Prognostic Modeling in HNSCC: The Role of Radiomic Parameter Settings and Graph-Based Feature Selection

Hajar Moradmand, Jason Molitoris, Ranee Mehra, Lisa Schumaker, Erin Allor, Daria A. Gaykalova, Lei Ren

University of Maryland School of Medicine | Greenebaum Comprehensive Cancer Center | Institute for Genome Sciences | Johns Hopkins University

BLUE RIBBON POSTER IMAGING | Abstract #27217 | 2026 Joint AAPM|COMP Annual Meeting

1. Background

Clinical problem

HNSCC outcomes differ by center, stage, treatment, subsite, HPV, and smoking context. Radiomics may capture tumor heterogeneity, but models can fail when preprocessing or feature selection changes.

Objective

Identify radiomics workflows that are externally predictive and feature-stable, rather than selecting only the single best AUC.

Clinical benefit

A reproducible CT-radiomics framework can support risk stratification when clinical variables are incomplete.

2. Study Design and Workflow

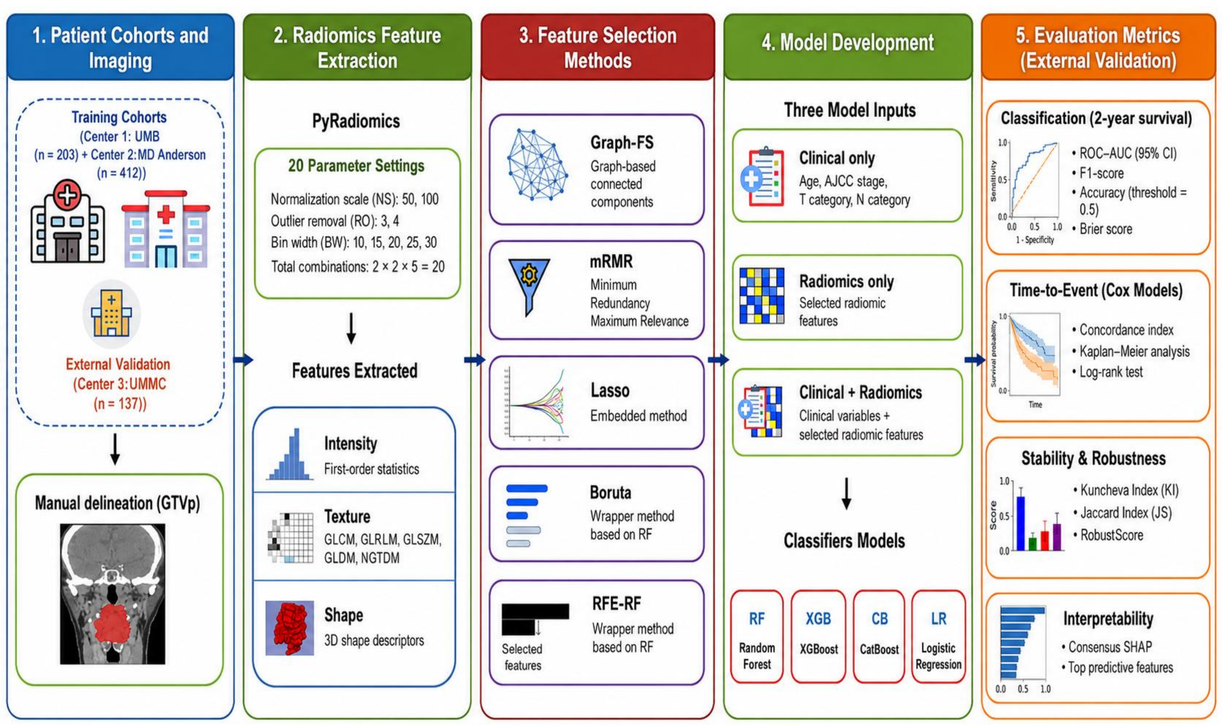


Figure 1. Study workflow.

3. Result: Impact of Radiomics Parameter

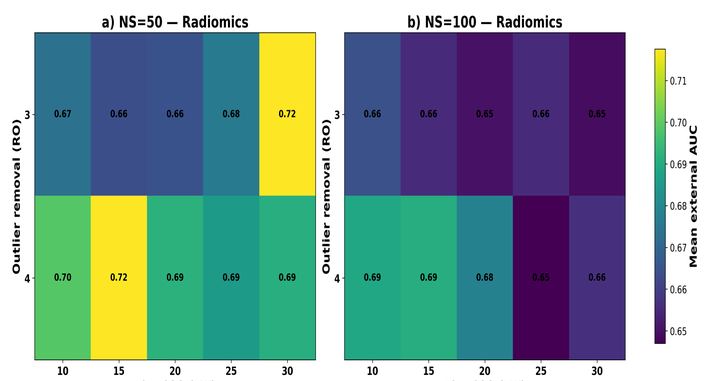


Figure 2. Impact of radiomics parameterization on radiomics-only model performance.

Interpretation

- NS = 50 generally outperformed NS = 100.
- Outlier removal and bin width changed the external AUC.
- Preprocessing is not a minor detail; it affects generalizability.

4. Result: Clinical-Radiomics Models

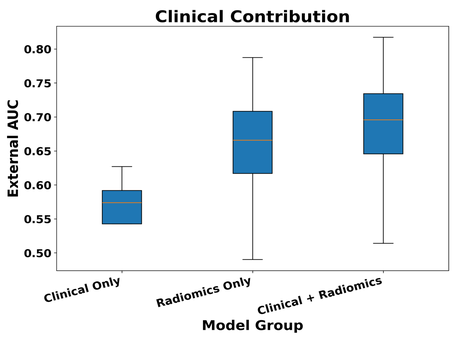


Figure 3. Clinical contribution and incremental value of radiomics.

Clinical-only	Radiomics-only	Clinical + radiomics
mean AUC 0.560	mean AUC 0.676	mean AUC 0.702

Interpretation

- Radiomics improved external discrimination beyond the available clinical baseline.
- Clinical + radiomics gave the strongest aggregate performance.
- Best individual classification model: external AUC 0.817.

5. Result: Prediction vs Stability Trade-off

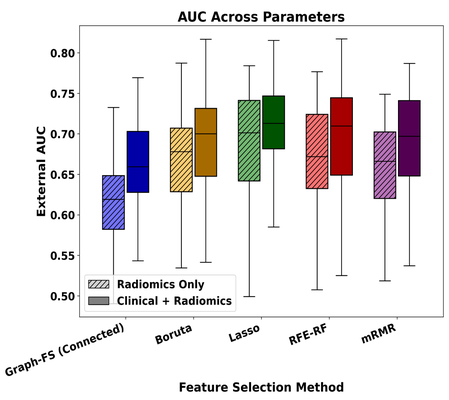


Figure 4. External AUC distributions across feature selection methods.

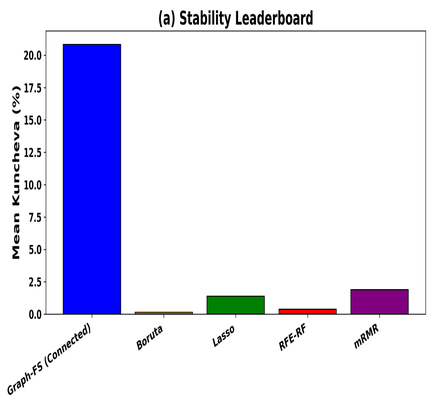
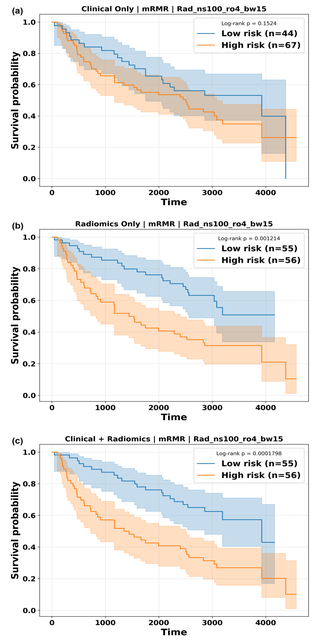


Figure 5. Feature-selection stability. (**a**) Overall mean Kuncheva index across feature selection methods.

Interpretation

Performance: mRMR and Lasso achieved the highest average external AUCs.
Stability: Graph-FS showed the highest feature-selection stability.
Graph-FS mean Kuncheva =18.5%.

6. Result: Survival Validation



Interpretation

- Cox models used full follow-up time beyond binary 2-year survival.
- Best clinical + radiomics configuration: mRMR | Rad_ns100_ro4_bw15.
- External C-index = 0.662.
- High- vs low-risk groups were significantly separated in the external cohort with log-rank p = 0.00018.

Figure 6. Kaplan–Meier curves for the external validation cohort using Cox risk scores.

7. Result: Consensus SHAP

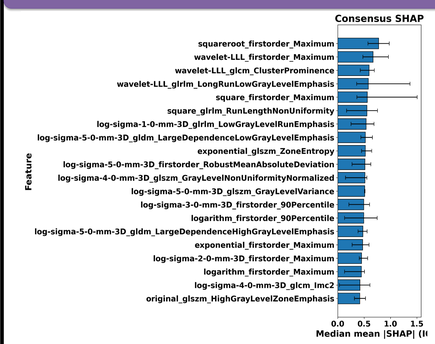


Figure 7. Consensus SHAP feature importance.

Interpretation

- First-order intensity and texture features dominated.
- Features reflect tumor heterogeneity patterns.
- These are model explanations, not validated biological biomarkers.

8. Clinical Impact and Take-Home Message

Clinical impact

- Do not judge radiomics only by best AUC.
- Evaluate external discrimination, calibration, feature stability, and time-to-event performance together.
- Graph-FS supports reproducibility; clinical + radiomics improves risk stratification.

Limitations

- Retrospective multicenter cohorts;
- incomplete HPV, smoking, subsite and treatment variables.
- Next: validate with richer clinical covariates and larger independent datasets.

Take-home message

Radiomics can add prognostic information in multicenter HNSCC, but robust clinical translation requires parameter-aware testing, external validation, and reproducible feature selection.

Reference: Moradmand H, Molitoris J, Mehra R, Schumaker L, Allor E, Gaykalova DA, Ren L. Impact of Radiomics Parameters and Clinical Integration on Prognostication in Head and Neck Squamous Cell Carcinoma: A Multicenter Study. *Life*. 2026;16(6):1027. doi:10.3390/life16061027

Funding: NIH R01EB032680, R01CA279013, R01DE033426, U54CA273956, U01CA288351 | IRB HP-00101754

Contact: hmoradmand@som.umaryland.edu