

RF was stable according to all different parameters analyzed, while the GLRLM RFs group and entropy histogram resulted to be robust according to all different analyzed parameters, except for intensity rescale factors. **Conclusion:** This study allowed to evaluate the impact of methodological aspects on the assessment of RFs robustness at  $^{68}\text{Ga}$ -DOTATOC PET/CT. To investigate different biological behaviours of NET with a radiomic approach, contouring methods and intensity rescale factors should be carefully evaluated in order to use repeatable RFs. **References:** None.

## OP-664

### Multi-level multi-modality fusion radiomics: application to PET and CT imaging for improved prognostication of head and neck cancer

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**Aim/Introduction:** Intra-tumor heterogeneity plays a key role in tumor development and responses to therapy. Radiomics analysis, incorporating measurement of heterogeneity, has been extensively investigated on individual imaging modalities. By contrast, multi-modality radiomics analysis has been much less commonly performed, and if applied, is usually performed by concatenation of features from different modalities. However, such an approach may not be able to effectively integrate the supplementary information provided by different modalities. Thus, the purpose of this study was to investigate a multi-level fusion strategy to combine the information provided by PET and CT at the image-, matrix- and feature-levels towards improved prognosis of multi-center head & neck cancer. **Materials and Methods:** 296 patients scanned with FDG-PET/CT imaging from 4 centers were collected from The Cancer Imaging Archive (TCIA). Three outcomes recurrence-free survival (RFS), metastasis-free survival (MFS) and overall survival (OS) were considered. 127 radiomics features were extracted from (1) PET images alone; (2-7) PET and CT images fused via wavelet-based fusion (WF) with CT-weights of 0.2, 0.4, 0.6 and 0.8, gradient transfer fusion (GTF), and guided filtering-based fusion (GFF); (8) fused matrices (sumMat), constructed by considering the voxel relationships in PET and CT simultaneously; (9-10) fused features constructed via feature averaging (avgFea), and feature concatenation (conFea); and finally, (11) use of CT images alone. Top 10 features with higher concordance index (C-index) in univariate Cox analysis were selected, and multivariate model was constructed by Akaike information criteria (AIC). **Results:** For RFS prediction, PET (C-index:  $0.62\pm 0.08$ ) and WF0.6 (C-index:  $0.61\pm 0.05$ ) showed higher performance than other 9 strategies

(C-index: 0.55-0.59). For MFS prediction, PET (C-index:  $0.69\pm 0.09$ ), WF0.8 (C-index:  $0.69\pm 0.09$ ) and sumMat (C-index:  $0.67\pm 0.10$ ) showed higher performance than other 8 strategies (C-index: 0.62-0.65). For OS prediction, WF0.8 showed highest C-index of  $0.64\pm 0.02$  compared with other 10 strategies (C-index: 0.58-0.63). **Conclusion:** Models constructed by image-level fusion outperformed matrix- and feature-level fusion, as well as use of single modality, indicating that integrating information at earlier stages (i.e. merging metabolic information from PET and anatomic information from CT voxel by voxel) can capture more useful characteristics. **References:** 1.Wong, A.J., et al., Radiomics in head and neck cancer: from exploration to application. *Transl Cancer Res*, 2016. 5(4): p. 371-382. 2.Lv, W., et al., Radiomics Analysis of PET and CT Components of PET/CT Imaging Integrated with Clinical Parameters: Application to Prognosis for Nasopharyngeal Carcinoma. *Mol Imaging Biol*, 2019, doi: 10.1007/s11307-018-01304-3.

## OP-665

### Comparison of machine learning-driven lesion classifiers in PET/MR images of prostate cancer patients

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**Aim/Introduction:** Positron Emission Tomography (PET) plays an important role in tumour characterization. Lately, the use of radiomics analysis of PET images has shown potential to positively impact diagnostic work-up of oncology patients. However, various radiomics features were reported to be sensitive to multi-centric imaging protocol variations. Here, we compared different Gleason pattern classifiers in prostate PET/MRI studies built on four multi-centric coefficient of variation (CoV) radiomic feature groups [1]. **Materials and Methods:** 74 prostate patients were included in this study having a multi-parametric prostate PET/MRI including 8 series:  $^{18}\text{F}$ -FMC and  $^{18}\text{F}$ -FMC+ $^{68}\text{Ga}$ -PSMA<sup>HBED-CC</sup> (dual-tracer) PET, furthermore, T2, ADC, iAUC, KEP, Ktrans and Ve MRI. Based on Gleason-annotated, full-mount histopathological slices, 120 lesions were delineated from each study (Hermes Nuclear Diagnostics, Sweden). Overall 589 radiomics features were extracted from the 8 series of each of the 120 lesions based on optimized radiomics [1]. Features were categorized as CoV<5%, CoV<10%, CoV<20% and all-CoV according to [1]. For each of the four CoV categories, a low risk ( $\leq$ Gleason 3) vs. high risk ( $\geq$ Gleason 4) machine learning predictor was established [2]. 1000-fold Monte Carlo cross-validation with 20% held-out sets was performed to estimate the sensitivity (SENS), specificity (SPEC), accuracy (ACC), positive-predictive-value (PPV) and negative-predictive-value (NPV) of the four predictive models. **Results:** The accuracy of the low-high risk predictive models over four CoV feature categories were 75% (CoV<5%), 76% (CoV<10%), 78% (CoV<20%) and 77%