Prognostic Prediction for Lung Stereotactic Body Radiotherapy Using Breath-Hold CT-Based Radiomic Features with Random Survival Forest: A Multi-Institutional Study

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PURPOSE

To predict local recurrence (LR) and distant metastasis (DM) in patients with early-stage NSCLC who underwent SBRT, using breath-hold CT-based radiomic features.

METHOD

Table 1: Patient characteristics

Clinical factors	Training (n = 464, 10 institutions)	Test (n = 109, 1 institution)	P-value
Age [years]	79 (41–92)	79 (57–92)	0.85
Sex [female/male]	125/339	45/64	0.04
BMI [<18.5/18.5 ≤, <25.0/25.0 ≤ (kg/m^2)]	106/282/76	23/75/11	1.00
PS [0–1/2–4]	409/55	89/20	0.89
Smoking [never/ever]	102/362	40/69	0.02
Histology [adeno./SqCC/others/unknown]	144/79/23/218	62/24/2/21	<0.0001
GTV size [cm^3]	6.1 (0.2–77.7)	8.2 (1.3–57.7)	0.004
Tumor location [peripheral/central]	409/55	83/26	0.02
BED$_{10}$ [100 <, ≤120/120 <, ≤160/160 < (Gy)]	388/33/43	109/0/0	<0.0001

1) Patients

Training: 464 (from ten institutions)
Test: 109 (from one institution)

2) CT images

Breath-hold CT images without contrast enhancement

3) Feature extraction

944 features

- PyRadiomics was used
- 1 x 1 x 1 mm^3 resampling
- LoG, Wavelet filter were applied

4) Feature selection

- Reproducibility
- GTV correlation
- Inter-feature correlation

Adaptive LASSO

5) Model construction

Random survival forest (RSF)

Constructed models
- Clinical
- Radiomic
- Combined

Two hyperparameters (HP) were optimized
1. the number of variables randomly sampled at each split: m_{try}
2. the average number of data points in a terminal node: n_{ave}

6) Performance test

Variable importance   Cumulative incidence

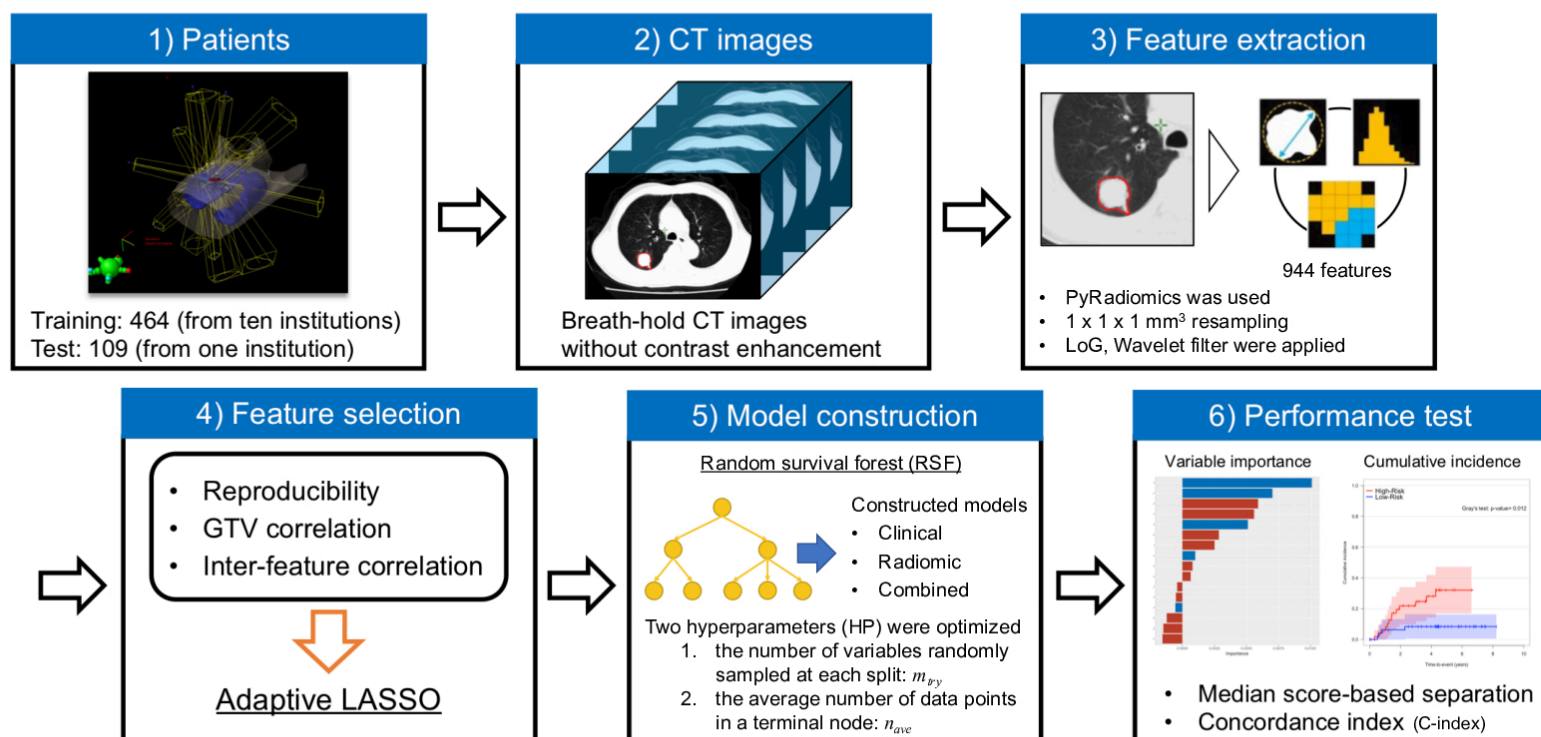- Median score-based separation
- Concordance index (C-index)

Fig. 1: Workflow of this study.

RESULTS

- The number of radiomic features were reduced to as many as clinical factors. Of the 944 radiomic features, 11 and 5 features remained as the prognostic factors for LR and DM, respectively, with reproducibility and non-redundancy.

- High- and low-risk score groups had **significant difference of DM prediction for the radiomic and combined models** (p < 0.05) (Fig. 2). No model in the test dataset yielded a significant separation for LR, and C-indices were ≈ 0.60.

- Two radiomic features (*wavelet.LH_glcm_MCC* and *wavelet.LL_glcm_imc2*) were identified as **a higher importance than any other clinical factors** (Fig. 3).

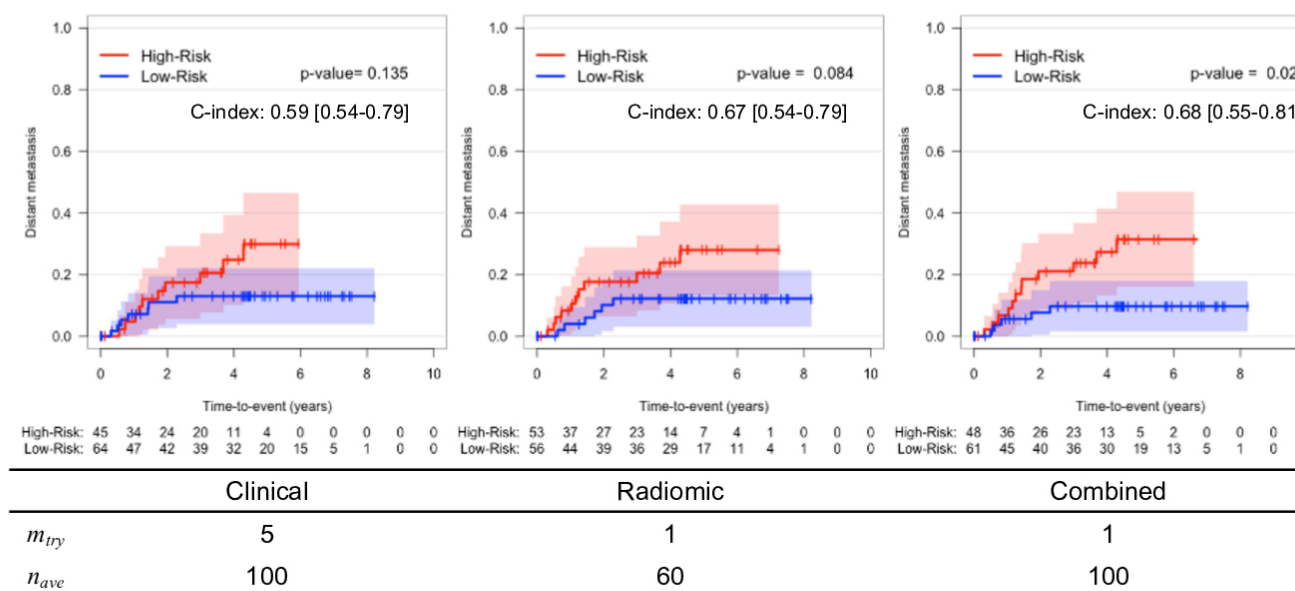- High- and low-risk score groups had different tendency of feature maps (Fig. 4).

Fig. 3: Variable importance in combined model for DM.

	Clinical	Radiomic	Combined
m_{try}	5	1	1
n_{ave}	100	60	100

Fig. 2: Cumulative incidence curves, C-indices with bootstrapping 95% confidence intervals, and HPs of DM for test datasets.
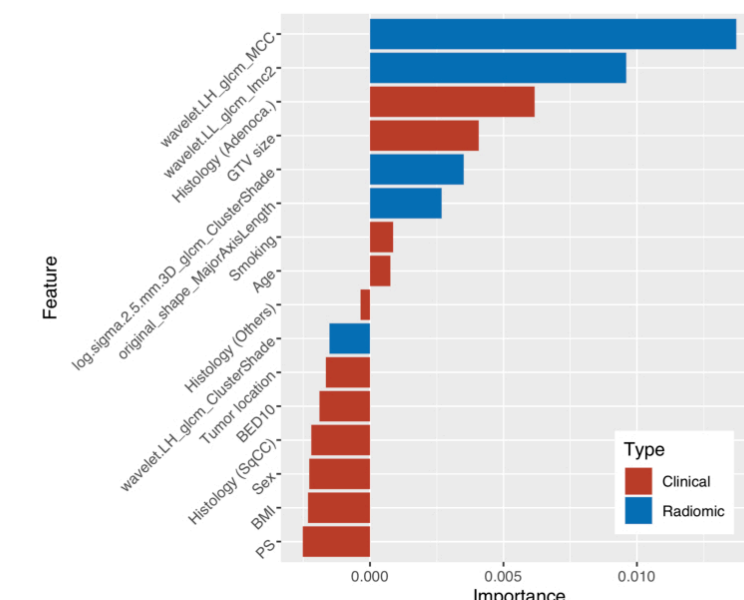

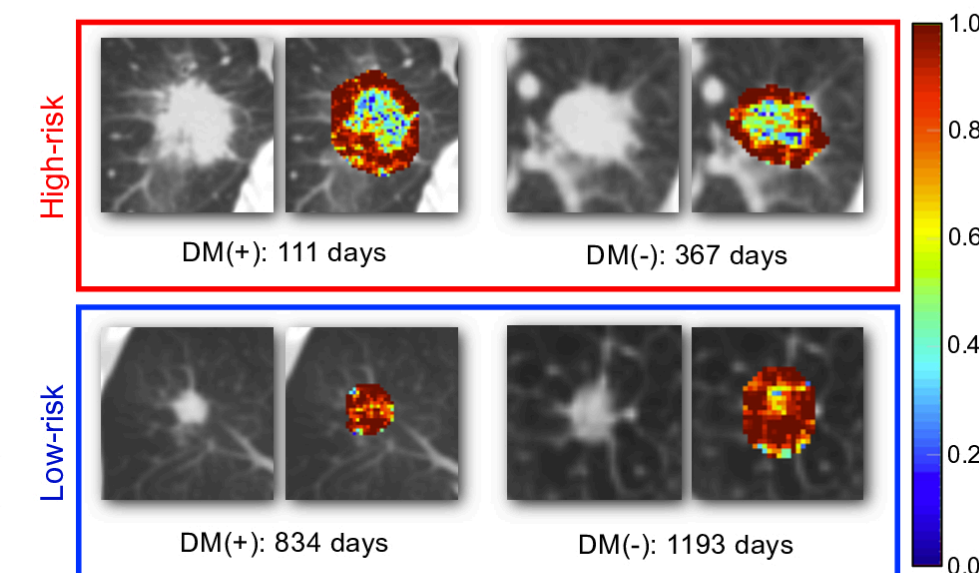DM(+): 111 days   DM(-): 367 days

DM(+): 834 days   DM(-): 1193 days

Fig. 4: The feature maps generated from *wavelet.LH_glcm_MCC*.

CONCLUSIONS

The radiomics approach with RSF using breath-hold CT images could predict DM in early-stage NSCLC patients although that may not have potential to predict LR.

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