

Texture-driven radiomics from longitudinal contrast-enhanced CT predicts short-term immunotherapy response in lung cancer: A retrospective cohort study

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Abstract

Background

Radiomic prediction of immunotherapy response has been widely reported, yet the nature and localization of the predictive signal remain unclear. We aimed to determine whether longitudinal delta-radiomics (change between serial scans) predicts short-term response in lung cancer, and to dissect the signal by benchmarking against pre-treatment and clinical models, separating texture from shape contributions, and localizing it across intratumoral and peritumoral compartments, and relating it to survival.

Methods

In a single-center cohort of 156 lung cancer patients receiving first-line immunotherapy, baseline and interim contrast-enhanced CT scans were analyzed. We extracted 1688 radiomic features from intratumoral, peritumoral (3/5/8/10-pixel shells), and combined ROIs, and computed delta features. Short-term response (RECIST 1.1) was modeled using stratified 5-fold cross-validation with all feature selection (univariate filtering, correlation pruning, LASSO) performed inside each training fold. Performance was evaluated by pooled out-of-fold AUC (mean over 5 seeds; 2000-sample bootstrap 95% CI). PFS and OS were assessed by C-index, Kaplan–Meier, and Cox models on cross-validation-averaged risk scores.

Results

Pre-treatment radiomics was uninformative across all ROIs (AUC 0.48–0.54), as were clinical variables (AUC 0.45). Intratumoral delta-radiomics predicted response with AUC 0.78 (95% CI 0.70–0.85). The signal was texture-driven: texture-only delta reproduced full performance (AUC 0.78), with five of six retained features being texture-based. The effect was consistent across all ROIs and peritumoral distances (AUC 0.74–0.78), and adding clinical, peritumoral, or multi-ROI features provided no improvement. The delta score modestly stratified PFS (HR 1.66, 95% CI 1.15–2.39; log-rank $p = 0.006$; C-index 0.56) but was not associated with OS ($p = 0.28$); prognostic signal resided specifically in intratumoral-containing ROIs.

Conclusions

The predictive information in serial CT is texture-driven, intratumoral, and exists only as change — it is not a restatement of tumor shrinkage, does not require peritumoral sampling, and is absent from static pre-treatment imaging. Longitudinal radiomics functions as an early response surrogate that partially tracks progression but does not predict overall survival.

Background

Immune checkpoint inhibitors targeting the PD-1/PD-L1 axis have reshaped the treatment of advanced lung cancer, yet clinical benefit remains confined to a subset of patients[1, 2, 3, 4]. Durable responses coexist with primary resistance, and a non-trivial fraction of patients experience atypical response patterns — pseudoprogression, dissociated or mixed response — that are poorly captured by size-based assessment. In this setting, the ability to identify responders early and non-invasively would allow timely continuation of effective therapy, avoidance of futile treatment and its toxicity, and more rational escalation or switching decisions. Response Evaluation Criteria in Solid Tumors (RECIST) provide only a late, unidimensional readout and are known to misclassify a subset of immunotherapy-treated tumors[5, 6, 7, 8, 9].

Radiomics — the high-throughput extraction of quantitative descriptors from routine imaging — has been proposed as a means to phenotype tumors beyond size, potentially exposing biology relevant to immune response[10, 11, 12, 13, 14]. However, the great majority of radiomic response-prediction studies rely on a single pre-treatment acquisition, and their reported performance has been inconsistent and frequently difficult to reproduce across cohorts and centers. A recurring concern is that features derived from one static scan are sensitive to cross-patient differences in acquisition, reconstruction and segmentation, which can dominate over any genuine biological signal[15, 16, 17, 18].

Delta-radiomics — the analysis of how radiomic features change between serial scans — offers a conceptually different approach that is particularly suited to a dynamic therapy. By referencing each patient to their own baseline, a delta representation cancels time-invariant, patient-specific offsets and isolates treatment-induced change, which may track the evolving tumor–immune interaction more faithfully than any snapshot. Reports of delta-radiomic response prediction are by now numerous, and the incremental value of yet another predictive model is correspondingly limited[19, 20, 21]. What remains largely unexamined is what such a signal actually is. Three questions are rarely asked. First, does a longitudinal radiomic model simply re-encode tumor shrinkage? Change in size is trivially related to response and is already captured by RECIST, so a delta model that merely restates it adds nothing; disentangling shape from texture is therefore essential to any claim of novelty, yet is seldom reported. Second, where does the signal reside? Peritumoral tissue is widely assumed to be immunologically informative, but whether the predictive information is intratumoral, peritumoral or both — and whether conclusions survive a change in the peritumoral margin — is rarely tested[22, 23, 24, 25]. Third, does the response signal carry prognostic meaning, or is it confined to the short-term readout? Without honest pre-treatment and clinical benchmarks under leakage-controlled validation, even the basic claim that change outperforms a static image cannot be substantiated.

We therefore approached serial contrast-enhanced CT in lung cancer treated with first-line immune checkpoint inhibitors not as another prediction exercise but as a dissection of the response signal. Using an interim on-treatment scan acquired before the formal response assessment, we asked (i) whether the baseline-to-interim change predicts short-term response where pre-treatment radiomics and clinical

variables — evaluated under identical, strictly leakage-controlled cross-validation — do not; (ii) whether the signal is texture-driven or merely a proxy for shrinkage; (iii) whether it is a property of the tumor, its periphery, or both, tested across three ROIs and four peritumoral expansion distances; and (iv) whether it extends to progression-free and overall survival. The aim is less to propose a model than to characterize what longitudinal radiomics of immunotherapy measures — and what it does not.

Methods

Study design and patients

We retrospectively analyzed patients with lung cancer treated with first-line immune checkpoint inhibitors at a single center at the First Hospital of Lanzhou University between August 2018 and December 2024. As a retrospective study, it was approved by the Ethics Committee of the First Hospital of Lanzhou University (Approval No. LDYYLL-2026-735), and was conducted in accordance with the Declaration of Helsinki. The requirement for informed consent was waived due to the retrospective nature of the study. Of 255 patients meeting eligibility criteria, 156 underwent an interim on-treatment contrast-enhanced CT (CTA) in addition to their baseline scan and constituted the analysis cohort for the present study. Inclusion required an evaluable baseline CTA, an interim on-treatment CTA acquired before the formal response-assessment scan, and a documented short-term response outcome. The inclusion criteria were as follows: (1) pathologically confirmed diagnosis of lung cancer; (2) at least one measurable lesion; (3) receipt of first-line PD-1/PD-L1 immune checkpoint inhibitor therapy, either as monotherapy or in combination with chemotherapy, for the first time at our institution. Patients were excluded if they met any of the following criteria: (1) absence of contrast-enhanced chest CT within one month prior to treatment initiation; (2) receipt of radiotherapy or surgery prior to immunotherapy; (3) maximum tumor diameter less than 5 mm, or indistinct tumor margins due to pulmonary infection, lung collapse, or other conditions that precluded accurate image segmentation; (4) concurrent diagnosis of other malignancies; (5) incomplete clinical data. (Figure 1)

Endpoints

The primary endpoint was short-term treatment response (responder vs non-responder), assessed by RECIST 1.1 criteria at the first imaging evaluation after treatment initiation[5]. Radiological response was independently evaluated by two medical oncologists. Secondary endpoints were progression-free survival (PFS) and overall survival (OS, data cutoff December 31, 2025). Because the clinical dataset recorded PFS time, OS time and vital status but not an explicit progression flag, PFS events were derived as follows: an event was assigned when PFS time was shorter than OS time (progression), or when PFS equaled OS time in a deceased patient (death); otherwise the observation was censored. This yielded 118 events and 38 censored patients, with no internal inconsistency (no case had PFS exceeding OS).

CT acquisition and treatment timepoints

Contrast-enhanced CT was acquired at baseline and at an interim on-treatment timepoint (after the second cycle of systemic therapy) on one of eight CT scanners from three vendors (Siemens SOMATOM go.Top, SOMATOM Definition, SOMATOM AS+, and NAEOTOM Alpha photon-counting CT; Philips IQon Spectral CT, Incisive CT, and Brilliance CT [Hulk platform]; and GE Revolution CT), with tube voltage of 100–120 kVp using automated tube current modulation, intravenous iodinated contrast administration (300–370 mgI/mL, 1.5 mL/kg) in the portal venous phase, and reconstructed slice thickness of 1.0–5.0 mm (resampled to 2.5 mm for radiomic analysis)]. The interim scan preceded and was distinct from the scan used for formal response assessment (median interval 4–6 weeks), so that neither the interim radiomic features nor the baseline-to-interim delta could encode the response label directly.

Segmentation and regions of interest

For each scan we defined three regions of interest: the intratumoral region (tumor), peritumoral shells obtained by morphological dilation of the tumor mask at 3, 5, 8 and 10 pixels, and a combined region (tumor plus peritumoral shell) at each distance. Tumor segmentation was independently performed using ITK-SNAP software by two radiologists, and interobserver reproducibility was assessed using the intraclass correlation coefficient (ICC). Radiomic features with ICC > 0.75 were considered reproducible and retained for subsequent analysis.

Radiomic feature extraction

Features were extracted with PyRadiomics, yielding 1688 features per ROI: 107 from the original image (first-order, shape, GLCM, GLRLM, GLSZM, GLDM, NGTDM) plus features from Laplacian-of-Gaussian ($\sigma = 1-5$), wavelet, square, square-root, logarithm and exponential filters[25]. CT-specific settings were a fixed bin width of 25 HU, resampling to 1×1×1 mm isotropic voxels, and no intensity normalization (preserving physical HU values). Delta features were computed per matched case as interim minus baseline, separately for each ROI and distance.

Feature selection and modeling

To prevent optimistic bias, every step of feature selection was performed inside each training fold of a stratified 5-fold cross-validation and never on held-out data. Within each fold, features were standardized, ranked by univariate association with the outcome (top 50 retained), pruned for redundancy (pairwise correlation $r > 0.9$), and entered into a LASSO logistic regression (L1 penalty, $C = 0.1$) to form a radiomic score. Only out-of-fold predictions were pooled for evaluation.

Evaluation and statistics

Response discrimination was quantified by the pooled out-of-fold AUC, reported as the mean over five random cross-validation seeds with standard deviation, and with a 2000-sample bootstrap 95%

confidence interval. To separate shape from texture contributions, models were refit after excluding shape features and, separately, using shape features alone. For survival, a per-patient risk score was obtained by fitting an in-fold penalized Cox model (top-25 univariate screen, correlation pruning, penalizer 0.1) and averaging the out-of-fold scores across five seeds to reduce partition variance; patients were dichotomized at the median score for Kaplan–Meier estimation and the log-rank test, with hazard ratios from Cox regression and discrimination summarized by the C-index. Baseline characteristics were compared between response groups with the Mann–Whitney U test (continuous) and χ^2 /Fisher exact tests (categorical). Analyses used Python (scikit-learn, lifelines).(Figure 2)

Results

Patient characteristics

Of 255 patients treated with first-line immunotherapy, 156 underwent an interim on-treatment contrast-enhanced CT and constituted the analysis cohort, of whom 82 (52.6%) were non-responders and 74 (47.4%) were responders by RECIST 1.1. Baseline demographic, clinical, and laboratory characteristics were generally comparable between responders and non-responders, although significant differences were observed in age and treatment regimen (immunotherapy monotherapy vs. combination therapy) (Table 1).

Table 1
Group statistics of clinical data in non-responders set and responders set

Variables	Non-response (N = 82)		Response (N = 74)		P
Baseline characteristics					
Gender					0.817
Female	19a	54.3%	16a	45.7%	
Male	63a	52.1%	58a	47.9%	
Age(years)					0.041
<62	50a	60.2%	33b	39.8%	
≥ 62	32a	43.8%	41b	56.2%	
Height(m)					0.488
<1.68	40a	55.6%	32a	44.4%	
≥ 1.68	42a	50.0%	42a	50.0%	
Weight(kg)					0.360
<66	47a	56.0%	37a	44.0%	
≥ 66	35a	48.6%	37a	51.4%	
Smoking habitat					0.532
Never	38a	50.0%	38a	50.0%	
Current/former	44a	55.0%	36a	45.0%	
Site					0.285
left	34a	47.9%	37a	52.1%	
right	48a	56.5%	37a	43.5%	
Dominant segmentation MAX					0.101
1	15a	57.7%	11a	42.3%	
1 + 2	10a	50.0%	10a	50.0%	
10	5a	27.8%	13b	72.2%	
2	3a	100.0%	0a	0.0%	
3	23a	56.1%	18a	43.9%	
4	8a	61.5%	5a	38.5%	

Variables	Non-response (N = 82)		Response (N = 74)		P
5	7a	70.0%	3a	30.0%	
6	3a	23.1%	10b	76.9%	
7	2a	100.0%	0a	0.0%	
7 + 8	2a	66.7%	1a	33.3%	
9	4a	57.1%	3a	42.9%	
Pathological type					0.236
Small cell	21a	42.0%	29a	58.0%	
Squamous	28a	52.8%	25a	47.2%	
Adenocarcinoma	30a	62.5%	18a	37.5%	
Others	3a	60.0%	2a	40.0%	
T					0.555
1	7a	70.0%	3a	30.0%	
2	22a	50.0%	22a	50.0%	
3	25a	56.8%	19a	43.2%	
4	28a	48.3%	30a	51.7%	
N					0.612
0	18a	62.1%	11a	37.9%	
1	5a	62.5%	3a	37.5%	
2	42a	50.0%	42a	50.0%	
3	17a	48.6%	18a	51.4%	
M					0.636
0	43a	54.4%	36a	45.6%	
1	39a	50.6%	38a	49.4%	
Stage					0.923
1	2a	50.0%	2a	50.0%	
2	8a	61.5%	5a	38.5%	
3	32a	52.5%	29a	47.5%	

Variables	Non-response (N = 82)		Response (N = 74)		P
4	40a	51.3%	38a	48.7%	
Adrenal metastasis					0.357
absent	73a	51.4%	69a	48.6%	
present	9a	64.3%	5a	35.7%	
Medication(PD-1/PD-L1) * R					0.056
PD-1	70a	56.5%	54a	43.5%	
PD-L1	12a	37.5%	20a	62.5%	
Treatment regimen					0.042
Single-agent	7a	87.5%	1b	12.5%	
combination chemotherapy	75a	50.7%	73b	49.3%	

Pre-treatment radiomics and clinical variables do not predict response

Under strictly in-fold feature selection, pre-treatment (baseline) radiomics carried little predictive information for short-term response. Intratumoral, peritumoral (8-pixel) and combined-ROI baseline models yielded out-of-fold AUCs of 0.54, 0.48 and 0.49, respectively — at or below chance. A model built from clinical variables alone performed no better (AUC 0.45). Radiomic features extracted from the interim scan alone gave only a marginal improvement (intratumoral AUC 0.59). These benchmarks (Fig. 3) establish that neither a static pre-treatment phenotype nor routinely available clinical data separates responders from non-responders in this cohort.

On-treatment delta-radiomics predicts short-term response

Delta features, defined as the per-patient change between the interim and baseline scans, markedly outperformed every static representation. The intratumoral delta model achieved an out-of-fold AUC of 0.78 (95% CI 0.70–0.85), with high stability across random seeds (0.784 ± 0.004). Its cross-validated ROC curve and the coefficients of the retained delta features are shown in Fig. 3. The gain over the baseline intratumoral model ($0.54 \rightarrow 0.78$) and over the interim-only model ($0.59 \rightarrow 0.78$) indicates that the predictive information resides in the temporal change rather than in any single acquisition.

The predictive signal reflects texture evolution, not shrinkage alone

Because change in tumor size is trivially related to response, we tested whether the delta signal was merely re-encoding shrinkage. Removing all shape/size features left the texture and intensity deltas, which independently reproduced the full performance (AUC 0.78); shape features alone reached 0.80. Consistently, the final LASSO radiomic score retained six non-zero delta features, of which five were texture descriptors (GLCM, GLDM, GLRLM families across LoG and other filtered images) and only one was a shape descriptor (Fig. 4B). Thus the model captures intratumoral textural reorganization beyond what size-based response criteria already measure.

The signal is robust to ROI and peritumoral definition

The delta effect was not specific to the intratumoral ROI or to a particular peritumoral margin. Delta models reproduced the predictive signal across all three ROIs – intratumoral 0.78, peritumoral (8 px) 0.76, combined 0.75 – and across all four peritumoral expansion distances tested (3/5/8/10 px), with AUCs ranging narrowly from 0.74 to 0.78 (Fig. 3,4A,5). This consistency across eight independent ROI/distance definitions indicates that the finding is a property of the underlying treatment-induced change rather than an artifact of any single segmentation choice.

Peritumoral, multi-ROI and clinical fusion do not improve performance

No fusion strategy exceeded the intratumoral delta model. Concatenating intratumoral, peritumoral and combined delta features (AUC 0.78) did not improve on intratumoral delta alone, and adding clinical variables left performance unchanged (0.78). Stacking all available feature sets likewise plateaued at 0.78 (Fig. 3). The peritumoral and combined ROIs, individually weaker and partly redundant with the intratumoral region, contributed no complementary information; in every fold the LASSO consistently reselected intratumoral delta features. The most parsimonious single-ROI delta model therefore represents the performance ceiling of the available data.

The response signal partially tracks progression-free but not overall survival

We next asked whether the delta-radiomics response signal extended to survival, using cross-validation-averaged out-of-fold Cox risk scores. The intratumoral delta risk score was modestly but significantly associated with PFS: the high-risk group had a hazard ratio of 1.66 (95% CI 1.15–2.39) relative to the low-risk group (log-rank $p = 0.006$), with a C-index of 0.56 (Fig. 6A). The interim-only tumor score showed a weaker association (HR 1.50, $p = 0.03$) and the baseline tumor score was borderline (HR 1.42, $p = 0.06$), so the PFS gradient, while following the same ordering as response, was softer and less delta-specific. The ROI comparison further revealed a compartment-specific pattern absent for response: only ROIs containing the tumor core stratified PFS – intratumoral delta and combined delta at a tight 3-pixel margin (HR 1.75, 95% CI 1.21–2.53, $p = 0.003$) performed comparably, whereas the combined signal decayed as the margin widened (5/8/10 px: $p = 0.07$ –0.13), and pure peritumoral delta did not stratify

PFS at any distance (C-index 0.48–0.53, all non-significant). In contrast, no feature set was associated with OS (intratumoral delta C-index 0.53; HR 1.24; log-rank $p = 0.28$) despite 104 deaths (Fig. 6B). At the level of individual cross-validation splits the PFS log-rank significance was not uniformly stable (significant in three of five partitions), consistent with the modest effect size; the C-index and averaged-score hazard ratio provide the more reliable summary. Overall, early textural response measurably tracked the risk of progression — through the intratumoral compartment specifically — but did not translate into an overall-survival difference in this cohort.

Discussion

This study set out to characterize, rather than merely demonstrate, the response signal carried by serial CT in lung cancer treated with immune checkpoint inhibitors. Four findings define it. The signal exists only as change: pre-treatment radiomics and clinical variables were uninformative (AUC 0.45–0.54), whereas the baseline-to-interim delta predicted response with an out-of-fold AUC of 0.78 under identical, leakage-controlled validation. It is texture-driven, not a restatement of shrinkage: a texture-only delta reproduced the full performance, and five of the six retained features were texture descriptors. It is intratumoral: although response was encoded across all ROIs and all peritumoral margins, no peritumoral or multi-ROI configuration improved on the tumor alone, and the prognostic signal for progression was confined to intratumoral-containing regions. And it is bounded: it stratified progression-free survival only modestly (HR 1.66, $p = 0.006$) and overall survival not at all. Taken together, these results describe what longitudinal radiomics of immunotherapy measures — and, equally informatively, what it does not.

The contrast between the failure of static radiomics and the success of the delta representation is the central result. Two explanations, not mutually exclusive, are plausible. Biologically, immunotherapy remodels the tumor and its microenvironment over time; a single pre-treatment image cannot observe this trajectory, whereas a delta captures its early manifestation. Methodologically, using each patient as their own reference cancels the patient- and acquisition-specific variation that plagues cross-sectional radiomics, so that the delta isolates change rather than confounded absolute values. The near-chance performance of every baseline model — consistent with an upstream feature-quality ceiling— makes the delta's performance all the more notable: the same features become informative once expressed as change.

That a texture-only delta reproduced the full predictive performance, and that five of the six features retained in the final score were texture descriptors, indicates the model is not simply re-encoding shrinkage. Shape-based delta features — essentially a proxy for the volume change that response criteria already measure — reached comparable accuracy on their own, but the persistence of the signal after their removal shows that intratumoral textural reorganization carries independent, RECIST-orthogonal information about early response. Physiologically, immune-mediated changes such as intratumoral inflammatory infiltration, necrosis and heterogeneity are expected to alter texture before, or independently of, gross size, providing a mechanistic rationale for the dominance of texture features.

The absence of benefit from peritumoral and combined ROIs runs counter to the common expectation that the peritumoral region, as a site of immune interaction, would be especially informative. Several factors likely contribute: the combined ROI already subsumes the intratumoral region, making its features partly redundant; peritumoral shells generated by dilation are anatomically approximate and more exposed to registration error and partial-volume effects across two timepoints, injecting noise into the delta; and the intratumoral delta already approached the achievable ceiling. The stability of response performance across four expansion distances (3–10 px) argues that this is not a matter of choosing the wrong margin but a genuine absence of added information. Notably, the survival analysis sharpened this picture into a compartment dissociation: whereas response was encoded across all ROIs, PFS was stratified only by ROIs containing the tumor core – intratumoral and tightly-margined combined delta – and not by pure peritumoral delta at any distance, with the combined signal decaying as the margin widened. This suggests that the early response readout is shared between the tumor and its immediate surround, but the prognostic information specific to progression is intratumoral, and that adding peritumoral tissue mainly adds noise to it. The convergence of intratumoral and small-margin combined ROIs on the same result argues the effect is genuine rather than a chance product of testing multiple margins, though the modest effect sizes still call for external confirmation.

The graded relationship between the response signal and the two survival endpoints is itself informative. Progression is the endpoint conceptually closest to short-term response, so an early textural change that forecasts response also partially forecasts time to progression, whereas by the time of death the signal is diluted by subsequent lines of therapy, pseudoprogression, mixed response and competing risks. The modest magnitude – a C-index near 0.56 and log-rank significance that was not uniform across cross-validation partitions – should temper interpretation: the delta score is a strong early-response marker but only a weak PFS stratifier, and not a prognostic score for OS in this cohort. Positioned this way, interim delta-radiomics is most useful for early on-treatment response assessment, with a secondary, exploratory signal for progression that warrants confirmation.

These findings should be interpreted in light of several limitations. The study is single-center and retrospective, without external or temporal validation, and the requirement for an interim scan reduced the analyzable cohort to 156 patients and may introduce selection toward patients who remained on treatment long enough to be re-imaged. PFS events were derived from the PFS/OS/vital-status relationship rather than a dedicated progression flag; although internally consistent, this may misclassify patients censored for progression but still followed for survival. Peritumoral regions were defined by dilation rather than anatomically, and residual variability in CT phase, resampling and segmentation reproducibility may limit absolute feature quality. Performance was estimated by cross-validation with multi-seed and bootstrap quantification of stability; while this guards against optimistic within-study bias, it does not substitute for independent validation. Confirmation in an external cohort and prospective evaluation are the natural next steps.

Conclusions

The response information carried by serial contrast-enhanced CT in immunotherapy-treated lung cancer is texture-driven, intratumoral, and exists only as change. It is not a proxy for tumor shrinkage, it does not require peritumoral sampling, and it is absent from static pre-treatment imaging — where radiomic and clinical models performed at chance under identical validation. Its reach is bounded: it stratified progression-free survival only modestly and overall survival not at all. Characterizing the signal in these terms, rather than reporting another predictive model, clarifies what longitudinal radiomics of immunotherapy actually measures and where future models should look. External and prospective validation remain necessary.

Abbreviations

AUC

Area under the curve

CI

Confidence interval

CT

Computed tomography

CTA

Contrast-enhanced computed tomography angiography / Contrast-enhanced computed tomography

CV

Cross-validation

GLCM

Gray-level co-occurrence matrix

GLDM

Gray-level dependence matrix

GLRLM

Gray-level run length matrix

GLSZM

Gray-level size zone matrix

HU

Hounsfield unit

ICC

Intraclass correlation coefficient

ICI

Immune checkpoint inhibitor

LASSO

Least absolute shrinkage and selection operator

LoG

Laplacian of Gaussian

ML

Machine learning

NGTDM

Neighborhood gray-tone difference matrix

OS

Overall survival

PD-1

Programmed cell death protein 1

PD-L1

Programmed death-ligand 1

PFS

Progression-free survival

RECIST

Response Evaluation Criteria in Solid Tumors

ROI

Region of interest

Declarations

Ethics approval and consent to participate

The research protocol was approved by the Ethics Committee of the First Hospital of Lanzhou University (Approval No. LDYYLL-2026-735). Given the retrospective nature of this study, the requirement for informed consent was waived. All methods were carried out in accordance with relevant guidelines and regulations. This study was conducted in accordance with the principles of the Declaration of Helsinki.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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Author Contribution

YG contributed to the study concept and design, data collection, data analysis and interpretation, and preparation of the manuscript. HC and FS contributed to the study design and manuscript review. YL, WX, BL, XH, WL, YLan, and DZ participated in data collection, data analysis and interpretation, and manuscript review. TZ contributed to the revision of the manuscript, team communication and coordination, acquisition of funding, and overall project supervision. JC contributed to the study design, data interpretation, manuscript revision, supervision of the research, and acquisition of funding. All authors read and approved the final manuscript.

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Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Figures

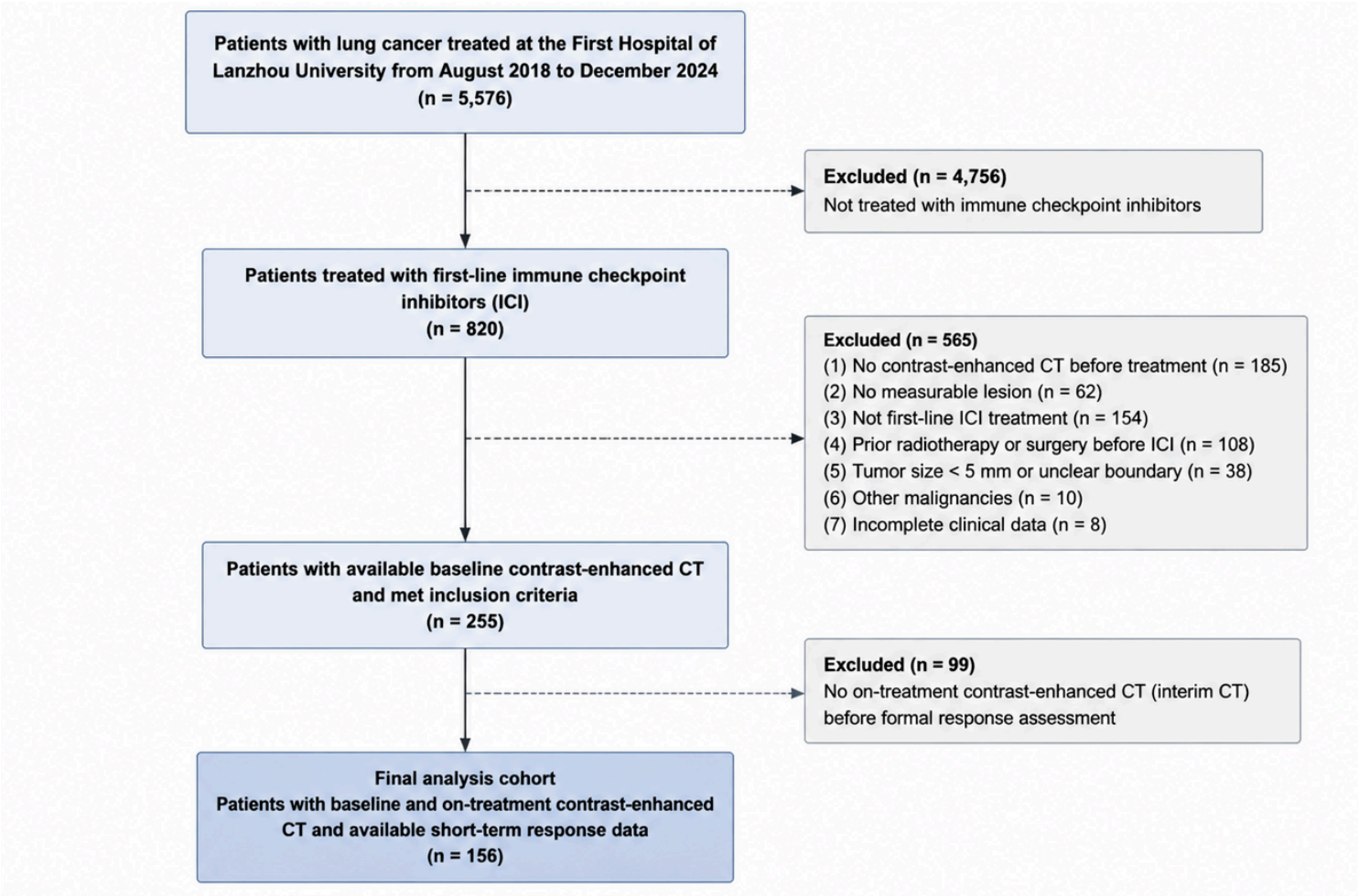


Figure 1

Patient inclusion and exclusion criteria and enrollment flowchart

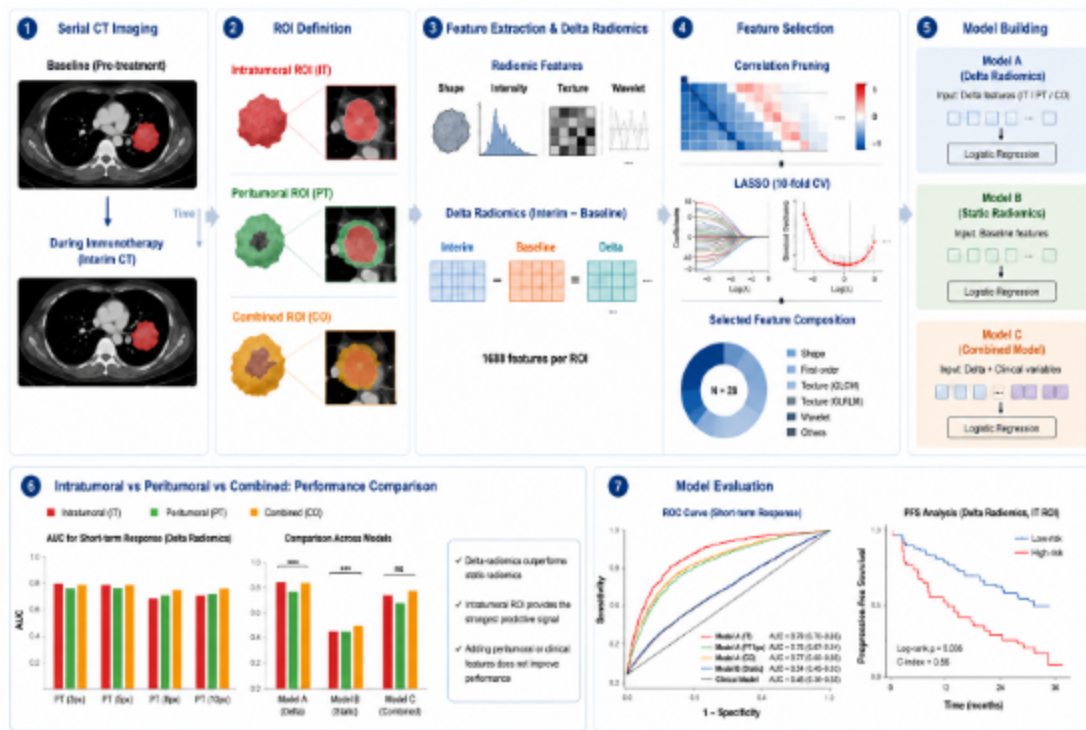


Figure 2

Overall flowchart

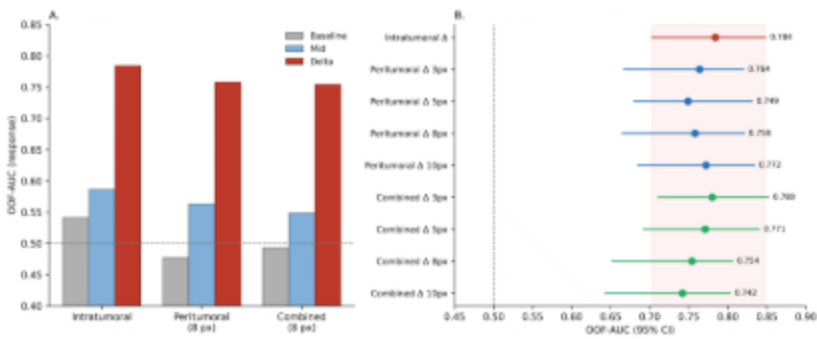


Figure 3

A. Baseline - Interim - Delta, by ROI; B. Robustness across ROI and peritumoral distance

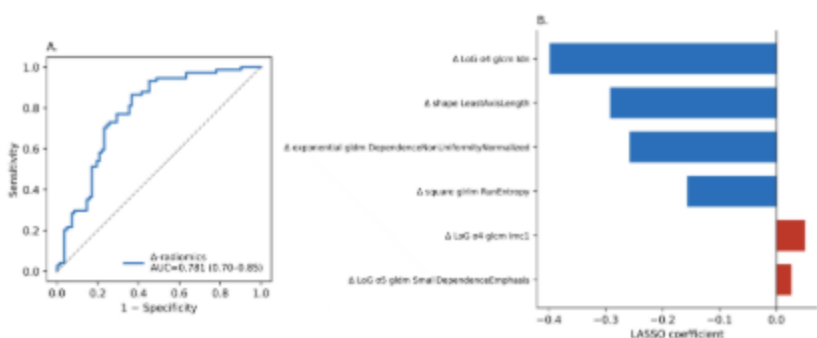


Figure 4

A. Cross-validated ROC (response);B. Selected -Δ features (n=6)

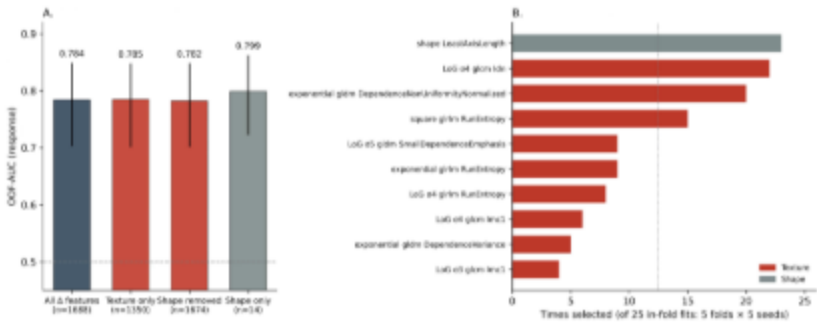


Figure 5

A. Texture carries the signal independently;B. Feature-selection stability

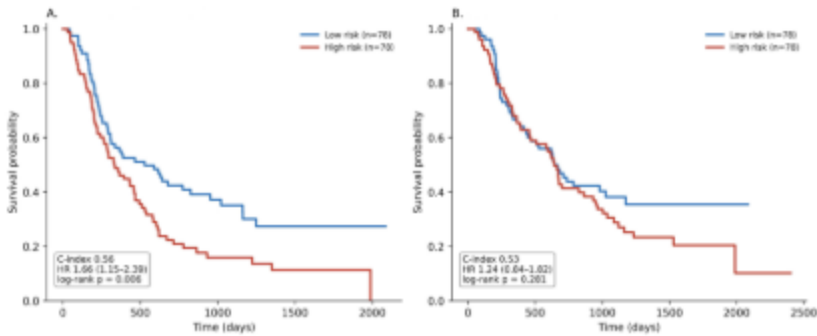


Figure 6

A. Progression-free survival;B. Overall survival