

ATS 2026 Highlights

Respiratory Structure and Function Early Career Professionals

Get to know members of the RSF Assembly



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(He, Him)

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Is your research clinical, basic science or translational?

Basic science and translational.

Tell us about your research?

My PhD research develops quantitative tools that use low-dose CT imaging, radiomics, and machine learning to predict which patients are likely to experience rapid emphysema progression and to improve malignancy risk assessment for lung nodules detected during screening.

Where do you see yourself in 5 years?

Working in a collaborative research environment developing new methods for lung disease prediction, enabling earlier detection, improved risk stratification, and informed clinical decisions.

What do you find is the major benefit of RSF Assembly Membership?

The greatest benefit of RSF Assembly Membership is its broad interdisciplinary community it offers, allowing me to engage with experts aligned with my research while also gaining valuable perspectives from outside my field.

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Early Prediction of Rapid Emphysema Progression in a Lung Cancer Screening Cohort Using Quantitative LDCT and an Ensemble-based Machine Learning Model

Objective: Lung cancer screening detects malignant nodules in only 2-5% of participants. Opportunistic evaluation of other lung diseases, such as emphysema, could extend the utility of CT screening. Identifying individuals at risk for rapid emphysema progression may inform smoking cessation strategies and closer pulmonary follow-up, even in the absence of lung cancer. We propose an ensemble-based machine learning approach leveraging whole-lung quantitative radiomics features for opportunistic risk prediction at the time of lung cancer screening.

Methods: A cohort of 576 LDCT subjects with at least two timepoints were selected from the National Lung Screening Trial (NLST). Low Attenuation Areas less than -950 Hounsfield Units (LAA-950) were calculated for each timepoint. Rapid emphysema progressors were defined as having a change in LAA-950 $\geq 1\%$ per year. Example progressor and non-Progressor cases with similar %LAA-950 at the time of screening are shown in Figure 1. The final cohort was split into Development (Dev.), Ensemble Validation (EnsVal.), and External (Ext.) datasets. Whole lung segmentations were created for the initial LDCT of each subject, followed by radiomic feature extraction, including first order, texture, shape, and wavelet feature variations. Radiomics features were harmonized to the GE:STANDARD reconstruction kernel cases in the Dev. dataset. Important features were selected from the Dev. dataset using Pearson's correlation and a round-based ElasticNet logistic regression model, which were then used to train 1000 artificial neural networks (ANNs). The final ensemble consisted of the 100 best performing networks, chosen according to the EnsVal. dataset sensitivity and specificity metrics at the Youden index threshold. Final ensemble predictions were made, and performances were compared using AUC-ROC, sensitivity, and specificity for the Dev., EnsVal., and Ext. datasets.

Results: 36 important whole-lung radiomics features were chosen, with a majority being wavelets (30 features). All datasets achieved ≥ 0.71 AUC-ROC (Dev.: 0.91, EnsSel.: 0.75, Ext: 0.71). Sensitivity for progressors ranged from 0.77 (EnsSel.) to 0.95 (Dev.). Specificity values ranged from 0.56 (Ext.) to 0.70 (Dev.).

Conclusion: Current results show promise for an ensemble-based ANN approach for predicting emphysema progression using LDCT images at the time of lung cancer screening, with all datasets achieved a greater than 0.71 AUC-ROC. Planned improvements include standardizing slice-spacing via resampling prior to radiomic feature extraction and selection, followed by optimization of ensemble training and selection to increase sensitivity and specificity for clinical detection of rapid emphysema progressors.

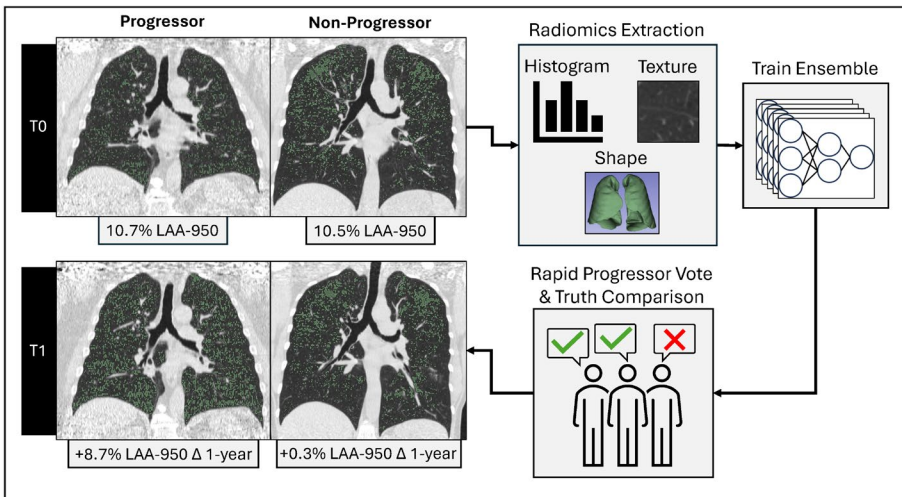


Figure 1. LDCT examples with ~10% baseline LAA-950 (green), showing rapid (+8.7% Δ 1-year) vs. minimal (+0.3%) progression. Baseline radiomics from initial screening images were used to train a radiomics ANN ensemble for rapid emphysema progression prediction.