Projet IMA201 « Radiomiques »

- Read the Pyradiomics documentation
- Read: **Perre** SV, Duron L, Milon A, Nougaret S, **Fournier** L, Thomassin-Naggara I. Radiomique: mode d'emploi. Méthodologie et **exemples** d'application en imagerie de la femme. Imagerie de la Femme. 2019 Mar 1;29(1):25-33.
- Test the Pyradiomics package
- Prepare very simple "synthetic" test images: a shape on a background with different pixel/texture distributions.

➔ **For all synthetic use-cases**: Simulate contour variability and image shift and contrast variability and document overall which parameters are more sensitive to which source of variability.

➔ Choose a subset of texture-based features to study more in depth

➔ **Choose one of the following medical imaging use-case aiming for your own coding contributions to:**

1. Replicate one of the proposed paper testing setup on a different cohort (eg. reproduce experiments from **Perre et al., Lecler at al.**, **Duron et al.)**
2. Document radiomics potential on a new medical imaging use-case
3. Document radiomics potential for whole field of view analysis (patch-based implementation on mask = small patch)
4. Modify the Pyradiomics pipeline with new image manipulation options or modified features (e.g. to have feature values in range [0,1]).

Medical Imaging Cohorts:

➔ Samples of medical images with masks for some structures are provided on this link: https://partage.imt.fr/index.php/s/HbrqG7K4c6Xxqge .

Nb: you might need to read volumes of images in nifty format (.nii) with dedicated Python libraries. You can also load those volumes in free software tools like itkSnap and save manually individual images and masks. Nb2: some masks have different label values (=1,2,3) for different structures. You need to extract your own binary mask from the label of the structure you want to study. Nb3: For examples without masks, you can try the patch-based approach. Nb4: for all images check the native range of pixel intensity values and consider clipping min/max value to "interesting" range of values.

1. **Cardiac ultrasound**: CAMUS dataset with segmented myocardium. Link to dataset: https://www.creatis.insa-lyon.fr/Challenge/camus/
2. **Brain MRI with tumors**. BRATS Link to dataset: http://braintumorsegmentation.org/
3. **Lung CT images** with COVID.
   - **MosMED** subset of **N=50** studies annotated with binary pixel masks for segmentation depicti ng regions of interest (ground-glass opacifications and consolidations) : Link to dataset: https://www.kaggle.com/datasets/andrewmvd/mosmed-covid19-ct-scans/code . Masks not available anymore.
   - **COVID Kaggle**: slices containing lesions already in png format.

4. **Breast mammography** (Xray) VinDr-Mammo, **N= 5K**, Image size = 3K x 3K pixels. Labels = breast density category (n=4). Link to dataset: https://vindr.ai/datasets/mammo

Biblio on Datasets

1. "Thoracic volume and pleural effusion segmentations in diseased lungs for benchmarking chest CT processing pipelines (plethora)." (2021), [Online]. Available: https://wiki.cancerimagingarchive. net/pages/viewpage.action?pageId=68551327 (visited on 05/29/2022).
2. "Nsclc-radiomics." (2022), [Online]. Available: https : / / wiki . cancerimagingarchive . net/display/Public/NSCLC-Radiomics (visited on 05/29/2022).
3. H. Aerts, E. Velazquez, R. Leijenaar, et al., "Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach," Undefined/Unknown, Nature Communications, vol. 5, 2014, ISSN: 2041-1723. DOI: 10.1038/ncomms5006.
4. "Nsclc-radiomics-genomics." (2021), [Online]. Available: https://wiki.cancerimagingarchive. net/display/Public/NSCLC-Radiomics-Genomics#16056856db10d39adf704eefa53e41edcf5ef41c
5. "Rider lung CT." (2022), [Online]. Available: https://wiki.cancerimagingarchive.net/ display/Public/RIDER+Lung+CT#2251273279368e51be0f4512a5934daff0cfe302 (visited on 05/29/2022).
6. "Lidc-idri." (2021), [Online]. Available: https://wiki.cancerimagingarchive.net/display/ Public/LIDC-IDRI (visited on 05/29/2022).
7. H. T. Nguyen, H. Q. Nguyen, H. H. Pham, et al., Vindr-mammo: A large-scale benchmark dataset for computer-aided diagnosis in full-field digital mammography, 2022. DOI: 10.48550/ ARXIV.2203.11205. [Online]. Available: https://arxiv.org/abs/2203.11205.

Biblio from Fournier et al.

Decoux A, Duron L, Habert P, Roblot V, Arsovic E, Chassagnon G, Arnoux A, **Fournier** L. Comparative performances of machine learning algorithms in radiomics and impacting factors. Scientific Reports, 2023 (*preprint*)

Fournier L, Costaridou L, Bidaut L, Michoux N, Lecouvet FE, de Geus-Oei LF, Boellaard R, Oprea-Lager DE, Obuchowski NA, Caroli A, Kunz WG. Incorporating radiomics into clinical trials: expert consensus endorsed by the European Society of Radiology on considerations for data-driven compared to biologically driven quantitative biomarkers. European radiology. 2021 Aug;31:6001-12.

Duron L, Balvay D, Vande Perre S, Bouchouicha A, Savatovsky J, Sadik JC, Thomassin-Naggara I, **Fournier** L, Lecler A. Gray-level discretization impacts reproducible MRI radiomics texture features. PLoS One. 2019 Mar 7;14(3):e0213459.

Duron L, Savatovsky J, **Fournier** L, Lecler A. Can we use radiomics in ultrasound imaging? Impact of preprocessing on feature repeatability. Diagnostic and Interventional Imaging. 2021 Nov 1;102(11):659-67.

Lecler A, Duron L, Balvay D, Savatovsky J, Bergès O, Zmuda M, Farah E, Galatoire O, Bouchouicha A, **Fournier** LS. Combining multiple magnetic resonance imaging sequences provides independent reproducible radiomics features. Scientific reports. 2019 Feb 14;9(1):2068.