Multimodal MRI Machine-Learning Radiomics for Standardized Metastasis-Risk Assessment in Soft-Tissue Sarcoma

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BACKGROUND

- Up to 50% of high-grade soft-tissue sarcomas (STS) develop distant metastases, which drive mortality.
- Current risk assessment relies on clinicopathologic factors and subjective MRI interpretation, leading to variable surveillance strategies.
- MRI radiomics can quantify intratumoral heterogeneity and may better reflect aggressive tumor biology than semantic assessment alone.
- Objective: build an explainable multimodal MRI framework combining radiomics, semantic MRI features, and clinical data to predict metastasis.

METHODS

- Retrospective single-center observational study (2008–2021).
- 246 adults with primary STS; inclusion required pre- and post-NAT MRI, no baseline metastasis, and ≥12 months follow-up or earlier documented metastasis.
- Inputs: T2, pre-contrast T1, post-contrast T1, non-fat-suppressed T1 MRI; 17 semantic MRI features; clinical/pathology variables; PyRadiomics features + delta radiomics.
- Two MSK radiologists segmented tumors on pre- and post-neoadjuvant therapy (NAT) MRI; agreement was high (Dice 0.87 ± 0.08; semantic weighted κ 0.92).
- XGBoost models: SC (semantic+clinical), RC (radiomics+clinical), and RCS (radiomics+clinical+semantic); patient-level 80/20 split, 3-fold cross-validation, random search, AUROC, SHAP.

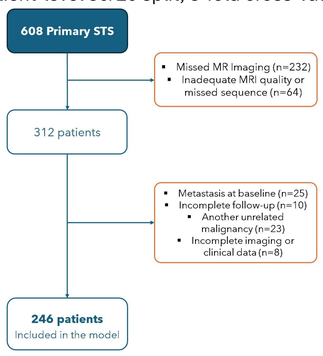

Figure 1: Study cohort assembly: 608 primary STS screened → 246 patients included in model development.

RESULTS

246 patients
102 metastases (41.5%)

Median 13 months
Time to metastasis

Lung 55%
Bone 16% of metastatic sites

Radiomics-containing models generalized better than semantic+clinical alone, but held-out test performance remained moderate.

Model	Train	CV	Test	Features
RCS	0.82	0.68	0.63	44
RC	0.79	0.66	0.64	6
SC	0.77	0.69	0.57	24

Best integrated model (RCS)
- Train AUROC 0.82
- Cross-validation AUROC 0.68
- Independent test AUROC 0.63.
- Radiomics dominated predictive signal; post-treatment tumor size was the main non-radiomic feature retained.

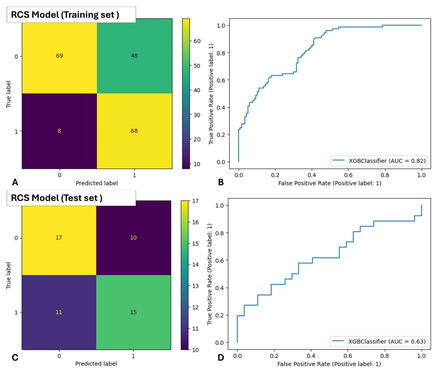

Figure 2: RCS model performance
Training AUROC 0.82; held-out test AUROC 0.63.

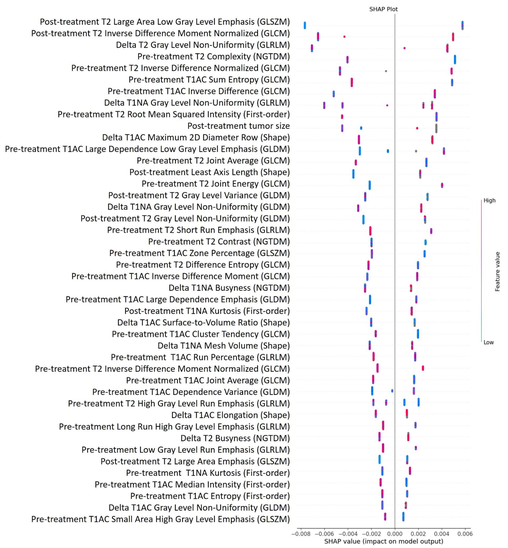

Figure 3: Multimodal SHAP summary
Texture and heterogeneity metrics from pre-, post-, and delta-T2/T1 sequences dominated the model.

DISCUSSION

- Radiomics-containing models outperformed the semantic+clinical model on held-out testing (RC 0.64; RCS 0.63; SC 0.57).
- Predictive signal was driven mainly by quantitative MRI heterogeneity features from T2 and post-contrast T1 sequences.
- Semantic MRI and clinicopathologic data improved interpretability but added limited incremental discrimination beyond radiomics.
- A standardized model-derived risk estimate could support more consistent surveillance intensity and chest imaging choices across clinicians.

CONCLUSIONS

- Multimodal MRI machine-learning provided a reproducible imaging-based estimate of metastasis risk in primary STS.
- Radiomics features were the dominant source of predictive signal; semantic MRI features added limited complementary value.
- Current discrimination is clinically promising but moderate; external multi-institutional validation is required before deployment.

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