

CT-Based Radiomics Analysis: A New Imaging Biomarker in Chronic Obstructive Pulmonary Disease?

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Rationale

- Radiomics has shown promise in the field of oncology to quantify image "texture", and have been used in determining cancer severity and recurrence^[1] – there have been few studies that investigate radiomics in COPD.
- Current radiomics studies deploy different techniques for image processing prior to generating radiomics features – how these image processing techniques affect measured radiomics features and impact disease detection is unknown.

Objective & Hypothesis

Objective

To investigate different image processing techniques commonly used in radiomics analysis, and assess their impact on COPD disease detection.

Hypothesis

We hypothesize that CT radiomics features measured using different image processing techniques will have an impact on radiomics features' ability to detect COPD.

Methods

Canadian Cohort Obstructive Lung Disease (CanCOLD)

- Cohort between 45-90 years of age selected by random digit dialling from the general population.^[2]

Image Processing

- Voxels were resampled to 1x1x1mm³ or left as original dimensions to investigate the effects of resampling on radiomics features.
- Airways were segmented out or left in the original CT image to investigate the effects of airways on radiomics features.
- CT images were processed using 3 different techniques: 1) HU thresholding between -1000HU to 0HU; 2) HU binning with bin size determined by the Freedman-Diaconis rule;^[3] or 3) a modified split-merge algorithm called edgmentation.^[4]
- Gray Level Co-occurrence Matrix (GLCM) was created from processed image, only considering the 3 non-diagonal neighboring voxels.
- 32 different GLCM features were extracted.

Table 1: Subject demographics and pulmonary function.

Parameters (±SD unless specified)	No COPD (n=602)	COPD (n=602)	P-value
Female, n (%)	279 (46)	232 (39)	0.006
Age, yrs	66 (10)	67 (10)	0.03
BMI, kg/m ²	28 (5)	27 (5)	0.2
Pack Years	11 (18)	23 (25)	<0.001
FEV ₁ /FVC, %	77 (5)	61 (8)	<0.001
DL _{CO} , mL/min/mm Hg	22 (6)	21 (7)	0.006

Results

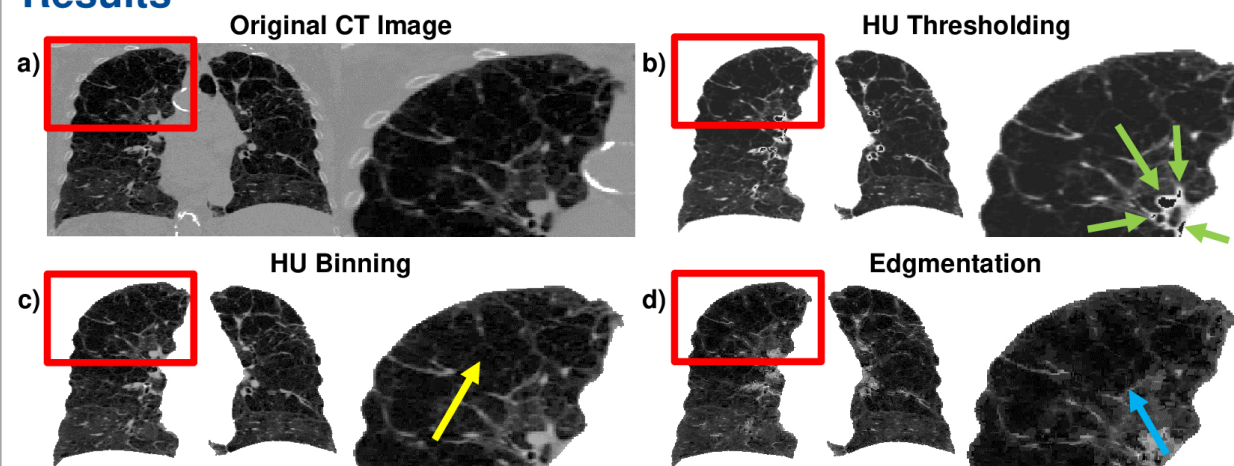


Figure 1: All whole lung images were of the same COPD participant with a zoomed-in portion of the upper right lung (area outlined with red box) to the right. **a)** Un-processed CT image; **b)** non-resampled, no airway segmentation, HU threshold image; **c)** non-resampled, no airway segmentation, HU binned image; and **d)** non-resampled, no airway segmentation, edgmentation image.

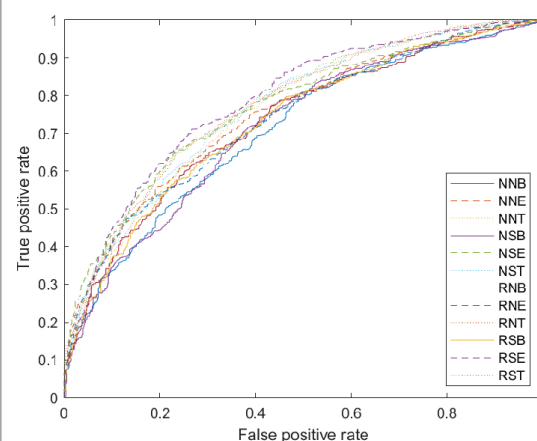


Figure 2: ROC for classification by logistic regression for all image processing combinations. Statistics shown in Table 2.

Table 2: Area Under the Curve and Accuracy values from ROC for classification by logistic regression for all imaging processing combinations (from Figure 2).

Method	HU Thresholding	HU Binning	Edgmentation
Area Under the Curve (AUC)			
NN	0.760	0.707	0.746
NS	0.765	0.713	0.767
RN	0.772	0.729	0.735
RS	0.774	0.729	0.785
Accuracy (%)			
NN	69.2	65.0	68.5
NS	69.8	66.6	71.0
RN	70.9	67.5	67.2
RS	70.8	67.1	72.2

NN = no resampling, no airway segmentation; NS = no resampling, airway segmentation; RN = resampling, no airway segmentation; and RS = resampling, airway segmentation.

Table 3: Adjusted R² of different multivariate linear regression models with different response variables. Each model consisted of the 32 radiomics features as predictor variables.

Response Variables	HU Thresholding	HU Binning	Edgmentation
No Resampling, No Airway Segmentation			
FEV ₁ /FVC, %	0.36	0.19	0.28
DL _{CO}	0.22	0.27	0.26
No Resampling, Airway Segmentation			
FEV ₁ /FVC, %	0.36	0.20	0.32
DL _{CO}	0.22	0.27	0.27
Resampling, No Airway Segmentation			
FEV ₁ /FVC, %	0.35	0.24	0.28
DL _{CO}	0.38	0.28	0.34
Resampling, Airway Segmentation			
FEV ₁ /FVC, %	0.35	0.25	0.37
DL _{CO}	0.38	0.25	0.32

Results Summary

- Radiomics features extracted using image resampling → airway segmentation → edgmentation (RSE) had the highest accuracy (72.2%) in classifying COPD status; features also explained the most variance in FEV₁/FVC (R²=0.37, p<0.001).
- Resampled images that were processed using HU thresholding explained the most variance in DL_{CO}, regardless of airway segmentation (R²=0.38, p<0.001).

Conclusions

- The image processing methods completed prior to CT radiomics feature extraction greatly affects the features calculated.
- CT radiomics features extracted from images processed using image resampling, airway segmentation, and edgmentation may provide the best imaging biomarker to assess COPD.
- Image processing techniques involving HU binning may not be as suitable in assessing COPD compared to HU thresholding or edgmentation.

Future Directions

- Assess the impact of other textural measurements as outlined in the Image Biomarker Standardization Initiative to assess COPD severity.^[5]
- Use CT radiomics features to investigate COPD disease progression.

References

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