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Post SBRT or Surgery Local Failure Prediction using Pre-treatment CT in Early-Stage NSCLC Patients Using a Novel Multi-Feature-Combined Model

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Abstract
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Abstract

Objectives:

To predict the risk of local failure using pre-treatment CT imaging for patients with early-stage non-small cell lung cancer (NSCLC) patients after either surgery or stereotactic body radiotherapy (SBRT) using a novel Multi-Feature-Combined (MFC) model, which combines classic radiomic features, deep learning features, and patient demographic information in an integrated workflow.

Methods:

The MFC model comprises three key steps. (1) Extraction of 92 classic radiomics features from the gross tumor volume (GTV) segmented on the pre-treatment CT image. (2) Calculation of 128 deep features from a pre-trained deep learning (DL) U-Net encoder structure. As a transfer learning strategy, the adopted U-Net encoder was fine-tuned specifically for our dataset. The 128 latent activation values from the last fully connected layers were used as the deep feature representations. The data augmentation was employed to prevent the potential overfitting issue due to the imbalanced outcome distribution. (3) The extracted 92 classic radiomic features, 128 deep features, along with 4 patient demographic information (gender, age, tumor volume, and Charlson comorbidity index), were synthesized as a multi-dimensional input to a random forest (RF) classifier to predict the local failure.

Two NSCLC patient cohorts from our institution were studied under an IRB: (1) the surgery cohort includes 83 patients who underwent segmentectomy or wedge resection (with 7 local failures), and (2) the SBRT cohort includes 84 patients who received lung SBRT (with 9 local failures). The developed MFC model was evaluated independently for both patient cohorts. For each cohort, the MFC model was compared against (1) RF prediction models using only radiomic features (R model), (2) RF prediction models using only patient demographic information (PI model), and (3) DL model that directly predicts the local failure based on the U-Net encoder (DL model). All models employed a 70%-30% train-test split with 100-fold Monte Carlo random validation assignments. Mean sensitivity and AUC analysis were used to evaluate the prediction performance. The t-test was performed to identify the statistically significant differences.

Results:

The proposed MFC model outperformed all other models with statistical differences. The AUC values for the MFC, R, PI, and DL models were 0.842±0.045, 0.639±0.200, 0.453±0.041, and 0.626±0.054 for the surgical cohort and 0.947±0.014, 0.687±0.141, 0.455±0.043, and 0.773±0.051 for the SBRT cohort, respectively. Compared to the MFC model, the P-values of AUC results for R, PI, and DL models were 0.000, 0.000, and 0.000 for the surgical cohort and 0.000, 0.000, and 0.000 for the SBRT cohort, respectively. The sensitivity values using MFC, R, PI, and DL models were 0.670±0.030, 0.125±0.275, 0.000±0.000, and 0.191±0.164 for the surgical cohort and 0.717±0.021, 0.000±0.000, 0.025±0.112, 0.713±0.071 for the SBRT cohort, respectively.

Conclusion(s):

The developed MFC prediction model innovatively synthesized feature information from multiple sources and systematically applied it to two unique patient cohorts for early-stage NSCLC to predict the risk of local failure. The comparison studies suggest that incorporating pre-treatment patient information from multiple sources improves the ability to predict the risk of local failure. The current developments may be useful to aid clinicians to optimize treatment procedures in future clinical applications.