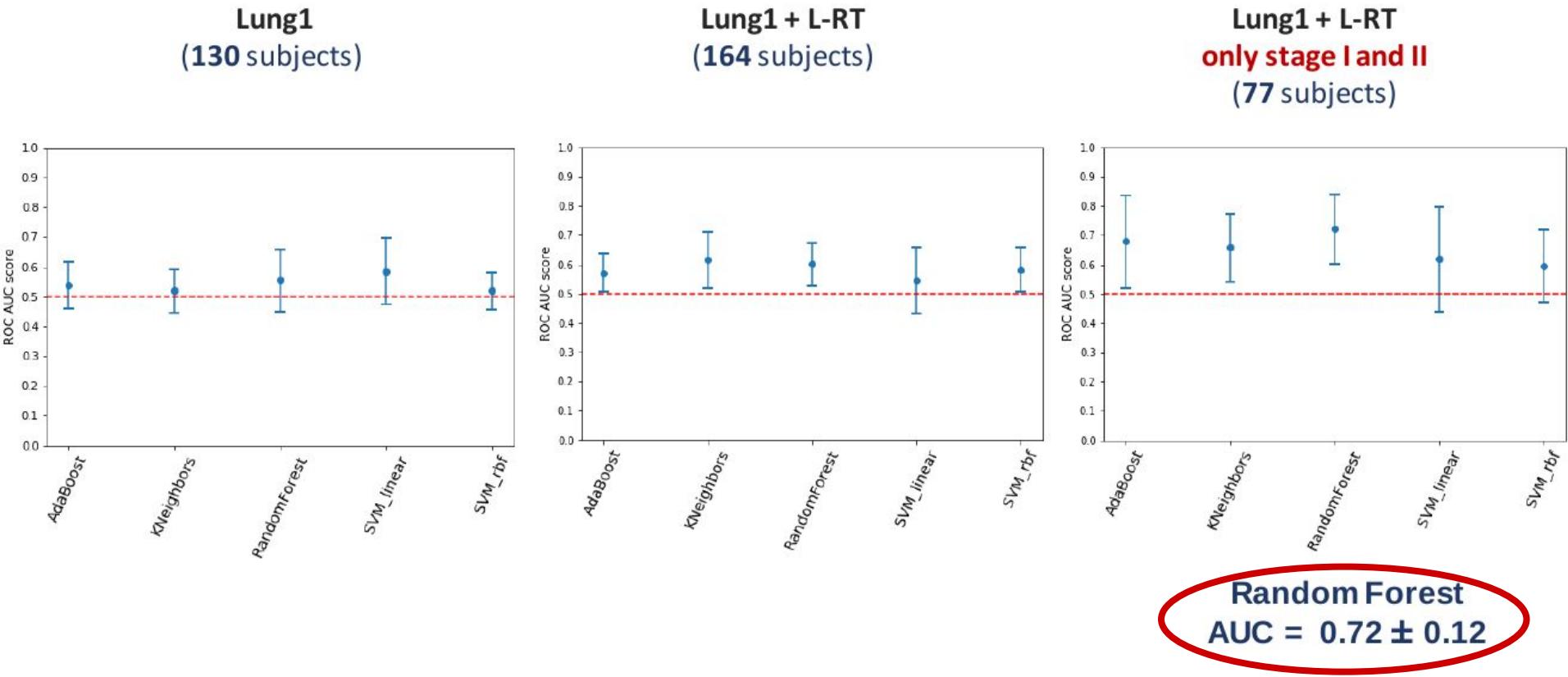
Overall stage	Lung1 (130)	L-RT (47)
I	27	42
II	13	5
IIIa	37	-
IIIb	53	-



# Histology prediction: Nested Cross-Validation



# Histology prediction: Nested CV



# Overall stage prediction

Overall stage	Lung1 (130)	L-RT (47)
I	27	42
II	13	5
IIIa	37	-
IIIb	53	-



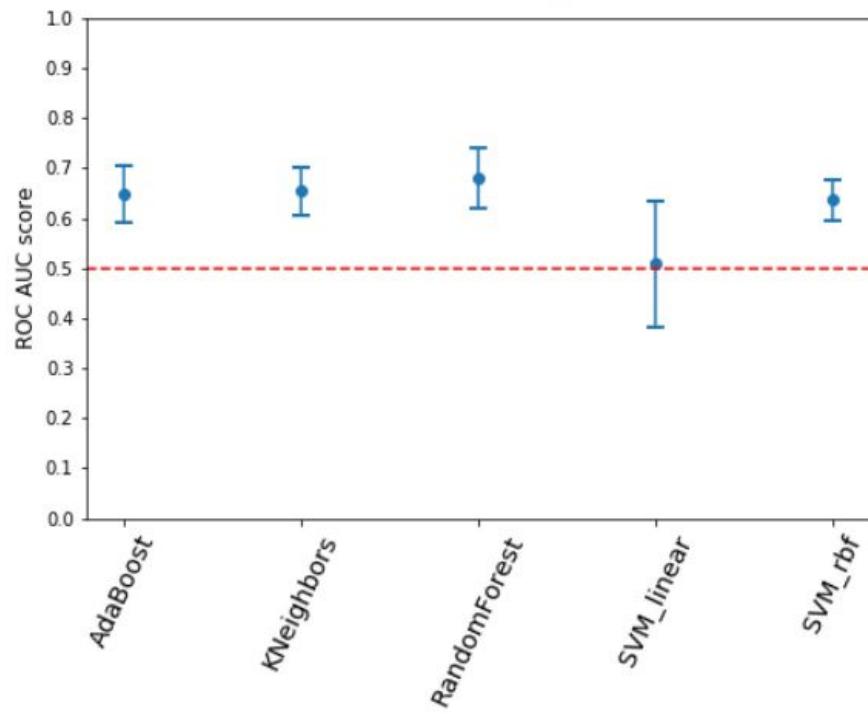
Only overall stage I and II are considered in the overall stage classification task

## Overall stage classification: **cross-validating across different data samples**

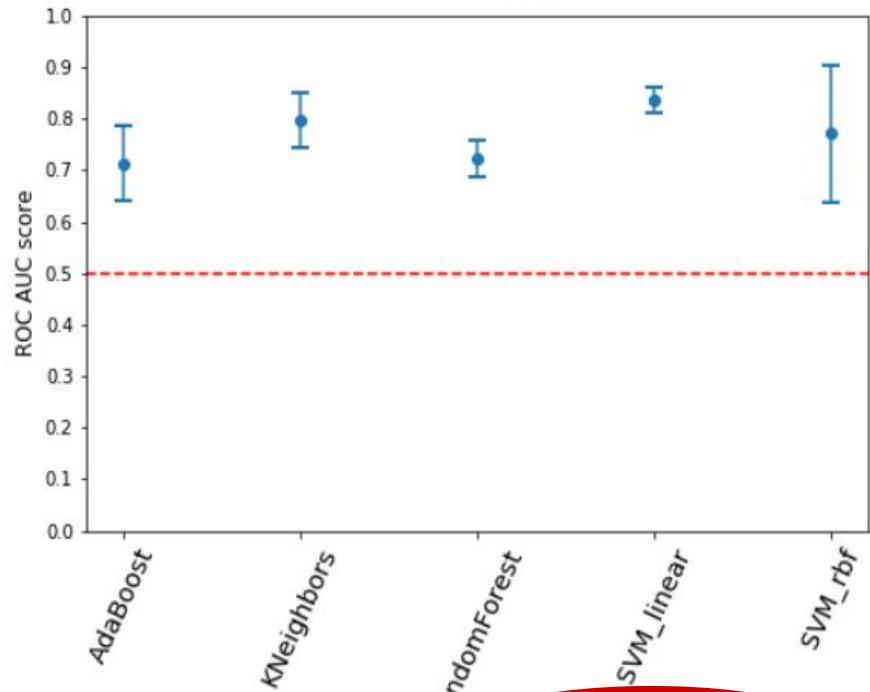
- The process of hyper-parameter optimization of the pipelines is performed through an **exhaustive search** in a **CV loop on the training set**.
- The process is repeated **10 times**

# Overall Stage prediction

Training set: L-RT  
Test set: Lung1



Training set: Lung1  
Test set: L-RT



SVM linear  
AUC =  $0.84 \pm 0.03$

# Results

Encouraging results:

- **Prediction of NSCLC histology** considering only the subjects with overall stage I and II.

Random Forest  
AUC =  $0.72 \pm 0.12$
- **Prediction of NSCLC overall stage** considering only the subjects with overall stage I and II.

SVM linear  
AUC =  $0.84 \pm 0.03$

# Next steps

- Repeat the classification with a new delineation of ROIs
- Study the stability of the radiomic features extracted.
- Deep learning approach based on transfer learning
  - For example a CNN trained on the ALOT public dataset which in composed by 27500 texture images can be tested on NSCLC classification task.

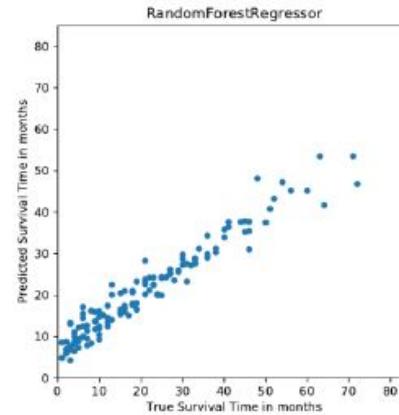
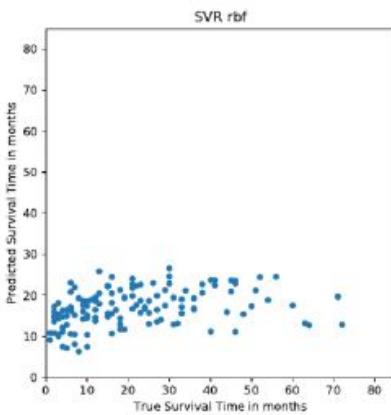
thank you



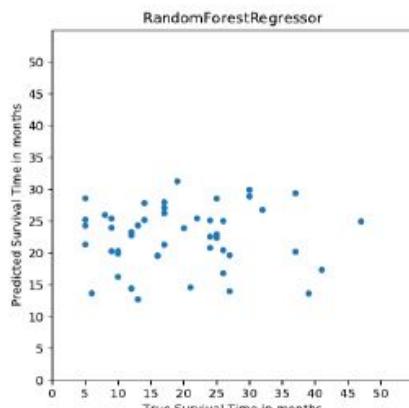
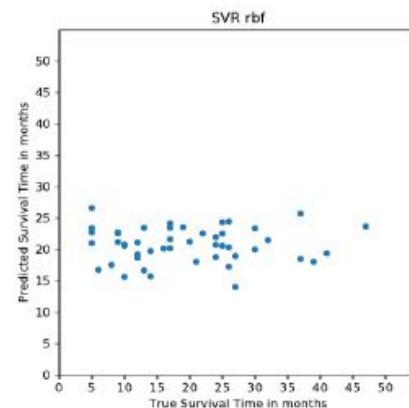


# Survival Time Regression

Regressor	MAE train [months]	MAE test [months]
SVM rbf	$10.9 \pm 1.5$	$10.3 \pm 1.7$
Random Forest	$5.0 \pm 0.3$	$10.0 \pm 0.04$



Train



Test

# First Order Statistics

- Energy: sommatoria dei quadrati dei valori dei voxel
- Entropy: misura la quantità media di informazioni necessaria per codificare i valori dell'immagine
- Skewness: misura l'asimmetria di una distribuzione rispetto al valore medio
- Kurtosis: misura quanto una distribuzione è piccata rispetto alla distribuzione normale
- Uniformity: misura di omogeneità

# Gray Level Co-occurrence Matrix

- Viene costruita la GLCM
  - E' una matrice che descrive le frequenze con cui ogni livello di grigio appare accanto ad altri livelli di grigio ad una distanza definita (offset)
- Vengono estratte features dalla matrice GLCM

# Gray Level Size Zone Matrix

- Viene costruita la matrice GLSZM
  - Descrive il numero di voxel adiacenti che contengono lo stesso valore di intensità di grigio, nelle tre dimensioni
- Vengono estratte features dalla matrice GLSZM

# Gray Level Run Length Matrix

- Viene costruita la matrice GLRLM
  - descrive con quale frequenza nell'immagine è possibile osservare file di elementi con una certa lunghezza e con una certa intensità
- Vengono estratte features dalla matrice GLRLM

# Neighbouring Gray Tone Difference in Matrix

- Viene costruita la matrice NGTDM
  - Descrive le differenze esistenti fra ogni elemento dell'immagine e quelli immediatamente confinanti
- Vengono estratte features dalla matrice NGTDM

# Recap database

- Distribuzione di dose → 57 soggetti
- Strutture → 55 soggetti
- MRI post-operatorie e pre-trattamento → 50 soggetti
  - T1 (3D) → ~ metà con MDC
  - DWI (ADC) → 50 soggetti
- ‘Radiological evidence of neuro damage’ → 40 soggetti
  - Outcome 0 → 7 soggetti
  - Outcome 1 → 33 soggetti
- Massima intersezione utilizzabile (utilizzando le ADC) → 35 soggetti
  - Outcome 0 → 6 soggetti
  - Outcome 1 → 29 soggetti

