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.

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 of 170 patients with non-metastatic lung cancer and 189 patients with spinal BM from our institution's radiation oncology information system were used under an REB-approved study.

The location of 631 BM lesions and 674 healthy bone regions were identified by experts using our in-house 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.

Different resampling (RS) 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.

Methodology

Figure 1: Examples of BM centers that were delineated using our diCOMBINE 3D lesion segmentation web app.

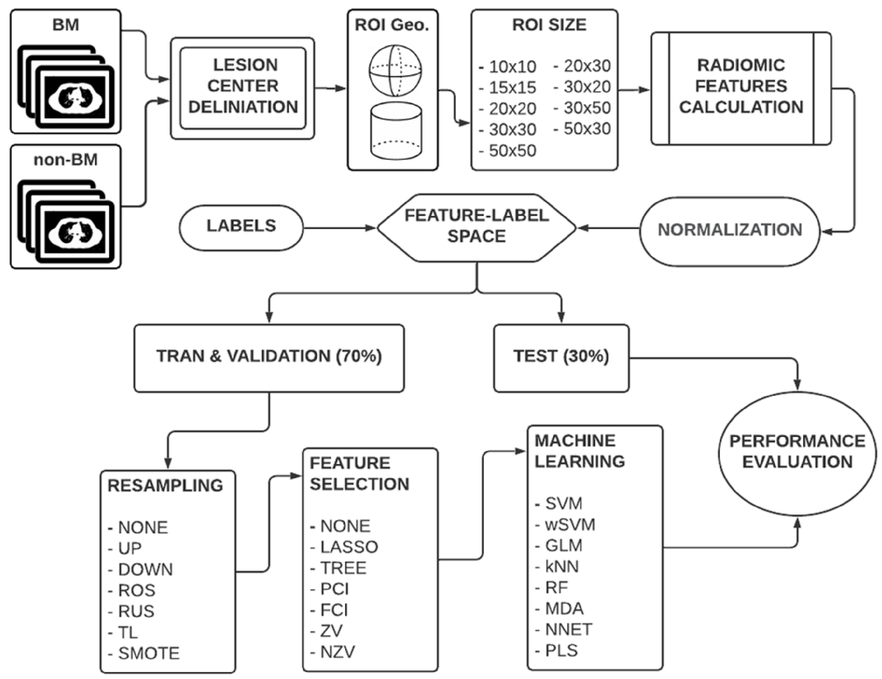

Figure 2: Our Radiomics pipeline for classifying metastatic and healthy spinal bones.

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

Results

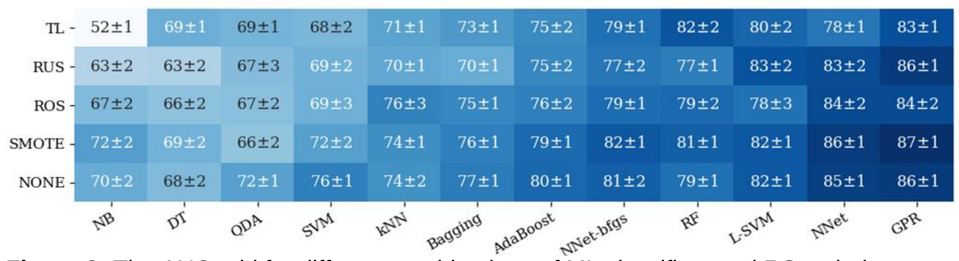

Figure 3: The AUC grid for different combinations of ML classifiers and RS techniques.

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.

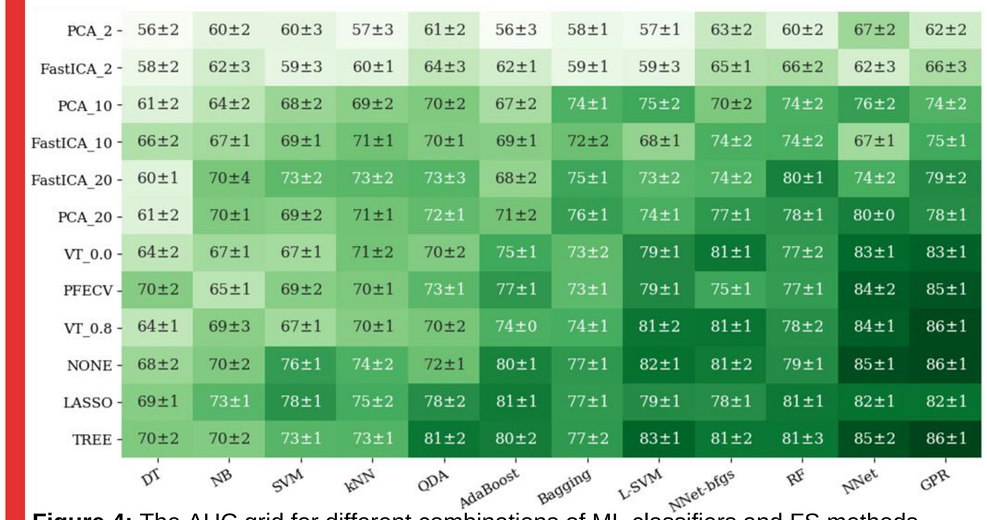

Figure 4: The AUC grid for different combinations of ML classifiers and FS methods.

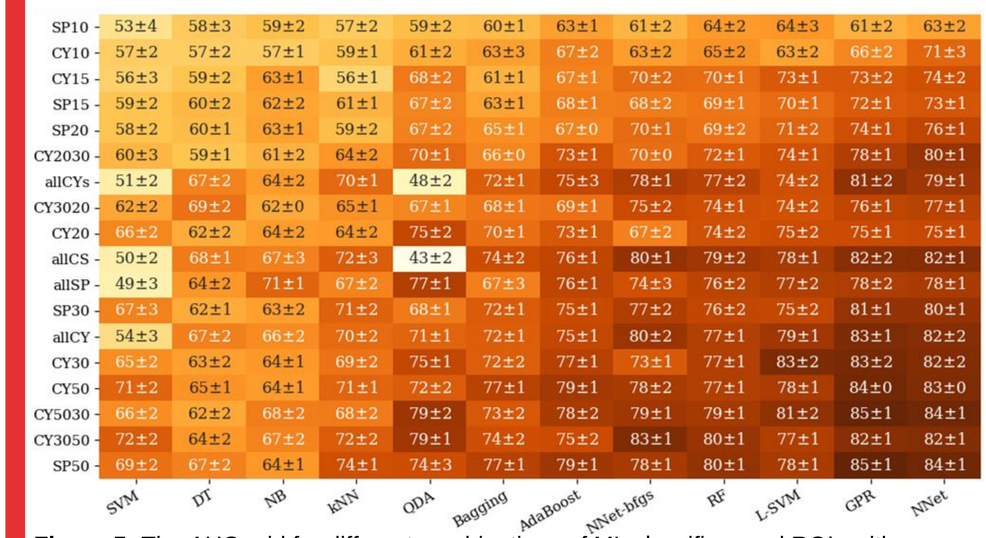

Figure 5: The AUC grid for different combinations of ML classifiers and ROIs with different sizes and with TREE as FS method and SMOTE as RS techniques.

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.

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