

Radiomics and ML-segmentation on Facio-Scapulo-Humeral dystrophy (FSHD) and lung tumor

next_AIM kickoff meeting
WP3: Applications to real data
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01

Facio-Scapulo-Humeral dystrophy (FSHD)

FSHD disorder: disease progression assessment

Quantitative Radiological Biomarkers

patient

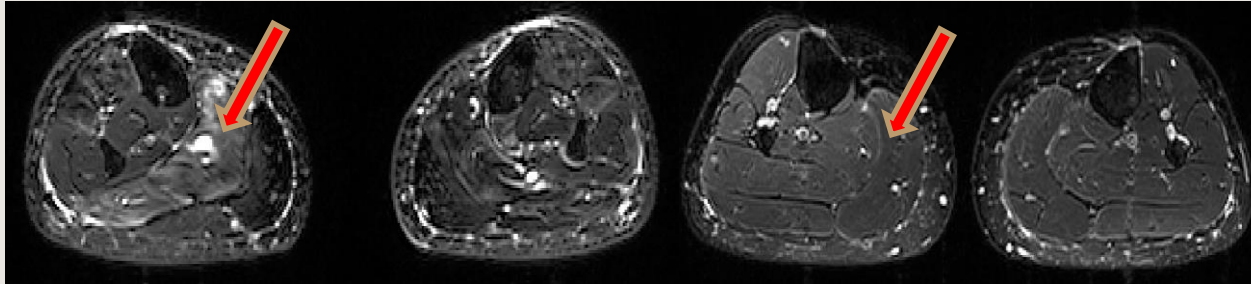
healthy control



- Fat Fraction (FF) by Fatty Riot algorithm ⁽¹⁾

patient

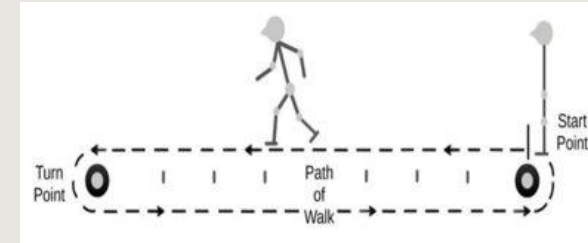
healthy control



- Edema (wT2) by EPG signal simulation ⁽²⁾

Clinical tests

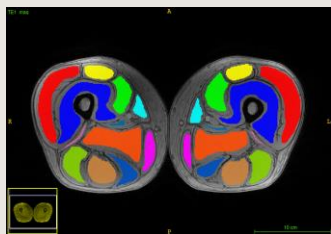
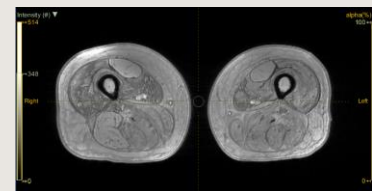
- Clinical Severity Score (CSS)
- Six Minutes Walking Test (6MWT)



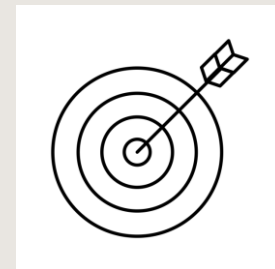
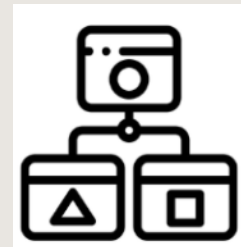
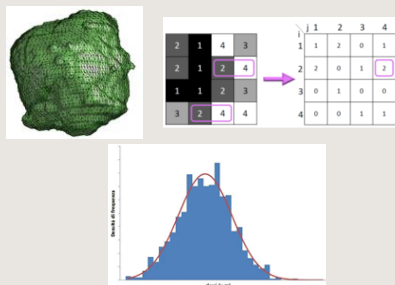
(1) E.B. Welch et al. Proc. 21st Sci. Meet. Int. Soc. Magn. Reson. Med. (2013) - (2) doi.org/10.1002/nbm.3459 & doi.org/10.1002/jmri.24619



Idea



VL RF AM BFL
VI AL G ST
VM SM S BFS



1. MRI acquisition
of patients' thighs

2. Pre-processing and
segmentation

3. Radiomics

4. ML algorithms

5. Quantitative
Fat Fraction and Water-T2
prediction



(Small) Dataset

24 patients @ 3T MRI scanner

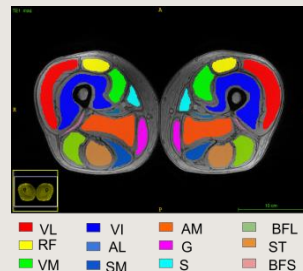
(Istituto Neurologico Nazionale IRCCS, Pavia)

- 3D 6-point multi-echo gradient echo (MEGE)
- multi-echo spin echo with 17 echoes (MESE)

Settings	MEGE	MESE
Number of slices	52	7
Slice Thickness (mm)	5	10
Distance Factor (%)	20	300
Resolution	1x1x5 mm ³	1.2x1.2x10 mm ³
Repetition Time TR (ms)	3.5	4100
Echo Time TE (ms)	1.7 - 9.2	10.9 - 185.3
Scan Time (min)	15	5.13

Features extraction and pre-processing

- 12 ROIs for thigh muscles
- Pre-processing (denoise of the images by a Gaussian Filter, N4 Bias Field Correction and Histogram Matching)
- Texture analysis was performed on MEGE images (LIFEx) - 42 radiomic features were obtained with 2D extraction from each region of interest



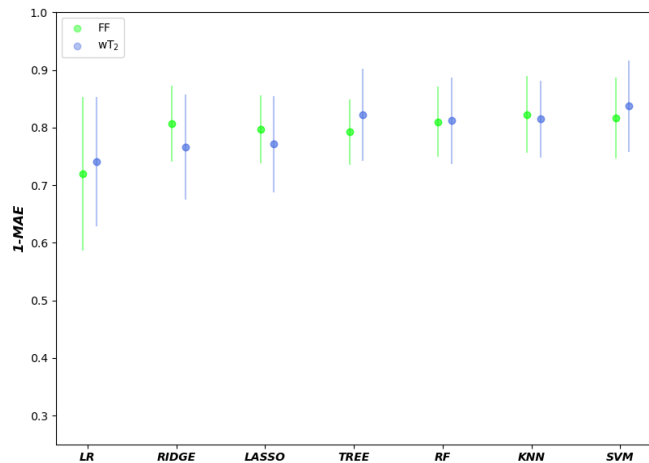
Muscle-wise Fat Fraction (FF) and Water-T2 (wT2) prediction

- Supervised regression problem
- Fatty Riot algorithm (MEGE sequence) and by EPG signal simulation (MESE sequence): ML **ground truth for FF and wT2**
- Parametric linear, ridge and lasso regression and the non-parametric KNN, SVM, tree, and RF algorithms.
- **FF mean algorithms accuracy floats around 80%** and alike considerations applied to the mean wT2 accuracy.
- **Lower prediction performance** both in FF and wT2 **for BFS and AL muscles** compared to the other muscles. This could be traced back to quick BFS and AL muscle degradation in neuromuscular disease that result in segmentation struggling → possible alteration of the texture analysis

Which is our  ?

Removal of the necessity of texture analysis -> deep learning methods

Mean accuracy Algorithm-wise



Mean Absolute Error

$$MAE_j = \frac{\sum_{i=1}^N |y_i - \bar{y}_i|}{N}$$

j runs over the different thigh muscles and i over the observations associated to each muscle



02

**Harmonization of features
Extraction on stage III
unresectable NSCLC**



(Small) dataset

23 patients with inoperable stage III lung adenocarcinoma undergoing radio-chemo-immuno therapy.

2 CT images acquired at 2 time points:

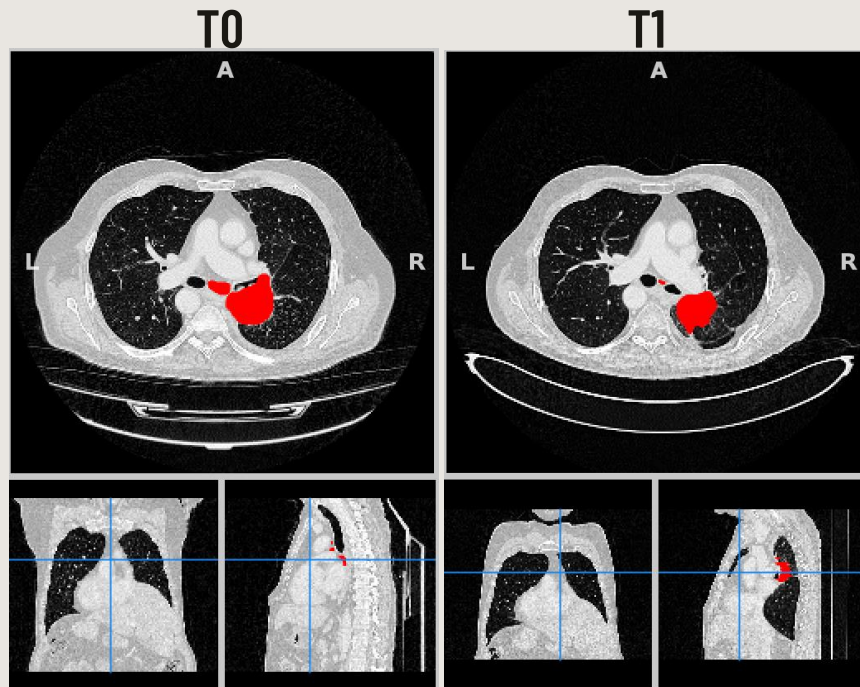
- Baseline: at the diagnosis
- After the chemo-radio-immuno therapy

Homogeneous dataset of clinical features

Aim

Predict:

- Probability of Metastasis
- Probability of Relapses
- Response to the therapy



(Small) dataset

Images from 10 different centers:

Image Parameters:

Pixel

From $(0.62 \times 0.62) \text{ mm}^2$ to $(0.98 \times 0.98) \text{ mm}^2$

Slice thickness

From 0.3 mm to 3.0 mm

Reconstruction Parameter:

Convolutional Kernel

11 types

Acquisition Parameters:

Scanner

4 different vendors

Current

From 56 mA to 581 mA

Contrast Agent

2 types

kV-peak

100 kVp, 120 kVp, 130 kVp, 140 kVp

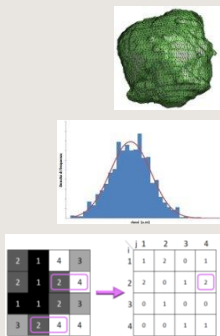
Exposure Time

From 350 s to 1000 s



Features Extraction

42 features computed by Lifex (IBSI standard compliant), including six categories of features:



4 Size- and Shape-based features

6 First-order Statistics features

32 Higher order Statistics features:

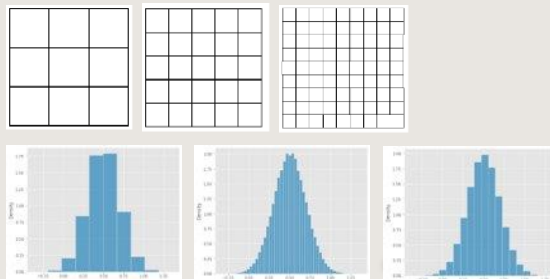
7 grey-level co-occurrence matrix features, 11 grey-level run length matrix features, 3 neighboring grey-level difference matrix features, 11 grey-level zone length matrix features



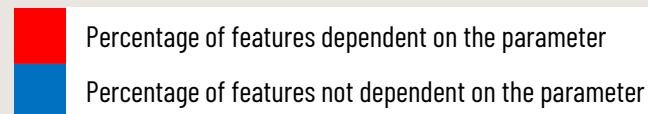
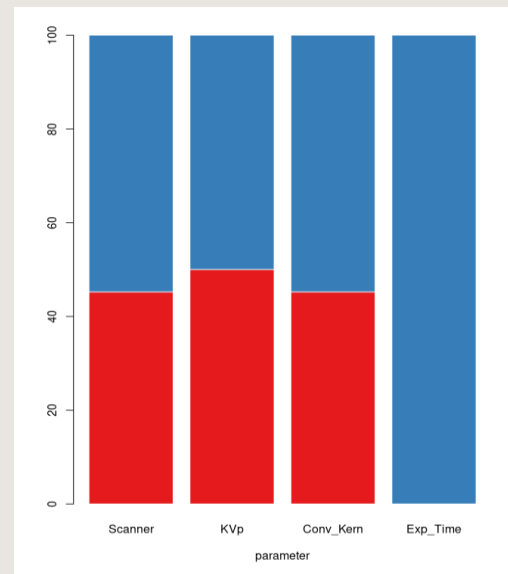
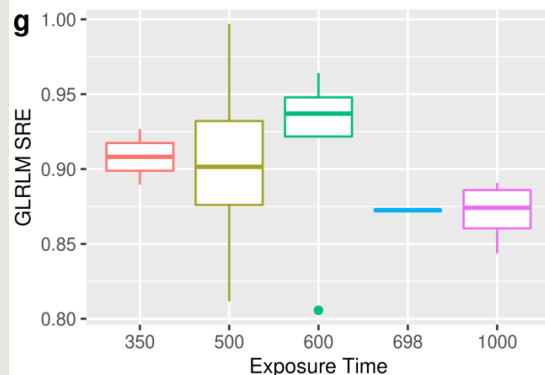
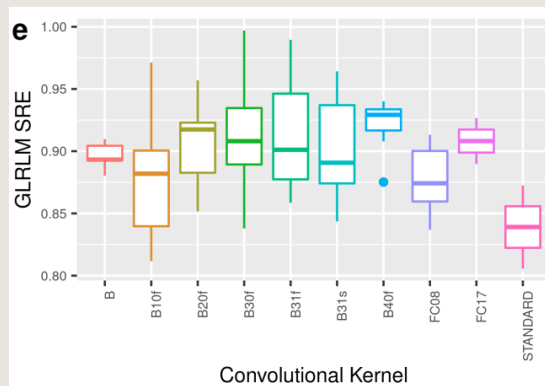
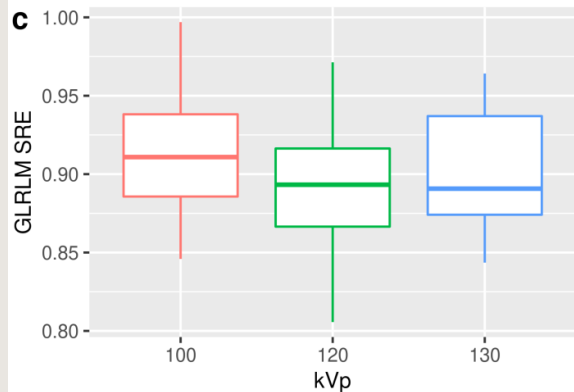
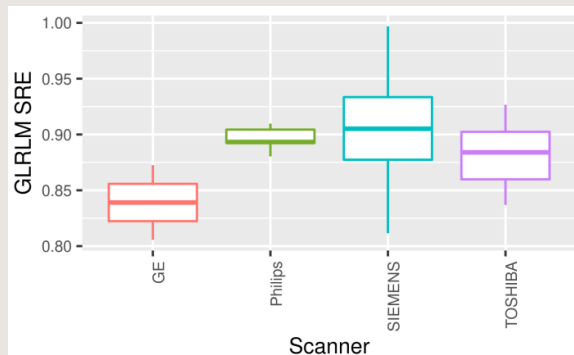
Images Parameters Harmonization

To harmonize images (before the extraction):

1. **Spatial Resampling:** 1mm x 1mm x 1mm
2. **Intensity Rescaling:** -1000 HU, 3000HU
3. **Intensity Discretization:** 400 bins of size 10 HU



Acquisition Parameters Harmonization



Scanner vendor, kVp and Convolutional Kernel have a statistically significant impact on features distributions



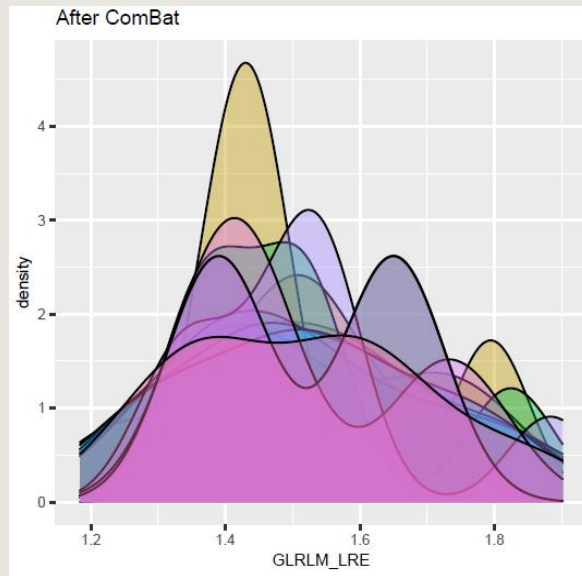
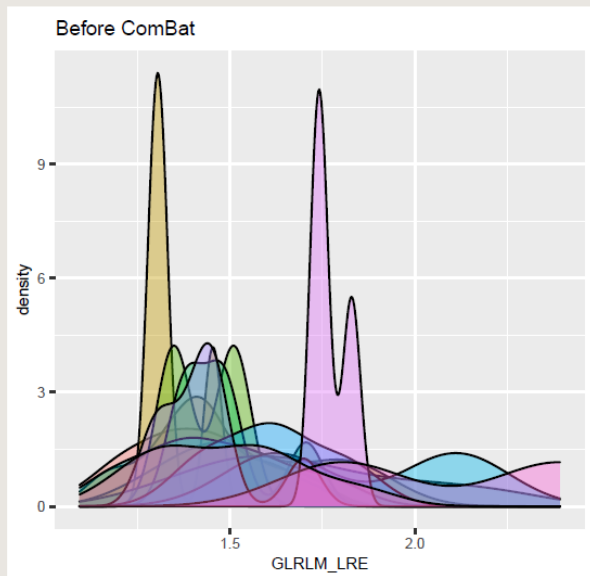
Acquisition Parameters Harmonization

ComBat: realigns features as a function of median and variance.

Long-ComBat: ComBat algorithm adapted to longitudinal data.

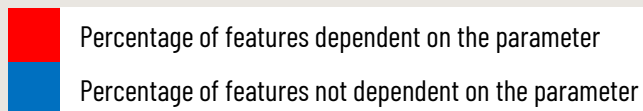
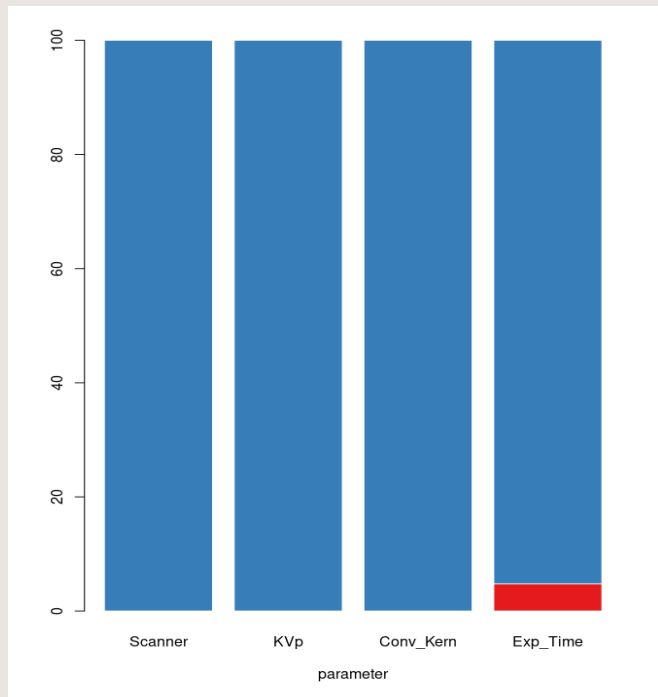
Batch: numeric value associated with each combination of parameters.

kV peak - convolution kernel combinations define **14 batches**

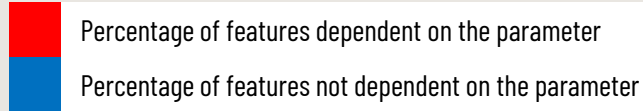
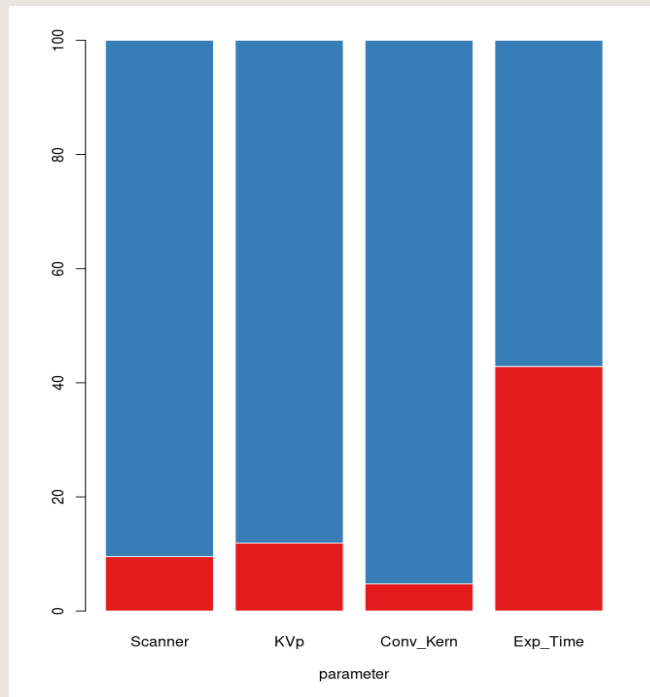


Acquisition Parameters Harmonization

Combat



Long-Combat



next AIM: study how harmonization processes influence predictive models

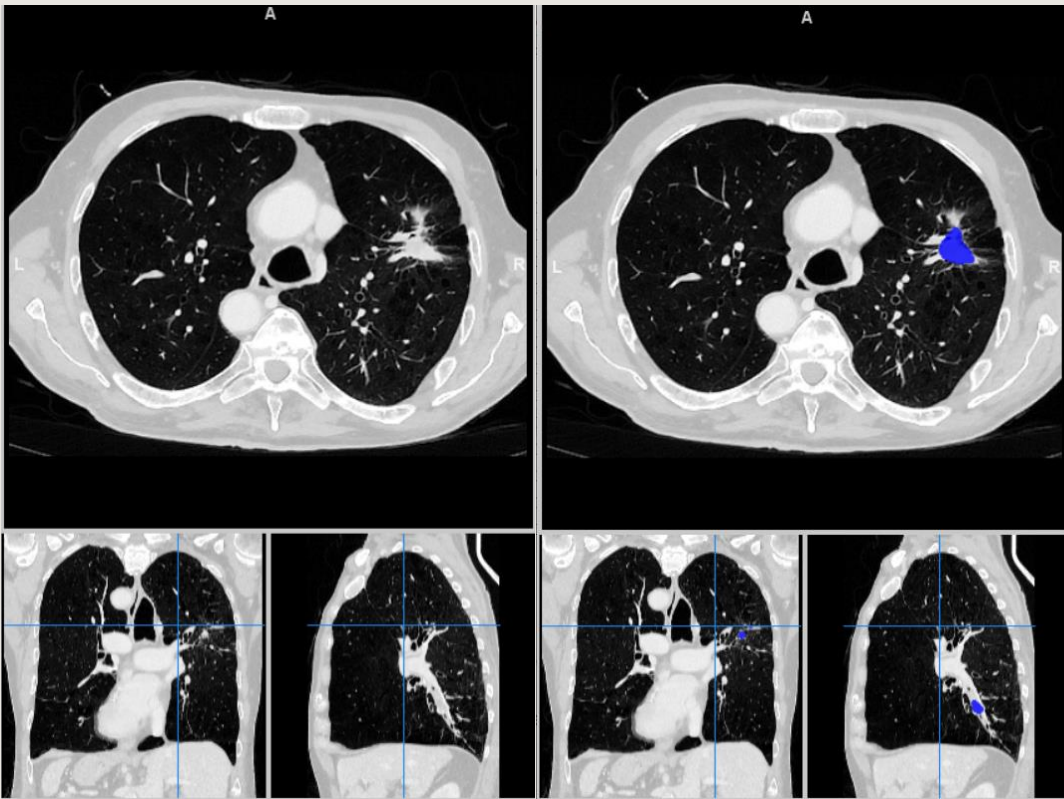


nn-Unet for tumor segmentation

Automatic segmentation to prevent human segmentation variability

Dataset:

- "Lung1" images dataset from The Cancer Imaging archive (<https://wiki.cancerimagingarchive.net/display/Public/NSCLC-Radiomics>) - 422 images
- Italian Lung Cancer database (from Policlinico San Matteo) - 178 images



Conclusions

1. Possibility of applying ML for different tasks such as quantitative biomarkers prediction in muscular dystrophy and automatic segmentation
2. Importance of the development of robust analysis pipeline for small-datasets
3. Images, features and segmentation harmonization steps are necessary with small-datasets
4. Importance of availability of public datasets useful for neural network training





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