Supplementary Materials

Radiomic Texture and Shape Descriptors of the Rectal Environment on Post-Chemoradiation T2-Weighted MRI are Associated with Pathologic Tumor Stage Regression in Rectal Cancers: A Retrospective, Multi-Institution Study

Charlems Alvarez-Jimenez, Jacob T. Antunes, Nitya Talasila, Kaustav Bera, Justin T. Brady, Jayakrishna Gollamudi, Eric Marderstein, Matthew F. Kalady, Andrei Purysko, Joseph E. Willis, Sharon Stein, Kenneth Friedman, Rajmohan Paspulati, Conor P. Delaney, Eduardo Romero, Anant Madabhushi and Satish E. Viswanath



Figure S1. Random forest model AUC performance while varying the number of radiomic features used (X-axis) when evaluated on (**a**) discovery, and (**b**) validation cohorts. The different colors and symbols correspond to F^{T} (orange), F^{s} (blue), and F^{T+s} (green); respectively. Error bars on (**a**) reflect ± 1 standard deviation of AUC in cross-validation on the discovery cohort.



Figure S2. Box plots of $(\mathbf{a}-\mathbf{f})$ top 6 radiomics descriptors in F^{T+S} ; when comparing ypT0-2 (green) to ypT3-4 (orange) tumors for the 3 different institutions involved in this study. Also shown are confusion matrices for the validation cohort comprising (**g**) Inst. 2 (CCF), and (**h**) Inst. 3 (VAMC) at the optimized threshold.



Figure S3. CONSORT style flow diagram of patient enrollment, eligibility, and exclusion criteria of the multi-institutional dataset used in this study.

Table S1. QDA model performance for F^{T+S} in sex-specific subgroups within discovery and validation cohorts.

	Discovery			Validation		
	Both	Male	Female	Both	Male	Female
Patients	52	30	22	42	31	11
AUC	0.67 ± 0.06	0.67 ± 0.08	0.68 ± 0.09	0.73	0.74	0.67
MCC	0.36 ± 0.1	0.36 ± 0.15	0.36 ± 0.18	0.42	0.51	0.15

Table S2. Implementation	details of radiomic texture	e features utilized in this study.	

Fastura Catagory	Implementation Dataile
I calule Calegoly	1) 1 distribution of algoral interesting and interesting of interest
	1) I distribution of global intensities in region of interest (2) $4 distributions calculated from maxim data size of the set of$
	2) 4 distributions calculated from m x m window size of kernels; m $\in \{3, 5, 7, 9, 11\}$
Intensity Histogram	1. Mean of m x m kernel
	ii. Median of m x m kernel
	iii. Kange of m x m kernel
	1) m v m vindevveige of komplex m c (2.5)
	1) If X if willow size of kernels, if $\in \{5,5\}$
	convolution and roturn only the control part which was the same size as the input
	3a) 1D Kernels used (for window size 3):
	L(I evel) = [121]
	$E (Edge) = [-1 \ 0 \ 1]$
	S (Spot) = [-1 2 - 1]
	3b) 1D Kernels used (for window size 5):
Laws	$L (Level) = \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \end{bmatrix}$
	$E (Edge) = [-1 - 2 \ 0 \ 2 \ 1]$
	$S(Spot) = [-1 \ 0 \ 2 \ 0 \ -1]$
	$W(Wave) = \begin{bmatrix} -1 & 2 & 0 & -2 \\ 0 & -2 & 1 \end{bmatrix}$
	R (Ripple) = [1 - 4 - 6 - 4 - 1]
	4) Two 1-D kernels were combined via matrix multiple to generate either a 3 x 3 kernel
	(for window size 3) or 5 x 5 kernel (for window size 5) all permutations of 1-D kernels
	were implemented
-	The real component of the Gabor filter response in 2D at a particular (x, y) location was
	defined as:
	$(x'^2 + \gamma^2 y'^2)$ (x')
	$g_{\lambda,\theta\varphi,\sigma,\gamma}(x,y) = exp\left(-\frac{1}{2\sigma^2}\right)\cos\left(2\pi\frac{1}{\lambda}+\varphi\right)$
	where
	$x' = x \cos \theta_{xy} - y \sin \theta_{xy}$
	$y' = xsin\theta_{xy} + ycos\theta_{xy}$
	$\lambda(2^B \pm 1)$ $ln(2)$
	$\sigma = \frac{\pi(2 + 1)}{\pi(2^{B} - 1)} \left \frac{m(2)}{2} \right $
Gabor	$n(2 - 1)\sqrt{2}$
Gubor	The necessary parameters are defined below along with their implemented values:
	• θ_{xy} : orientation in x-y plane; $\theta_{xy} \in \{0, \frac{1}{6}, \frac{1}{3}, \frac{1}{2}, \frac{1}{3}, \frac{1}{6}\}$ radians
	• γ : anisotropic scaling factor in y (for isotropy, fixed at $\gamma = 1$)
	• B: bandwidth, or hair-response spatial frequency; fixed at $B = 1$ (therefore $\sigma \approx 0.561$)
	U.30A)
	• X. wavelength of cosine factor, determined such that 70 would approximate han the window size of a m x m kernel $\cdot \lambda \in [0.3827, 0.6378, 0.8926, 1.1480, 1.4142]$ such that m $\epsilon / 3$
	5 7 9 11
	• σ specified based on $B = \lambda$ Isotronic filter so σ same in all directions
	• 0. specified based of <i>b</i> , <i>x</i> . isotropic file, so 0 sufficient an electrons • (a) phase offset: fixed at $a = 0$ in all directions
	1) image quantization approach - Uniform (i.e. equal distances between original grav
	levels and quantized bins)
	2) number of bins - 128 (i.e. 128 grav levels)
	3) offset - 1 (i.e., search D = 1 pixels away from pixel of interest)
	4) number of directions - 4 directions (bi-directional),
	- right diagonal: 45 or 135degrees
	- vertical: 90 or 270degrees
	- left diagonal:135 or 315degrees
TT 1º 1	- horizontal: 0 or 180degrees
Haralick	5) extraction method - symmetrically
	6) aggregation approach for final feature estimation
	- For each pixel of interest, gray-level co-occurrence (GLCM) calculations were
	summed among all pixels within a fixed m x m x m window centered around the pixel, to
	create a single co-occurrence matrix. Varying window sizes were tested (m ϵ {3, 5, 7, 9, 11}
	pixels).
	- Features were extracted from the co-occurrence matrix for each pixel of interest,
	yielding 13 GLCM feature representations for each pixel of interest (visualized as
	heatmaps)
	10 kernels of size 3 x 3 designed to capture unique directional gradients
Gradient	- Gradient sobel x: $[-101 - 202 - 101]$
	- Gradient sobel y: $[121000 - 1 - 2 - 1]$

	- Gradient sobel xy : [0 1 2 - 1 0 1 - 2 - 1 0]				
	- Gradient sobel yx: [2 1 0 1 0 − 1 0 − 1 − 2]				
	- Gradient x: $\frac{dF}{dx}$ (F is image intensities); MATLAB command gradient				
	- Gradient y: $\frac{dF}{dy'}$ MATLAB command gradient				
	- Gradient magnitude: $\sqrt{\frac{dF^2}{dx} + \frac{dF^2}{dx}}$				
	- Gradient dx: MATLAB command conv2(img, [-1 1], 'same')				
	 Gradient dy: MATLAB command conv2(img, [-1; 1], 'same') 				
	- Gradient diagonal: MATLAB command conv2(img, [-1 0; 0 1], 'same')				
CoLlAGe	 MATLAB command gradient applied to image to get gradients between each pair of neighbouring pixels in horizontal, vertical and diagonal directions (bi-directional) The dominant orientation (based on maximum gradient magnitude) is identified and assigned to the pixel in radians on the scale [0, 2π), generating a pixel-wise map of gradient orientations GLCM computations (from Haralick features) are calculated off the gradient orientation maps, using the same methodology aforementioned, in either 3 x 3 or 5 x 5 windows Features were extracted from the co-occurrence matrix for each pixel of interest, yielding 13 GLCM feature representations for each pixel of interest (visualized as heatmaps) at each window size 				



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