MRI Radiomics Features for Prediction of Treatment Response in Colorectal Patients

Sajad P. Shayesteh, Mostafa Nazari, Ali Salahshour, Saleh Sandoughdaran, Ghasem Hajianfar, Maziar Khateri, Ali Yaghobi Joybari, Fariba Jozian, Seyed Hasan Fatehi Feyzabad, Hossein Arabi, Isaac Shiri, and Habib Zaidi, *Fellow, IEEE*

2020 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC) | 978-1-7281-7693-2/20/$31.00 ©2020 IEEE | DOI: 10.1109/NSS/MIC42677.2020.9508060

Abstract– **In this study, we assess the power of MRI radiomic features for prediction of locally advanced rectal cancer (LARC) patients' response to neoadjuvant chemoradiation. T2-Weighted MR images acquired 2 weeks before and 4 weeks after treatment of 50 patients were used. The tumor volume was delineated by an experienced radiologist on T2-weighted MR images followed by the extraction of radiomics features, including morphology, first-order, histogram, and texture from volumes of interest (VOI). First, univariate analysis was applied on features to identify predictive power of features. To build a predictive model, we used Random Forest (RF) algorithm along with Max-Relevance-Min-Redundancy (MRMR) feature selection algorithm for reducing complexity and improving generalization. Finally, the model was evaluated through the area under the receiver operator characteristic (ROC) curve (AUC), sensitivity, specificity and accuracy metrics. In univariate analysis, delta radiomics of LAE and LALGLE features from GLSZM had the highest predictive performance (AUC=0.67). In multivariate analysis, the highest predictive performance for response prediction in LARC patients was achieved using delta-radiomic features with AUC of 0.92 and 0.88 in training and validation datasets, respectively. The achieved results were promising to move towards personalized treatment for LARC patients.*Index Terms*— MRI, gadolinium enhancement, radiomics, machine learning, myocardial infarction**

Index Terms— **Radiomics, Colorectal, MRI, Delta**

Manuscript was submitted Dec 21, 2020. This work was supported by the Swiss National Science foundation under grant SNFN 320030_176052.

S P.Shayesteh is with division of Physiology, Pharmacology and Medical Physics, Alborz University of Medical Sciences, Karaj, Iran. (e-mail: shayeste_sajad@yahoo.com)

M. Nazari is with divesion of Biomedical Engineering and Medical Physics, Shahid Beheshti University of Medical Sciences, Tehran, Iran. (e-mail: msnaa1392@gmail.com)

A. Salahshour is with division of Radiology, Alborz University of Medical Sciences, Karaj, Iran. (e-mail: Alisalahshoor11@yahoo.com)

S. Sandoughdaran, F. Jozian, and A. Y. Joybari are with division of Radiation Oncology, Shahid Beheshti University of Medical Sciences, Tehran, Iran. (e-mail: saleh.sandoughdaran@gmail.com, F.Jozian@sbum.ac.ir, AY.Joybari@sbum.ac.ir)

G. Hajianfar and S. H. F. Feyzabad are with Rajaie Cardiovascular, Medical & Research Center, Iran University of Medical Science, Tehran, Iran. (e-mail: hajianfar.gh@gmail.com, HF.Feyzabad@gmail.com)

M. Khateri is with Finetech in Medicine Research Center, Iran University of Medical Sciences (IUMS), Tehran, Iran. (e-mail: mazym4004@gmail.com,)

I. Shiri and H. Arabi and H. Zaidi are with division of Nuclear Medicine and Molecular Imaging, Geneva University Hospital, CH-1211, Geneva 4, Switzerland. (e-mail: Isaac.shirilord@unige.ch, Hossein.Arabi@unige.ch habib.zaidi@hcuge.ch).

H. Zaidi is with Geneva University Neurocenter, Geneva University, Geneva, Switzerland.

I. Introduction

COLORECTAL cancer is the second cause of death related to cancer [1]. The colorectal tumors due to intertumoral and intratumor molecular heterogeneity show variable response to neoadjuvant chemoradiation from patient to patient [2]. It has been challenging to preoperatively predict the tumor's behavior to neoadjuvant chemoradiation treatment for a given patient [3]. Accordingly, predict of tumor response to treatment is a valuable factor to guide treatment and patient management.

These quantitative image-based signatures can be used as accurate, reliable and noninvasive biomarkers for diagnosis, treatment [4-8] and also providing a powerful tool in modern healthcare which called radiomics [9-11]. The aim of this study was to determine whether pre-treatment, post-treatment and therapy-induced changes in radiomic features (called delta-radiomics) extracted from T2-Weighted MRI can improve response prediction in LARC patients.

II. Materials and Methods

In this work, 50 locally advanced rectal cancer (LARC) patients between May 2017 and September 2019 were included. All images of training and validation datasets were acquired 2 weeks before and 4 weeks after nCRT respectively. All specimens were analyzed by an experienced pathologist and response to therapy reported according to the 5-category guidelines.

Rectal Gross Tumor Volume (GTV) was delineated on T2W MR Images by 10 years experienced radiation oncologist. Feature calculation was performed using the PyRadiomics [12]. Extracted features included shape features (n = 13), first order features (n=18), grey level co-occurrence matrix (GLCM) features (n=24), gray level dependence matrix (GLDM) features (n = 14), grey-level run length matrix (GLRLM) features (n = 16), gray level size zone matrix (GLSZM) features (n = 16) and neighborhood gray-tone difference matrix (NGTDM) features (n = 5). Delta-radiomics considers changes in features during treatment. In this work, delta radiomic features for each point calculated by following formula:

Delta-Features = (Feature value2 − Feature value1)/ Feature value1.

Here, features with value1 and value2 are the values of the feature two weeks after and four weeks before treatment, respectively [13, 14].

After features normalization to archived Z-scores, the significance of the differences between the two groups were investigated by paired t-test. AUC was used for result report and response prediction ability of models. Data were split to train (60%) and test sets (40%)

For multivariate analysis, at first, Max-Relevance and Min-Redundancy (MRMR) features selection algorithm was used to select most robust features. In this study, we used supervised random forest (RF) algorithm as classifier. The RF algorithm, in which multiple decision trees are used to create a forest, is widely used for classification of data in medical image analysis

III. RESULT

A. *Univariate analysis*

The results of univariate analysis for response prediction using delta-radiomic features are shown in Fig 1. As shown, delta radiomics of LAE and LALGLE features from GLSZM have the highest predictive performance (AUC=0.67). For post treatment features, entropy from FO, LRLGLE from GLRLM, SRE from GLRLM yield highest AUC (0.64). For pre treatment images, GLV and HGLE from GLDM and GLNUN from GLRLM results in highest AUC (0.64).

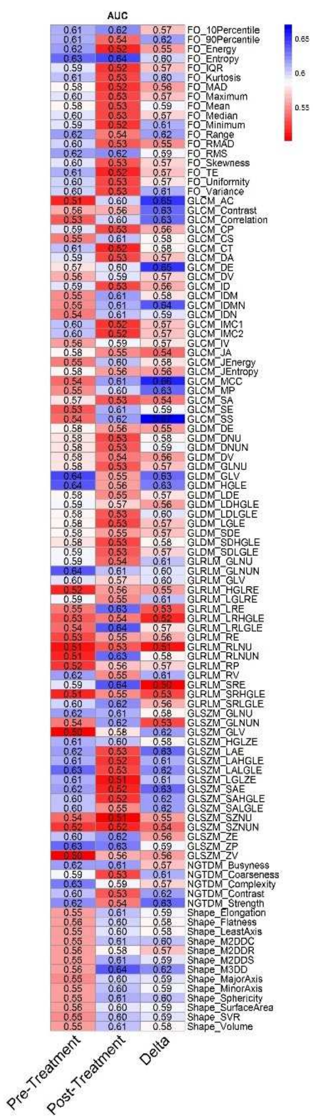

Fig. 1. Univariate analysis results.

B. *Multivariate analysis*

Our multivariate analysis results for response prediction using pre-, post- and delta-radiomic features are summarized in Table 1. As shown, pre-treatment feature AUC for response prediction was 0.86 and 0.82 in training and validation datasets, respectively. In addition, post-treatment feature AUC for response prediction was 0.87 and 0.65 in the training and validation datasets, respectively. Lastly, the highest predictive performance for response prediction in LARC patients was gained using delta-radiomic features with AUC of 0.92 and 0.88 in training and validation datasets, respectively (Fig. 2).

Table I. Multivariate analysis results for pre-, post- and delta-radiomic features of T2w MR Images in the training and test datasets.

Pre-Treatment				
	AUC	Sensitivity	Specificity	Acuracy
Training	0.86	0.79	0.81	0.81
Validation	0.82	0.66	0.8	0.72
Post-Treatment				
	AUC	Sensitivity	Specificity	Acuracy
Training	0.87	0.75	0.85	0.8
Validation	0.65	0.6	0.66	0.630.9
Delta				
	AUC	Sensitivity	Specificity	Acuracy
Training	0.9	0.77	0.94	0.85
Validation	0.85	0.75	0.92	0.84

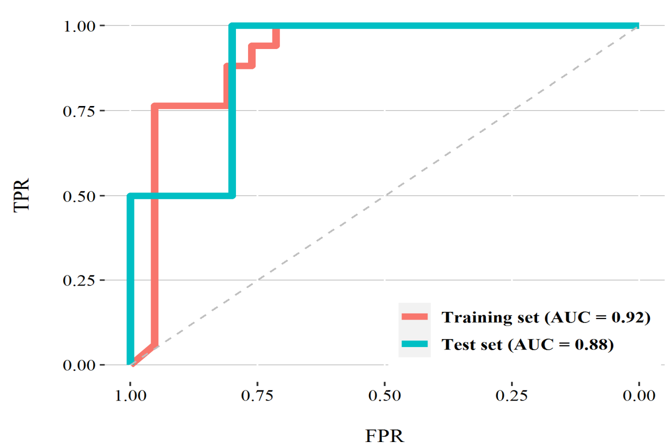

Fig 2. Area under the receiver operator characteristic curve (AUC) of response prediction in LARC patients using delta-radiomic MR image features in the training and test datasets

IV. DISCUSSION

In this work, we investigated the performance of MRI-based pre-, post- and delta-radiomic features for the prediction of response to nCRT in rectal cancer patients. In univariate analysis, the highest predictive performance was an AUC of 0.69. We also found that radiomic features variation in different medical images throughout the treatment, named as delta radiomic features, can improve the predictive performance of our models. In this study we used radiomic features of pre and post treatment MRI based radiomic features to measure the features change during therapy as delta-radiomic features and then applied machine learning algorithm as multivariate analysis which results in high accuracy predictive model [15].

In this work, we split train and test set and evaluated model on unseen datasets, however the size of data was limited for both training and test sets. Future studies need more sample size in training and validation dataset and also need to evaluate the reproducible and repeatable features for robust prediction [16-18].

References

[1] R. Siegel, C. DeSantis, and A. Jemal, "Colorectal cancer statistics, 2014," CA: a cancer journal for clinicians, vol. 64, no. 2, pp. 104-117, 2014.

[2] A. Greenbaum, D. R. Martin, T. Bocklage, J. H. Lee, S. A. Ness, and A. Rajput, "Tumor Heterogeneity as a Predictor of Response to Neoadjuvant Chemotherapy in Locally Advanced Rectal Cancer," (in eng), Clin Colorectal Cancer, vol. 18, no. 2, pp. 102-109, Jun 2019, doi: 10.1016/j.clcc.2019.02.003.

[3] S. Masood, "Neoadjuvant chemotherapy in breast cancers," (in eng), Womens Health (Lond), vol. 12, no. 5, pp. 480-491, 2016, doi: 10.1177/1745505716677139.

[4] M. Nazari et al., "Noninvasive Fuhrman grading of clear cell renal cell carcinoma using computed tomography radiomic features and machine learning," (in eng), Radiol Med, vol. 125, no. 8, pp. 754-762, Aug 2020, doi: 10.1007/s11547-020-01169-z.

[5] S. Rastegar et al., "Radiomics for classification of bone mineral loss: A machine learning study," (in eng), Diagn Interv Imaging, vol. 101, no. 9, pp. 599-610, Sep 2020, doi: 10.1016/j.diii.2020.01.008.

[6] I. Shiri et al., "Machine learning-based prognostic modeling using clinical data and quantitative radiomic features from chest CT images in COVID-19 patients," (in eng), Comput Biol Med, vol. 132, p. 104304, May 2021, doi: 10.1016/j.compbiomed.2021.104304.

[7] H. Arabi, A. AkhavanAllaf, A. Sanaat, I. Shiri, and H. Zaidi, "The promise of artificial intelligence and deep learning in PET and SPECT imaging," (in eng), Phys Med, vol. 83, pp. 122-137, Mar 22 2021, doi: 10.1016/j.ejmp.2021.03.008.

[8] M. Nazari, I. Shiri, and H. Zaidi, "Radiomics-based machine learning model to predict risk of death within 5-years in clear cell renal cell carcinoma patients," (in eng), Comput Biol Med, vol. 129, p. 104135, Feb 2021, doi: 10.1016/j.compbiomed.2020.104135.

[9] M. Nazari, I. Shiri, and H. Zaidi, "Radiomics-based machine learning model to predict risk of death within 5-years in clear cell renal cell carcinoma patients," (in eng), Comput Biol Med, vol. 129, p. 104135, Nov 23 2020, doi: 10.1016/j.compbiomed.2020.104135.

[10] S. Mostafaei et al., "CT imaging markers to improve radiation toxicity prediction in prostate cancer radiotherapy by stacking regression algorithm," (in eng), Radiol Med, vol. 125, no. 1, pp. 87-97, Jan 2020, doi: 10.1007/s11547-019-01082-0.

[11] G. Hajianfar et al., "Noninvasive O6 Methylguanine-DNA Methyltransferase Status Prediction in Glioblastoma Multiforme Cancer Using Magnetic Resonance Imaging Radiomics Features: Univariate and Multivariate Radiogenomics Analysis," World Neurosurgery, vol. 132, pp. e140-e161, 2019/12/01/ 2019, doi: https://doi.org/10.1016/j.wneu.2019.08.232.

[12] J. J. M. van Griethuysen et al., "Computational Radiomics System to Decode the Radiographic Phenotype," (in eng), Cancer Res, vol. 77, no. 21, pp. e104-e107, Nov 1 2017, doi: 10.1158/0008-5472.Can-17-0339.

[13] S. P. Shayesteh et al., "Prediction of Response to Neoadjuvant Chemoradiotherapy by MRI-Based Machine Learning Texture Analysis in Rectal Cancer Patients," Journal of Gastrointestinal Cancer, vol. 51, no. 2, pp. 601-609, 2020/06/01 2020, doi: 10.1007/s12029-019-00291-0.

[14] S. P. Shayesteh et al., "Neo-adjuvant chemoradiotherapy response prediction using MRI based ensemble learning method in rectal cancer patients," Physica Medica, vol. 62, pp. 111-119, 2019/06/01/ 2019, doi: https://doi.org/10.1016/j.ejmp.2019.03.013.

[15] S. P. Shayesteh et al., "Treatment Response Prediction using MRI-based Pre-, Post- and Delta-Radiomic Features and Machine Learning Algorithms in Colorectal Cancer," (in eng), Med Phys, Apr 24 2021, doi: 10.1002/mp.14896.

[16] H. Abdollahi, I. Shiri, and M. Heydari, "Medical Imaging Technologists in Radiomics Era: An Alice in Wonderland Problem," (in eng), Iran J Public Health, vol. 48, no. 1, pp. 184-186, Jan 2019.

[17] M. Edalat-Javid et al., "Cardiac SPECT radiomic features repeatability and reproducibility: A multi-scanner phantom study," (in eng), J Nucl Cardiol, Apr 24 2020, doi: 10.1007/s12350-020-02109-0.

[18] I. Shiri et al., "Repeatability of radiomic features in magnetic resonance imaging of glioblastoma: Test-retest and image registration analyses," (in eng), Med Phys, vol. 47, no. 9, pp. 4265-4280, Sep 2020, doi: 10.1002/mp.14368.