

Applying a Machine Learning Approach to Predict Acute Radiation Toxicities for Head and Neck Cancer Patients

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Disclosures for Dr. Reddy

- I am employed by MD Anderson Cancer Center.
- I have previously received travel expenses from VisionRT.

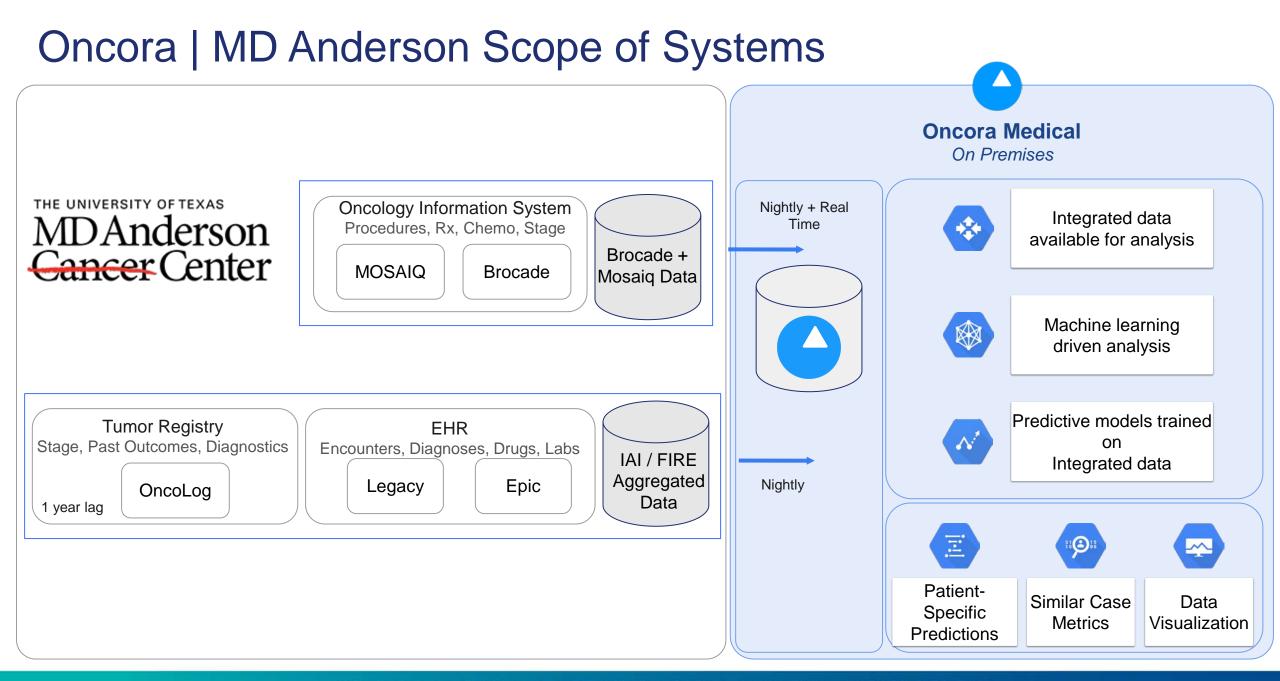
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Background

- Radiation therapy (RT) plays an integral role in the management of head and neck cancers.
- Nearly all patients receiving RT will experience some toxicity.
 - Dysphagia weight loss and need for feeding tube
 - Hospitalization for pain management, rehydration, nutritional support
- When and how to intervene represents a common clinical decision in the management of these patients.
- Precision oncology refers to the application of big data and predictive analytics to tailor specific treatments to patients and offer expected outcomes and toxicities
- This approach requires structured data for multiple variables, including clinical and pathologic characteristics, outcome, and acute toxicities



Oncora Analytics



Oncora Patient Care

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Objective

- To develop predictive models of acute toxicity during radiation for HN cancer patients.
 - Unplanned hospitalization (< 3 months from RT start)
 - Significant weight loss (>10% during RT)
 - Feeding tube placement

Methods

- 2121 consecutive courses of radiation treatment for HN cancer from May 2016— Aug 2018
- >700 clinical and treatment variables extracted
 - Demographics
 - Clinical and pathological characteristics
 - Treatment variables (RT details)
- Outcomes
 - Unplanned hospitalization (< 3 months from RT start)
 - Significant weight loss (>10% during RT)
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Methods

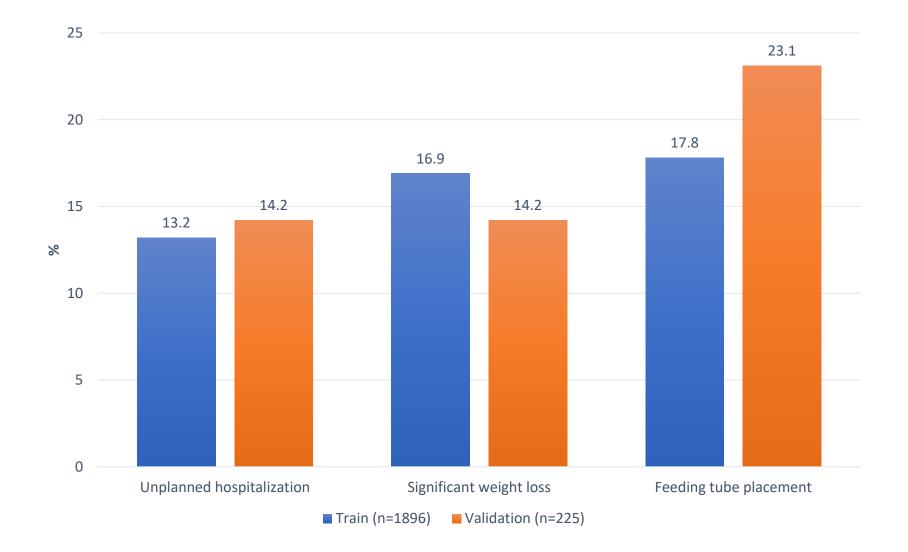
- Training set: first 1896 RT courses for HN cancer
 - Three machine learning models to predict outcome
 - Random forest—100 boosted decision trees
 - Extreme gradient boosted decision tree—100 boosted decision trees
 - Logistic regression with trained L1 regularization
- Validation set: subsequent 225 courses of RT
 - Final models for each toxicity were then evaluated
 - AUC > 0.7 considered clinically valid

Descriptive Statistics (n=2121)

Gender, count (%)	
Female	527 (24.8%)
Male	1594 (75.2%)
Age, median (IQR)	63 yrs (55.1—70.3)
RT Dose, median (IQR)	60 Gy (30—69.3)
No. of fractions, median (IQR)	30 (9—33)

Treatment Site	No. (%)
Oropharynx	743 (35.1%)
Oral cavity	314 (14.8%)
Skin	233 (11%)
Larynx	171 (8.1%)
Salivary gland	129 (6.1 %)
Thyroid	106 (5.0 %)
Nasopharynx	87 (4.1 %)
Nasal cavity	62 (2.9 %)
Sinus	48 (2.3 %)

Outcomes



AUC for Training Set Models (n=1896)

	Unplanned hospitalization (13.2%)	Significant weight loss (16.9%)	Feeding tube placement (17.8%)
Random forest	0.676	0.834	0.783
Gradient boosted decision trees	0.672	0.843	0.787
Logistic regression	0.666	0.838	0.779

AUC for Validation Set Models (n=225)

	Unplanned hospitalization (14.2%)	Significant weight loss (14.2%)	Feeding tube placement (23.1%)
Random forest	0.640		
Gradient boosted decision trees		0.751	0.755
Logistic regression			

Conclusions

- Application of three machine-learning models to a structured dataset enabled the development of predictive models for acute radiation toxicities for HN cancer patients.
- The models for predicting significant weight loss and feeding tube placement met criteria for clinical validity.
- This study demonstrates the feasibility of employing precision oncology to predict acute radiation toxicities.
- May facilitate the identification of patients for whom early intervention is warranted.

