

The value of quantitative computed tomography lung parenchymal analysis for stratification of acute respiratory failure patients admitted in intensive care unit

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Research Article

Keywords:

Posted Date: May 25th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9588450/v1>

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Additional Declarations: No competing interests reported.

Abstract

Introduction:

Effective management of acute respiratory failure necessitates understanding of the underlying pathophysiology and precise evaluation of severity. Quantitative CT (QCT) provides an objective approach for assessing lung involvement and disease distribution, perhaps assisting in severity categorization.

Objectives:

To investigate the usefulness of AI-based CT quantification in predicting the severity of respiratory failure

Methods:

CT scans of 60 individuals with acute respiratory failure were evaluated using AI algorithms for automatic lung segmentation. Normal lung parenchyma was defined within - 950 to - 700 Hounsfield units (HU). The percentage of abnormal lung volume was estimated and correlated with disease severity, and cut-off values were determined.

Results:

A mild positive association ($r = 0.27$) was identified between abnormal lung volume and severity of respiratory failure. Thresholds of $> 29.43\%$ and $> 70.43\%$ abnormal lung volume were associated with moderate and severe respiratory failure, respectively.

Conclusions:

AI-based CT quantification offers a rapid and objective way for detecting lung involvement and determining disease severity. However, its prognostic value is limited by patient heterogeneity and technical issues, necessitating integration with clinical and radiological evaluation. Further validation in larger cohorts is required.

Introduction

Acute respiratory failure is a life-threatening condition. The hallmark of it is the inability of the respiratory system to maintain adequate gas exchange which result in hypoxemia and/or hypercapnia (MacIntyre, 2018) (Helms, et al. 2024). Several diseases condition can cause respiratory failure including

pneumonia, exacerbations of chronic obstructive pulmonary disease, bronchial asthma, pulmonary embolism and interstitial pulmonary fibrosis (Rabe et al., 2018). Effective management strategies necessitate good understanding of the underlying patho physiology.

Management of respiratory failure range from treatment of the underlying cause to supportive and advanced therapeutic interventions (Schreiber & Kuehl, 2016). Early recognition and timely intervention are critical for improving patient outcomes (McCance & Huether, 2019).

Assessment of the degree of severity respiratory failure is crucial for clinical decision-making and typically relies on a combination of clinical evaluation, arterial blood gas (ABG) analysis, and imaging modalities (O'Driscoll et al., 2017).

Computed tomography (CT) has the ability to provide quantitative analysis of lung parenchyma based on tissue density. And because of this advantage, Quantitative CT (QCT) analysis has shown promise as a mean of objectively assessing lung involvement and measuring diseases extent and distribution and hence predicting severity based on QCT.

In the present study we aimed to assess the utility of computer-aided lung parenchymal analysis in patients with acute respiratory failure admitted to the respiratory intensive care unit, with a focus on quantifying disease extent and distribution and predicting disease severity based on QCT-derived parameters.

Methods

Study Design and Population

This prospective study included 60 consecutive adult patients admitted to the respiratory intensive care unit (ICU) with acute respiratory failure (ARF). Ethical approval was obtained from Institutional Review Board (IRB). Approval Number 1949, April 2026, and the study was conducted in accordance with institutional and international ethical standards.

Inclusion criteria: any patient aged ≥ 18 years and met diagnostic criteria for ARF. The diagnosis of ARF was depending on the presence of any of the following criteria: arterial partial pressure of oxygen (PaO_2) < 60 mmHg, oxygen saturation (SpO_2) $< 90\%$ on room air, or $\text{PaO}_2/\text{FiO}_2$ ratio ≤ 300 mmHg. For all included patients, non-contrast chest computed tomography (CT), ABG and relevant laboratory investigations were performed within 24 hours of ICU admission.

Exclusion criteria included: age < 18 years; hemodynamic instability precluding CT acquisition; poor-quality CT images (e.g., motion artifacts or incomplete lung coverage); prior lung surgery or significant anatomical distortion interfering with automated segmentation; known diffuse pulmonary malignancy; pregnancy; and incomplete clinical or imaging datasets. Patients with both parenchymal and extra-parenchymal causes of respiratory failure (e.g., pleural effusion) were not excluded, in order to reflect

real-world clinical heterogeneity. However, this variability was considered during data interpretation and statistical analysis.

Clinical Data Collection

Baseline demographic and clinical data were recorded at time of admission. The $\text{PaO}_2/\text{FiO}_2$ ratio was calculated using the first arterial blood gas analysis obtained in the emergency department. Severity of respiratory failure was categorized according to Berlin definition of acute respiratory distress syndrome (ARDS): Normal: >300 mmHg, Mild: $201-300$ mmHg, Moderate: $101-200$ mmHg, Severe: ≤ 100 mmHg (Berlin et al., 2012)

CT Acquisition Protocol

CT Acquisition Protocol

All patients underwent non-contrast chest CT using a 128-slice multi-detector CT scanner (GE Healthcare, Waukesha, WI, USA) using 120 kVp, automatic tube current modulation based on patient size, slice thickness 0.625 mm for post-processing and 2.5–5 mm for image review, and scan time of 3–5 seconds during a single breath-hold.

Quantitative CT Analysis

Quantitative lung analysis was performed using Thoracic VCAR (Volume Computer-Assisted Radiology) software on an advanced workstation (AW server version 3.2, GE Healthcare). The density thresholds were the foundation of automated segmentation of lung parenchyma. According to Hounsfield unit (HU) ranges, the Lung parenchyma was categorized into the following groups: Emphysematous changes (colour coded blue): -1024 to < -977 HU, Normal parenchyma (colour coded black): -977 to -703 HU, Consolidation and dense reticular opacities (colour coded orange): -703 to -100 HU, Fibrotic changes (colour coded red): -100 to 100 HU

The quantitative outputs of the software included the following information: total lung volume, percentage of well-aerated lung, abnormal lung volume, predominant abnormality type, and distribution asymmetry. When needed manual adjustments were performed to adjust for imperfect segmentation such as missed apical or basal regions.

Laboratory Data collection:

The study report, in addition to CT results, arterial blood gases analyses, and biochemical tests, including complete blood picture, urea, and creatinine. The laboratory tests were performed within the first 24 hours of hospital admission. Blood samples were collected as follows: 2 ml in ethylene diamine tetra acetic acid (EDTA) containing tube for determination of complete blood count (CBC). It was determined

by fully automated cell counter (Celltac G, Nihon Kohden Corporation Automated Hematology Analyser, Japan). Differential blood count was confirmed by microscopic examination of Lishman-stained blood film, and 1.8 ml of blood on a heparinized syringe to evaluate arterial blood gases measured by COBAS b211, Roch diagnostic, Switzerland while 3 ml were let to be clotted in a plain tube for thirty minutes then centrifuged for fifteen minutes at about 3000 rpm. Resulted serum was used for determination of renal function tests (serum urea, serum creatinine) measured by auto-analyzer SELECTRA PRO XL,ELITech Group, Clinical Chemistry Automation systems, Netherland.

Data Integration

To ensure temporal consistency, CT findings were analyzed in conjunction with laboratory parameters obtained on the same day as imaging.

Statistical analysis

Data were analysed using MedCalc version 23.4.8, for windows. The normality of the data distribution was tested using Shapiro-Wilk test. Numerical data were expressed as mean $\pm$ standard deviation (SD) or as percentages. Spearman correlation coefficient was used for correlations between respiratory failure severity and other variables. One way analysis of variance (ANOVA) test followed by post-hoc test (Tukey-Kramer test) were used to compare quantitative CT parameters across different subgroups. P-value of less than 0.05 was considered statistically significant. Receiver operating characteristic (ROC) curve analysis was used to investigate usefulness of quantitative CT analyses results for predicting respiratory failure degree.

Results

The baseline characteristics of studied population are shown in (Table 1). A total of 60 patients with acute respiratory failure were included. They were 31 patients (51.7%) who had mild respiratory failure, 25 (41.7%) moderate, and 4 (6.7%) severe. At admission, 30 patients (50%) required Venturi mask oxygen therapy, 25 (41.7%) received non-invasive ventilation, and 5 (8.3%) required invasive mechanical ventilation. The underlying causes of respiratory failure in the studied patients are illustrated in Fig. 1 where the commonest cause was interstitial lung disease (ILD) present in 33% of cases followed by COPD present in 25% of cases.

Table (1): The baseline characteristics of the studied patients are described in Table 1.

	WHOLE (N = 60)	MILD RF (N = 31)	MODERATE RF (N = 25)	SEVERE RF (N = 4)	P value
Age, mean $\pm$ SD	56.63 (16.24)	64.55 (13.15)	45.24 (14.25)	66.5 (3.11)	0.093
Male, No, %	22 (36.67%)	9 (29%)	10 (40%)	3 (75%)	0.854
Smoker, No, %	23 (38.33%)	8 (25.81%)	11 (44%)	4 (100%)	0.021*
Respiratory support (Invasive, No, %)	5 (8.3%)	1 (3.23%)	2 (8%)	2 (50%)	0.005**
Type of RF, type 1	38 (63.33%)	16 (51.62%)	18 (72%)	4 (100%)	0.086
PaCO ₂ , mean $\pm$ SD	55.47 (13.27)	56.71 (15.44)	52.6 (10.58)	63.75 (2.63)	0.226
PaO ₂ , mean $\pm$ SD	88.8 (21.39)	99.87 (20.05)	78.52 (16.22)	67.25 (10.34)	<0.001***
FiO ₂ , mean $\pm$ SD	46.9 (11.09)	41.09 (9.27)	51.2 (8.69)	65 (4.08)	<0.001***
S-F, mean $\pm$ SD	217.52 (65.57)	246.87 (65.18)	194.16 (49.59)	136 (8.21)	<0.001***
P-F, mean $\pm$ SD	188.02 (60.54)	227.42 (53.49)	154.08 (27.81)	94.75 (4.99)	<0.001***
A-a gradient, mean +/- SD	171.82 (80.34)	118.39 (62.22)	216.6 (45.07)	306 (42.07)	<0.001***
APACHI II, mean $\pm$ SD	9.02 (2.63)	7.74 (2.02)	10.08 (2.56)	12.25 (1.71)	<0.001***
HR, mean $\pm$ SD	102 (11)	98 (10)	107 (12)	106 (7)	0.063
HB, mean +/- SD	12.65 (1.48)	12.9 (1.3)	12.05 (1.52)	13.73 (1.07)	0.108
BP, Hypertensive, No, %	20 (33.33%)	7 (22.58%)	11 (44%)	2 (50%)	0.497
Platelets, mean $\pm$ SD	256.33 (91.27)	221.71 (84.91)	289.68 (90.23)	316.25 (12.5)	0.037*
WBCs, mean $\pm$ SD	9.79 (2.81)	9.74 (2.55)	9.38 (3.11)	12.73 (0.21)	0.084
Neutrophils, mean $\pm$ SD	74.73 (5.57)	76.19 (5.06)	73.24 (6.15)	72.75 (2.06)	0.107

Lymphocytes, mean $\pm$ SD	13.08 (4.25)	11.3 (3.36)	14.52 (3.69)	20.25 (1.71)	0.135
Urea, mean $\pm$ SD	37.83 (4.17)	39.26 (3.83)	36.76 (4.16)	33.5 (1.29)	0.168
Creatinine, mean $\pm$ SD	1.04 (0.22)	1.04 (0.18)	1.01 (0.25)	1.28 (0.09)	0.071

SD: Standard Deviation, RF: Respiratory Failure, PaCO₂: Partial Pressure of arterial Carbon Dioxide, PaO₂: Partial Pressure of arterial Oxygen, FiO₂: Fraction of inspired oxygen, S-F: peripheral oxygen saturation to fraction of inspired oxygen, P-F: Ratio of arterial oxygen partial pressure to fractional inspired oxygen, APACHE: Acute Physiology and Chronic Health Evaluation II score, HR: Heart rate, HB: Haemoglobin, BP: Blood Pressure, WBCs: White Blood Cells

We observed significant differences across severity groups in many of the studied parameters, including: PaO₂, FiO₂, A-a gradient and APACHE II score (all $p < 0.001$). Additionally, there were significant differences in smoking status and platelet count between the groups ($p = 0.021$ and $p = 0.037$, respectively).

The Findings of Quantitative CT (QCT) analyses are shown in (Table 2). Unequal lung involvement ($> 25\%$ difference between lungs) was observed in 23.3% of patients, more frequently affecting the left lung, although this was not statistically significant. We found significant differences in lung parenchymal involvement across severity groups (Fig. 2). The percentage of well-aerated lung tissues decreased significantly from mild to severe disease (66.9% vs. 53.1% vs. 22.1%, $p < 0.001$), while the percentage of abnormal lung volume increased significantly (33.1% vs. 46.9% vs. 77.9%, $p < 0.001$).

Table 2 shows the results of the quantitative analysis of CT images.

	ALL PATIENTS (N=60)	MILD RF (N=31)	MODERATE RF (N=25)	SEVERE RF (N=4)	P value
Percentage of well aerated lung volume, mean $\pm$ SD	58.18% (22.98%)	66.93% (22.71%)	53.11% (17.61%)	22.13% (1.76%)	< 0.001 ***
Percentage of abnormal lung volume, mean $\pm$ SD	41.82% (22.97%)	33.07% (22.72%)	46.89% (17.61%)	77.87% (1.76%)	< 0.001 ***
Unequal lungs involvement, No, %	14 (23.33%)	6 (19.35%)	8, (32%)	-	0.291
More affected lung in case of unequal involvement, No, %	Left lung, 10 (16.67%)	Left lung, 4 (12.91%)	Left lung, 2, (8%)	-	0.509
Type of predominant abnormal lung density, emphysematous, No, %	22, (36.67%)	13, (41.94%)	2, (8%)	-	0.613
Degree of emphysematous changes, as abnormal predominant density, mean $\pm$ SD	18.07% (4.26%)	15.68% (3.81%)	12.58 (4.45%)	-	0.338
Type of predominant abnormal lung density, consolidation, and interstitial changes, No, %	38, (63.33%)	18 (58%)	23, (92%)	4 (100%)	0.532
Degree of consolidations and reticulations, as abnormal predominant density, mean $\pm$ SD	49.42% (20.98%)	39.09% (25.06%)	45.56% (15.41%)	74.46% (2.14%)	0.037*

SD: Standard Deviation, RF: Respiratory Failure

The majority of patients (63.3%) exhibited consolidation and interstitial patterns as the predominant abnormality, whereas 36.7% demonstrated emphysematous changes. The degree of consolidation and reticulation was significantly higher in more severe groups ($p = 0.037$), while emphysema severity did not differ significantly.

The degree of severity for pneumonia and interstitial lung diseases (ILD) using computed tomography (CT) is primarily based on the extent of lung involvement, graded by the percentage of lung involvement as follows, minimal/grade 1: 1–25% involvement, mild/grade 2: 26–50% (or 5–25% depending on the specific scoring system) involvement, moderate/grade 3: 51–75% (or 26–49%) involvement, and severe/grade 4: >75% involvement (Inoue A et al. 2019 and Almasi Nokiani A, 2022). In this study, we had had 38 (63.33%) of patients who had predominant consolidation and interstitial lung affection. They were 12 (31.58%) patients of mild severity, 22 (57.89%) patients of moderate severity and 4 (10.53%) patients who had severe degree of respiratory failure. The percentage of their lung parenchymal affection ranged between 15.243% and 77.519% according to CT lung parenchymal analyses, and their

classifications were as follows: 5 (13.16%) patients had grade 1 affection, 17 (44.74%) of patients who had grade 2 affection, and 4 (10.53%) of patients had grade 3 affection, while 12 (31.58%) patients had grade 4 involvement.

The emphysema index (EI) was calculated as the percentage of lung voxels with attenuation values below - 950 HU. Among patients with emphysema (n = 22), all demonstrated an airway-predominant COPD phenotype with emphysema index (EI) < 35%. Most of these patients (86.4%) had moderate respiratory failure, while the remainder had mild disease. EI ranged from 12.4% to 37.1%, with the majority (81.8%) classified as level 1 (EI 5%-25%) and a smaller proportion (18.2%) as level 2 (EI 25%-50%)

Receiver operating characteristic (ROC) curve analyses (Fig. 3) demonstrated good diagnostic performance of QCT parameters. A threshold of > 32.3% abnormal lung volume predicted moderate respiratory failure with 84% sensitivity and 74.2% specificity (AUC = 0.747, p = 0.001). A higher threshold of > 70.6% predicted severe respiratory failure with 100% sensitivity and 88% specificity (AUC = 0.935, p < 0.001).

In this study we investigated the association between percentage of abnormal lung densities as detected by QCT analyses and respective features in different respiratory failure groups. There was a positive yet mild correlation between percentage of abnormal lung volume according to QCT lung parenchymal analyses and severity of respiratory failure (r = 0.27). Different examples of illustrative cases for lung parenchymal analyses for interstitial lung disease (ILD) and emphysema (COPD) patients in our study had been shows at (Fig. 4) through (Fig. 6).

Discussion

The visual measurement of parenchymal alterations in the lungs using CT scan is frequently a challenging task. There is a need to have a fast automated tool which can provide segmentation and quantification of either normal or abnormal lung parenchymatous involvement (Silva et al. 2018, Nagpal et al, 2021, and Iwasawa, T. et al, 2023). Recently, various computational approaches have been introduced for the detection and quantification of lung lesions based on CT density (Carvalho et al. 2025). The objective evaluation by means of artificial intelligence (AI) tool scan allow reliable data quantification, and therefore, an accurate definition of disease progression and predicting outcome (Chiumello, D.; 2024, Chang et al, 2026, and Kuzmanovic Y et al, 2026).

In the present study, we evaluated the utility of quantitative computed tomography (QCT) for assessing lung parenchymal involvement and predicting the severity of acute respiratory failure in ICU patients. Our findings demonstrate that the degree of abnormal lung parenchyma is positively associated with the severity of respiratory failure, and that AI-based CT quantification delivers objective and clinically useful data. A notable finding in our study was the progressive increase in abnormal lung volume and the corresponding decline in well-aerated lung throughout severity categories. Patients with severe respiratory failure exhibited markedly higher percentages of abnormal lung parenchyma and significantly

reduced aerated lung volumes in contrast to mild and moderate cases. These findings are consistent with the physiological basis of respiratory failure, where increasing parenchymal involvement leads to impaired gas exchange and worsening hypoxemia.

Despite this clear trend, the correlation between abnormal lung volume and severity of respiratory failure was relatively weak ($r = 0.27$). This can be attributed to the heterogeneity of the study population, which included patients with respiratory failure with diverse etiologies including emphysema, interstitial lung disease, and extra-parenchymal causes like pleural effusion. In such cases, multiple factors influence the degree of gas exchange impairment in addition to the parenchymal involvement such as ventilation–perfusion mismatch, airway disease and mechanical factors. This finding aligns with earlier studies indicating that imaging-based metrics alone may not fully explain the complexity of respiratory failure.

Colombi D. et al. reported that a proportion of well aerated lung parenchyma below 71%, as assessed by software, predicted ICU admission and mortality (Colombi D. et al. 2020). Nishiyama et al. indicated that survival outcomes significantly correlate with the volume of well-aerated lung, demonstrating an improved survival rate when well-aerated lung capacity is $\geq 40\%$ (Nishiyama et al. 2020). According to Lanza E. et al. (2020), a compromised lung capacity between 6 and 23% was associated with increased risk of the need oxygen support, while a value greater than 23% was associated with a higher chance of intubation (Lanza et al. 2020). According to the study conducted by Rorat et al., a strong predictor of mortality in COVID-19 patients is the involvement of at least 37.8% of total lung volumes by consolidations and ground glass opacities (Rorat et al, 2021). In the meantime, a systematic analysis by Hashimoto et al. demonstrated that integration of CT findings might not be enough for predicting short-term mortality in adult respiratory distress patients (ARDS) (Hashimoto et al, 2022). The difference in research methodology and selection criteria with varying thresholds for normal and abnormal lung densities may be the cause of the variations in different studies.

The present study demonstrates an inverse relationship between the severity respiratory failure (RF) and the percentage of healthy lung volume, with progressive loss of aerated lung tissue noticed across increasing severity categories. these structural changes can be directly linked to impairment in oxygenation, commonly assessed using the $\text{PaO}_2/\text{FiO}_2$ (P/F). The reduction in healthy lung volume reflects increased proportions of non-aerated or poorly aerated tissue due to alveolar collapse, edema, and consolidation. These changes contribute to intrapulmonary shunting and ventilation–perfusion (V/Q) mismatch, ultimately leading to a decline in arterial oxygenation and a corresponding decrease in the P/F ratio. Thus, the observed decrease in healthy lung percentage across RF severity levels in our data is consistent with worsening hypoxemia. (Luciano, et al, 2001)

Chiumello et al. demonstrated that quantitative CT-derived measures of lung aeration correlate with gas exchange abnormalities, including the P/F ratio, confirming that imaging-based lung volume assessment reflects functional impairment (Chiumello et al, 2005). Leiser et al. further quantified this relationship, reporting a significant inverse correlation between non-aerated lung tissue and oxygenation status, reinforcing that loss of aerated lung is a key determinant of reduced P/F ratios in ARDS patients (Leiser

et al, 2020). Also, Gattinoni and colleagues established that CT imaging provides a direct link between structural lung alterations and gas exchange abnormalities (Gattinoni et al, 2001).

Our ROC analysis demonstrated that QCT-derived abnormal lung volume has good diagnostic performance in predicting disease severity. A threshold of approximately 32% abnormal lung volume provided reasonable discrimination for moderate respiratory failure. A threshold of more than 70% showed good performance for identifying severe cases (AUC = 0.935). These findings support the potential clinical utility of QCT as a risk stratification tool. However, the variability in reported thresholds across studies highlights the lack of standardization in CT-based quantification methods, including differences in attenuation cut-offs and segmentation algorithms.

Subgroup analysis further highlights the importance of disease phenotype. While Patients with emphysema showed relatively lower degrees of parenchymal abnormality yet still developed respiratory failure. This is likely due to airflow limitation and impaired ventilation rather than extensive alveolar involvement. On the other hand, patients with consolidation and interstitial changes demonstrated a stronger association between the extent of lung involvement and severity, reflecting the direct impact of alveolar filling and fibrosis on oxygenation.

Importantly, our findings must be interpreted in the context of clinical parameters. Oxygenation indices remain to be of significant value in disease classification as demonstrated by the reported rise in FiO_2 requirements and fall in P/F ratios across severity categories. It is worth noting that supplemental oxygen therapy can account for the comparatively high PaO_2 levels in mild cases which highlight the importance of using P/F ratio rather than absolute PaO_2 for severity assessment.

However, as any AI tool, these software programs might have its pitfalls and mistakes. The automatic segmentation using thoracic VCAR tool may be incomplete, demanding manual adjustment by adding missing areas or removing extra-structures for some cases. It may overestimate emphysema quantification through misclassification of low-attenuation regions by considering low attenuation areas of bronchiectatic changes and or honey combing changes as areas of emphysematous changes. Moreover, it is not able to segment complex cases with conspicuous effusions, also not reliably differentiate some areas of dense consolidations from reticulations and fibrotic like changes (Maiello L, et al. 2022). Therefore, combination with visual assessment is mandatory to avoid misleading and pitfalls. These technical challenges, combined with inter-software variability, limit the generalizability of quantitative thresholds.

The relatively small sample size, particularly in the severe group, may limit statistical power and robustness of conclusions. The observed correlations may be weakened by confounding factors introduced by the heterogeneity of underlying etiologies. Furthermore, evaluation of temporal changes and outcome prediction are impossible without longitudinal follow-up. The etiology of associated pleural effusions was not systematically evaluated, which may further influence interpretation of imaging findings.

Abbreviations

ABG: Arterial Blood Gases

AI: Artificial Intelligence.

APACHE II: Acute Physiology and Chronic Health Evaluation II score

ARDS: Acute Respiratory Distress Syndrome

ARF: Acute respiratory failure

COPD: chronic obstructive pulmonary disease

EI: Emphysema Index

FiO₂: The fraction of inspired oxygen

HU: Hounsfield Unit

ICU: intensive care unit

ILD: interstitial lung disease

PaO₂: Partial Pressure of Oxygen in arterial blood

PaO₂/FiO₂: the ratio of arterial oxygen partial pressure (PaO₂ in mmHg) to fractional inspired oxygen

PaCO₂: partial pressure of arterial carbon dioxide)

QCT: Quantitative Computed Tomography.

SpO₂: Peripheral Oxygen Saturation

S/F ratio: peripheral oxygen saturation to the fraction of inspired oxygen

TLV: Total Lung Volume

VCAR: Volume Computer Assisted Radiology

Declarations

Conflict of interest: None

Funding: None

Author Contribution

Mahmoud M. Higazi: Study design, collection of radiological data, interpretation of computed tomography results, statistical analysis, tables and figures preparation, Aly O. Abdel Aziz: Clinical evaluation of patients, and revision of clinical data, Mohamed M.A. Zaitoon: Interpretation of computed tomography results, and revision of the manuscript, Reem Y. Abdelazeem Elgarhy: Laboratory data collection, laboratory results analysis, and sharing in manuscript writing, Aliaa Mounir Higazi: Laboratory data collection, laboratory results analysis, and reviewing the manuscript, Mariam I. Ali: sharing in statistical analysis, and manuscript writing, Nada A. Abdel Aziz: sharing in statistical analysis, and manuscript writing, Rasha A. Abdel Fattah: Collection of clinical data, clinical evaluation of patients, preparing and revision of clinical data, and sharing in manuscript writing.

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Figures

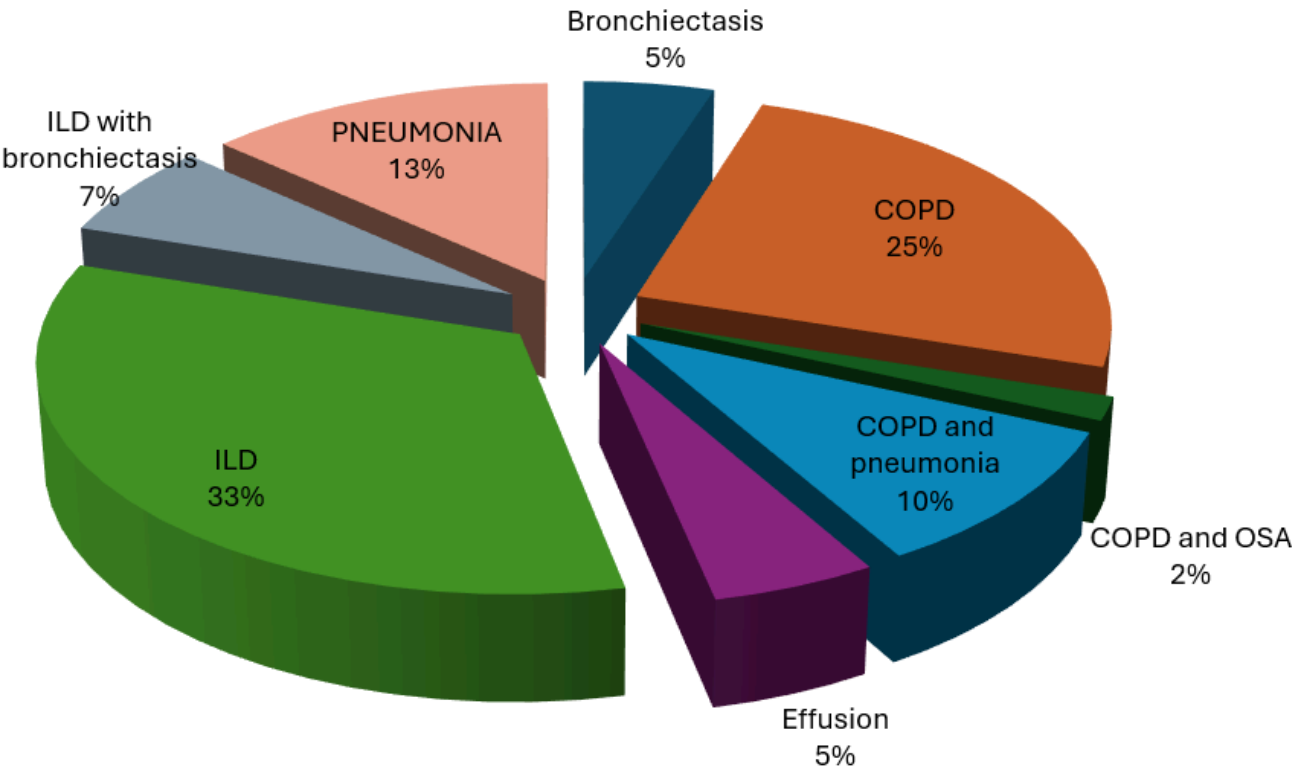


Figure 1

Pie chart representing variable causes of respiratory failure in this study with their percentages.

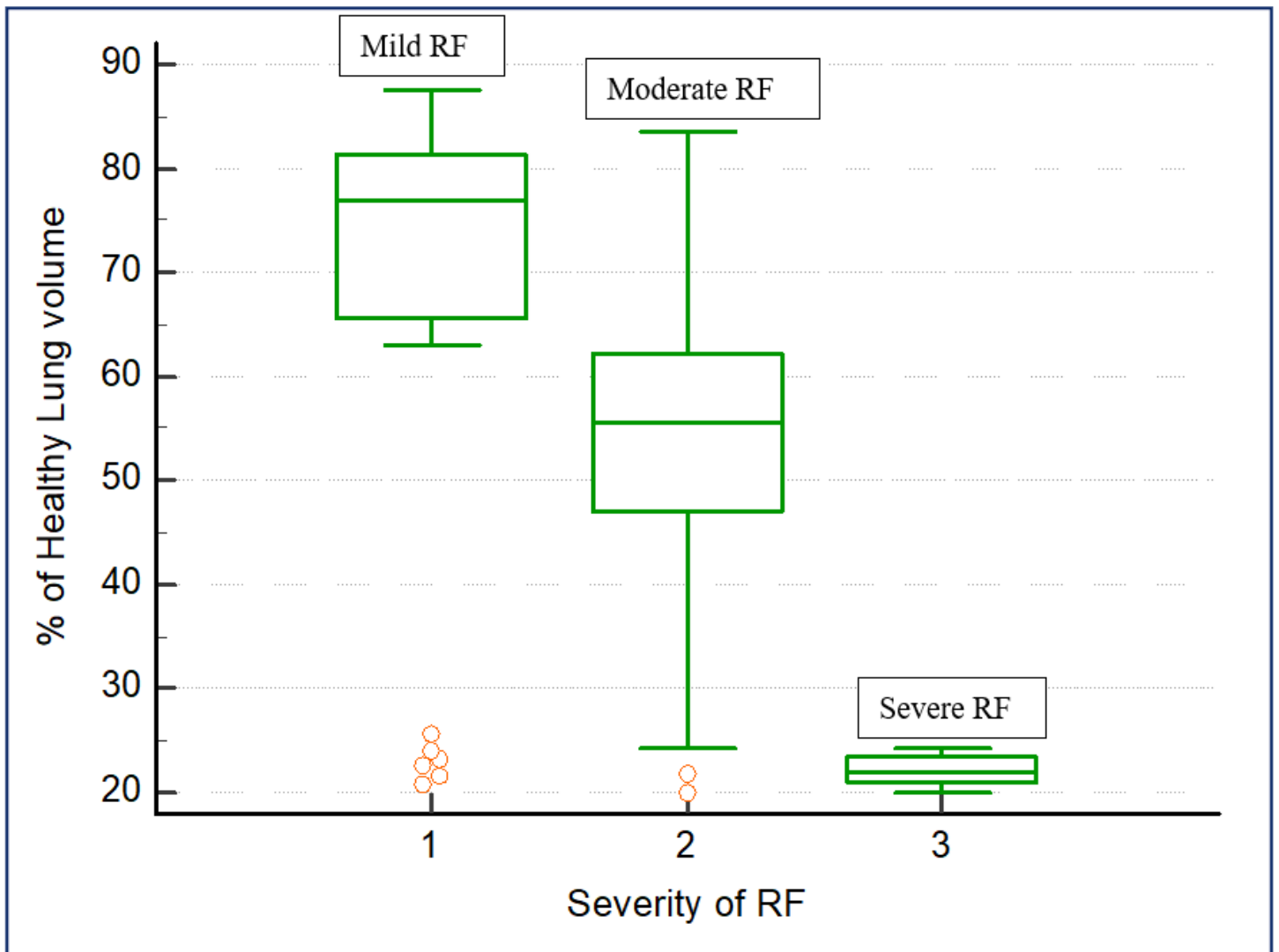
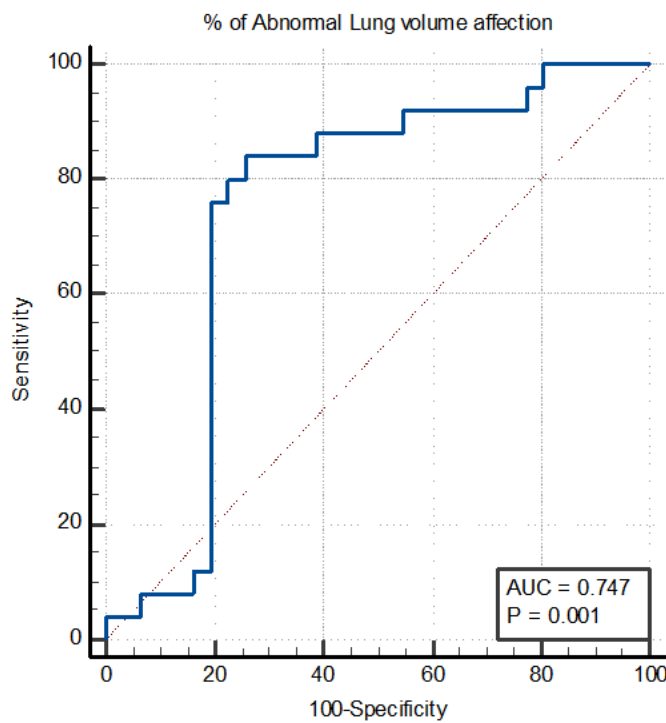
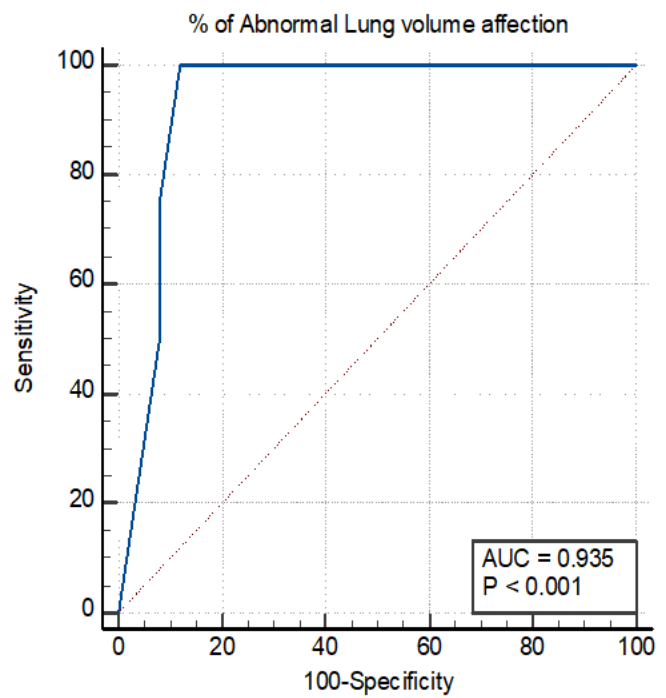


Figure 2

Box plot showing significant differences between mild, moderate and severe groups of respiratory failure regarding volume of well aerated lungs, where 1 is MILD group and 2 is MODERATE group, whereas 3 is SEVERE group.



Mild Vs Moderate RF



Mild Vs Severe RF

Figure 3

Receiver Operator Characteristics (ROC) analyses for detection of the diagnostic capabilities of CT quantitative parameters to predict respiratory failure severity.

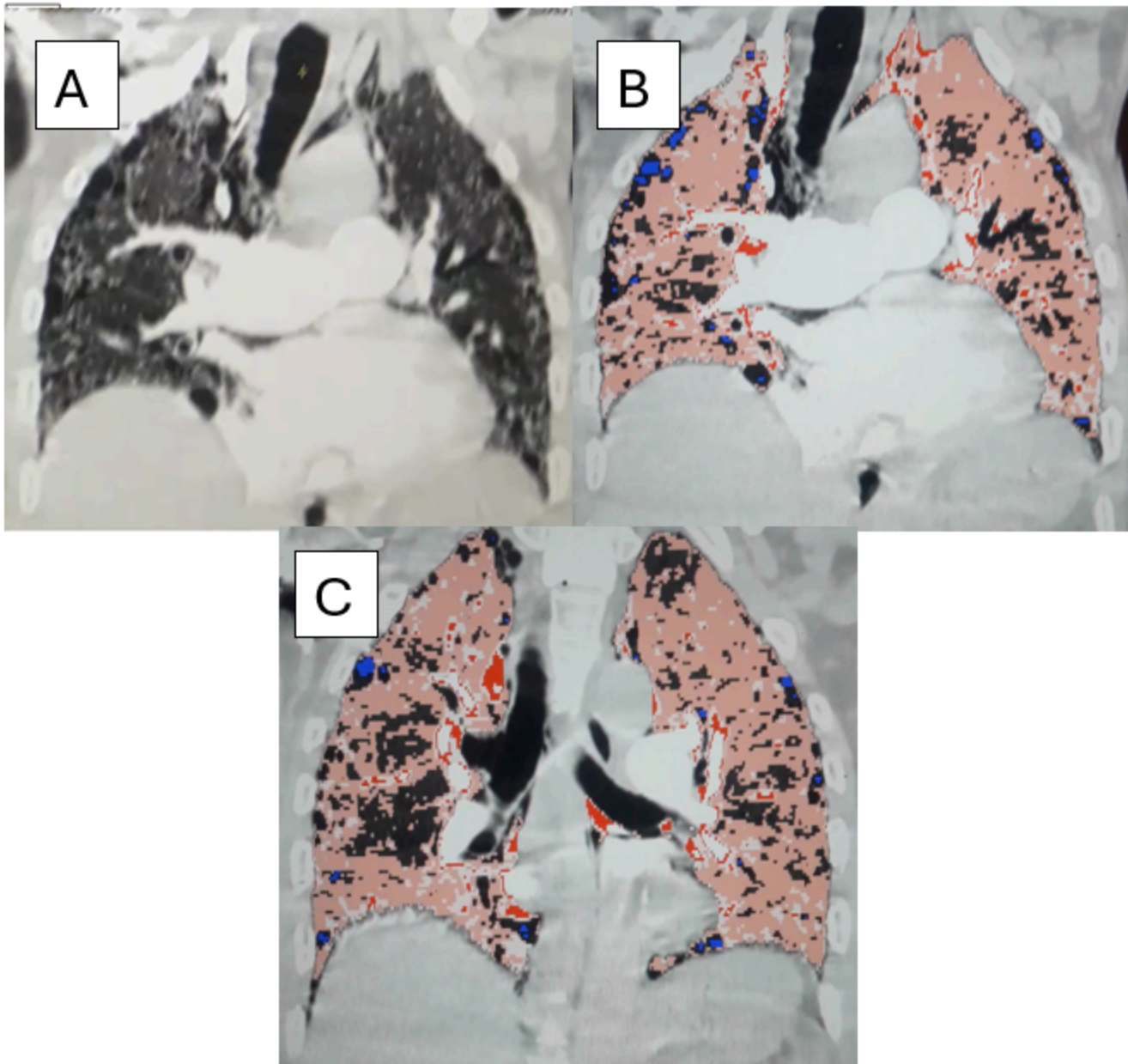


Figure 4

A 55-years-old man, smoker, with interstitial lung disease, type 2 severe respiratory failure. APACHI II score was 14 and PF ratio was 90. The patient was on non –invasive ventilation. Coronal NCCT (a) and densitometric overlay images (b, and c) are shown. The quantitative computed tomography (QCT) results using Thoracic VCAR software were as follows: 1.172 % emphysematous, 21.562 % well aerated lung, and the predominant densities coded by orange colour were ground glass, consolidation and reticular densities representing 73.831 % of total lung volume, while 3.435 % for fibrotic densities, respectively. The blue color represents areas of low attenuation cystic changes of honey combing appearance which were misinterpreted by the software as emphysematous changes highlighting the added value of combined visual assessment.

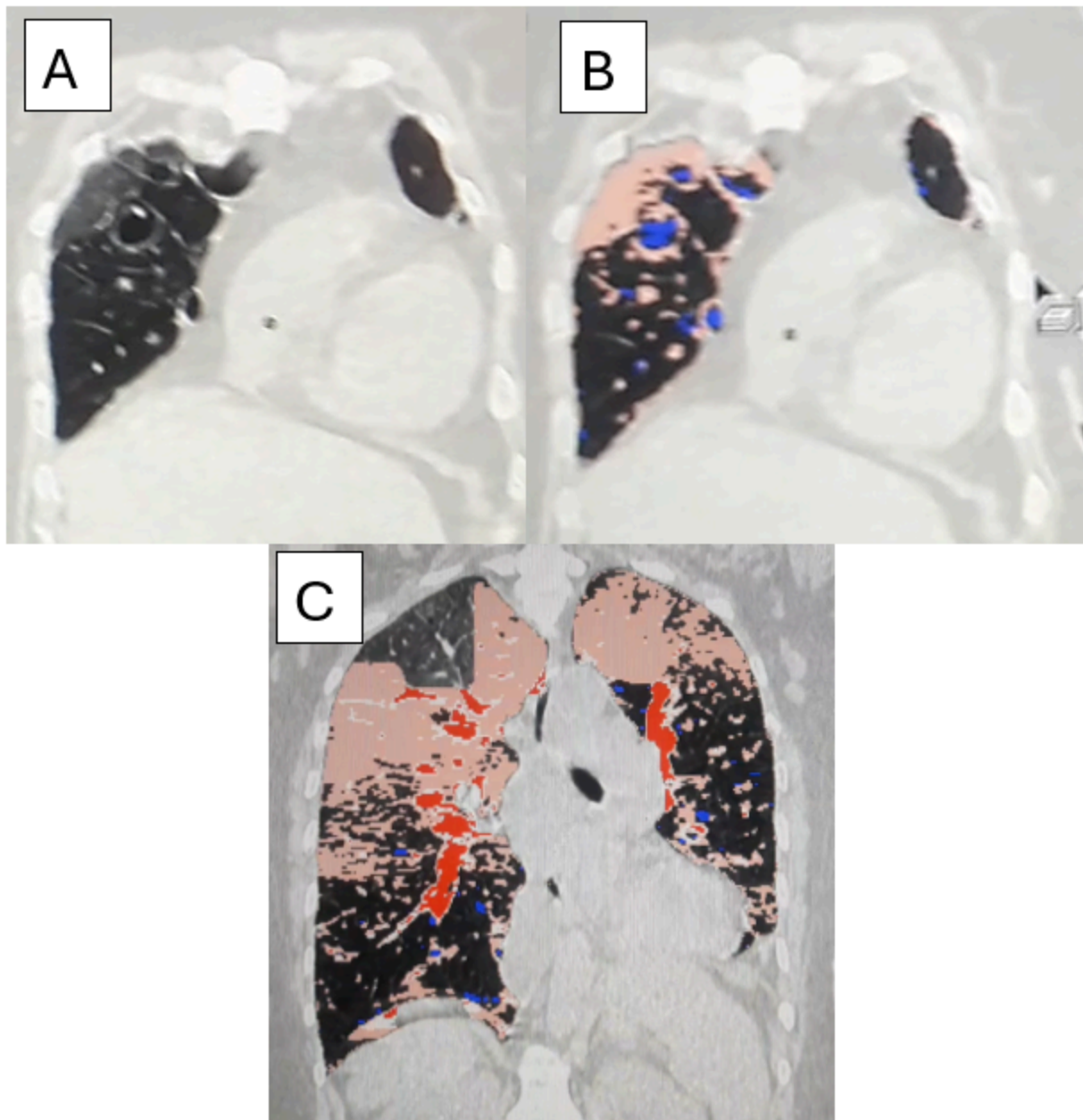


Figure 5

A 39-years-old woman, diabetic, non-smoker, admitted to respiratory ICU with interstitial lung disease, on ventory, type 2 RF, of MODERATE severity. APACHI II score was 7 and PF ratio 168. Axial and coronal NCCT (a) and (b) as well as densitometric images (c) and (d) are shown. The quantitative computed tomography (QCT) results using Thoracic VCAR software revealed abnormal lung volume of 47.171 % with predominant consolidation and interstitial densities of 42.343% coded by orange colour with unequal lung involvement, the right lung was more affected than left lung, with corresponding abnormal density volumes of 45.985 %, and 22.143 % respectively. The blue color represents areas of low attenuation corresponding to bronchiectatic changes misinterpreted by the software as emphysematous changes.

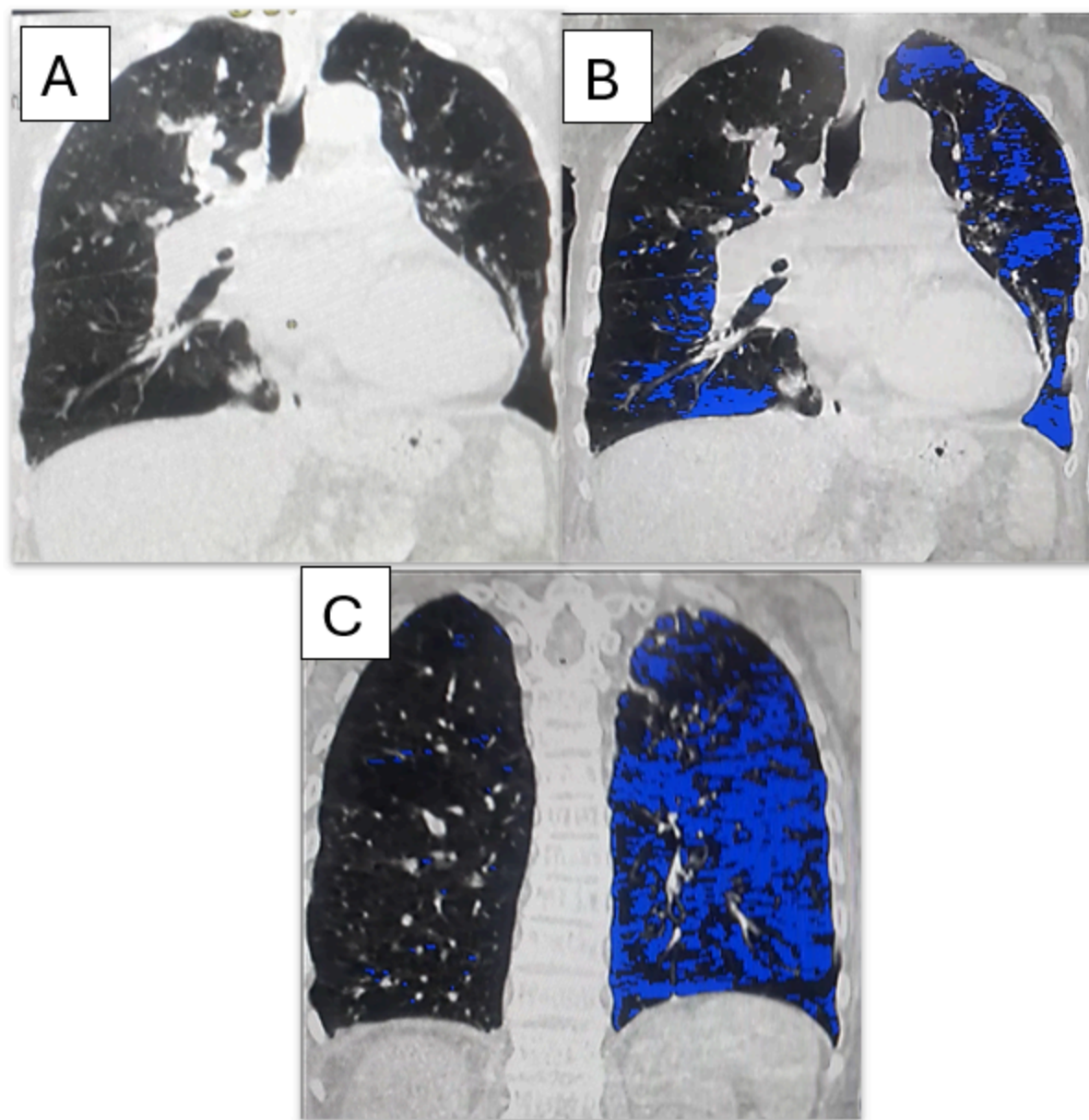


Figure 6

A 70-years-old female, non-smoker, with chronic obstructive pulmonary disease and type 2 ARF of MILD severity. APACHI II score was 8 and PF ratio 244. The patient was on non-invasive ventilation on admission. NCCT **(a), (b)** and densitometric images **(c), (d)** The total lung parenchyma analysis results were as follows: 19.58561HU emphysematous, and 80.4139 HU normal. The blue spectrum indicates areas of reduced lung density corresponding to low attenuation areas, characteristic of emphysematous tissue which were much more obvious in left lung. Emphysema indices for right lung, and left lung were as follows: 5.0975%, and 41.2336% respectively, with significant unequal involvement of both lungs, the left lung being more affected. Still, EI was < 35% denoting airway predominant phenotype.