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Preoperative CT Radiomics for Prognosis Prediction in Resected Early-Stage Non-Small Cell Lung Cancer

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BACKGROUND

Approximately 20% of non-small cell lung cancer (NSCLC) cases are diagnosed at an early stage (ES), allowing for potentially curative surgical resection. However, a significant proportion of these patients still experience disease recurrence. Although the TNM staging system remains the cornerstone for prognostic assessment and clinical decision-making, it does not fully account for outcome variability among patients within the same stage [1]. This highlights the need for novel biomarkers to complement TNM staging and support more personalized treatment strategies. Despite extensive efforts to identify such biomarkers, stage remains the sole factor currently guiding treatment and follow-up in ES-NSCLC. In this context, radiomics has recently gained attention as a promising, non-invasive tool to enhance prognostic evaluation [2].

OBJECTIVE

This study aims to develop and preliminarily validate models that use preoperative CT radiomic features—alone and in combination with clinically relevant factors—to predict post-surgical outcomes for ES-NSCLC.

METHODS

Imaging and clinical data were obtained from the MIRACLE study—a multicenter, retrospective and prospective investigation aimed at developing a prognostic algorithm by integrating biological, radiological, and clinical information. This project was supported by Italian Ministry of Health, under the frame of ERA PerMed (project code: ERP-2021-23680708). The current analysis focuses exclusively on retrospective data and preoperative CT images from patients enrolled at IRST-IRCCS between 2018 and 2021. The primary endpoint was disease-free survival (DFS), defined as the time from surgery to disease recurrence or death from any cause, whichever occurred first. The last follow-up update was in January 2024.

Tumors were manually segmented by two independent expert radiologists. Radiomic features were extracted from preoperative CT scans, acquired with or without contrast medium, using the open-source package PyRadiomics [3]. In some cases, both contrast-enhanced and non-contrast scans were available for the same patient.

Two analytical approaches were employed: one based on an extension of the Cox model, and the other using random survival forests (RSF). For the Cox-based models, radiomic feature selection involved bootstrap resampling, feature inclusion frequency analysis, and consensus clustering. In each bootstrap replicate, an elastic net Cox model was fitted, accounting for within-patient scan correlations. Features most frequently selected were then clustered via consensus clustering using Kendall's tau distance and complete linkage, and one representative feature per cluster was chosen. For RSF, two modeling strategies were considered: one using all radiomic features, and one incorporating feature selection via hierarchical clustering on Kendall's tau distances, with one representative feature retained per cluster.

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All models underwent hyperparameter tuning using stratified 3-fold cross-validation (CV), and final models were trained with the optimal parameter set. Evaluation was performed using the same 5 repeats of 5-fold CV across models, with concordance index, integrated Brier score, and 3-year time-dependent AUC as performance metrics. Results are reported as mean ± standard deviation across the repeated CV runs.

RESULTS

A total of 78 patients were included, accounting for 115 CT scans. The majority were male (60.3 %), with a median age at surgery of 71 years [IQR: 65–75]. Adenocarcinoma was the most common histotype, observed in 83 % of cases. Most patients (87.2 %) underwent lobectomy, and 68.0 % presented with a stage I tumor. The median follow-up time was 42.5 months (95 % CI: 37.9-45.43) and the median DFS was not reached. Overall, 25 failures were observed.

From the Cox-based pipeline, two radiomic features—GLCM Cluster Shade and Shape Maximum 2D Diameter Column—were ultimately selected and included in a standard Cox model. This model achieved a C-index of 0.767 ± 0.103, IBS of 0.153 ± 0.032, and 3-year AUC of 0.804 ± 0.136. Adding pathological stage improved performance to a C-index of 0.777 ± 0.098, IBS of 0.152 ± 0.034, and AUC of 0.815 ± 0.134. The stage-only model performed worse across all metrics (C-index: 0.729 ± 0.119; IBS: 0.155 ± 0.042; AUC: 0.739 ± 0.155).

Similar patterns were observed with RSF models. The stage-only RSF model yielded a C-index of 0.720 ± 0.120, IBS of 0.163 ± 0.041, and AUC of 0.739 ± 0.160. Incorporating all radiomic features improved performance (C-index: 0.776 ± 0.095; IBS: 0.145 ± 0.041; AUC: 0.828 ± 0.135), but the best results were obtained using selected radiomic features (C-index: 0.788 ± 0.096; IBS: 0.147 ± 0.032; AUC: 0.837 ± 0.115). These included morphology-based (Shape Elongation and Shape Least Axis Length), intensity-based (Firstorder 10th Percentile, Firstorder Entropy, and Firstorder Interquartile Range), and texture-based (GLCM Difference Variance and GLCM ID) features. Adding stage to the selected radiomics model did not yield further improvement.

Additional analyses incorporating patient characteristics (e.g., age and sex) did not improve predictive performance and are not reported.

CONCLUSIONS

Our study shows that CT-derived radiomic features improve prognostic performance compared to stage alone. Although these results are promising, external validation on an independent dataset is essential to confirm their generalizability. Future work will also focus on investigating the explainability of the models to better understand the biological relevance of selected radiomic features.

REFERENCES

1. Rajaram R., Huang Q., Li R.Z. et al., Recurrence-Free Survival in Patients With Surgically Resected Non-Small Cell Lung Cancer. A Systematic Literature Review and Meta-Analysis. CHEST, 2024; 165(5):1260–1270.
2. Libling W.A., Korn R., Weiss G.J. Review of the use of radiomics to assess the risk of recurrence in early-stage non-small cell lung cancer. Transl Lung cancer res, 2023; 12(7): 1575-1589
3. van Griethuysen J.J.M., Fedorov A., Parmar C. et al., Computational Radiomics System to Decode the Radiographic Phenotype. Cancer Res, 2017; 77(21): e104–e107.

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