

A simulation CT-based radiomics model for detecting metastatic spinal bone lesions.

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Introduction

Bone is one of the most common sites for cancer to metastasize to. Early diagnosis and treatment of bone metastases (BM) can help improve the quality of life of cancer patients and treatment outcomes. Radiotherapy treatment planning for BM is often based on a patient's simulation-CT scans alone without using diagnostic CT or PET images. However, accurate detection of metastases is difficult when using a simulation-CT alone.

Methodology



Results

TL -	52±1	69 ± 1	69±1	68±2	71±1	73±1	75±2	79±1	82±2	80±2	78±1	83±1
RUS -	63±2	63±2	67±3	69±2	70±1	70±1	75±2	77±2	77±1	83±2	83±2	86±1
ROS -	67±2	66±2	67±2	69±3	76±3	75±1	76±2	79±1	79±2	78±3	84±2	84±2
SMOTE -	72±2	69±2	66±2	72±2	74±1	76±1	79±1	82±1	81±1	82±1	86±1	87±1
NONE -	70±2	68±2	72±1	76±1	74±2	77±1	80±1	81±2	79±1	82±1	85±1	86±1
	NB	DI	ODA	SVM	KAVIN	aging	Boost	t-bfgs	RE	SVM	WNet	GPR

Objective

The objective of this study is to investigate the feasibility of building a simulation CT-based radiomics model to identify spinal BM.

Methodology

Simulation CT images 170 OŤ patients with non-metastatic lung Figure 1: Examples of BM centers that were delineated using our diCOMBINE 3D lesion segmentation web app.



Figure 3: The AUC grid for different combinations of ML classifiers and RS techniques.

L-SVM; linear support vector classifier, SVM; SVM with Radial-basis function kernel, NB; Gaussian Naive Bayes, kNN; K-Nearest Neighbors, QDA; Quadratic Discriminant Analysis, GPR; Gaussian Process Regression, DT; Decision Tree, RF; Random Forest, Bagging, AdaBoost, Nnet; Neural network with stochastic gradient-based solver, and NNet-LBFGS; NNet with Limited-memory Broyden-Fletcher–Goldfarb–Shanno solver.

PCA_	2 - 56	5±2	60±2	60±3	57±3	61±2	56±3	58±1	57±1	63±2	60±2	67±2	62±2
FastICA_	2 - 58	±2	62±3	59±3	60±1	64±3	62±1	59±1	59±3	65±1	66±2	62±3	66±3
PCA_1	.0 - 61	±2	64±2	68±2	69±2	70±2	67±2	74±1	75±2	70±2	74±2	76±2	74±2
FastICA_1	.0 - 66	5±2	67±1	69±1	71±1	70±1	69±1	72±2	68±1	74±2	74±2	67±1	75±1
FastICA_2	20 - 60)±1	70±4	73±2	73±2	73±3	68±2	75±1	73±2	74±2	80±1	74±2	79±2
PCA_2	20 - 61	±2	70±1	69±2	71±1	72±1	71±2	76±1	74±1	77±1	78±1	80±0	78±1
VT 0.	.0 - 64	±2	67±1	67±1	71±2	70±2	75±1	73±2	79±1	81±1	77±2	83±1	83±1
PFEC	v - 70	±2	65±1	69±2	70±1	73±1	77±1	73±1	79±1	75±1	77±1	84±2	85±1
VT 0	8 - 64	±1	69±3	67±1	70±1	70±2	74±0	74±1	81±2	81±1	78±2	84±1	86±1
NON	E - 68	+2	70+2	76±1	74+2	72+1	80+1	77+1	82+1	81+2	79+1	85+1	86+1
LASS	0 60	+1	72+1	70±1	75+2	70+0	00 - 1	77+1	70+1	79+1	91+1	92+1	00±1
LASS	- 0: - 7(-1	70±2	70±1	7314	01+2	00+2	77±1	02+1	01+0	01±1	0211	06+1
TRE	E - 70)±2	70±2	73±1	73±1	81±2	80±2	77±2	83±1	81±2	81±3	85±2	86±1
	Ø	2	NB	SVM	KANN	ODA	Boost	aging	SVM	t-bfgs	RE	Whet	GPR
Figure 4: The AUC arid for different combinations of ML classifiers and FS methods													
3			3										_
SP10 -	53±4	5	58±3	59±2	57±2	59±2	60±1	63±1	61±2	64±2	64±3	61±2	63±2
CY10 -	57±2	2 5	57±2	57±1	59±1	61±2	63±3	67±2	63±2	65±2	63±2	66±2	71±3
CY15 -	56±3	3 5	59±2	63±1	56±1	68±2	61±1	67±1	70±2	70±1	73±1	73±2	74±2
SP15 -	59±2	2 6	50±2	62±2	61±1	67±2	63±1	68±1	68±2	69 ± 1	70±1	72±1	73±1
SP20 -	58±2	2 (50±1	63±1	59±2	67±2	65±1	67±0	70±1	69±2	71±2	74±1	76±1
CY2030 -	60±3	3 5	59±1	61±2	64±2	70±1	66±0	73±1	70±0	72±1	74±1	78±1	80±1
allCYs -	51±2	2 6	57±2	64±2	70±1	48±2	72±1	75±3	78±1	77±2	74±2	81±2	79±1
CY3020 -	62±2	2 (69±2	62±0	65±1	67±1	68±1	69±1	75±2	74±1	74±2	76±1	77±1
CY20 -	66±2	2 6	52±2	64±2	64±2	75±2	70±1	73±1	67±2	74±2	75±2	75±1	75±1
allCS -	50±2	2 (68±1	67±3	72±3	43±2	74±2	76±1	80±1	79±2	78±1	82±2	82±1
allSP -	49±3	3 6	64±2	71±1	67±2	77±1	67±3	76±1	74±3	76±2	77±2	78±2	78±1
SP30 -	67±3	3 (62±1	63±2	71±2	68±1	72±1	75±1	77±2	76±2	75±2	81±1	80±1
allCY -	54±3	3 (67±2	66±2	70±2	71±1	72±1	75±1	80±2	77±1	79±1	83±1	82±2
CY30 -	65±2	2 6	53±2	64±1	69±2	75±1	72±2	77±1	73±1	77±1	83±2	83±2	82±2
CY50 -	71±	2 (65±1	64±1	71±1	72±2	77±1	79±1	78±2	77±1	78±1	84±0	83±0
CY5030 -	66±3	2 6	62±2	68±2	68±2	79±2	73±2	78±2	79±1	79±1	81±2	85±1	84±1
CY3050 -	72±	2 6	64±2	67±2	72±2	79±1	74±2	75±2	83±1	80±1	77±1	82±1	82±1
SP50 -	69±	2 6	67±2	64±1	74±1	74±3	77±1	79±1	78±1	80±1	78±1	85±1	84±1
	IN		or	NB	MA	-04	eng	ost	wfd ^S	RF	NA	CPR	Net
SV. Ka OL Baggin AdaBoo NNet-bis LSV. Gr. NNet													
Figure 5. The ALIC and for different combinations of ML closed flare and DOLe with													

cancer and 189 patients with spinal BM from our institution's radiation oncology information system were under an REB-approved used study.

The location of 631 BM lesions and healthy bone regions were 674 identified by experts using our inhouse 3D lesion segmentation web application (diCOMBINE). Regions of interest (ROIs) with

various geometric shapes (spherical and cylindrical-along-z-axis) were delineated on the images and 107 radiomic features were extracted. The data were divided into 70% training and 30% testing sets. (RS) Different resampling

Figure 2: Our Radiomics pipeline for classifying metastatic and healthy spinal bones.

		1	1		
Spherical ROI (SP) Diameter (mm)	50	30	20	15	10
Cylindrical along the z-axis	50x50	30x30	20x20	15x15	10x10
ROI (CY) vidth (mm) x height (mm)	30x20	20x30	50x30	30x50	

Table 1: Segmentation of ROI from CT images performed using cylindrical and spherical ROI with various sizes around the expert extracted lesion centers.

Discussion & Conclusions

Among machine learning classifiers, Gaussian process regression (GPR), neural network (NNet), and random forest (RF) classifiers achieved higher prognosis performance. AUC, precision and recall of our best performing model were 0.86, 0.81, and 0.81, respectively. Our lesion-center-based radiomics model was successful in identifying spinal BM lesions in simulation-CT images.

different sizes and with TREE as FS method and SMOTE as RS techniques.

Acknowledgements







techniques, feature selection (FS) methods, and machine learning classifiers were evaluated using the area under the receiver operating characteristic curve (AUC) for obtaining optimal prognosis models.