Radiomics analysis performed preoperatively of radical prostatectomy to predict lymph node metastases of high-grade prostate cancers

D. LEBLANC [1, 2], F. RASEKH[1, 2], G. COUTURE[1, 2], P. DESPRÈS[1, 2], J-M. BEAUREGARD[2], F. POULIOT[2], L. ARCHAMBAULT[1, 2]

1 Université Laval, Québec, Canada

2 CHU de Québec-Université Laval, Québec, Canada

JULY 12–16 2020 VIRTUAL JOINT AAPM | COMP MEETING

EASTERN TIME [GMT-4]

INTRODUCTION

Prior research:

We recently showed that intraprostatic 18F-fluorodesoxyglucose (FDG) uptake as measured by Positron Emission Tomography (PET) before radical prostatectomy (RP) was a prognostic marker [2]. Indeed, this marker was associated with more advanced cancer stage, lymph node metastases at pathology and earlier recurrence. However, only one parameter (degree of capture or intraprostatic SUVmax for maximum standardized uptake value) was used to characterize the association between imaging and cancer recurrence.

Definition radiomic features:

Quantitative extraction of high-dimensional usable data from medical images. They are biomarkers not easily visible to the naked eye such as texture and intensity.

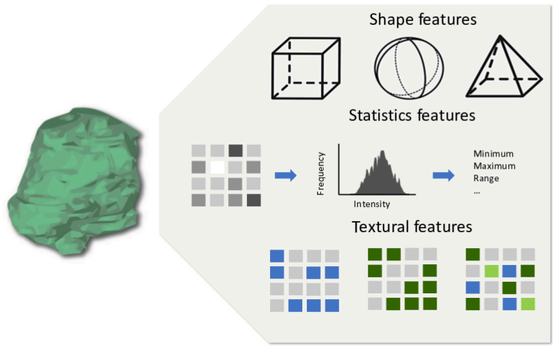


Figure 1: Description of radiomic features that can be extracted from solid tumors [1].

AIM

To predict pathological lymph node metastases from the radiomic characteristics extracted from prostate segmentations of preoperative FDG-PET/CT images..

METHOD

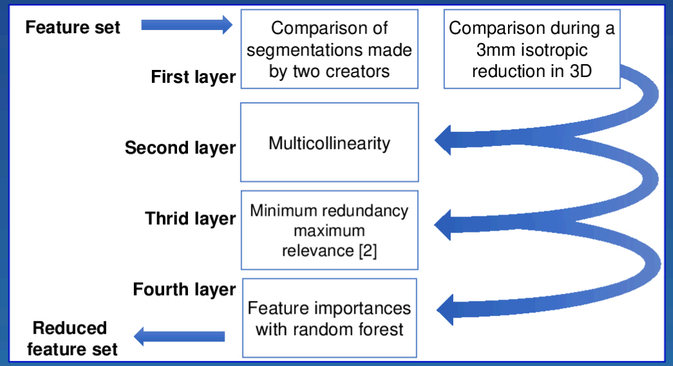
FDG-PET/CT images were acquired as a staging procedure prior to prostatectomy in **160 patients** diagnosed with prostate cancer with a **Gleason sum of ≥ 8 at biopsy**.

Three filters are applied to the images to extract more features:
- gradient, wavelet and Laplacian of Gaussian filters

A **total of 1015 radiomic** features extracted with Pyradiomics [4].

A **random forest classifier** is used to predict the presence of lymph node metastasis. The training is achieved over the 67% of the dataset in 3-fold cross-validation.

Diagram of feature selection method



RESULTS

Table 1 presents the number of radiomic features selected after each additional layer of filtration.

Layers comparison:

It can be seen from Figure 2 that reducing the number of markers does not alter the accuracy or even improve the prediction of the system.

In fact, with only 2% of all the radiomics features extracted, the accuracy is at its maximum for each modality: an augmentation of 14%, 2% and 3% for PET, CT and PET/CT for the training cohort.

Modalities comparison to predict pathological lymph node metastasis:

The results obtained with PET are better with an AUC of 80 ± 6% for training and 68 ± 5% for validation. The ROC curve is shown in Figure 3.

Best model composition :

To sum up, the best model is obtained after the fourth selection layer with PET markers, i.e. with only 18 markers. This group consists of:

- 56% of textural features and 44 % of first order statistics features (no shape features),
- 50% are extracted after the application of the wavelet filter.

Modality	Number of radiomic features				
	None	First layer	Second layer	Third layer	Fourth layer
PET	1015	556	143	80	18
CT	1015	710	171	80	22
PET/CT	2030	1256	368	80	18

Table 1: Number of radiomic features selected after each additional layer of filtration.

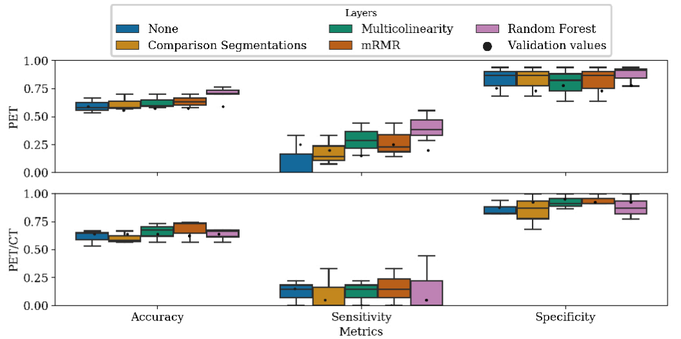


Figure 2: Comparison of pN number prediction models after the addition of each of the radiomic markers selection layers. The PN number indicates the presence of lymph node metastases.

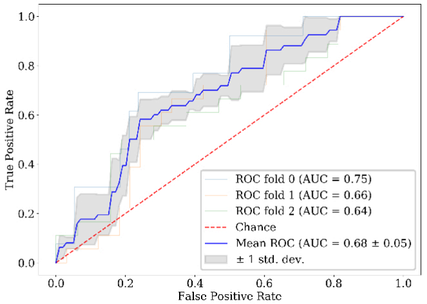


Figure 3: Receiver operating characteristic (ROC) curve analysis of lymph node metastasis prediction according to PET features after the fourth layer of selection. The area under the ROC curve was 0.68 ± 0.05.

CONCLUSIONS

Extensive analysis of intraprostatic radiomic features can improve the accuracy of FDG-PET/CT to predict lymph node metastasis before radical prostatectomy, generating

Reducing the number of characteristics reduces variance.

Ultimately, the algorithm will better predict the risk of prostate cancer recurrence and help improve treatment choices.

REFERENCES

1. **Coroller, T. P et al.** Combining data science and medical imaging: Advancing cancer precision medicine with radiomics. Datawyse / Universitaire Pers Maastricht. 2017;https://doi.org/10.26481/dis.20171214tc
2. **Lavallée, E et al.** Increased Prostate Cancer Glucose Metabolism Detected by 18F-fluorodeoxyglucose Positron Emission Tomography/Computed Tomography in Localised Gleason 8–10 Prostate Cancers Identifies Very High–risk Patients for Early Recurrence and Resistance to Castration. European urology focus 2019; 5(6): 998-1006.
3. **Peng, H. et al.** Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy. IEEE Transactions on pattern analysis and machine intelligence 2005; 27(8); 1226-1238.
4. **van Griethuysen, J. J. M et al.** Computational Radiomics System to Decode the Radiographic Phenotype. Cancer Research 2017; 77(21); e104–e107.https://doi.org/10.1158/0008-5472.CAN-17-0339

CONTACT INFORMATION

Contact Danahé LeBlanc with any questions:
danahe.leblanc@hotmail.com