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 Medical
On Premises

OncoLog
EHR
Encounters, Diagnoses, Drugs, Labs
Legacy, Epic

Tumor Registry
Stage, Past Outcomes, Diagnostics
1 year lag

Oncology Information System
Procedures, Rx, Chemo, Stage
MOSAIQ, Brocade

Brocade + Mosaic Data

IAI / FIRE Aggregated Data

Nightly + Real Time

Integrated data available for analysis
Machine learning driven analysis
Predictive models trained on Integrated data
Patient-Specific Predictions
Similar Case Metrics
Data Visualization

Oncora | MD Anderson Scope of Systems

2019 AMERICAN SOCIETY FOR RADIATION ONCOLOGY (ASTRO) ANNUAL MEETING
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)
  • Feeding tube placement
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)

<table>
<thead>
<tr>
<th>Gender, count (%)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>527 (24.8%)</td>
</tr>
<tr>
<td>Male</td>
<td>1594 (75.2%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age, median (IQR)</th>
<th>63 yrs (55.1—70.3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RT Dose, median (IQR)</td>
<td>60 Gy (30—69.3)</td>
</tr>
<tr>
<td>No. of fractions, median (IQR)</td>
<td>30 (9—33)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Treatment Site</th>
<th>No. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oropharynx</td>
<td>743 (35.1%)</td>
</tr>
<tr>
<td>Oral cavity</td>
<td>314 (14.8%)</td>
</tr>
<tr>
<td>Skin</td>
<td>233 (11%)</td>
</tr>
<tr>
<td>Larynx</td>
<td>171 (8.1%)</td>
</tr>
<tr>
<td>Salivary gland</td>
<td>129 (6.1 %)</td>
</tr>
<tr>
<td>Thyroid</td>
<td>106 (5.0 %)</td>
</tr>
<tr>
<td>Nasopharynx</td>
<td>87 (4.1 %)</td>
</tr>
<tr>
<td>Nasal cavity</td>
<td>62 (2.9 %)</td>
</tr>
<tr>
<td>Sinus</td>
<td>48 (2.3 %)</td>
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</tbody>
</table>
Outcomes

- Unplanned hospitalization: 13.2% (Train) vs. 14.2% (Validation)
- Significant weight loss: 16.9% (Train) vs. 14.2% (Validation)
- Feeding tube placement: 17.8% (Train) vs. 23.1% (Validation)
### AUC for Training Set Models (n=1896)

<table>
<thead>
<tr>
<th>Model</th>
<th>Unplanned hospitalization (13.2%)</th>
<th>Significant weight loss (16.9%)</th>
<th>Feeding tube placement (17.8%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random forest</td>
<td>0.676</td>
<td>0.834</td>
<td>0.783</td>
</tr>
<tr>
<td>Gradient boosted decision trees</td>
<td>0.672</td>
<td>0.843</td>
<td>0.787</td>
</tr>
<tr>
<td>Logistic regression</td>
<td>0.666</td>
<td>0.838</td>
<td>0.779</td>
</tr>
</tbody>
</table>
AUC for Validation Set Models (n=225)

<table>
<thead>
<tr>
<th></th>
<th>Unplanned hospitalization (14.2%)</th>
<th>Significant weight loss (14.2%)</th>
<th>Feeding tube placement (23.1%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random forest</td>
<td>0.640</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gradient boosted decision trees</td>
<td></td>
<td>0.751</td>
<td>0.755</td>
</tr>
<tr>
<td>Logistic regression</td>
<td></td>
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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.
Future Use Case

Unplanned hospitalization: 23%
Significant weight loss: 47%
Feeding tube placement: 40%

Decision Support
- Place feeding tube up front
- Nutritional supplementation
- Wait and monitor

Personalized Predictions

ML Model

Age
BMI
Stage
Biomarker
Risk Factors
Vitals
Treatment Plan