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Advancing Diagnostic Precision of Emphysema in Chronic Obstructive Pulmonary Disease: Machine-learning Classification Integrating Non-invasive Biomarkers, Clinical Characteristics, and Pulmonary Function

L. Egerod^{1,2}, C. B. Nanthakumar³, M. A. Karsdal², D. J. Leeming², J. C. Yates⁴, J. M. B. Sand²

¹Department of Biomedical Sciences, University of Copenhagen, Copenhagen, Denmark; ²Nordic Bioscience, Herlev, Denmark; ³Clinical Sciences-Respiratory, GSK R&D, Brentford, UK; ⁴GSK, Research Triangle Park, NC, USA

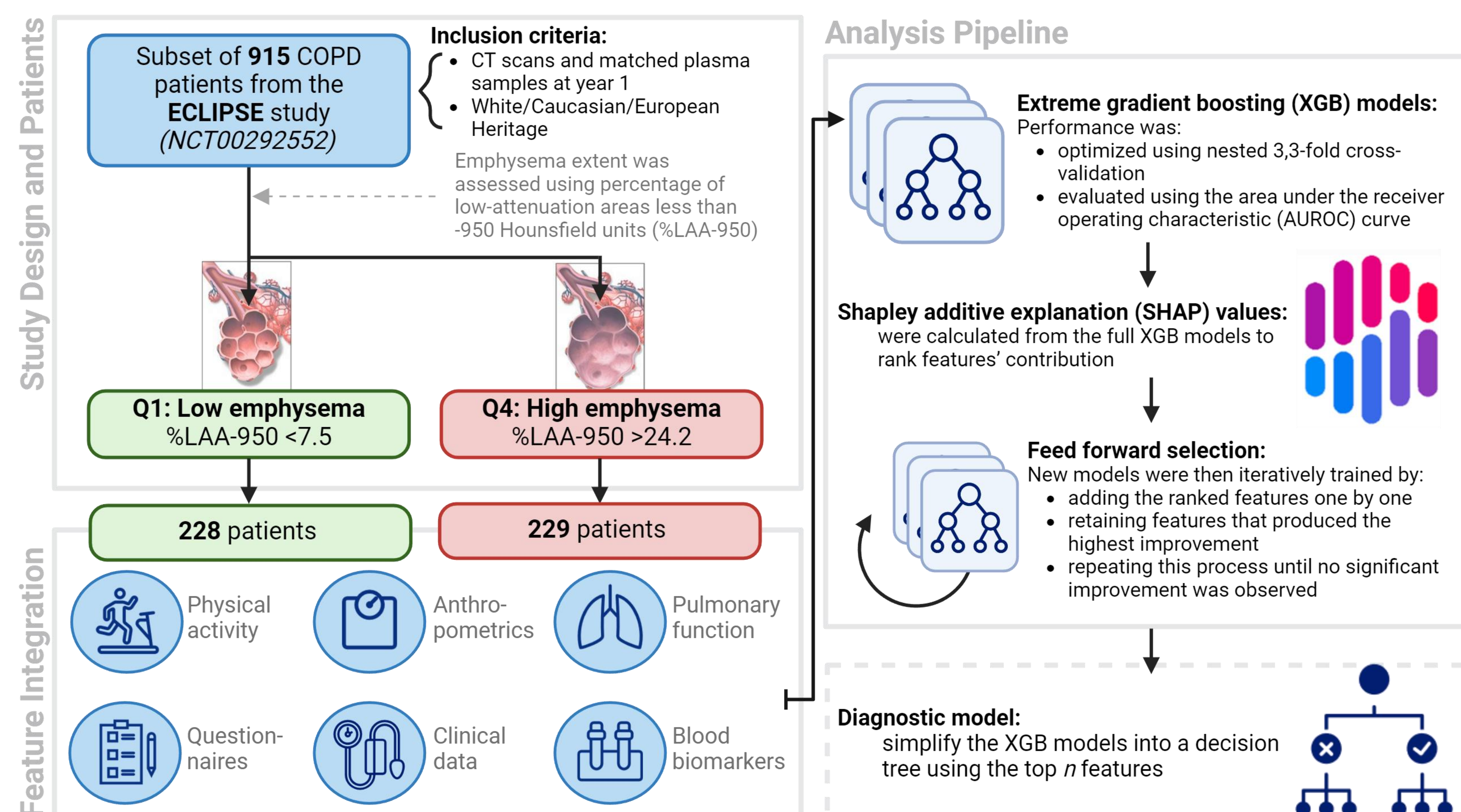


Introduction

Computed tomography (CT) is used for evaluating phenotypic abnormalities in chronic obstructive pulmonary disease (COPD), yet its cost and time-intensive nature limit routine use. Developing an easily implementable technique for classifying emphysema extent is thus essential.

This study aimed to develop a diagnostic model to classify emphysema extent in COPD patients relying solely on easily obtained measures such as clinical characteristics and non-invasive biomarkers.

Methods



Year 1 characteristics

	Low emphysema (n=228)	High emphysema (n=229)	P-value
Age, years	60.8 ± 7.9	63.2 ± 6.7	<0.001
Male, n (%)	134 (58.8)	151 (65.9)	0.138
BMI, kg/m ²	27.8 ± 5.7	24.5 ± 4.8	<0.001
Tissue fat, %	32.8 ± 8.5	31.5 ± 8.6	0.104
FEV ₁ , % predicted	59.8 ± 14.3	39.0 ± 13.4	<0.001
6MWT, m	413 ± 114	367 ± 123	<0.001
mMRC score	1.4 ± 1.1	1.9 ± 1.1	<0.001
SGRQ-C, activity score	49.3 ± 28.1	71.6 ± 22.6	<0.001
AECOPD*	0.7 ± 1.1	0.9 ± 1.1	0.03

BMI: body mass index; FFMI: fat-free mass index; FEV₁: forced expiratory volume in 1 second; 6MWT: 6-minute walking test; mMRC: Modified Medical Research Council; SGRQ-C: St. George's Respiratory Questionnaire (COPD); AECOPD: acute exacerbation of COPD *Average number of moderate exacerbations recorded in the 12 months prior.

Summary statistics are expressed as mean ± standard deviation, except for "Male", which is presented as total numbers and frequency distributions.

Results

XGB models integrating 32 features achieved an AUROC of 0.82 (95%CI 0.80-0.84)

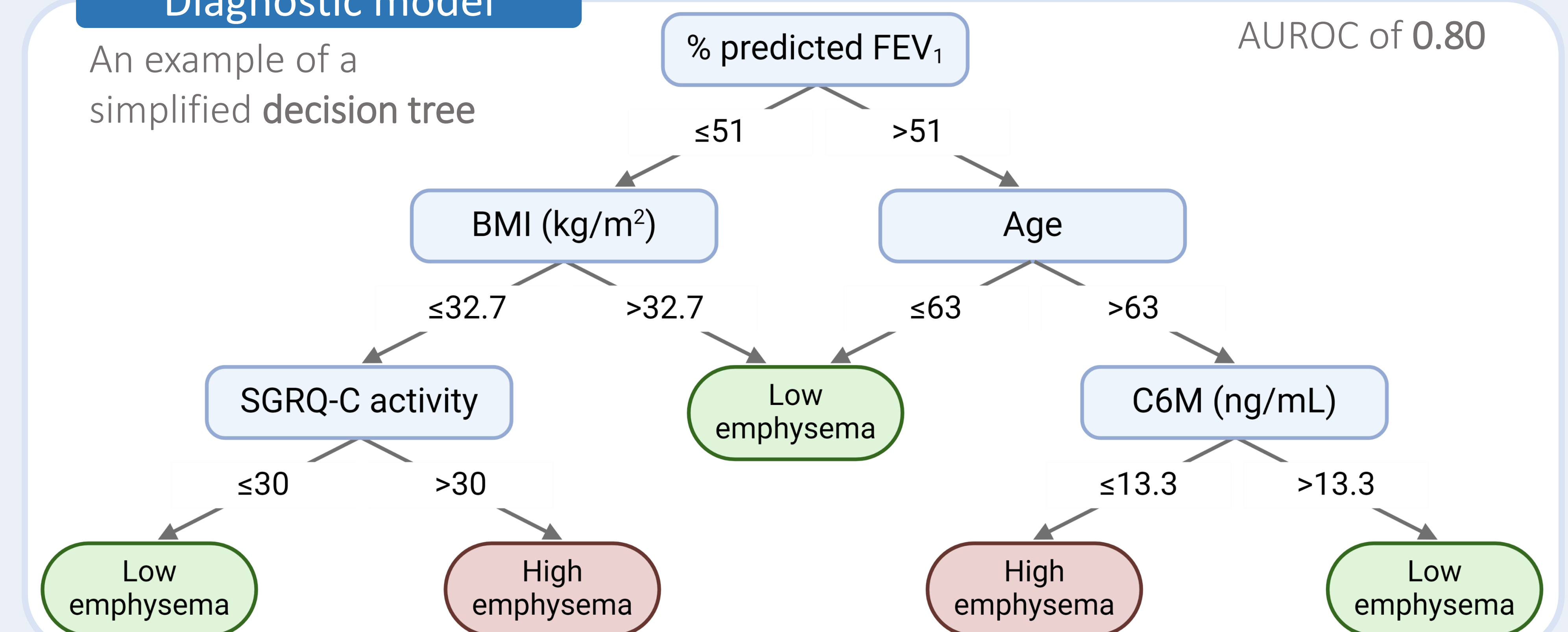
Feed forward selection retained **top 5 ranked features**, which demonstrated an AUROC of 0.86 (95%CI 0.84-0.87)

Top 5 features of high emphysema:

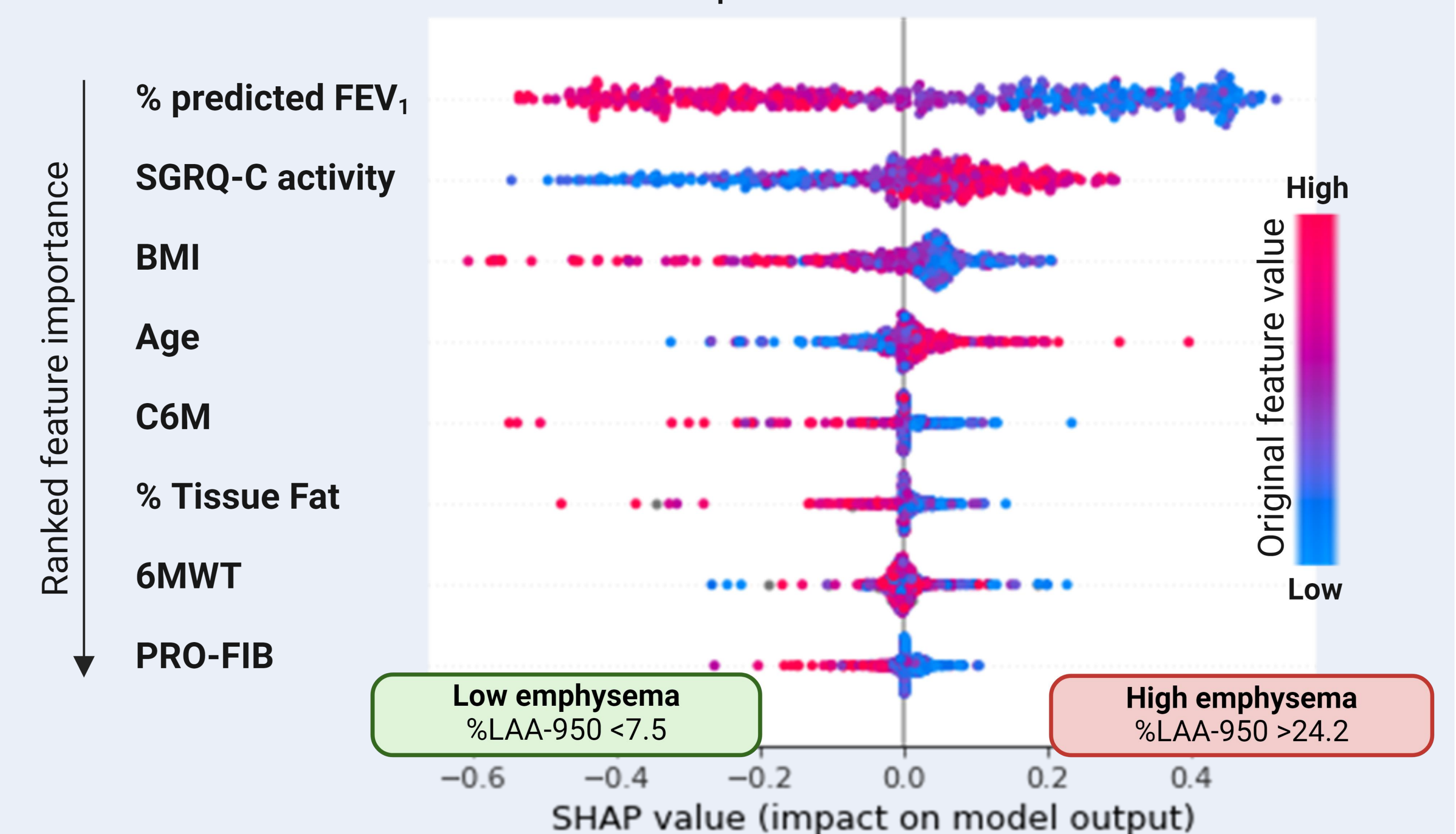
- Low % predicted FEV₁
- High SGRQ-C activity score
- Low BMI
- High age
- Low levels of C6M

Diagnostic model

An example of a simplified decision tree



Top 8 out of 32 features



SHAP figure explained: Y-axis indicates the feature names in order of importance from top to bottom. X-axis represents the SHAP value, which indicates the degree of change in log odds. The color of each point on the graph represents the value of the corresponding feature, with red indicating high values and blue indicating low values. Each point represents a row of data/patient from the original dataset. C6M: Blood biomarker for type VI collagen degradation; PRO-FIB: Blood biomarker for degradation of fibrinogen.

Conclusion

Diagnostic models incorporating easily obtainable measures effectively distinguished COPD patients with high emphysema extent from those with low extent. Such models for classifying emphysema patterns have the **potential for clinical implementation**, aiding in diagnosis or serving as a decision-making tool to determine the necessity of further CT scans.



Contact: Line Egerod, lelu@nordicbio.com

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