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Predicting Replanning in Head-and-Neck Patients Using Dosiomics and Clinical Features

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ABSTRACT

- **Purpose:** Adaptive replanning in head and neck (H&N) radiotherapy can be resource-intensive and can also disrupt clinical workflow. We developed and validated a machine learning model that combines dosiomics and clinical features to predict which patients are likely to require replanning and the associated risk factors.
- **Methods:** A retrospective cohort of 149 H&N patients was analyzed. A total of 1,009 candidate predictors were extracted from dose distributions (DVH and spatial dose features) and clinical data. A multi-stage feature selection pipeline was applied (variance and correlation filtering, ANOVA and mutual information screening, L1-regularized logistic regression, permutation importance, and bootstrap stability selection). Iterative filtering to remove low-variance, redundant, and unstable features, and retaining a small set of consistently predictive variables, was necessary to avoid overfitting and improve generalization in high-dimensional, limited-sample datasets. Finally, a logistic regression classifier was trained and evaluated using stratified 5-fold cross-validation.
- **Results:** 53 of 149 patients (35.6%) required replanning. The pipeline reduced dimensionality by 99.5% and identified five robust predictors: extent of volume receiving dose ≥50 Gy, fraction of the parotid volume that receives at least 100% of the prescription dose, optic nerve D0.1cc, post-operative status, and chemotherapy. The model achieved an ROC AUC of 0.76, sensitivity of 81.1%, specificity of 64.6%, and accuracy of 70.5%. The model output categorized patients into groups: 27 (18.1%) were very high risk (probability >70%), and 47 (31.5%) were high risk (50-70%). In each category, the final five predictors that determine the decision and the potential for early replan prediction are identified.
- **Conclusion:** A model using five clinically interpretable dosiomics and clinical predictors demonstrated moderate discrimination for replanning need in H&N patients and may enable early identification of high-risk patients and the factors involved, for proactive replanning. A larger cohort and refinement of the dosiomics predictors can further improve the model.

KEY FINDINGS

- **153 patients — 36% re-planned**
- **Test AUC 0.741 | Specificity 95% | Precision 80%**
- **Strongest predictor: mean max dose change (100%)**
- **BHI Spread (73.5%) beat Max BHI (41.7%) and Mean BHI (28.3%) alone**
- **6 of 8 predicted re-plans flipped after simulated plan improvement**

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INTRODUCTION

- **Clinical burden:** ~30–35% of HN proton patients need adaptive re-planning; each takes ~1 week of extra imaging, planning and QA while treatment continues on the original plan.
- **Why proton:** IMPT spares organs at risk, but its steep dose gradients are highly sensitive to weight loss, tumor regression and setup change, driving the need for adaptation.
- **Gap:** Most published re-plan models are photon-based and imaging-only; few use plan-quality dosimetry, and interpretability for clinicians remains limited.
- **Our approach:** Combine dosimetric beam heterogeneity (BHI) and robustness with clinical features in one interpretable model.
- **Goal:** identify the likely re-plan cases early and reveal, per patient, which factors drive risk so planners can act before treatment.

METHODS AND MATERIALS

- **Patients:** 171 HN proton patients (RayStation 9A, robust optimization, 21 scenarios); 153 retained after outlier removal.
- **Dosimetric features:** Beam Heterogeneity Index (BHI = max beam dose / prescription at 0.03 cc): Mean BHI, Max BHI, and BHI Spread = Max BHI − Mean BHI.
- **Other features:** Plan robustness (mean max dose change) plus 5 clinical variables are tumor site, stage, surgery, chemotherapy, age (9 total).
- **Model:** Gradient boosting classifier (depth 2, 40 estimators, lr 0.05) shallow trees regularize a small clinical dataset.
- **Evaluation:** Accuracy, sensitivity, specificity, precision, ROC-AUC; 5-fold stratified CV; train–test AUC gap minimized during grid search.

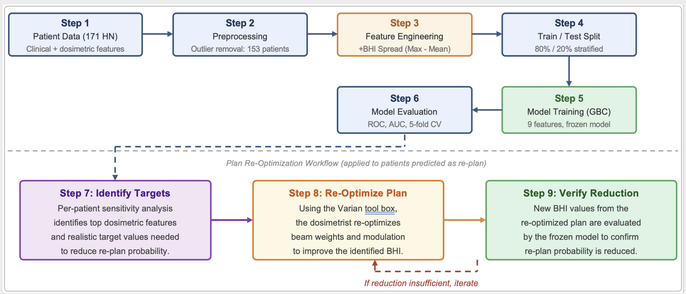

Figure 1. Modeling and plan re-optimization pipeline (steps 1–6 model development; steps 7–9 re-optimization loop).

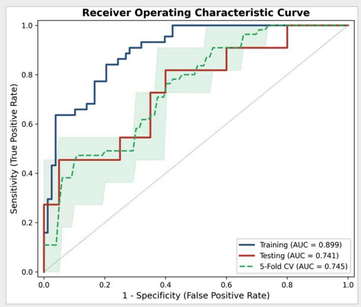

Figure 2. ROC curves for training, testing and 5-fold cross-validation (shaded band).

RESULTS

- **Cohort:** 153 patients, 55 (36%) re-planned, 98 (64%) not; split 122 train / 31 test (stratified).
- **Discrimination:** Test AUC 0.741; specificity 95% and precision 80% means few false alarms.
- **Top predictors:** Mean max dose change (100%), BHI Spread (73.5%) and tumor site (62.8%); stage contributed 0%.
- **BHI Spread:** The engineered feature outranked Max BHI and Mean BHI alone as within-plan beam variability carries more signal.
- **Plan modification:** Lowering mean max dose change to ~0.020 cut re-plan probability by 0.15–0.22; 6 of 8 cases flipped to "no re-plan".

Table 1. Gradient boosting classifier performance.

Metric	Training (122)	Testing (31)
AUC	0.899	0.741
Accuracy	83.6%	74.2%
Sensitivity	61.4%	36.4%
Specificity	96.2%	95.0%
Precision	90.0%	80.0%

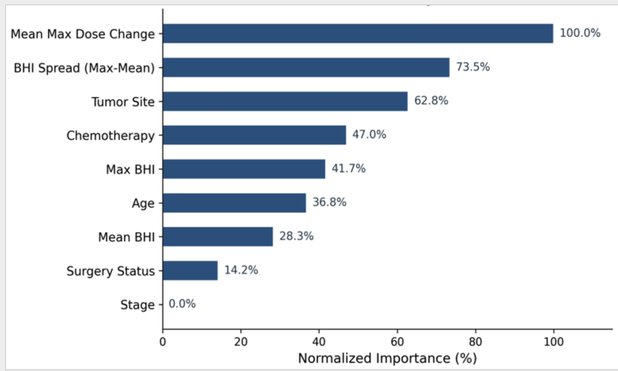

Figure 3. Normalized feature importance. Mean max dose change and the engineered BHI Spread dominate.

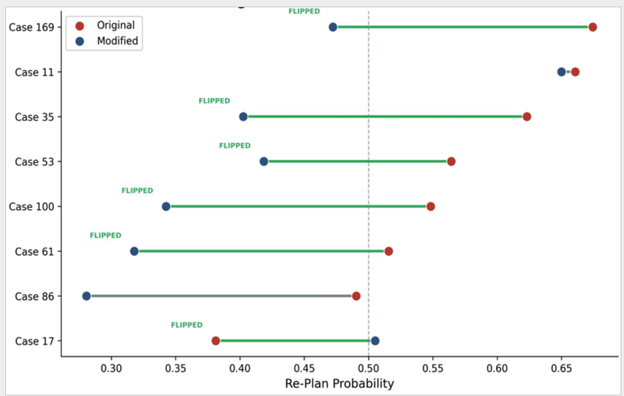

Figure 4. Predicted re-plan probability before (red) and after (blue) dosimetric improvement for 8 cases; green links mark predictions that flipped across the 0.5 threshold.

DISCUSSION

- **Proton-specific:** Most published re-plan models target photon therapy; proton dose deposition and anatomic sensitivity make those results non-transferable.
- **Interpretable by design:** Per-patient feature importance tells the dosimetrist team what drives each case's risk, not just a black-box score.
- **Actionable dosimetry:** BHI and robustness are plan-controllable, so high-risk plans can be revisited to reduce heterogeneity before treatment.
- **Variability matters:** BHI Spread shows a single hot beam can dominate risk even when average heterogeneity looks acceptable.
- **Operating point:** High specificity and precision with lower sensitivity (36% test) means few false alarms but some re-plans missed which is expected with a small test set.
- **Limitations:** Single institution, modest cohort, retrospective plan-modification analysis; prospective multi-center validation is next.

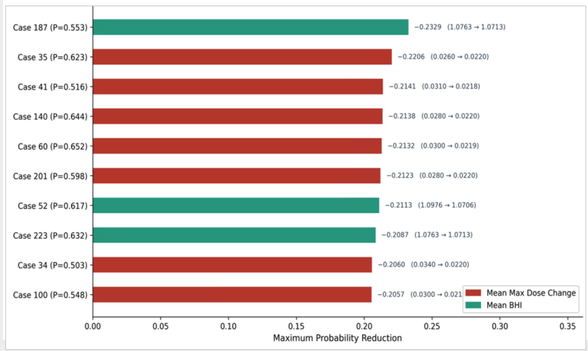

Figure 5. Top 10 re-plan patients with the greatest potential probability reduction from improving a single dosimetric feature.

CONCLUSIONS

- An interpretable gradient boosting model predicts HN proton re-planning from routinely available clinical and dosimetric features (test AUC 0.741).
- Beam heterogeneity: especially the engineered BHI Spread and plan robustness are the dominant, plan-controllable drivers of re-plan risk.
- Simulated dosimetric improvement lowered predicted risk and flipped most cases, supporting a prospective decision-support and re-optimization tool.

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