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Purpose/Objectives

- To determine the radiomic predictors for xerostomia (dry mouth)
- Hypothesis: Imaging features of pretreatment images can quantify the baseline salivary gland function for predicting xerostomia.

Materials/Methods

- Primary endpoint: prediction of grade xerostomia during 3 to 6 month post-l Algorithm: LASSO logistic regression
 - Three models were developed with
 - (1) both imaging features and DVH
 - (2) only DVH
 - (3) only imaging features.
- Data: 87 head and neck IMRT patients
 - **Imaging**: from planning CT
 - 5,000 imaging features for each R (L/R parotid/submandibular gland
 - intensity, volumetry, shape, textu
 - **Dosimetry**: DVH of parotid and submandibular glands
 - **Clinical**: xerostomia

Table 1. Demographic data (N=87)

| | _ |
|----------------|----------|
| Variable | N (%) |
| Age ≥ 60 | 33 (38%) |
| Male | 71 (82%) |
| Caucasian | 43 (49%) |
| Chemotherapy | 69 (79%) |
| T stage ≥ T3 | 27 (31%) |
| N Stage ≥ N2 | 52 (60%) |
| Site, pharynx | 37 (43%) |
| Xerostomia ≥ 2 | 42 (48%) |

Radiomic analysis of salivary glands and its role for predicting xerostomia in irradiated head and neck cancer patients

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|--|---|--|------------------------------------|--|
| Imaging features combined with DVH improved AUC of predicting xerostomia (p < 0.05) | | | | |
| | | Table 2. AUC of the prediction mod | els | |
| Ś | | Variables in the Prediction Model | AUC | |
| | | (1) Both imaging features and DVH | 0.81 | |
| | | (2) Only DVH data | 0.70 | |
| | | (3) Only imaging features | 0.63 | |
| Table 3. Odds ratio of the prediction model | | | | |
| e 2 2 | | Predictive Factor | odds ratio | |
| RT | | NGTDM (ipsilateral parotid) | 0.58 | |
| | Texture | GLCM (ipsilateral parotid) | 0.45 | |
| | | RLE (ipsilateral parotid) | 2.05 | |
| | Shape | aspect ratio (ipsilateral submandibular) | 0.51 | |
| | | combo parotid D95 [Gy] | 1.19 | |
| | υνη | combo submandibular D50 [Gy] | 1.09 | |
| S 201 | NGTDM: Neighborhood Gray-Tone Difference Ma GLCM: Grey Level Co-occurrence Matrix RLE: grey level Run Length Encoding OI | | | |
| Ire | <section-header>Imaging dataDosimetry dataClinical dataImaging feature calculation ongrinoImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature calculationImaging feature<br< th=""></br<></br></br></br></br></br></section-header> | | | |
| | | tion engine feature of OARs Machine learning algorithm | Prediction model of toxicity | |

Figure 1. Radiomic analysis of OARs for toxicity prediction

esults



- large.
- actual age.



Figure 2. Trend of grey-level run length of the ipsilateral parotid gland against age



management.



Texture predictors showed changing trends against age (parotid RLE, p < 0.05). • Decrease of density and increase of heterogeneity in parotid glands are reflected. • Xerostomia risk is high when parotid RLE is

• Some patients have older parotid gland than

Conclusions

Pre-RT radiomics is associated with the risk of xerostomia. This may reflect personalized baseline function of salivary glands. A potentially novel finding that imaging features of organs at risk (normal tissue) have a prognostic role for toxicity. Prediction of xerostomia can support clinical decision for RT-planning and toxicity