Evaluation of a radiomics-based predictive model for radiation pneumonitis using lung ventilation imaging

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INTRODUCTION

Radiation Pneumonitis (RP)

Grade 2 or higher RP has been reported to occur in approximately 30% of non-small cell lung cancer (NSCLC) patients[1)]. Since the occurrence of Grade 2 or higher RP necessitates discontinuation of immune checkpoint inhibitors, it leads to interruption of radiotherapy and a decrease in the local control rate. Therefore, predicting the occurrence of RP before the initiation of radiotherapy is important.

Applications of Lung Ventilation Imaging

Previous studies developed RP prediction models using features from planning CT and dose distributions. Although RP incidence correlates strongly with the dose to highly ventilated lung regions[2)], few studies have used lung ventilation images. We therefore constructed an RP risk prediction model integrating features from lung ventilation images to improve predictive accuracy. The model may also be applicable to radiotherapy planning reflecting individual lung function and RP risk.

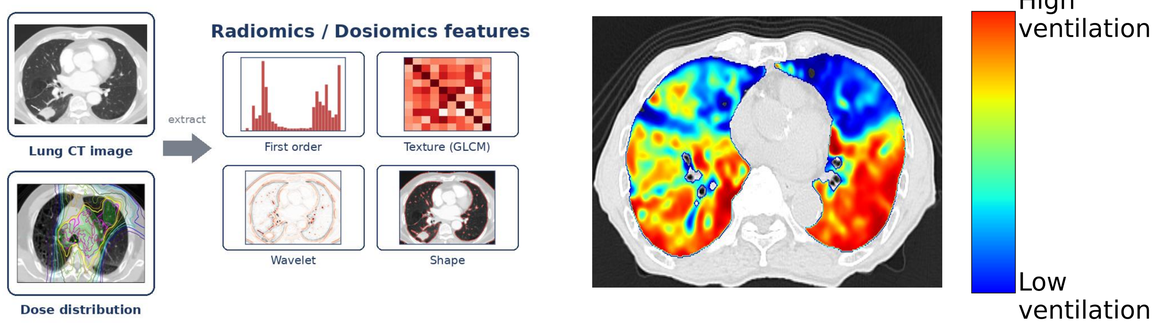

Figure 1. Conventional feature analysis and lung ventilation images

METHODS AND MATERIALS

Patient data

- 77 NSCLC patients who underwent definitive radiotherapy.
- Patients for whom planning CT images, dose distributions, and lung ventilation images derived from 4D-CT were all available.

Table 1. Patient data

Age (median)	72.5 (47-92)
Sex：F / M	23 / 54
Total dose	60 Gy (54–66Gy)
Stage：I / II / III / IV	1 / 5 / 70 / 1
RP：G2+ / G1-	24 / 53

Analysis method

Six RP prediction models were constructed using the random forest method: (1) clinical factors alone, (2) CT image features alone, (3) dose distribution features alone, (4) lung ventilation image features alone, (5) a combination of CT image, dose distribution, and lung ventilation image features, and (6) a combination of clinical factors, CT image, dose distribution, and lung ventilation image features.

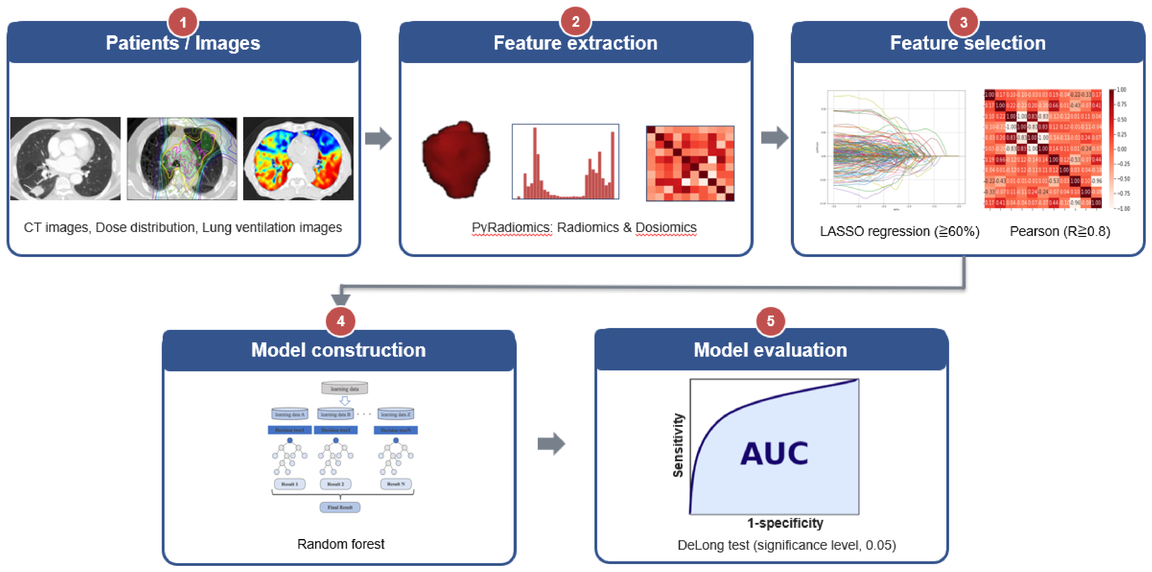

Figure 1. Flowchart of the analysis

RESULTS

Selected features

Finally, a total of eight features were selected: two clinical features, one feature from CT images, three features from dose distributions, and two features from lung ventilation images.

Performance and validation of the prediction models

The model combining clinical factors, CT images, dose distributions, and lung ventilation images showed the highest AUC and was the only model that showed a significant difference from the clinical-factors-only model.

Table 2. Each feature and the results of the univariate and multivariate analyses

Clinical, CT, Dosiomics, Ventilation	Filter	Class	Feature	Univariate analysis			Multivariable analysis		
				OR	95% CI	p-value	OR	95% CI	p-value
Clinical	-	-	PTV Volume	1.01	1.00-1.01	<0.01	1.00	1.00-1.01	0.05
Clinical	-	-	Lung V5	1.06	1.02-1.11	<0.01	1.05	1.00-1.09	0.03
CT	HHH	First Order	Median	0.51	0.29-0.90	0.02	0.50	0.22-1.14	0.10
Dosiomics	LLL	GLCM	Imc2	3.87	1.58-9.47	<0.01	4.33	0.55-34.4	0.17
Dosiomics	LLL	GLRLM	GLNN	0.19	0.06-0.59	<0.01	0.38	0.03-4.63	0.48
Dosiomics	σ=1.0mm	GLCM	Idn	2.57	1.32-4.99	<0.01	2.88	1.95-8.74	0.06
Ventilation	HLL	First Order	Minimum	0.44	0.24-0.80	<0.01	0.24	0.01-0.60	<0.01
Ventilation	σ=3.0mm	GLSZM	SAHGLE	0.50	0.30-0.84	<0.01	0.50	0.25-1.01	0.05

GLNN : Gray Level Non Uniformity Normalized, SAHGLE : Small Area High Gray Level Emphasis
OR : Odds ratio, 95%CI : 95% confidence interval

Table 3. AUC, sensitivity, specificity, and p-value of each model

Model	AUC (95% CI)	Sensitivity (95%CI)	Specificity (95% CI)	p-value
Clinical	0.71 (0.58-0.83)	0.71 (0.53-0.89)	0.68 (0.55-0.81)	-
CT	0.69 (0.56-0.82)	0.75 (0.58-0.92)	0.62 (0.49-0.75)	0.89
Dosiomics	0.67 (0.53-0.80)	0.79 (0.63-0.95)	0.60 (0.47-0.74)	0.60
Ventilation	0.73 (0.60-0.85)	0.88 (0.74-1.00)	0.55 (0.41-0.68)	0.81
CT, Dosiomics, Ventilation	0.79 (0.67-0.91)	0.79 (0.63-0.95)	0.72 (0.60-0.84)	0.31
Clinical, CT, Dosiomics, Ventilation	0.84 (0.74-0.93)	0.96 (0.88-1.00)	0.57 (0.43-0.70)	0.02

Model performance was assessed using the DeLong test (significance level, 0.05).

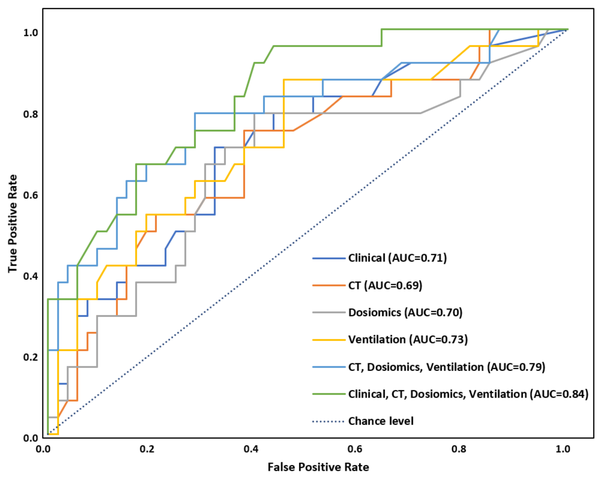

Figure 3. ROC curve of each model

DISCUSSION

Summary of this study

This study is the first to construct an RP risk prediction model by integrating features extracted from lung ventilation images in addition to those extracted from clinical factors, CT images, and dose distributions. The prediction model combining clinical factors, CT images, dose distributions, and lung ventilation images showed the highest accuracy (AUC = 0.84).

Predictive Performance of the Lung Ventilation Image–Based Model

This is consistent with several previous studies, which have reported that combining clinical factors, CT images, and dose distributions improves predictive accuracy. The present study is consistent with these previous studies in that adding lung ventilation images improved predictive accuracy. In the future, we aim to secure a larger number of cases to develop a stable model that can be used in clinical practice.

CONCLUSIONS

These results demonstrated that adding features extracted from lung ventilation images to the factors conventionally used in constructing RP prediction models improves predictive accuracy.

REFERENCES

1. Palma DA, et al. Int J Radiat Oncol Biol Phys. 2013;85:444-450.
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This study was conducted with the approval of the institutional review boards of Tokyo Metropolitan Komagome Hospital and Komazawa University.