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## Finding reproducible and informative radiomic features associated to clinical endpoints and to immunohistochemistry biomarkers from CT imaging data in an immunotherapy-treated NSCLC cohort

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### Abstract

- Purpose

The objective of this study is to find reproducible and predictive radiomic features from Computed Tomography (CT) images that are correlated to clinical endpoints and immunohistochemistry (IHC) biomarkers in an immunotherapy treated non-small cell lung cancer (NSCLC) cohort.

- Materials and Methods

A retrospective study of NSCLC patients receiving immunotherapy was undertaken. The dataset includes 164 patients that have CT-scans and survival end points, while 34 of them have IHC data as well. For all of the patients, we extracted 1224 and 441 radiomics features using two IBSI-compliant pipelines, Pyradiomics and RaCat respectively. They were grouped into shape-, intensity-, and textural-based categories. The intraclass comparison between features across these two pipelines was assessed by the Pearson, Spearman, F-test, and Mutual Information estimators and corrected for false positives using the False Discovery Rate (FDR) method. To assess the influence of the clustering of pixels based on their intensity (defined as the gray-level discretization), on the robustness of features, we computed their association with two survival endpoints (Overall Survival (OS) and Progression Free Survival (PFS)) and with eight IHC markers (CD3, CD4, CD8, CD56, CD163, Lag3, PD1, and TIM) considering two different bin counts and bin width for a sub-group of 34 Samples.

- Results

Our results showed that first-order radiomic features were amongst the most reproducible features. Importantly, our findings conveyed that while the values of radiomic features were strongly pipeline-dependent, the textural radiomic features that were associated to the clinical parameters and IHC markers were strongly dependent to the type of discretization too. When changing the bin width or bin count, only 20% of the overall texture-based radiomic features have a lower rank differential change (less than 50) in the target prediction ranking score. Whereas, this value is 100% for the shape-based features and 90% for the intensity-based features.

- Conclusions

Through this work, we highlighted a significant heterogeneity between radiomic pipelines as well as the impact of gray-level discretization on the discovery of immunotherapy biomarkers in NSCLC patients. Based on this, it is crucial to standardize the radiomics processing methods to develop clinically robust predictive models in future studies.

**OBJECTIVES**

The objective of this study is to find reproducible and predictive radiomic features from Computed Tomography (CT) images by comparing two different radiomics pipelines and four different types of gray-level discretization to predict clinical endpoints and immunohistochemistry (IHC) biomarkers in an immunotherapy treated non-small cell lung cancer (NSCLC) cohort.

**MATERIAL & METHODS**

- We retrospectively identified 164 NSCLC patients treated with ICI, out of which 54 of them also had IHC data.
- 1224 and 441 radiomic features from Pyradiomics and RaCat pipelines, were extracted assuming the same gray-level discretization out of which 75 features were common between the two pipelines.
- 1224 radiomic features from Pyradiomics were extracted assuming four different bin counts and bin widths.
- The extracted features from two pipelines were compared in terms of shape-, intensity-, and texture-based features using the Pearson, Spearman, and Kendall estimators.
- The impact of feature extraction pipeline and grid clustering, based on gray-level discretization, on feature robustness was examined by evaluating the association of features with progression free survival (PFS), PD-L1 and CD8 immune counts.

**RESULTS**

- Features with consistent directionality between pipelines that are associated with clinical endpoints were demonstrated as potentially stable features.
- Feature-based features were found to be significantly associated with PFS.
- Pyradiomics extracted features showed more univariate statistical significance with PFS, while RaCat resulted in more significant features with PD-L1.
- By varying the gray-level discretization, the intensity-based features were found to be more stable.
- Among the 29 features that showed significant correlation with PFS considering different settings for gray-level discretization in Pyradiomics, 45% were intensity-based. Around 65% of these features were extracted using various filters on the original image.
- No particular bin size or bin count was found that led to a higher number of significant features linked to PFS, PD-L1, and CD8.

**RESULTS: PIPELINE COMPARISON**

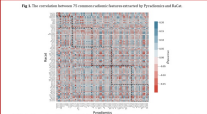


Fig. 1. The correlation between Pyradiomics and RaCat pipelines for various radiomic features. The color scale represents the correlation coefficient from -0.5 to 0.5.

Table 1. The number of features extracted by Pyradiomics and RaCat pipelines.

Feature Type	Pyradiomics	RaCat
Shape	1224	441
Intensity	1224	441
Texture	1224	441
Total	1224	441

Table 2. The number of features extracted by Pyradiomics and RaCat pipelines with significant association with PFS.

Feature Type	Pyradiomics	RaCat
Shape	1224	441
Intensity	1224	441
Texture	1224	441
Total	1224	441

Fig. 2. The number of features extracted by Pyradiomics and RaCat pipelines with significant association with PFS.

**RESULTS: GRAY-LEVEL DISCRETIZATION COMPARISON**

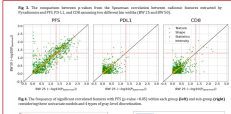


Fig. 3. The association between PFS and various radiomic features for different gray-level discretization methods. The color scale represents the correlation coefficient from -0.5 to 0.5.



Fig. 4. The distribution of radiomic features for different gray-level discretization methods. The color scale represents the correlation coefficient from -0.5 to 0.5.

**CONCLUSIONS**

Our study has revealed a considerable degree of heterogeneity between radiomics pipelines and highlighted the importance of gray-level discretization in discovering immunotherapy biomarkers in NSCLC patients. These findings emphasize the need to standardize radiomics processing methods to improve reproducibility and reliability of radiomics analysis for developing clinically robust predictive models in NSCLC patients. Future studies could investigate how patient demographics may influence the reproducibility and predictive value of radiomic features to enhance the accuracy of predictive models.

**REFERENCES**

1. J.M. van Groenou et al. Computational radiomics in breast MRI: Radiomics. *Physics in Medicine and Biology*, 2017, 62(11), p. R114-R147.  
 2. R. Frazier et al. An open source and easy to use radiomics software tool. *Frontiers in Oncology*, 2019, 9, p. 1021223.  
 3. M.L. Shinde et al. Immunotherapy for Advanced Non-Small Cell Lung Cancer: A Review of Progress. *Annals of the Royal College of Physicians*, 2021, 43(1), p. 1-10.  
 4. R.W.L. Aerts et al. Developing tumor phenotype by non-invasive imaging using quantitative radiomics: approach. *Nature Communications*, 2014, 5(2), p. 4006.  
 5. R. Wang et al. Quantitative-based prediction of response to immune checkpoint inhibitor treatment for metastatic lung cancer using computed tomography: a real-world study of two centers. *BMJ Open*, 2021, 21(1), p. e002814.  
 6. J. Parkerson Wood et al. Reliability and prognostic value of radiomic features are highly dependent on choice of feature extraction pipeline. *Int J Radiat Oncol Biol Phys*, 2020, 108(1), p. 161-167.  
 7. R. Larue et al. Influence of gray level discretization on accuracy and reproducibility of radiomics phenotypic study. *Acta Oncol*, 2017, 56(11), p. 1564-1570.

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