

Prediction of Radiation Pneumonitis Using Deep Learning Applied to Dose–Function Metrics

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INTRODUCTION

✓ Clinical Problem

- Radiation pneumonitis (RP) occurs in ~30% of lung cancer patients receiving RT [1].
- Grade ≥ 2 RP mandates ICI discontinuation
→ directly compromises survival [2]

✓ Research Gap

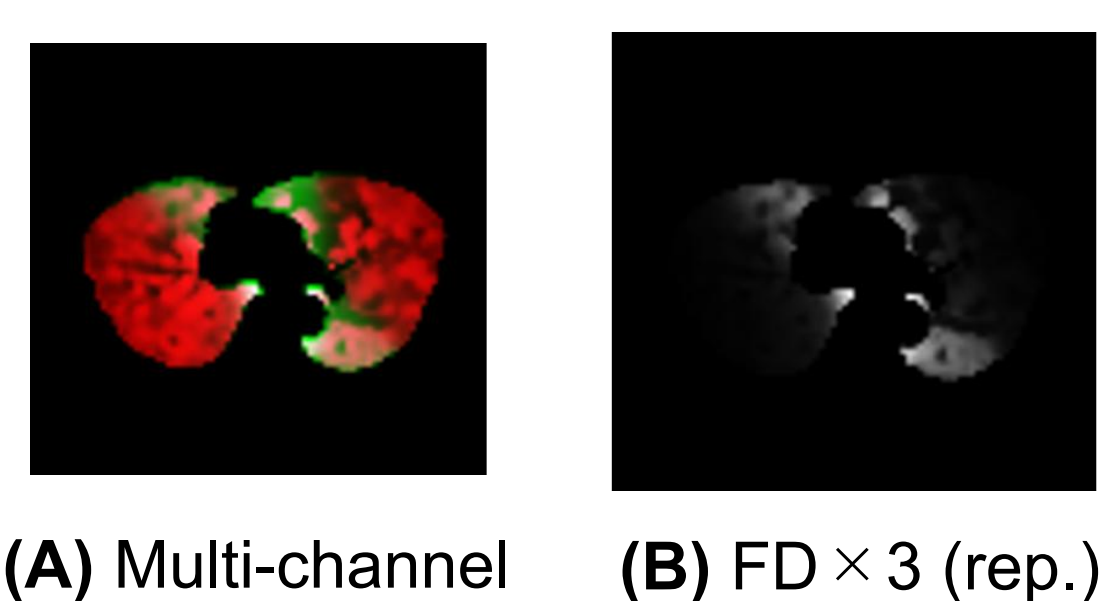
- Conventional dose–volume metrics fail to capture spatial dose–function relationships.
- Deep learning models integrating CTVI are promising, but the optimal input strategy remains unestablished [3]

MATERIALS AND METHODS

✓ Patient cohort

- Retrospective study at Komagome Hosp. (IRB No. 2930) and Komazawa Univ. (No. 22-26)
- 95 NSCLC patients (Stage IB–IIIC); 26 (27.4%) developed CTCAE grade ≥ 2 RP

Input Images



✓ Image preprocessing

- CT ventilation image : Jacobian method
- Down sampling -> Isotropic 4 mm voxel
- Functional dose (FD) = CT ventilation value $\times$ Dose

✓ Input channels (A)(B)(C)

- Multi-channel model: CT ventilation / Dose / FD
- Single-channel model: FD $\times$ 3 (replicated) and Dose $\times$ 3 (replicated)

✓ Deep learning model

- pretrained on the combined dataset with Kinetics-700 and Moments in Time [4].
- Fine-tuning: layer 3 + layer 4 + Fully connected (FC) layer with Focal Loss ($\gamma = 1.5$), Adam, Learning rate = 10^{-5} and early stopping (10 epochs, patience = 5)
- Fixed model (ImageNet weights frozen) vs Fine-tuned model

✓ Classifier

- FC layer used in fine-tuning only for training the CNN (for Loss / AUC); bypassed afterward
- Features taken up to Layer 4 → Logistic Regression (classical ML)

✓ Evaluation

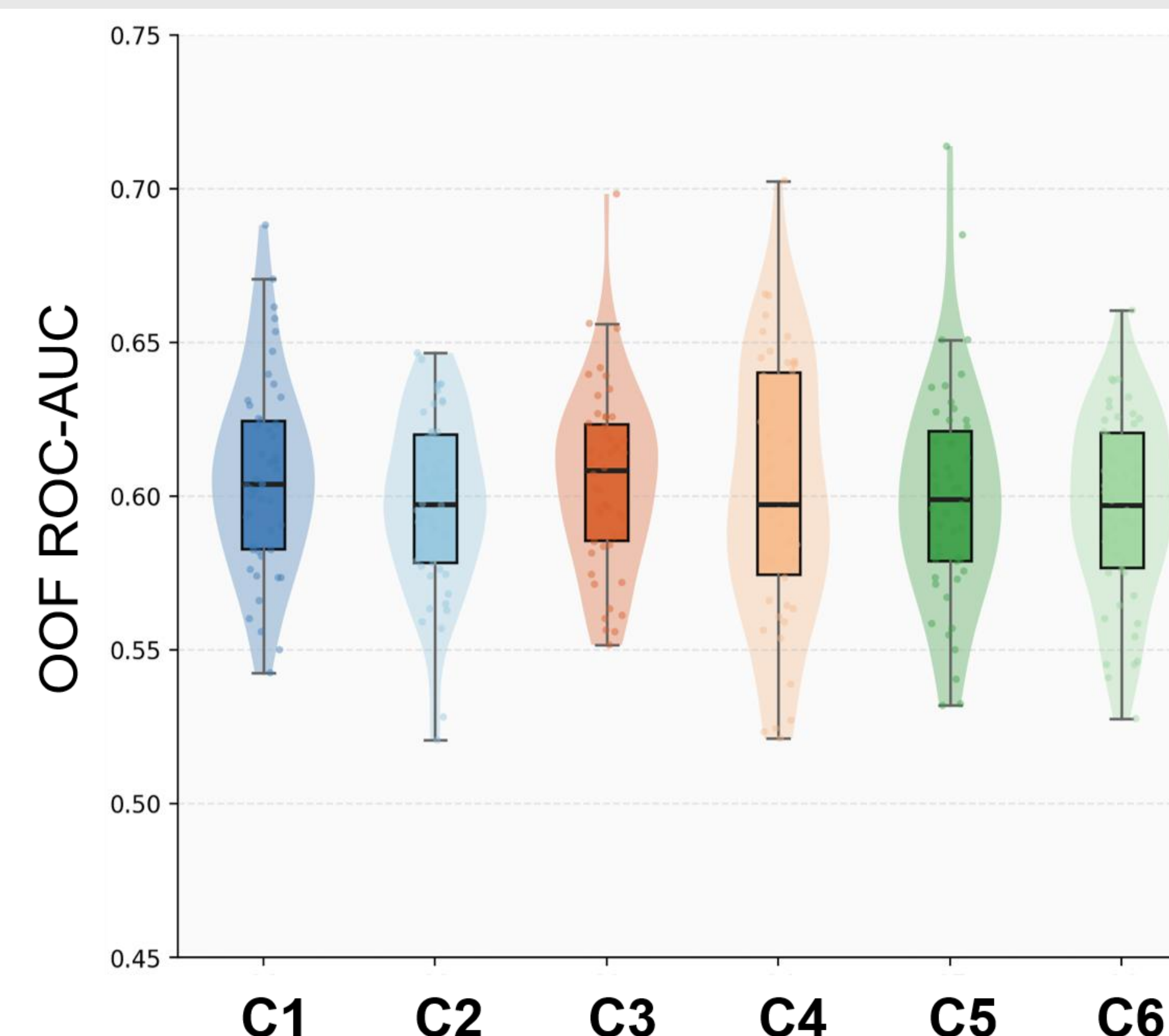
- 50-repeat $\times$ 5-fold cross validation
- ROC-AUC, PR-AUC

3D ResNet-50
(feature extractor)

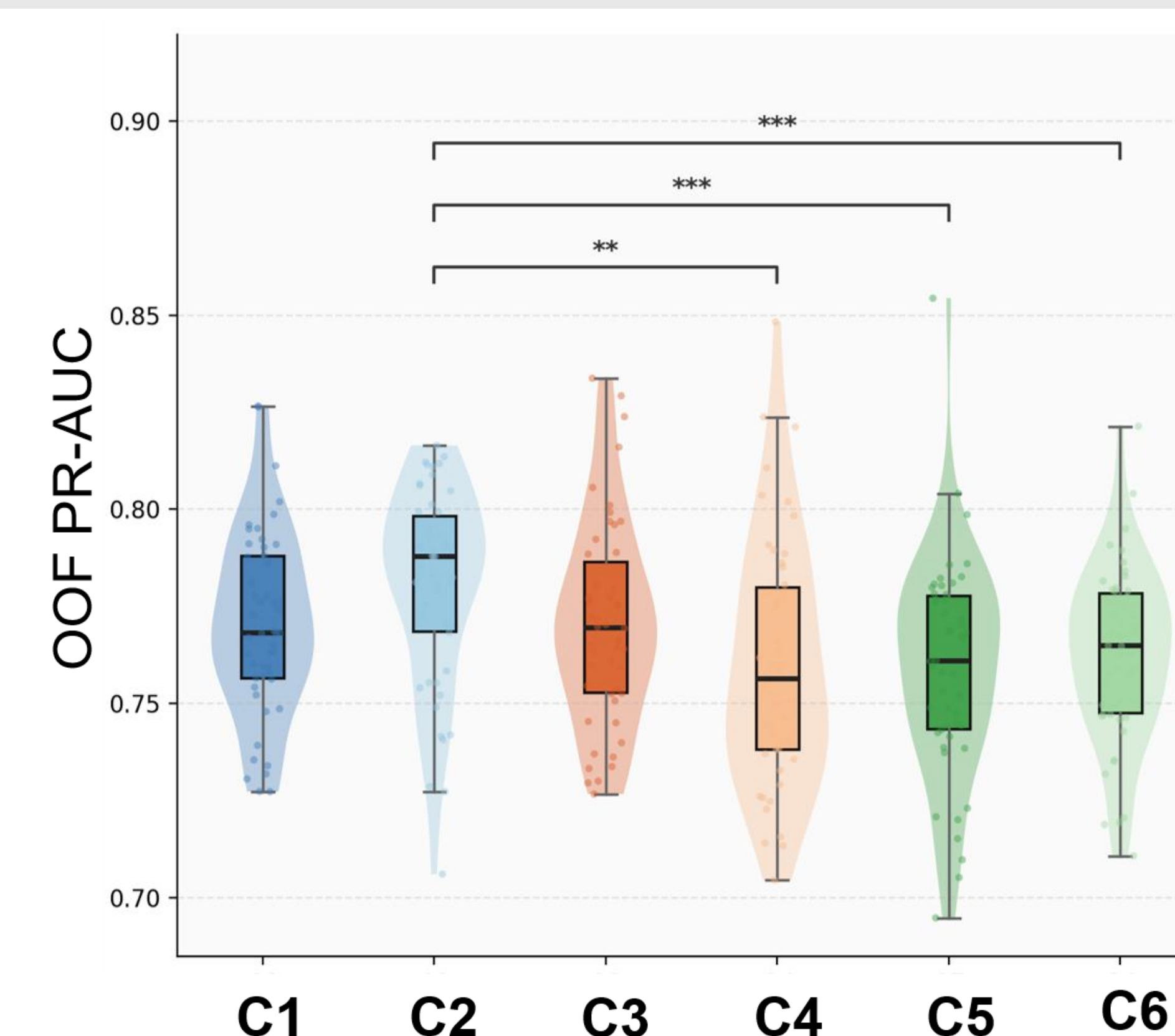
Logistic regression model
(feature filtering & selection)

RP prediction (grade ≥ 2)

RESULTS



(A) OOF ROC-AUC



(B) OOF PR-AUC

Deep learning model training conditions

Condition	Input	Fine-tuning
C1	CTVI + Dose + FD (3ch)	Fine-tuning
C2	CTVI + Dose + FD (3ch)	None
C3	FD $\times$ 3 (rep.)	Fine-tuning
C4	FD $\times$ 3 (rep.)	None
C5	Dose $\times$ 3 (rep.)	Fine-tuning
C6	Dose $\times$ 3 (rep.)	None

Figure shows violin plots with individual repeat values (n=50) for Out-Of-Fold (OOF) ROC-AUC (A) and OOF PR-AUC (B) across six conditions (C1–C6, defined in the table below) evaluated with Logistic Regression. Box-and-whisker overlays indicate median, interquartile range, and 1.5×IQR. Dashed lines indicate random-classifier baselines (ROC-AUC = 0.50; PR-AUC = 0.274, prevalence). Mean $\pm$ SD are shown below each condition. Significance brackets indicate Bonferroni-corrected paired t-tests (30 total comparisons).

KEY FINDINGS

- OOF ROC-AUC: 0.596–0.606 across all conditions — **no significant differences** found.
- OOF PR-AUC: C2 (CTVI+Dose+FD, fixed; 0.780 ± 0.026) was significantly higher than C4 (0.760), C5 (0.759), C6 (0.763)
- All conditions exceeded random baselines (ROC-AUC 0.50; PR-AUC 0.274).

DISCUSSION

- The narrow ROC-AUC range across all conditions suggests a **biological ceiling**; neither input channel nor fine-tuning strategy significantly altered overall discrimination.
- Fine-tuning **reduced PR-AUC**, likely due to overfitting to RP-positive cases. Fixed ImageNet (video-pretrained) features (C2) achieved the highest precision–recall performance without domain-specific training.
- Dose-only inputs (C5, C6) showed the lowest PR-AUC, confirming the **added value of CT ventilation value** beyond dosimetric features alone.
- FD $\times$ 3ch was equivalent to CTVI+Dose+FD, as FD encodes the **joint functional-dose distribution**, simplifying the preprocessing pipeline without performance loss.

CONCLUSIONS

- Fixed 3D ResNet-50 (video-pretrained) with CTVI+Dose+FD input achieved **OOF PR-AUC = 0.780**, well above the random baseline (0.274), demonstrating clinical potential for pre-treatment RP risk stratification.
- Functional dose (FD) as a **single-channel input** provides equivalent performance to full 3ch fusion, offering a streamlined pipeline for clinical implementation.
- External validation with larger, multi-institutional cohorts is required before clinical translation (proof-of-concept, n = 95).

REFERENCES

1. Palma DA, et al. Int J Radiat Oncol Biol Phys. 2013.
2. Spigel DR, et al. J Clin Oncol. 2022.
3. Bin L, et al. Med Phys. 2021.
4. Kensho Hara, et al. arXiv 1711.09577. 2018.

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