Henry Ford Health

Henry Ford Health Scholarly Commons

Radiation Oncology Meeting Abstracts

Radiation Oncology

12-1-2022

Medical Imaging Utilization Trends in Radiation Oncology over the Past Decade

S. Quirk

M. Roumeliotis

L. Van Dyke

K. Martell

L. Barbera

See next page for additional authors

Follow this and additional works at: https://scholarlycommons.henryford.com/radiationoncology_mtgabstracts

Authors

S. Quirk, M. Roumeliotis, L. Van Dyke, K. Martell, L. Barbera, W. L. Smith, and Kundan Thind

Author Disclosure: S. SAHA: None. M. Arunsingh: None. S. Prasath: None. A. Balakrishnan: None. S.J. Kalita: None. N. Elavarasan: None. I. Mallick: None.

2252

Medical Imaging Utilization Trends in Radiation Oncology over the Past Decade

S. Quirk,[1] M. Roumeliotis,[2] L. Van Dyke,[3] K. Martell,[4] L. Barbera,[5] W.L. Smith,[6] and K. Thind[7]; [1]*University of Calgary, Tom Baker Cancer Centre, Calgary, AB, Canada,* [2]*Tom Baker Cancer Centre, University of Calgary, Calgary, AB, Canada,* [3]*Alberta Health Services, Calgary, AB, Canada,* [4]*Department of Radiation Oncology, Tom Baker Cancer Centre, Calgary, AB, Canada,* [5]*Division of Radiation Oncology, University of Calgary, Tom Baker Cancer Centre, Calgary, AB, Canada,* [6]*University of Calgary, Calgary, AB, Canada,* [7]*Henry Ford Health Systems, Detroit, MI*

Purpose/Objective(s): We quantify the increase in use of pre-treatment imaging and verification imaging in radiation oncology over the past decade. We also quantify the trend towards hypofractionation, which has partially led to increased imaging.

Materials/Methods: The pre-treatment and verification imaging data used are from a single, tertiary, university-affiliated cancer center. Pre-treatment imaging was defined as magnetic resonance imaging (MRI), positron emission tomography (PET) and four-dimensional computed tomography (4DCT). Verification imaging was defined as cone-beam computed tomography (CBCT). All treatment approved plans were included from 2012 to 2021. Data extraction was performed using custom scripts interfacing with the treatment planning system (TPS) and patient information system. All registered image-sets of planning CT images with either advanced pre-treatment advanced imaging or verification images in the TPS were included. Hypofractionation sub-analysis was performed according to plans above and below 4 Gy per fraction that received a combination of pre-treatment and verification imaging.

Results: Between 2012 and 2021, a total of 42,214 plans were included. In 2021, MRI, PET, and 4DCT pre-treatment imaging modalities were used for 14%, 5%, and 3% of patients, respectively, which was an increase from 5%, 2%, and 0%, in 2012. In 2021, 55% of patients received CBCT for verification imaging compared to only 2% of patients in 2012. In the sub-analysis, cohort receiving greater than or equal to 4 Gy per fraction from 2012 to 2021, the percent of patients receiving one of MRI or PET for pre-treatment imaging and CBCT guidance for verification imaging increased from 1% to 22%. For the cohort receiving less than 4 Gy per fraction, there was an increase from 2012 to 2021 of 0% to 14% of patients receiving at least one of MRI or PET pretreatment imaging and CBCT for verification imaging. Table 1: Annual use of advanced pre-treatment, verification imaging, hypofractionation, and associated combination imaging shown. Entries indicate the percent (%) of patients per year with the imaging modality used in their treatment.

Conclusion: An increase in the adoption of advanced medical imaging was observed in standard of care treatments over the past 10 years. Imaging utilization continues to increase as clinical trial evidence matures. Further analysis could focus on the gap between desired standard of care for patients and the current offerings as well as the increase in capital and human resource requirement for implementation of these advancements.

Abstract 2252 − Table 1

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
# Plans	3424	3206	3444	3832	4013	4380	4682	4780	4970	5483
% MRIs	5%	5%	7%	6%	8%	11%	16%	15%	16%	14%
% PET-CTs	2%	3%	4%	5%	5%	5%	5%	5%	5%	5%
% 4DCTs	0%	0%	0%	0%	0%	2%	4%	4%	3%	3%
% CBCTs	2%	4%	6%	10%	16%	21%	29%	34%	48%	55%
% plans < 4 Gy/fx	74%	71%	70%	68%	68%	66%	63%	65%	62%	58%
% plans >= 4 Gy/fx	26%	29%	30%	32%	32%	34%	37%	35%	38%	42%
*%, MRI or PET + CBCT < 4 Gy/fx**	0%	0%	0%	2%	2%	4%	4%	6%	12%	14%
*%, MRI or PET + CBCT >= 4 Gy/fx**	1%	3%	4%	5%	5%	13%	26%	25%	26%	22%

Author Disclosure: S. Quirk: None. M. Roumeliotis: None. L. Van Dyke: None. K. Martell: None. L. Barbera: None. W.L. Smith: None. K. Thind: None.

2253

Interpretable Machine Learning Model for Predicting Pathologic Complete Response in Patients with Rectal Adenocarcinoma Treated with Chemoradiation Therapy

D. Wang,[1] S.H. Lee,[1] H. Geng,[1] H. Zhong,[1] J.P. Plastaras,[1] A.P. Wojcieszynski, Jr[2] R. Caruana,[3] and Y. Xiao[1]; [1]*Department of Radiation Oncology, University of Pennsylvania, Philadelphia, PA,* [2]*Denver Oncology, Denver, CO,* [3]*Microsoft Research, Redmond, WA*

Purpose/Objective(s): Following neoadjuvant chemoradiotherapy (nCRT), pathologic complete response (pCR) strongly influences the decision to proceed with surgery versus "watchful waiting" in rectal cancer (RC) patients. The purpose of this study is to predict pCR without using invasive procedures. An interpretable machine learning model trained with clinical and imaging data from diagnosis and treatment, with extracted radiomics (R) and dosiomics (D) features is utilized to gain insight into contributing factors.

Materials/Methods: This study used multi-institutional datasets, including a training set of 180 patients from our institution and an independent test set of 37 patients from the RTOG 0822 clinical trial. Each patient had a radiotherapy planning CT and the associated contours of the gross tumor volume (GTV) and the organ-at-risks (OARs) including the bladder, bowel_samll, and femur_heads. A total of 296 features including clinical parameters (CP), GTV and OAR dose-volume histogram (DVH), GTV R, and GTV D features were extracted. R and D features were subcategorized into the first- (L1), second- (L2), and higher-order (L3) local texture features. Multiview input data analysis was performed to identify an optimal set of input feature categories by using an exhaustive search. For each input, feature selection was performed using Boruta, followed by collinearity removal based on the variance inflation factor. Explainable boosting machine (EBM), an interpretable glass-box model, was trained using selected features. The performance of EBM on the test set was evaluated using the area under the receiver operating characteristic curve (AUC) and compared with that of 3 state-of-the-art black-box models: extreme gradient boosting (XGB), random forest (RF), and support vector machine (SVM).

Downloaded for Anonymous User (n/a) at Henry Ford Hospital / Henry Ford Health System (CS North America) from ClinicalKey.com by Elsevier on January 03, 2023. For personal use only. No other uses without permission. Copyright ©2023. Elsevier Inc. All rights reserved.