Unsupervised machine learning of radiomic features for predicting treatment response and survival of early-stage non-small cell lung cancer patients treated with stereotactic body radiation therapy

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Purpose/Objectives:
To identify radiomic biomarkers for predicting treatment response and survival of early-stage non-small cell lung cancer (NSCLC) patients treated stereotactic body radiation therapy (SBRT), we developed an unsupervised machine learning based radiomic technique and validated our method on imaging data of stage I NSCLC patients. We hypothesize this will allow us to distinguish patients with good response and survival from those with poor outcomes.

Materials/Methods:
An unsupervised two-way clustering method was used to find sub-clusters of patients and radiomic features simultaneously, aiming to distinguish patients with different treatment responses and at the same time reducing feature dimensionality for survival analysis.

This study was performed based on a longitudinal FDG-PET dataset of 100 consecutive patients who were treated with SBRT for stage I NSCLC with a median follow-up of 2 years. All patients had a solid component of their NSCLC tumor. Although all patients were treated uniformly, they had different primary tumor outcomes.

From the PET scan of each patient, we extracted 343 radiomic features including Intensity statistics, Gray level co-occurrence matrix, Gray level run-length matrix, and Local binary patterns. Then, patients were grouped into clusters with distinctive radiomic representations with respect to feature subgroups using the two-way clustering method. Survival analysis with respect to death and nodal failure at the group level was performed for each cluster of patients using the Kaplan-Meier estimator. Finally, the radiomic features in each feature subgroup were summarized as one meta-feature, and survival models were built using Cox proportional hazards model, Cox-Lasso, and Random Survival Forests (RSF) based on the meta-features for predicting patients’ survival and nodal failure risks.

Results:
Patients were grouped into 3 clusters based on their radiomic features that were simultaneously grouped into a different numbers of subgroups. Significant differences between clusters of patients were observed for survival and nodal failure, estimated by the Kaplan-Meier estimator (log-rank tests). The survival regression models were validated using 5-fold cross-validation (with 200 repetitions), and the best concordance index measures for predicting survival and nodal failure were 0.65 and 0.76 respectively.

Conclusions:
To achieve robust performance for predicting treatment response and survival based on radiomic features, we proposed a novel unsupervised machine learning based method. The evaluation results demonstrate that our method can achieve promising performance for distinguishing patients with different outcomes. Research to validate the proposed method on a larger dataset is ongoing.