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MRI-based multilevel radiomics and transformer features for predicting radiation-induced carotid artery injury after nasopharyngeal carcinoma radiotherapy: a multicenter study

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ABSTRACT

Purpose:
To develop and validate an MRI–based fusion model (Rad–SRad–SwinT) integrating conventional radiomics (Rad), subregional radiomics (SRad), and Transformer–derived deep learning features (Swin Transformer, SwinT) to predict post–radiotherapy radiation–induced carotid artery injury (RICAI) in nasopharyngeal carcinoma (NPC).
Materials and methods:
In this multicenter retrospective study, 500 NPC patients from four hospitals were allocated to training (n=274), internal testing (n=118), and external testing cohorts (n=108). Rad features were extracted from MRI–defined carotid artery regions of interest, SRad features from K-means–derived subregions, and deep features from a SwinT backbone. Single-source and fusion models were developed. Discrimination (AUC), classification (ACC/SEN/SPE), calibration (Brier score and calibration curves), reclassification (NRI/IDI), and interpretability (SHAP) were assessed.
Results:
RICAI was observed in 48.5%, 48.3%, and 54.6% of the training, internal testing, and external testing cohorts, respectively. Among single–source models, SwinT and SRad showed comparable performance, with Rad slightly inferior; all outperformed the clinical model. The fused Rad–SRad–SwinT achieved the best performance, with AUCs of 0.814 (95% CI: 0.737–0.891) in internal testing and 0.871 (95% CI: 0.794–0.932) in external testing, alongside favorable classification in external testing (ACC 0.815, SEN 0.763, SPE 0.878) and good calibration (Brier score 0.148). NRI/IDI analyses indicated significantly improved reclassification versus single-source models. SHAP analyses demonstrated that SwinT-derived features contributed most to model decisions, followed by SRad and Rad, supporting complementary gains from deep semantic representation and subregional heterogeneity quantification.
Conclusion:
Integrating multilevel radiomics with Transformer–derived deep learning features enhances prediction of RICAI after NPC radiotherapy and shows promise as a noninvasive risk–stratification tool.

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INTRODUCTION

Radiation-induced carotid artery injury (RICAI) is an important late vascular toxicity after nasopharyngeal carcinoma (NPC) radiotherapy and may increase the risk of transient ischemic attack and ischemic stroke. Because the carotid arteries are close to target volumes, dose exposure is often unavoidable, yet carotid dose constraints and standardized vascular surveillance remain underused in routine practice.
Pretreatment MRI is routinely performed in NPC and may capture patient-specific vascular susceptibility before overt injury occurs, providing a practical window for noninvasive risk stratification. However, whole-ROI radiomics mainly summarizes global texture and may dilute focal injury-prone heterogeneity. Subregional radiomics can preserve spatial phenotypes, while Swin Transformer features capture higher-order semantic patterns.
Therefore, this study aimed to develop and externally validate an MRI-based Rad-SRad-SwinT fusion model to predict RICAI after NPC radiotherapy and support carotid organ-at-risk management.

METHODS AND MATERIALS

Study design
- Multicenter retrospective cohort: 500 NPC patients from four hospitals.
- Training/internal testing: 274/118 patients; external testing: 108 patients.
- RICAI was adjudicated on paired pre- and post-radiotherapy MRI after at least 1 year of follow-up.

Feature pipeline
- Carotid ROIs were manually delineated on pretreatment MRI.
- Rad: whole-ROI PyRadiomics features after standardized preprocessing.
- SRad: K-means subregion features characterizing spatial heterogeneity.
- SwinT: Transformer-derived deep features from representative ROI patches.

Modeling and evaluation
- RF/SVM/KNN classifiers; fusion signatures combined Rad, SRad, and SwinT.
- Performance: AUC, ACC/SEN/SPE, Brier score, calibration, DCA, NRI/IDI, and SHAP.

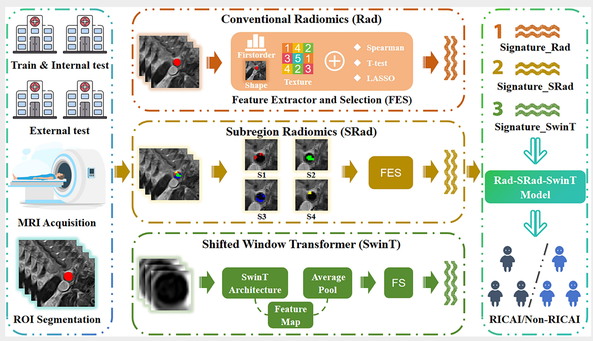

Fig. 1. Workflow for MRI preprocessing, carotid ROI segmentation, Rad/SRad/SwinT feature extraction, fusion modeling, and RICAI prediction.

RESULTS

- MRI-derived models consistently outperformed the clinical model, indicating that pretreatment MRI encoded stronger RICAI-related risk information than routine clinical and dosimetric variables alone.
- Among single-source signatures, SRad and SwinT showed stronger and more stable discrimination than conventional Rad, supporting the value of spatial heterogeneity and Transformer-derived semantic features.
- The Rad-SRad-SwinT fusion model achieved the best overall performance, with AUCs of 0.814 in internal testing and 0.871 in external testing; external ACC, SEN, SPE, and Brier score were 0.815, 0.763, 0.878, and 0.148, respectively.
- NRI/IDI and decision-curve analyses demonstrated improved reclassification and higher clinical net benefit compared with single-source and dual-fusion models.
- SHAP analysis showed that SwinT contributed most to model decisions, followed by SRad and Rad; case-level waterfall plots illustrated how complementary features shifted predictions toward RICAI or non-RICAI.

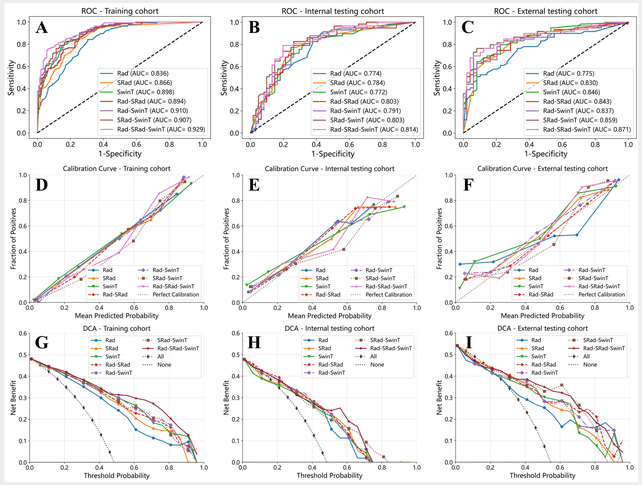

Fig. 2. ROC, calibration and DCA curves show that Rad-SRad-SwinT outperformed single-source and dual-fusion models.

Tab. 1. NRI/IDI analysis between the Rad–SRad–SwinT fusion prediction model and its sub–models.

Rad–SRad–SwinT	Training cohort		Internal testing cohort		External testing cohort	
VS.	NRI ↑	IDI ↑	NRI ↑	IDI ↑	NRI ↑	IDI ↑
Rad	0.948/0.000	0.225/0.000	0.622/0.000	0.150/0.001	0.578/0.002	0.122/0.006
SRad	1.203/0.000	0.151/0.000	0.629/0.000	0.081/0.017	0.684/0.000	0.108/0.016
SwinT	0.775/0.000	0.091/0.000	0.331/0.047	0.062/0.035	0.703/0.000	0.076/0.036
Rad–SRad	0.587/0.000	0.096/0.000	0.421/0.008	0.073/0.023	0.303/0.053	0.043/0.142
Rad–SwinT	0.431/0.000	0.065/0.000	0.282/0.067	0.047/0.060	0.346/0.030	0.070/0.018
SRad–SwinT	0.660/0.000	0.068/0.000	0.069/0.665	0.015/0.504	0.255/0.153	0.015/0.591

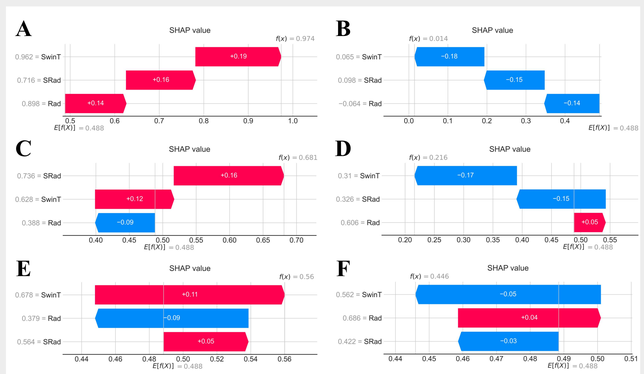

Fig. 3. SHAP waterfall plots demonstrate complementary effects of SwinT, SRad and Rad in patient-level decisions.

DISCUSSION

This study addresses an unmet need for pretreatment stratification of radiation-accelerated carotid vasculopathy in patients with NPC. By integrating complementary MRI-derived information, the proposed model moves beyond conventional whole-ROI radiomics, which may dilute focal injury-prone heterogeneity through global averaging. In contrast, SRad preserves spatial heterogeneity within the carotid ROI, while SwinT captures global-local semantic representations and showed the largest SHAP contribution to model decisions.
The superior performance of the Rad-SRad-SwinT model suggests that tripartite fusion provides additive value over handcrafted radiomics, deep features, or clinical variables alone, improving discrimination, calibration, and clinical net benefit. Clinically, this approach may help identify high-risk patients before radiotherapy, support carotid-sparing planning priorities, and guide individualized vascular follow-up.
Several limitations should be acknowledged, including the retrospective design, finite sample size, lack of laboratory or genomic biomarkers, and limited multimodal vascular confirmation. Prospective validation with broader clinical and vascular imaging data is warranted.

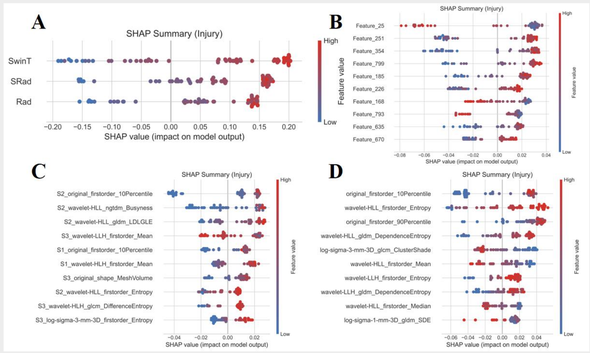

Fig. 4. Feature importance based on RF algorithm with SHAP analysis.

CONCLUSIONS

- Pretreatment MRI-based Rad-SRad-SwinT robustly predicted RICAI after NPC radiotherapy.
- Radiomics and Transformer features were complementary, supporting multilevel fusion.
- Findings may inform carotid organ-at-risk management and risk-adaptive surveillance.
- Prospective validation with ultrasound/CTA and biomarkers is warranted.

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