16th Symposium of the Japanese Scandinavian Radiological Society

Predictive Modeling of Oral Squamous Cell Carcinoma Outcomes Using PET Texture Analysis and Machine Learning

Mai Kim[1)], Yasuhiro Fukushima[2)], Keisuke Suzuki[1)], Masaru Ogawa[1)], Souma Kumasaka[2)], Azusa Tokue[2)], Tetsuya Higuchi[2)], Yoshito Tsushima[2)], Satoshi Yokoo[1)]

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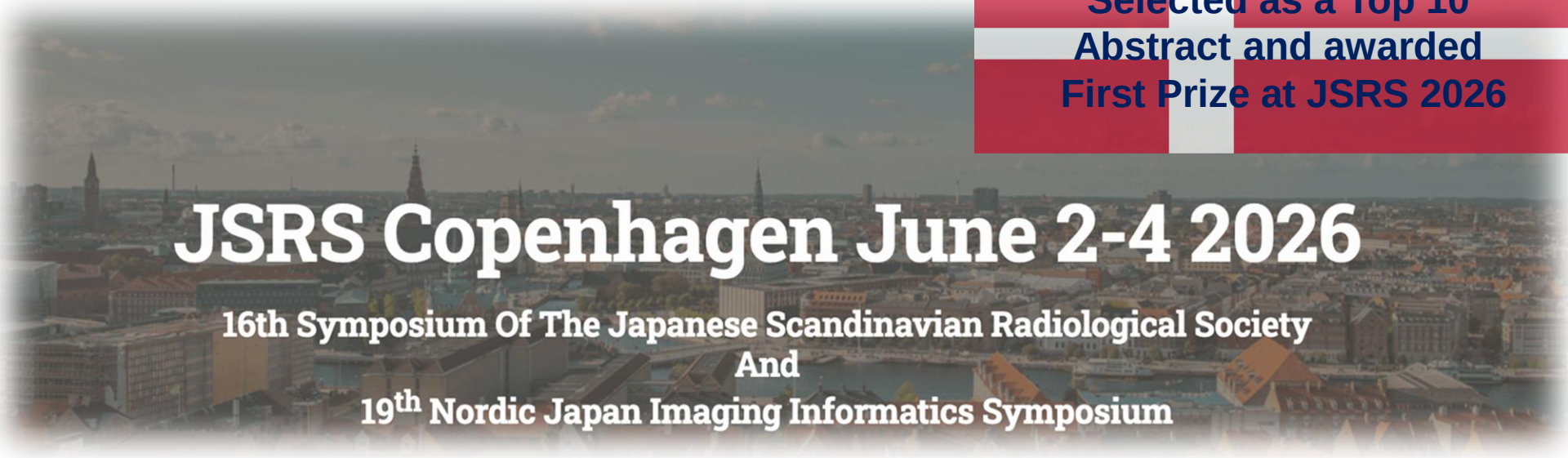
Selected as a Top 10 Abstract and awarded First Prize at JSRS 2026



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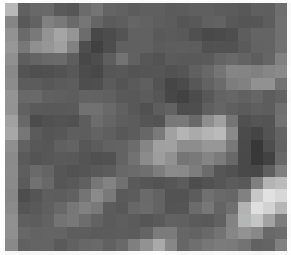
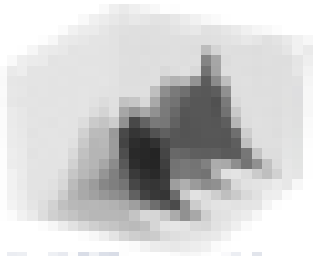
Background: Need for better outcome prediction

Radiomic features

Intensity features

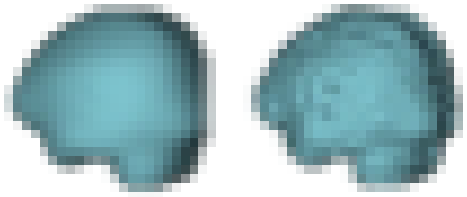


Local contrast



Histogram

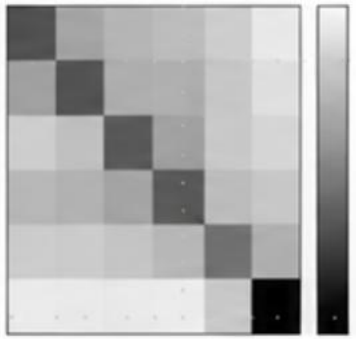
Morphological features



Volume

Curvature

Texture features



Gray-Level Co-occurrence Matrix (GLCM)

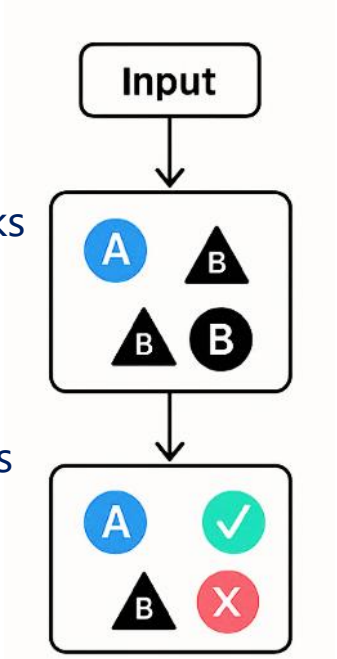
Focus on intratumoral metabolic heterogeneity

Background: PET radiomcs analysis and machine learning

Machine Learning (ML)

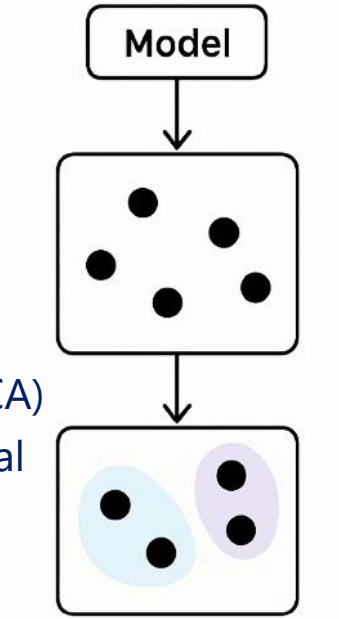
① Supervised learning

- Neural networks
- Deep learning
- Support vector machines (SVM)
- Random forests



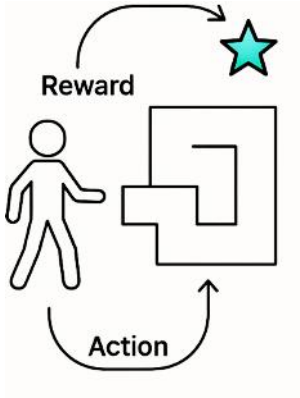
② Unsupervised learning

- k-means clustering
- Principal component analysis (PCA)
- Hierarchical clustering



③ Reinforcement learning

- Temporal-difference (TD) learning
- Q-learning
- SARSA



Learns prognostic patterns from imaging features

Purpose: Development and validation of prediction models

Primary objective:
To develop and validate ML models using ^{18}F-FDG PET radiomic features for prognostic prediction in oral squamous cell carcinoma (OSCC)

Secondary objective:
To develop, validate, and compare **DFS** prediction
by a radiomics-only ML model (^{18}F-FDG PET features) versus
a clinical-covariate–only Cox model

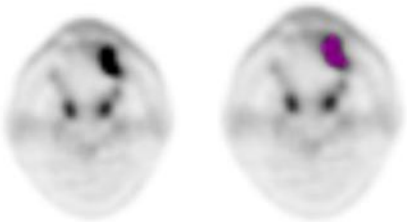
Develop and validate PET radiomics models in OSCC

Methods: Patients, endpoints, and PET radiomics workflow

Design and setting: single-center retrospective cohort (Department of Oral and Maxillofacial Surgery, Gunma University Hospital)
Period: July 2009– October 2020
Screened: 781 patients undergoing definitive OSCC surgery; preoperative ^{18}F-FDG PET/CT in 406
Included for analysis: 240 patients with successful lesion ROI delineation and PET radiomic feature extraction

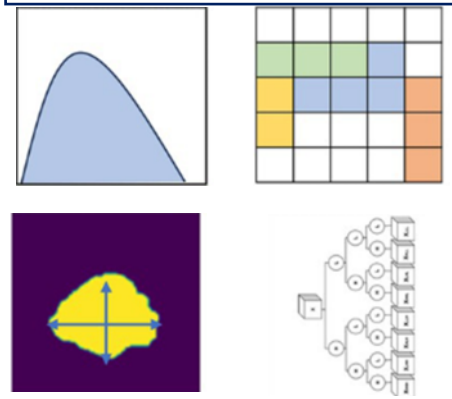
Primary endpoint
DFS: time from first visit to the first oncologic event (local recurrence, regional nodal metastasis, or distant metastasis); event-free patients were censored at last follow-up
OS: time from any cause; otherwise censored at last follow-up
Covariates: age, sex, histological grade (G1–G3), TNM stage
Split / leakage control: stratified 70/30 train–test by event; preprocessing fit on training, applied to test only

VOI delineation



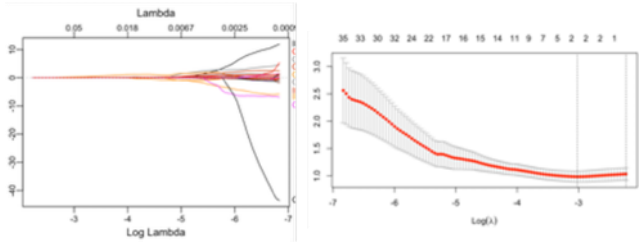
- Define primary tumor VOI (3D, isotropic voxels)
- Threshold-based extraction: fixed threshold = 40% of SUV_{max}

Radiomic feature extraction



- LIFEx (IBSI-compliant)
- Categories: morphological (shape), first-order intensity (SUVbw), GLCM, GLRLM, NGTDM, GLSZM; 3D aggregation

Harmonization and feature selection



- ComBat harmonization across all radiomic features
- LASSO–Cox with 5-fold CV, then repeated LASSO –Cox to compute selection frequency
- Retain stable features with selection frequency ≥ 0.70

Compare PET radiomics and clinical models for DFS prediction

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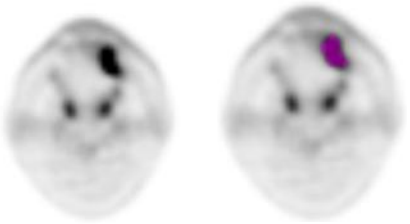

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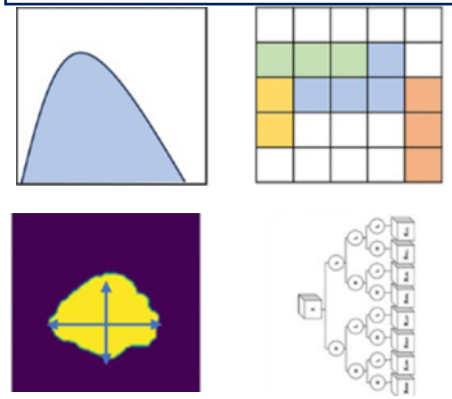

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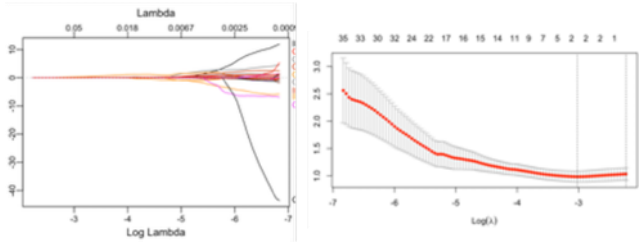

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- Retain stable features with selection frequency ≥ 0.70

Methods: Model construction and validation

ML model (DFS, ^{18}F-FDG PET features): performance validation and benchmarking against the clinical model

Data collection

- Outcomes: DFS (primary); OS (exploratory)
- Predictors: ^{18}F-FDG PET radiomic (texture) features
- Clinical covariates: age, histological grade (G1–G3), TNM stage

Model construction

- Harmonization: ComBat (batch = manufacturer)
- Feature selection: training-only LASSO–Cox (5-fold CV)
  → non-zero coefficients preselect; repeated LASSO–Cox (60% subsample ×100)
  → retain features with selection frequency ≥ 0.70
- Learner: XGBoost (survival:aft) for censored time-to-event prediction; standard regularization and early stopping

Model assessment

- Metrics (test): Harrell's C, Uno's C, time-dependent AUC at 1/3/5 years
- Explainability: SHAP (mean |SHAP|) for global importance; alignment checked with model gain rankings
- Cutoff: optimal risk threshold from training via maximally selected rank statistics (surv_cutpoint) with minimum-proportion constraint

Test-set evaluation (Kaplan–Meier)

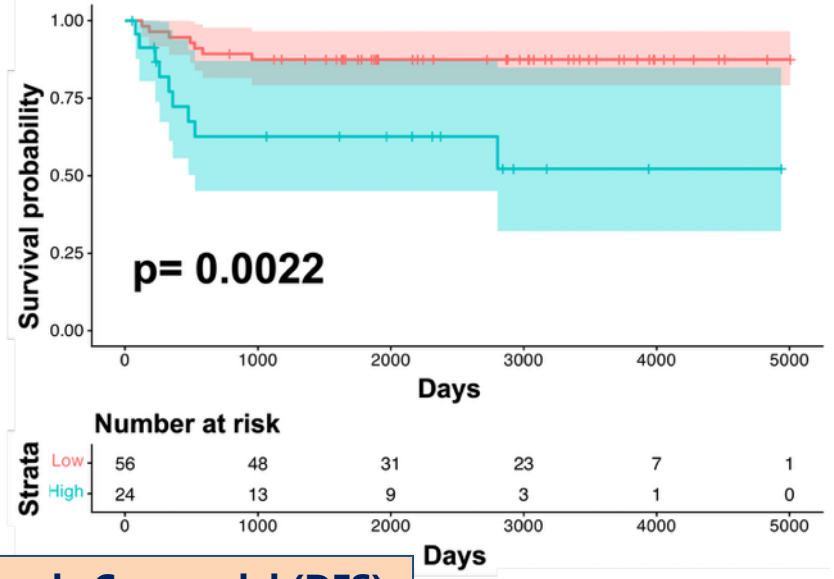
- Apply training-derived cutoff → High vs Low risk
- Kaplan–Meier curves and log-rank test for separation
- Bootstrap of cutoff (n = 200) to display threshold uncertainty
- Comparison vs clinical Cox model: C-index, time-dependent AUC, KM separation

Results: PET radiomics model stratified DFS

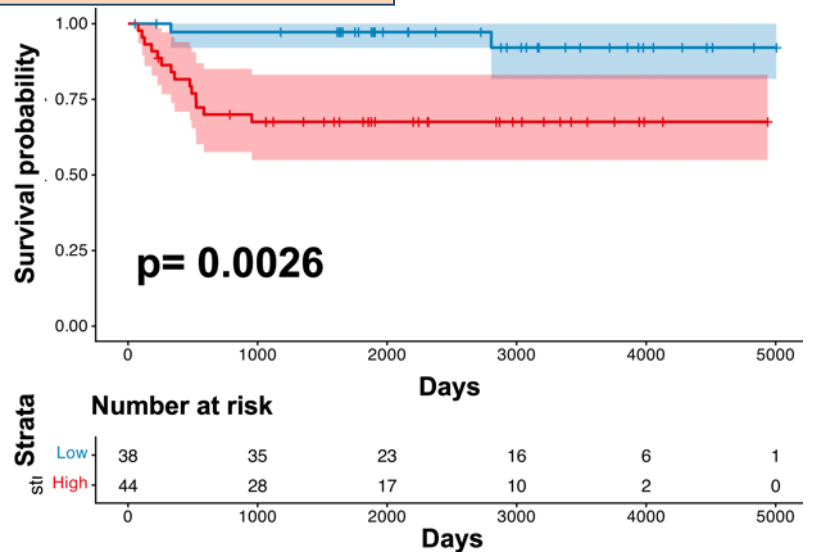
Characteristic	N	N = 240[1]
Age (years)	240	71.0 [61.0, 77.5]
Sex		
Female		114 (48%)
Male		126 (52%)
Stage		
I		56 (24%)
II		116 (49%)
III		29 (12%)
IV		39 (14%)
T category		
1		56 (24%)
2		130 (55%)
3		25 (11%)
4		29 (11%)
N category		
0		205 (85%)
1		17 (7.1%)
2		18 (7.5%)
Differentiation		
Gr1		185 (77%)
Gr2		47 (20%)
Gr2-3		8 (3.3%)
Manufacturer		
GE		144 (60%)
SIEMENS		96 (40%)
DFS (days)		2,143.0 [1,071.0, 3,306.0]
OS (days)		2,297.0 [1,648.0, 3,430.5]

[1]Median [Q1, Q3]; n (%)

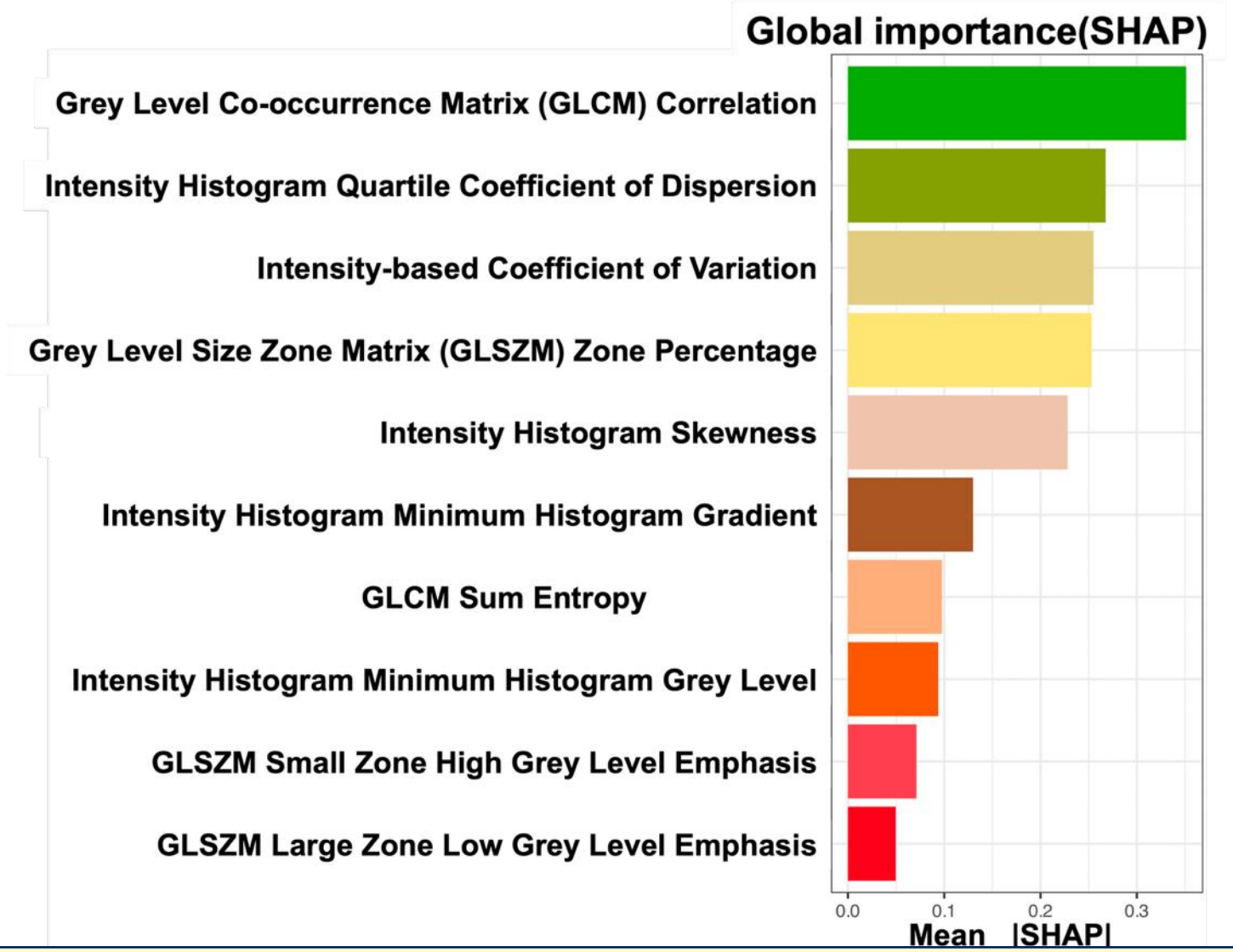
Clinical-covariate–only Cox model (DFS)



Radiomics-only Cox model (DFS)



Results: SHAP analysis



Radiomics features reflecting intratumoral heterogeneity

Discussion: PET radiomics may capture tumor heterogeneity

Clinical prognostic factors

- TNM stage, and DOI are established OSCC prognostic factors [1–3]
- Clinical model stratified DFS

Complementary value of PET radiomics

- PET radiomics model stratified DFS
- May add value beyond conventional imaging

Biological meaning of texture features

- GLCM/GLSZM and dispersion features were SHAP-important
- May reflect heterogeneous FDG uptake [4–5]

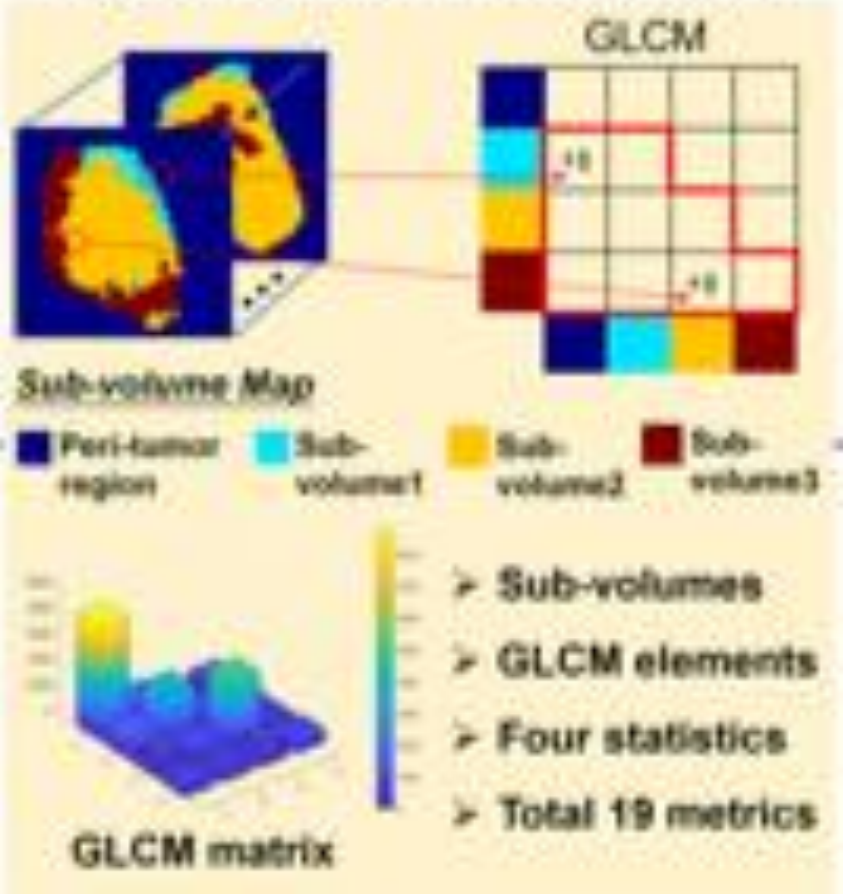
Clinical implication

- May support pretreatment risk stratification
- May inform follow-up planning and treatment intensification

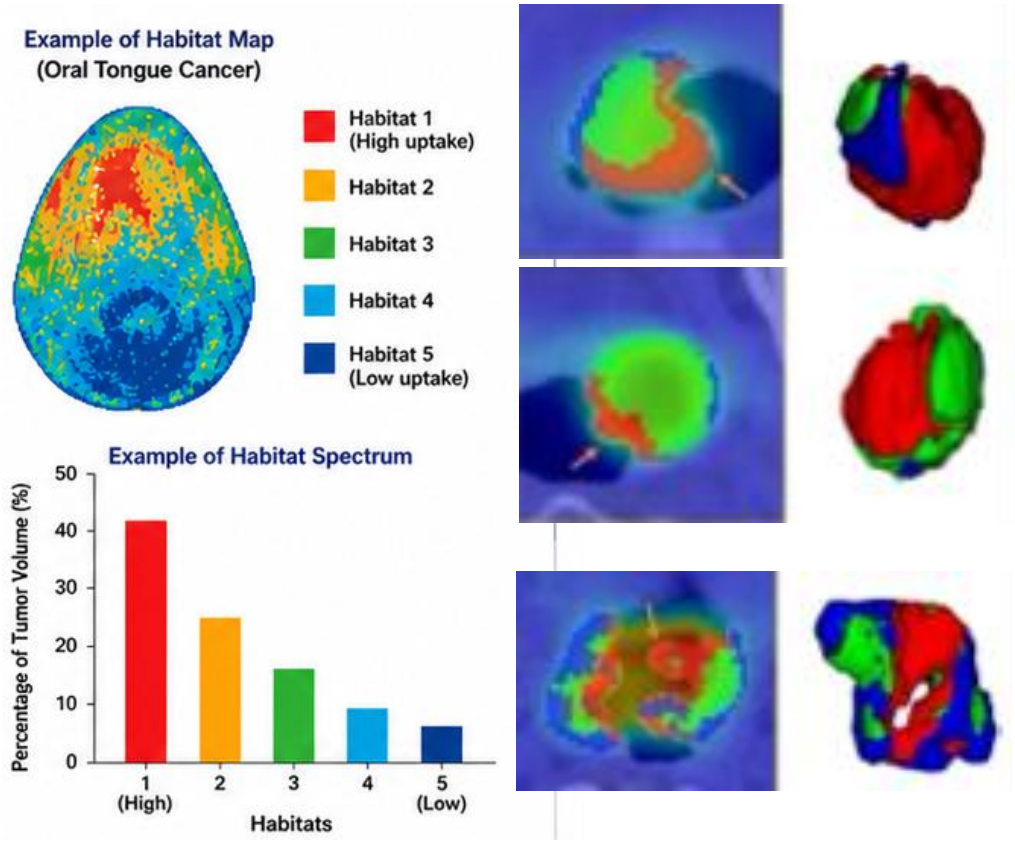
1) Kademani D, et al. J Oral Maxillofac Surg. 2005;63:1599-1605.
2) Noguchi M, et al. Br J Oral Maxillofac Surg. 1999;37:433-437.
3) Kim MJ, Ahn KM. Maxillofac Plast Reconstr Surg. 2024;46:8.
4) Martens RM, et al. EJNMMI Res. 2020;10:102.
5) Kim M, et al. Mol Imaging Biol. 2025;27:421-430.

Future direction: SHAP-guided PET habitat analysis

Heterogeneity Measurement



PET Habitat radiomics in OSCC



Habitat analysis may spatially visualize PET heterogeneity

7) Xu H, et al. Eur J Nucl Med Mol Imaging. 2023;50:1720-1734.

Conclusion: PET texture as an imaging biomarker

- **PET radiomics provides significant DFS stratification in OSCC.**

  independent test set; log-rank p = 0.0026

- **GLCM correlation is identified as the most important SHAP feature.**

- **PET texture analysis may serve as a promising imaging biomarker.**