Cross-Regional Radiomic Consistency in Squamous Cell Carcinoma: Common PET/CT Features and Their Prognostic Value

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ABSTRACT

- Radiomics-based prediction is often limited by small datasets, **making transfer and semi-supervised learning (SSL) attractive approaches** for improving model performance.
- We investigated shared PET and CT radiomics features between lung and head and neck (H&N) squamous cell carcinoma (SCC), **which share a common histopathological origin, and assessed their prognostic value**.
- PET and CT images from 42 lung SCC and 42 HN SCC patients were analyzed using PyRadiomics.
- Thirteen PET and nine CT features showed no significant differences between cancer types. Three shared PET first-order features consistently ranked among the strongest predictors of survival, whereas only one CT feature demonstrated similar importance.
- These findings suggest that **PET radiomic features are more transferable across lung and HN SCC than CT features**, supporting their use in transfer and **SSL** to improve prognostic modeling in cancers with limited labeled data.

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INTRODUCTION

Transfer and semi-supervised learning (SSL) can improve prediction when disease-specific data are limited [1,2].

This study identifies **shared radiomic features between lung and H&N-SCC,** and evaluates their prognostic value for survival prediction.

METHODS AND MATERIALS

- PET and CT images from 42 lung-SCC and 42 H&N-SCC patients were collected from multicenter datasets: TCIA, BC Cancer, and HECKTOR.
- PET images were SUV-normalized, CT intensities were clipped, and 107 tumor radiomics features were extracted (PyRadiomics).
- Survival outcomes were predicted using 11 classifiers for HN CT, lung CT, H&N PET, and lung PET, followed by SHapley Additive exPlanations (SHAP) analysis.

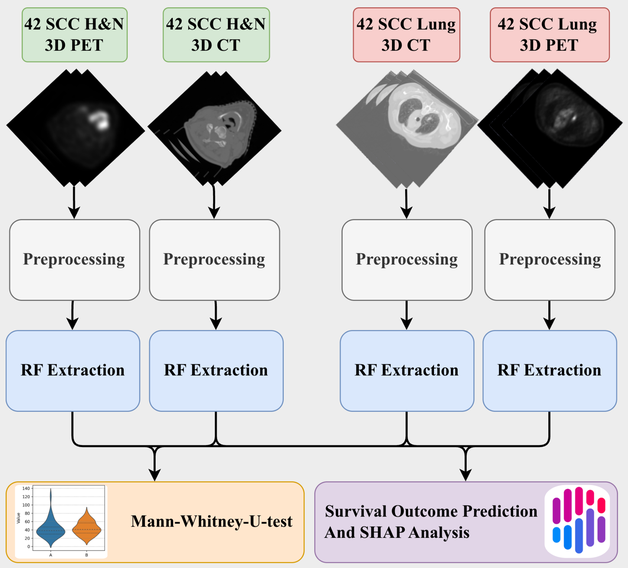

Figure 1. All PET and CT images were registered and preprocessed, and radiomic features were extracted (PyRadiomics). Feature distributions were then analyzed using the Mann-Whitney U test, followed by classification and SHAP analyses. RF: radiomic feature; SCC: squamous cell carcinoma; H&N: head and neck.

RESULTS

- **13** PET and **9** CT radiomic features (RFs) showed no significant distributional differences between lung- and H&N-SCC ($p>0.05$).
- In PET imaging, **3** shared 1st-order features (**mean, 90th percentile, and total energy**) ranked among **top** outcome predictors, whereas only one CT-feature (**90th percentile**) demonstrated comparable importance (Figs. 2 and 3).
- For lung-SCC, best predictive performance was achieved with **AUC=0.675±0.17** via Multilayer Perceptron (MLP) for PET, and **0.683±0.10** via Gradient Boosting for CT.
- In H&N-SCC, CT achieved **AUC=0.865±0.10** via MLP, while PET reached **AUC=0.795±16** via Random Forest.

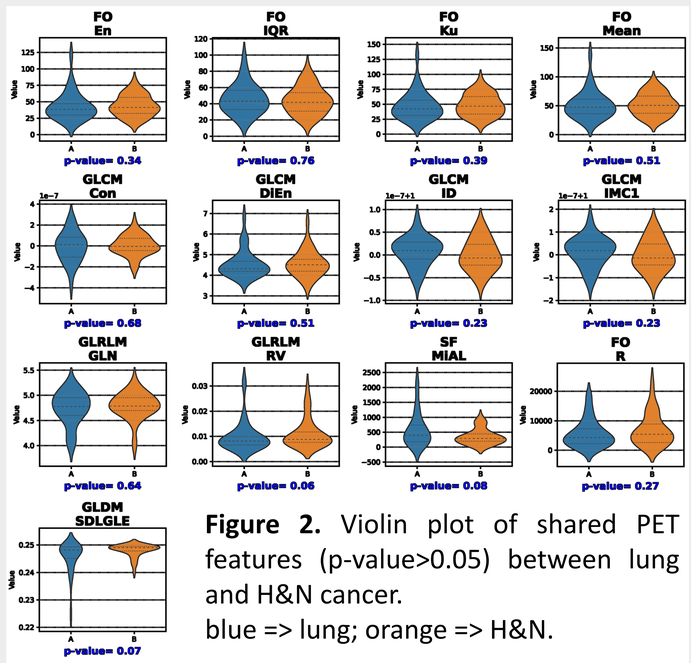

Figure 2. Violin plot of shared PET features (p-value>0.05) between lung and H&N cancer.
blue => lung; orange => H&N.

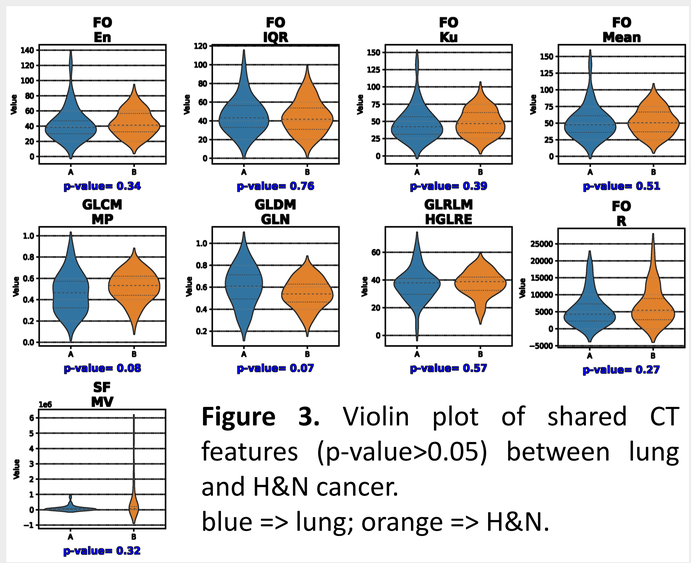

Figure 3. Violin plot of shared CT features (p-value>0.05) between lung and H&N cancer.
blue => lung; orange => H&N.

FO: First Order, SF: Shape Feature, GLCM: Gray Level Co-occurrence Matrix, GLDM: Gray Level Dependence Matrix, GLRLM: Gray Level Run Length Matrix, En: Entropy, IQR: Interquartile Range, KU: Kurtosis, R: Range, Con: Contrast, DiEn: Difference Entropy, ID: Inverse Difference, IMC1: Informational Measure Correlation 1, SDLGLE: Small Dependence Low Gray Level Emphasis, RV: Run Variance, GLN: Gray Level Non-Uniformity, MiAL: Minor Axis Length, MP: Maximum Probability, HGLRE: High Gray Level Run Emphasis, MV: Mesh Volume, DA: Difference Average, 90P: 90th Percentile, IV: Inverse Variance, TE: Total Energy, Min: Minimum, SA: Surface Area, Corr: Correlation, MAL: Major Axis Length, E: Energy, CS: Contrast, GLNN: Gray Level Non-Uniformity Normalized.

- Fig. 4 shows top 10 H&N radiomics features. **Low FO_Min & FO_90P and high FO_TE** (shared features) predicted poor overall survival.

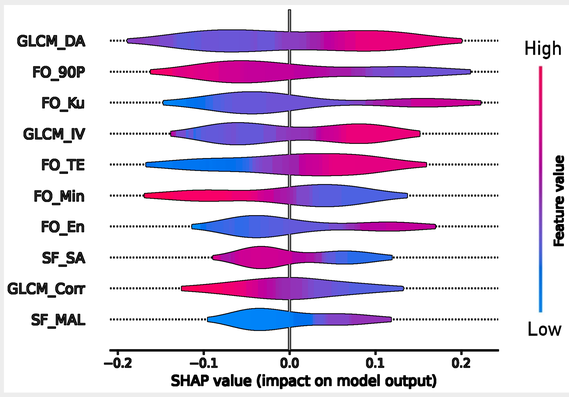

Figure 4. Summary plot of 10 most important H&N PET radiomic features.

- Fig. 5 shows top 10 lung PET RFs. **High FO_TE, FO_90P and FO_Min** (shared features) predicted poor overall survival.

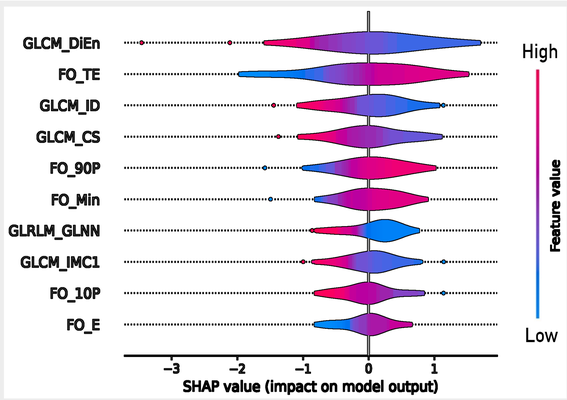

Figure 5. Summary plot of 10 most important lung PET radiomic features.

CONCLUSIONS

- RFs were **more consistently** shared between lung-SCC and HN-SCC for PET than CT, providing a **biological basis for cross-cancer transfer**.
- SHAP identified shared prognostic PET-RFs that may support explainable transfer learning and SSL with unlabeled data, improving prediction in data-scarce settings.

REFERENCES

1. Salmanpour, Mohammad R., et al. "Enhanced lung cancer survival prediction using semi-supervised pseudo-labeling and learning from diverse PET/CT datasets." *Cancers* 17.2 (2025)
2. Pan, Sinno Jialin, and Qiang Yang. "A survey on transfer learning." *IEEE Transactions on knowledge and data engineering* 22.10 (2009): 1345-1359.