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A prognostic model based on computed tomography radiomics to evaluate response of immunotherapy in non-small cell lung cancer using clinical data

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► ***Original article***

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ABSTRACT

Background: This study aimed to develop and validate a computed tomography (CT) radiomics–based model for predicting immunotherapy response and prognosis in patients with advanced non-small cell lung cancer (NSCLC). ***Materials and Methods:*** A total of 117 patients with advanced NSCLC treated with PD-1/PD-L1 immune checkpoint inhibitors were retrospectively enrolled from two centers. Baseline CT scans obtained before immunotherapy and follow-up CT scans acquired 6–8 weeks after treatment initiation were analyzed. Tumor lesions were manually segmented, and radiomics features were extracted. Two support vector machine–based models were constructed: a pre-treatment CT (pre-CT) model and a delta-CT model derived from changes in radiomics features before and after immunotherapy. Model performance for predicting immunotherapy response, defined according to RECIST 1.1 criteria, was evaluated using receiver operating characteristic (ROC) analysis. Kaplan–Meier survival analysis was performed to assess the prognostic value of radiomics scores. ***Results:*** In the training cohort, the pre-CT and delta-CT models achieved area under the ROC curve (AUC) values of 0.825 and 0.844, respectively. In the validation cohort, the delta-CT model demonstrated superior predictive performance (AUC: 0.795) compared with the pre-CT model (AUC: 0.686). Subgroup analysis showed that the delta-CT model performed well in adenocarcinoma patients, whereas the pre-CT model showed better discrimination in squamous cell carcinoma patients. Higher delta -CT radiomics scores were significantly associated with poorer OS and PFS. ***Conclusion:*** CT radiomics models, particularly those based on longitudinal changes after immunotherapy, can effectively predict immunotherapy response and prognosis in advanced NSCLC, providing a non-invasive tool to support clinical decision-making.

INTRODUCTION

Lung cancer is one of the leading causes of cancer-related deaths worldwide. Among them, non-small cell lung cancer (NSCLC) accounts for 85% or more of lung cancers [1, 2]. Currently, the common treatment methods for NSCLC are surgery, radiotherapy and chemotherapy, as well as immunotherapy [3]. Different single or combined treatment regimens will be given to NSCLC patients at different stages. NSCLC is mostly diagnosed at an advanced stage [4, 5]. Currently, immune checkpoint inhibitors (ICI) have become a common treatment method for advanced NSCLC. However, not all patients will have a good response after immunotherapy [1, 6]. Therefore, predicting the immunotherapy effect of NSCLC patients as early as possible will help to screen out the beneficial population. Previous prediction models mostly combined imaging features and laboratory indicators for prediction, but the efficacy and predictive value of these models were limited [6]. Radiomics can obtain hidden information within imaging images in a high-throughput manner, and this information largely reflects the heterogeneity of the tumor. Currently, numerous studies have shown that radiomics-based prediction models have significant advantages in reflecting the therapeutic effect and prognosis of tumors [7]. Therefore, developing new radiomics-based immunotherapy response prediction models has positive significance for the immunotherapy drug regimens for NSCLC patients.

With the widespread application of imaging biomarkers in the diagnosis and prognosis prediction of NSCLC, many new predictive models have been established and validated [8, 9]. Among them, computed-tomography (CT), positron-emission-tomography (PET) and Magnetic-Resonance-Imaging (MRI) are the more common types of imaging data [10, 11]. Many researchers analyze the tumor's phenotype

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by extracting the features from CT imaging, thereby assessing the heterogeneity of the tumor. Some machine learning models based on CT imaging biomarkers have also been used to predict the efficacy of immunotherapy [12]. Wu and his partners constructed a short-term prediction model for immunotherapy response based on NCE/CE CT images and verified the predictive performance of the model [13]. Some researchers have segmented the radiomics features of chest CT images of NSCLC patients and constructed a model for predicting the response to PD-1 inhibitor immunotherapy and pulmonary toxicity [14]. Previous reports have suggested that the immunotherapy prediction model constructed based on CT radiomics has a very promising application prospect in the prediction of immunotherapy for NSCLC [13, 15]. On the other hand, due to the complexity of CT imaging data, more novel methods of imaging biomarker models need to be developed and validated [9].

This study enrolled patients with advanced NSCLC from two centers. Two CT image-based machine learning models were constructed by extracting CT images of the patients at two different time points before and after immunotherapy. Furthermore, we measured the roles of two models in predicting the immune treatment response of patients and in evaluating their prognosis. The model constructed in this study provides a theoretical foundation for the clinical application of imaging-based methods to predict the immune treatment response of advanced NSCLC patients and guide medication usage.

MATERIAL AND METHODS

Patient recruitment status

A total of 117 patients with advanced non-small cell lung cancer (NSCLC) were retrospectively enrolled from two independent medical centers. The sample included 92 males and 25 females with a total mean age 62.47 ± 10.99. Among them, 62 patients treated at Shanghai Pudong Hospital were included in the training cohort, and 55 patients treated at Hefei First People's Hospital were included in the external validation cohort. All enrolled patients met the predefined inclusion and exclusion criteria.

Inclusion criteria for patients: (1) NSCLC patients treated with PD-1/PD-L1 ICI; (2) DICOM raw files of plain CT images before and 6-8 weeks after PD-1/PD-L1 inhibitor treatment can be obtained; (3) Follow-up data after treatment can be obtained. Exclusion criteria: (1) Poor quality CT images that interfere with lesion segmentation; (2) Incomplete clinical data or inability to obtain. Evaluate the efficacy of the first immunotherapy in the follow-up patients, according to the RECIST 1.1 standard, the efficacy is classified into the response group with 30 cases (including CR, PR) and the non-response group with 32 cases (including PD, SD) in Shanghai Pudong Hospital (Training set). Another 55 cases from Hefei First People's Hospital were collected for the validation set, among which there are 21 cases in the response group and 34 cases in the non-response group.

Immunotherapy protocol and response assessment

All patients received immune checkpoint inhibitor –based immunotherapy targeting the PD-1/PD-L1 pathway, administered according to standard clinical practice and contemporary treatment guidelines. Immunotherapy agents included approved PD-1 or PD-L1 monoclonal antibodies, delivered either as monotherapy or in combination with other systemic treatments, based on individual clinical indications and physician discretion. Treatment was continued until radiographic disease progression, unacceptable toxicity, or clinical decision to discontinue therapy.

Treatment response was evaluated using contrast -enhanced chest CT performed 6–8 weeks after initiation of immunotherapy. Tumor response was assessed according to the Response Evaluation Criteria in Solid Tumors (RECIST) version 1.1 by experienced clinicians blinded to radiomics results. Patients were classified into two groups based on their best overall response: (1) Immunotherapy-sensitive (responder) group, including patients who achieved complete response (CR) or partial response (PR); and (2) Immunotherapy-resistant (non-responder) group, including patients with stable disease (SD) or progressive disease (PD).

Ethical statement

This study strictly adheres to the Declaration of Helsinki and has obtained approval from the Ethics Committee of Shanghai Pudong Hospital (2022-KYQWJW-003) and Hefei First People's Hospital (2023-KY-001).

CT image acquisition and lesion segmentation

All CT images were obtained using multi-slice spiral CT machines (GE-Medical-Systems; Minfound ScintCare; Philips Brilliance; Toshiba Aquilion) after full inspiration and during breath-holding (Figure 1). CT parameters are as follows: tube voltage (120 KV); tube current (50 - 350 Ma); detector collimation (64 × 0.625 mm) or (128 × 0.625 mm); field of view (350mm × 350 mm); (matrix 512 × 512); slice thickness (2.5 mm). All images were retrieved from the PACS workstation and searched in DICOM format.

The CT images were imported into the ITK-SNAP software (Version 3.4.0) for lesion segmentation. The determination of the lesion contours was carried out by two physicians with more than 5 years of diagnostic experience in the lungs. The two physicians delineated the regions of interest (ROI) layer by layer. The ROI covers areas such as the trachea, hemorrhage, necrosis, and calcification

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within the lesion.

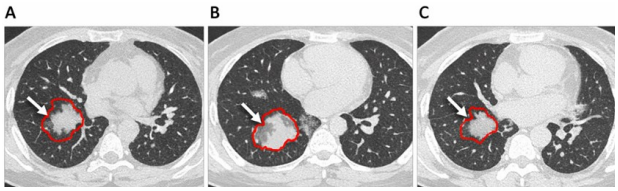


Figure 1. Representative axial chest CT images from patients with non-small cell lung cancer used for radiomics analysis.

Feature extraction and selection

Using Python 3.9.7 to import Pyradiomics (http://pyradiomics.readthedocs.io/), define the feature extractor, and set different feature extraction parameters based on the characteristics of the CT images. The configuration is made to extract features in a way that balances model complexity and computational efficiency. In the feature extraction process, this study does not apply any form of image filter and only extracts features from the original images to reduce the risk of overfitting caused by excessive feature dimensions. Based on the CT images, 102 original, 202 LoG and 672 wavelet features were extracted respectively. These include shape: 11, first-order: 16, gray-level co-occurrence matrix (GLCM): 20, gray-level difference matrix (GLDM): 16, gray-level run-length matrix (GLRLM): 17, gray-level size zone matrix (GLSZM) : 15, and neighborhood gray-level tone difference matrix (NGTDM): 7. After the analysis of CT image-based features was completed, we classified these features according to the time of image detection into pre-treatment influencing features (Pre-CT) and post-treatment influencing features. Furthermore, we will calculate the difference between the post-treatment and pre-treatment impact features to obtain the delta -CT features.

Construction of the radiomics model

A predictive model for immunotherapy was constructed using the SVM learning algorithm from the machine learning methods. Based on the detection time of CT images, Pre-CT radiomics and delta-CT radiomics models were constructed. Calculate the radiomics score (RS) for each patient. Two models were trained and validated using the training set and validation set of patients.

Statistical Analysis

All statistical analyses were performed with SPSS 25.0 software. *F* test was performed for the normality of the measurement data. The statistically significant between groups were analyzed using Student's *t*, chi-squared or Fisher test. Survival analysis was conducted using the Kaplan-Meier method, and risk stratification was based on the median value of RS. Log-rank test was used to compare the survival differences between groups. Draw the receiver operating characteristic (ROC) curve to evaluate the predictive performance of the two models. $P < 0.05$ was considered statistically significant (two-sided tests).

RESULTS

The characteristics of advanced NSCLC patients in training set and validation set

This study recruited 62 advanced NSCLC patients in hospital of training set and 55 advanced NSCLC patients in hospital of validation set. First, we compared the age, gender, body mass index, adverse medical history (smoking, alcohol consumption), complications (COPD, diabetes, hyperlipidemia), family history, type of lung cancer, clinical stage and PD-L1 positive rate of the two groups of patients (table 1). The baseline data of the two groups of patients were basically the same. (All $P > 0.05$, table 1). For the training set and validation set respectively, we compared the characteristic differences between patients with immunotherapy response and non-response. In training set, the proportion of patients with a history of smoking in the response group was significantly higher than that in the non-response group (P=0.026, table 1). In two set, the proportion of PD-L1 positive patients in the response group was higher than that in the non-response group (All $P < 0.05$, table 1).

Optimal features selection

Furthermore, we conducted a screening of the Pre -CT radiomics and delta-CT radiomics features. The screening results show that the Pre-CT radiomics model consists of 6 optimal features. The 6 optimal features were PreF1 = original_shape_Flatness, PreF2 = exponential_glcm_DifferenceAverage, PreF3 = LoG-glszm_SizeZoneNonUniformity, PreF4 = wavelet-LLL_glcm_Correlation, PreF5 = wavelet-HLL_firstorder_Skewness, PreF6 = wave_LLL_glszm_GrayLevelVariance (figure 2A). Delta -CT radiomics model consists 4 optimal features. The 4 optimal features were ΔF1 = wavelet_HHH_first_TotalEnergy, ΔF2 = wavelet_LHL_glszm_ZoneEnergy, ΔF3 = wavelet_LHH_glszm_Idmn, ΔF4 = wavelet_LLL_glszm_MaximumProbability (figure 2B).

Two models for predicting the immunotherapy response of patients in the training set and validation set

After successfully constructing two prediction models, we used these two models to predict the immunotherapy responses of patients. The results show that the Pre-CT radiomics (AUC: 0.825) and delta-CT radiomics models (AUC: 0.844) have relatively high predictive capabilities in the training set (figure 3A, table 2). In the validation set, the predictive ability of delta-CT radiomics (AUC: 0.795) was significantly higher than that of the Pre-CT

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radiomics model (AUC: 0.686) in the training set (figure 3B, table 2). The above results suggest that compared to Pre-CT radiomics, the delta-CT radiomics models have a higher predictive ability for the immunotherapy response in patients with advanced NSCLC.

Table 1. Clinical characteristic data of patients in the training set and validation set.

Characteristics	Training set (n=62)		*P* value	Validation set (n=55)		*P* value	*P* value *
	Responders (n=30)	Non-Responders (n=32)		Responders (n=21)	Non-Responders (n=34)		0.267
Age, mean ± SD, years	61.84 ± 12.13	62.49 ± 11.77	0.607	63.02 ± 10.22	62.69 ± 10.07	0.796	0.636
Gender, n (%)			0.176			0.579	0.734
Male	21 (70.0)	27 (84.4)		16 (76.2)	28 (82.4)		
Female	9 (30.0)	5 (15.6)		5 (23.8)	6 (17.6)		
Body mass index (IQR)	21.86 (4.18)	21.79 (4.18)	0.088	21.43 (3.11)	21.44 (3.17)	0.753	0.417
Smoking, n (%)			0.026			0.677	0.875
Current or Former	11 (36.7)	4 (12.5)		6 (28.6)	8 (23.5)		
Never	19 (63.3)	28 (87.5)		15 (71.4)	26 (76.5)		
Drinking alcohol, n (%)			0.901			0.288	0.742
Current or Former	6 (20.0)	6 (18.8)		3 (14.3)	9 (26.5)		
Never	24 (80.0)	26 (81.2)		18 (85.7)	25 (73.5)		
COPD, n (%)			0.456			0.896	0.557
Yes	8 (26.7)	6 (18.8)		4 (19.0)	6 (17.6)		
No	22 (73.3)	26 (81.2)		17 (81.0)	28 (82.4)		
diabetes, n (%)			0.086			0.592	0.880
Yes	0 (0.0)	3 (9.4)		1 (4.8)	2 (5.9)		
No	30 (100.0)	29 (90.6)		20 (95.2)	32 (94.1)		
Hyperlipidemia, n (%)			0.381			1.000	0.344
Yes	1 (3.3)	0 (0.0)		0 (0.0)	0 (0.0)		
No	29 (96.7)	32 (100.0)		21 (100.0)	34 (100.0)		
Family history, n (%)			0.329			1.000	0.344
Yes	0 (0.0)	1 (3.1)		0 (0.0)	0 (0.0)		
No	30 (100.0)	31 (96.9)		21 (100.0)	34 (100.0)		
Pathology, n (%)			0.793			0.701	0.785
Adenocarcinoma	14 (46.7)	16 (50.0)		10 (47.6)	18 (52.9)		
Squamous cell carcinoma	16 (53.3)	16 (50.0)		11 (52.4)	16 (47.1)		
Clinical stage, n (%)			0.660			0.826	0.875
III	8 (26.7)	7 (21.9)		5 (23.8)	9 (26.5)		
IV	22 (73.3)	25 (78.1)		16 (76.2)	25 (73.5)		
PD-L1, n (%)			0.008			0.025	0.674
<1%	12 (40.0)	25 (78.1)		9 (42.9)	26 (76.5)		
1-49%	15 (50.0)	5 (15.6)		8 (38.1)	6 (17.6)		
≥50%	3 (10.0)	2 (6.3)		4 (19.0)	2 (5.9)		

SD: Standard deviation; IQR: Interquartile range; COPD: Chronic obstructive pulmonary disease *represents Comparison between the training set and the validation set.

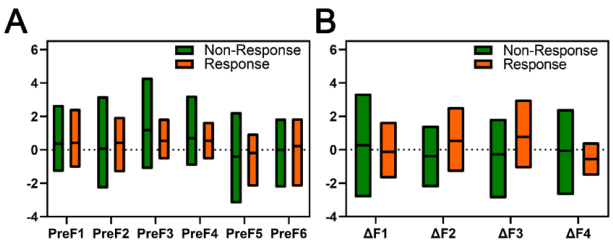


Figure 2. The features of pre-CT radiomics and delta-CT radiomics models. **(A)** Six features of pre-CT model. **(B)** Four features of delta-CT model. CT, computed tomography.

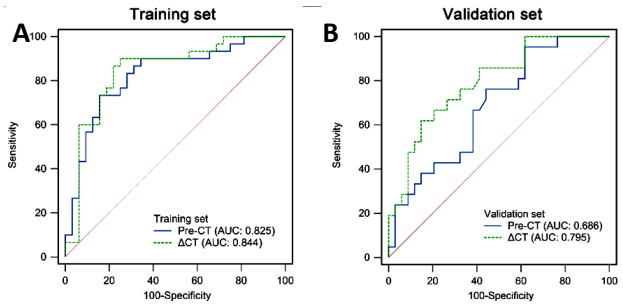


Figure 3. Two CT radiomics models for predicting the immunotherapy responses of patients in the training set and validation set. **(A)** Comparison of ROC curves of the two models in the training set. **(B)** Comparison of ROC curves of the two models in the validation set. ROC, receiver operating characteristic.

Table 2. AUC results of ROC curve analysis by pre-CT model, delta-CT model in advanced NSCLC patients.

Model		AUC	*P* value	Sensitivity (%)	Specificity (%)	Youden index
Training set	pre-CT	0.825	<0.001	73.33	84.37	0.577
	delta-CT	0.844	<0.001	90.00	75.00	0.650
Validation set	pre-CT	0.686	0.011	95.24	38.24	0.335
	delta-CT	0.795	<0.001	61.90	85.29	0.472

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Two models for predicting the immunotherapy response of adenocarcinoma (LUAD) and squamous cell carcinoma (LUSC) patients

After exploring the predictive value of the two models for the immunotherapy response of patients with advanced NSCLC, we further analyzed their predictive value for different types of NSCLC patients. For adenocarcinoma patients, both of the two CT radiomics models (AUC of Pre-CT: 0.848; AUC of delta -CT: 0.853) have relatively high predictive capabilities in training set (figure 4A, table 3). In validation set, the AUC value of the delta-CT radiomics model (AUC: 0.903) was significantly higher than that of the Pre-CT radiomics model (AUC: 0.533; figure 4B, table 3). For squamous cell carcinoma patients, both of the two CT radiomics models (AUC of Pre-CT: 0.816; AUC of delta-CT: 0.840) have relatively high predictive capabilities in training set (figure 4C, table 3). In validation set, the AUC value of the Pre-CT radiomics model (AUC: 0.841) was significantly higher than that of the delta-CT radiomics model (AUC: 0.682; figure 4D, table 3). Therefore, these two CT radiomics models also have certain predictive value for the immunotherapy response of patients with different types of advanced NSCLC.

Models used to assess the prognosis of advanced NSCLC patients undergoing immunotherapy

Furthermore, we evaluated the value of the two CT radiomics models in predicting patient prognosis. In terms of overall survival (OS), Pre-CT radiomics model did not have prognostic value for the OS of patients in the training set and the validation set (All $P > 0.05$, figure 5A and C). Delta-CT radiomics model being able to distinguish the OS of patients in training set (P=0.002, HR=2.608; figure 5B) and validation set (P=0.019, HR=2.255; figure 5D). In terms of progression-free survival (PFS), pre-CT radiomics model did not have prognostic value for the PFS of patients in the training set and the validation set (All $P > 0.05$, Figure 6A and C). Delta-CT radiomics model being able to distinguish the PFS of patients in training set (P=0.028, HR=2.131; figure 6B) and validation set (P=0.021, HR=2.020; figure 6D). The above results indicate that, delta-CT radiomics model may be applicable for evaluating the prognosis of patients with advanced NSCLC.

Table 3. AUC results of ROC curve analysis by pre-CT model, delta-CT model in adenocarcinoma and squamous cell carcinoma patients.

Subtype	Model		AUC (95% CI)	*P* value	Sensitivity (%)	Specificity (%)	Youden index
Adenocarcinoma	Training set	pre-CT	0.848	<0.001	85.71	75.00	0.607
		delta-CT	0.853	<0.001	85.71	75.00	0.607
	Validation set	pre-CT	0.533	0.784	100.00	22.22	0.222
		delta-CT	0.903	<0.001	80.00	88.89	0.689
Squamous cell carcinoma	Training set	pre-CT	0.816	<0.001	93.75	62.50	0.563
		delta-CT	0.840	<0.001	93.75	75.00	0.688
	Validation set	pre-CT	0.841	<0.001	81.82	87.50	0.693
		delta-CT	0.682	0.086	63.64	68.75	0.330

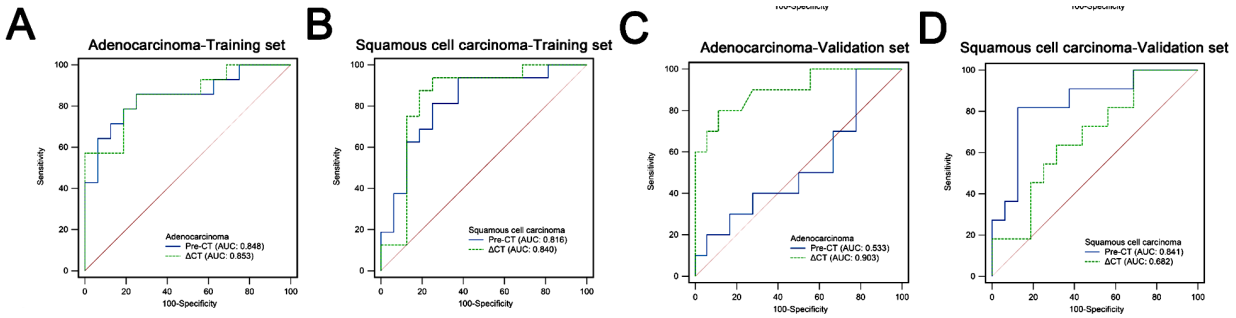


Figure 4. Two CT radiomics models for predicting the immunotherapy responses of adenocarcinoma and squamous cell carcinoma patients. **(A)** Comparison of ROC curves of the two models in the training set of adenocarcinoma patients. **(B)** Comparison of ROC curves of the two models in the training set of squamous cell carcinoma patients. **(C)** Comparison of ROC curves of the two models in the validation set of adenocarcinoma patients. **(D)** Comparison of ROC curves of the two models in the validation set of squamous cell carcinoma patients.

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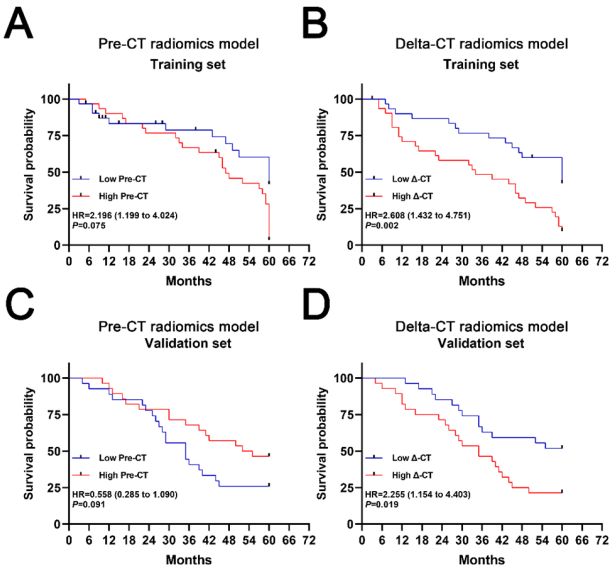


Figure 5. Evaluation of patient OS by two CT radiomics models. **(A)** Evaluation of OS for patients in the training set by pre-CT radiomics model. **(B)** Evaluation of OS for patients in the training set by delta-CT radiomics model. **(C)** Evaluation of OS for patients in the validation set by pre-CT radiomics model. **(D)** Evaluation of OS for patients in the validation set by delta-CT radiomics model. OS, overall survival.

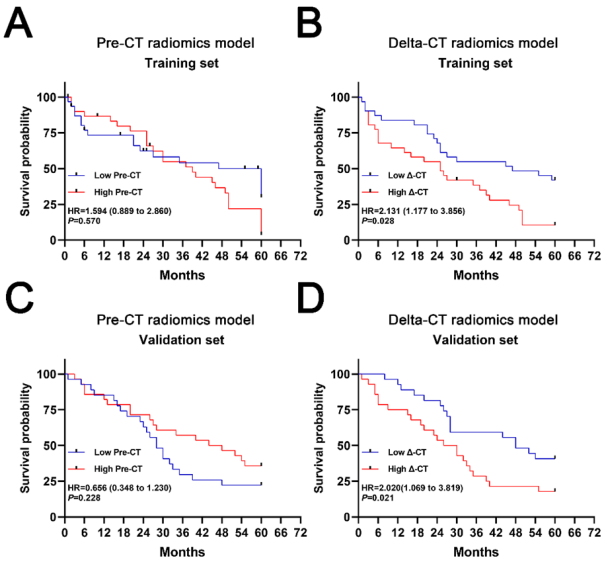


Figure 6. Evaluation of patient PFS by two CT radiomics models. **(A)** Evaluation of PFS for patients in the training set by pre-CT radiomics model. **(B)** Evaluation of PFS for patients in the training set by delta-CT radiomics model. **(C)** Evaluation of PFS for patients in the validation set by pre-CT radiomics model. **(D)** Evaluation of PFS for patients in the validation set by delta-CT radiomics model. PFS, progression-free survival.

DISCUSSION

In the diagnosis and assessment of therapeutic responses for patients with NSCLC, biopsy remains the gold standard for testing. However, some patients may not be able to tolerate invasive tissue biopsies or liquid biopsies, resulting in unsatisfactory results [16, 17]. Therefore, it is an urgent task to find a non-invasive, simple and repeatable method to accurately identify the therapeutic response effect. This study constructed two detection models for patients' immune treatment response and prognosis based on the CT radiomics method. Furthermore, the predictive performance of the models was verified.

In previous studies, many researchers have constructed various CT radiomics-based prediction models based on real clinical data [18, 19]. Tong *et al.* constructed a model for predicting CD8 expression using the radiomics features of 221 NSCLC patients' PET/CT images, with an AUC value as high as 0.907 [20]. Similarly, researchers retrospectively enrolled 296 patients with NSCLC. A predictive model for immunotherapy was constructed based on the CT images of the patients before treatment, and its predictive performance was an AUC value of 0.702 [21]. Regarding the advanced NSCLC patients mentioned in this study, Jin and his colleagues enrolled 138 advanced NSCLC patients who had received chemo-immunotherapy. By using the pre-treatment chest CT images, the researchers constructed a radiomics nomogram model. The AUC value of this model was higher than 0.8 in training-set and validation-set [22]. Another group of researchers combined deep imaging genetics and clinical data to build a predictive model for the short-term benefits of anti-PD-1/PD-L1 immunotherapy in patients with advanced NSCLC. The construction of the model has enhanced the predictive efficacy for the benefits of immunotherapy [23]. Previous studies have fully demonstrated the feasibility of CT radiomics features in predicting the response to immunotherapy [13, 15]. Meanwhile, there are few reports on constructing prediction models based on CT images before and after the combined treatment. This study constructed a delta-CT radiomics model based on CT images of patients with advanced NSCLC before and after the first treatment. Compared with the Pre-CT model, it is more accurate in predicting the immune treatment response of patients. This phenomenon suggests that the CT images after immunotherapy can better reflect the immune characteristics of the patients.

After determining the predictive performance of the model constructed, we further evaluated the predictive effect of the model on the immune treatment response of patients at different subtypes levels for adenocarcinoma and squamous cell carcinoma. Previous studies have mainly focused on predicting immunotherapy efficacy for NSCLC patients, with a particular emphasis on patients with lung adenocarcinoma [13, 15]. Lei *et al.* combined CT imaging biomarkers and immune infiltration analysis to construct a predictive model for immune checkpoint blockade (ICI) therapy in patients with lung adenocarcinoma. The prediction accuracy rate reached an AUC value of 0.89 [24]. Another group of researchers used a volumetric CT-based rMB to assess the TMB of patients with lung adenocarcinoma [25]. Reports on lung squamous cell carcinoma are

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extremely scarce [9]. This study was the first to divide patients into two subtypes and the two models we constructed were respectively validated in patients of these two subtypes. Interestingly, compared to adenocarcinoma patients, the Pre-CT radiomics model has a better predictive performance for adenocarcinoma patients. And the delta-CT radiomics model has a higher predictive performance for squamous cell carcinoma. The reason for this phenomenon needs to be verified through more data from the centers in the future.

The prognosis evaluation of immunotherapy has always been a key indicator for assessing the therapeutic effect. The prognostic model constructed based on CT radiomics is also regarded as a promising model for evaluating the prognosis of immunotherapy. Some researchers have constructed a model based on CT radiomics features to predict the PFS and OS of NSCLC patients. It has a high predictive value in both the training set and the validation set [15]. Mu *et al.* utilized PET/CT imaging of advanced NSCLC patients to predict the clinical outcomes of NSCLC patients. This model has certain discriminatory value in both OS and PFS for patients with adenocarcinoma [26]. Our research also trained and verified the predictive value of the model for OS and PFS. The results showed that the high scores of the delta-CT radiomics models were associated with lower OS and PFS. The aforementioned reports and our results indicate that the delta-CT radiomics models can serve as prognostic prediction models for patients with advanced NSCLC.

The present study has certain limitations that should be acknowledged. Firstly, this study mainly focuses on the predictive role of CT radiomics features in immune responses. Other clinical and imaging features were not included in the study. Furthermore, this study mainly relied on manual analysis for lesion analysis. The analysis methods constructed through new learning approaches such as deep learning need to be applied in the future. Finally, the results obtained from this study need to be verified by a larger sample from more centers.

CONCLUSION

In summary, we based on the CT radiomics features of advanced NSCLC patients before and after treatment, constructed two prediction models for the immune treatment responses of the patients and conducted validations. The model obtained by our study is conducive to the future clinical application of imaging in predicting the response to immunotherapy and prognosis for NSCLC.

***Data sharing statement*:** All the results are presented in the article. Further inquiries can be directed to the corresponding authors.

***Ethics statement*:** This study strictly adheres to the Declaration of Helsinki and has obtained approval from the Ethics Committee of Shanghai Pudong Hospital (2022-KYQWJW-003) and Hefei First People's Hospital (2023-KY-001).

***Author contributions*:** D.W.: Conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, visualization, writing – original draft, writing – review and editing. X.W.: Conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, visualization, writing – original draft, writing – review and editing. Z.W.: Formal analysis, supervision, validation, visualization. Y.X.: Conceptualization, formal analysis, writing – original draft, writing – review and editing.

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