Artificial Intelligence in Interstitial Lung Disease Diagnosis

Subjects: Radiology, Nuclear Medicine & Medical Imaging

Contributor: Gaetano Rea , Nicola Sverzellati , Marialuisa Bocchino , Roberta Lieto , Gianluca Milanese , Michele D'Alto , Giorgio Bocchini , Mauro Maniscalco , Tullio Valente , Giacomo Sica

Diffuse lung disorders (DLDs) and interstitial lung diseases (ILDs) are pathological conditions affecting the lung parenchyma and interstitial network. There are approximately 200 different entities within this category. Radiologists play an increasingly important role in diagnosing and monitoring ILDs, as they can provide non-invasive, rapid, and repeatable assessments using high-resolution computed tomography (HRCT). HRCT offers a detailed view of the lung parenchyma, resembling a low-magnification anatomical preparation from a histological perspective. The intrinsic contrast provided by air in HRCT enables the identification of even the subtlest morphological changes in the lung tissue. By interpreting the findings observed on HRCT, radiologists can make a differential diagnosis and provide a pattern diagnosis in collaboration with the clinical and functional data. The use of quantitative software and artificial intelligence (AI) further enhances the analysis of ILDs, providing an objective and comprehensive evaluation.

HRCT (high-resolution computed tomography) ILDs (interstitial lung diseases) AI (artificial intelligence)

1. Introduction

Diffuse lung disorders (DLDs) and interstitial lung diseases (ILDs) represent a category of pathological conditions that manifest with widespread involvement of the lung parenchyma and interstitial network. From a purely classificatory point of view, they encompass a heterogeneous group of conditions that amount to approximately 200 distinct entities in the literature [1][2][3][4][5][6]. Radiology is increasingly integrated into the multidisciplinary diagnosis (MDD) and follow-up process of ILDs management thanks to high-resolution computed tomography (HRCT) of the chest, a rapid, repeatable, and essentially safe technique capable of providing highly accurate diagnostic information. It enables a refined detection of pulmonary abnormalities, allows for the evaluation of longitudinal changes during follow-up and resembles a low-magnification anatomical preparation from a histological point of view [7].

HRCT of the chest is a crucial tool for identifying distinctive patterns in DLDs and ILDs, playing a pivotal role in achieving an accurate diagnosis. Additionally, it provides valuable insights into alternative diagnostic possibilities and aids in characterizing mixed phenotypes, including the presence of small airway disease, comorbidities, and other factors contributing to progressive fibrotic patterns. The accurate interpretation of basic semiotic alterations

observed during HRCT examination facilitates a comprehensive differential diagnosis in which the radiologist is called to express their judgment until a pattern diagnosis. This process requires high “skills” and, in agreement with the clinical and functional data, allows the multidisciplinary team (MDT) to often arrive at a confident diagnosis of pattern and finally of disease. In cases where the pattern-based diagnosis is not confident enough to reach a definitive diagnosis, such as an “indeterminate pattern” for usual interstitial pneumonia (UIP) according to idiopathic pulmonary fibrosis (IPF) guidelines or an “unclassifiable pattern” at the time of the initial diagnostic evaluation, the use of MDT is recommended. This is crucial for discussing atypical or extremely complex cases in order to achieve, at least in the early diagnostic phase, a “working diagnosis”, a procedure that, according to recent literature studies, can attain high levels of diagnostic confidence. MDT plays a pivotal role in the management of ILDs, serving as the gold standard for diagnosing various ILDs beyond IPF. This encompasses a broad spectrum of conditions, ranging from ILDs with autoimmune features (IPAFs: interstitial pneumonia autoimmune features) to fibrotic hypersensitivity pneumonia (f-HP) and non-specific interstitial pneumonia (NSIP). Nevertheless, the absence of definitive classification and standardized diagnostic criteria for certain entities poses a diagnostic challenge, particularly since a substantial number of inflammation-mediated ILD disorders may progress to fibrosis [5][8].

2. Unlocking the Potential: Artificial Intelligence Revolutionizes Interstitial Lung Disease Diagnosis with Quantitative Imaging and Advanced Data Analysis

AI is a novel term used to describe computer systems able to solve specific tasks that commonly require human intelligence. AI is revolutionizing the field of ILD diagnosis through the integration of quantitative imaging and advanced data analysis techniques. By leveraging AI algorithms, researchers and clinicians can unlock the full potential of medical imaging data, enabling a more precise and accurate detection, classification, and prognosis of ILDs. This cutting-edge approach combines machine learning, deep learning, neural networks, and radiomics, empowering healthcare professionals with powerful tools to enhance diagnostic accuracy and optimize treatment strategies for ILD patients. Machine learning, an integral part of AI, revolves around the concept of computer systems adapting and learning from data samples to execute specific tasks. Unlike traditional programming methods with explicit rules and instructions, machine learning algorithms are designed to be trained or fitted using specific datasets. Among the AI techniques, supervised and unsupervised learning stand as powerful tools, each offering a unique perspective in unraveling the mysteries of ILDs. “Supervised Learning”: by utilizing labeled training data, this approach enables AI models to learn patterns and associations, ultimately aiding in disease classification and prediction. Through a process of meticulous training and validation, supervised learning algorithms acquire the ability to accurately identify specific ILD subtypes, such as IPF or HP, based on defined features and characteristics. This enables clinicians to make informed decisions regarding treatment strategies and prognostic evaluations, elevating patient care to unprecedented levels of precision. “Unsupervised Learning”: on the other hand, this approach serves as a beacon in unveiling the hidden patterns within ILDs. Without the need for predefined labels, unsupervised AI models excel at discovering intrinsic structures and relationships within complex ILD datasets. By applying advanced clustering and dimensionality reduction techniques, these models can unravel

novel disease subtypes and identify intricate patterns that may elude human observation. Unsupervised learning empowers researchers to explore the vast landscape of ILDs, potentially uncovering new insights, biomarkers, and novel avenues for targeted therapies. While supervised and unsupervised learning differ in their methodologies, they are not mutually exclusive. In fact, their synergy holds the key to unlocking a deeper understanding of ILDs. By combining the strengths of both approaches, AI models can leverage the meticulous classification capabilities of supervised learning while simultaneously exploring the uncharted territories of unsupervised learning; this holistic approach not only enhances diagnostic accuracy but also opens doors to personalized treatment strategies, early detection, and improved patient outcomes. Achieving precise and clinically valuable algorithms in machine learning necessitates the utilization of suitable AI computational analysis and the incorporation of pertinent outcomes or ground truth. Powerful computing processors and machine learning methods were introduced by researchers, able to analyze volumetric data and to extract by CT scans image features and other informatics information on the densitometric variations on tiny pulmonary areas in order to evaluate diffuse lung disorders with the possibility of obtaining, also with colorimetric regional lung variations, a subtle difference between the HRCT areas (for example, normal lung, emphysema, GGO, consolidations, reticulations, honeycombing). These computational analyses, also called adaptative multiple-feature methods in a lung texture analysis, can provide “intelligent” maps of pulmonary morphological and densitometric variations, associated with an almost perfect computerized analysis of lung damage, to obtain distinct features for classifying different regional areas in a CT image. Machine learning models can also assist in ILD prognosis by analyzing a multitude of clinical and imaging variables to predict disease progression, survival outcomes, and treatment response. These models can integrate diverse datasets, including longitudinal imaging data, pulmonary function tests, genetic markers, and clinical features, to generate personalized prognostic assessments for ILD patients. Such prognostic tools can aid in treatment decision making and facilitate the development of tailored management plans. In the context of ILD management, machine learning algorithms can also contribute to the development of computer-aided systems for the automated detection and segmentation of ILD-related abnormalities on radiographic images. By automating the identification of specific lung patterns and lesions, these algorithms can improve efficiency, reduce inter-observer variability, and provide quantitative measurements of disease extent and progression. Therefore, the subsequent evolution of advanced pulmonary analysis techniques after “the lung tissue density analysis” has involved the introduction of “texture analysis”, which refers to a set of methods and algorithms for the extraction of information regarding the structural characteristics of an image and is also capable of extrapolating and evaluating different groups of radiomics parameters. This analysis can involve various approaches, including traditional feature engineering methods such as Gabor filters or texture co-occurrence matrices, as well as more advanced techniques such as machine learning or deep learning. One of the most well-known, effective, and widely used software applications for texture analysis is Computer-Aided Lung Informatics for Pathology Evaluation and Rating (CALIPER) [9].

3. Unleashing the Potential of AI: Unraveling ILDs Mysteries through Deep Learning, CNN, Radiomics, and Lung Shrinkage

3.1. Deep Learning

Deep learning, a subfield of machine learning, has gained significant attention in recent years due to its remarkable ability to learn hierarchical representations from complex data. In the context of ILDs, deep learning techniques have shown great potential in several applications, revolutionizing the field of ILD research and management [10][11]. One of the primary applications of deep learning in ILDs is in the automated analysis and interpretation of medical images, particularly HRCT scans. Deep learning models, such as convolutional neural networks (CNNs), can be trained on large datasets of annotated HRCT images to automatically detect and classify various ILD patterns and abnormalities. Numerous studies have investigated the utilization of advanced imaging techniques and AI for the prediction and diagnosis of histopathologic conditions such as UIP. For example, a study introduced a CNN that utilized virtual wedges of the peripheral lung on HRCT to predict UIP [12]. CNN demonstrated moderate agreement with expert radiologists. In a more recent study, a DL model trained on a dataset of pathologically proven ILD was employed. The findings showed that the DL model outperformed visual CT analysis in predicting the histopathologic diagnosis of UIP and exhibited a higher reproducibility compared to expert radiologists. Specifically, when classifying cases as probable UIP based on a guideline, the DL model achieved a higher specificity compared to expert radiologists [12][13][14]. These models can learn to identify subtle radiological features indicative of specific ILD subtypes, including honeycombing, ground-glass opacities, reticulation, and traction bronchiectasis [15][16][17]. DL-based automated lung CT volumetry and fibrosis scoring have been shown to correlate with functional data and provide insights into the prognosis of IPF. DL algorithms have demonstrated a superior performance compared to thoracic radiologists in ILD classification and predicting survival outcomes. DL models have also outperformed experts in predicting histopathologic diagnoses and shown a better reproducibility. Additionally, the DL quantification of ILD patterns and extent has improved disease characterization and correlated well with functional data [15]. The deep texture analysis (DTA) provided by deep learning algorithms can aid radiologists in accurate and efficient ILD diagnosis and classification and in the prediction of disease progression and treatment response with HRCT; it is trained to distinguish fibrosis by utilizing image regions identified by radiologists as exhibiting normal lung parenchyma and typical patterns of fibrotic features. Representative regions labeled as reticulation, honeycombing, or traction bronchiectasis are employed to define the fibrosis category. In a sliding window manner, the algorithm classifies local regions within axial sections as either normal lung or fibrosis, which are identified through a separate segmentation process applied to the lung fields. The DTA fibrosis score is computed as the percentage of the total number of window regions classified as fibrosis.

Deep learning models can integrate longitudinal imaging data, clinical variables, and other relevant biomarkers to generate predictive models; by capturing complex relationships and temporal dynamics within the data, these models can provide valuable prognostic information for ILD patients [18][19][20]. Additionally, deep learning models can help to identify patients who are likely to respond positively to specific treatments, facilitating personalized therapeutic strategies and being valuable for ILD risk stratification and early detection. By utilizing extensive datasets including health records, genetics, and environmental factors, deep learning models can identify individuals at a higher risk of ILD development. Early detection is crucial for timely intervention and improved outcomes. These models could also help in identifying high-risk individuals and facilitating targeted screening. However, challenges exist in applying deep learning to ILDs: large and diverse datasets are needed for training, which may be limited for rare or specific subtypes. It is important to note that AI in general and deep learning

specifically in this context are designed to assist radiologists rather than replace them. The primary objective of the software is to streamline the interpretation process, alleviate the workload, and enhance the accuracy and consistency of ILD diagnoses. Radiologists, in collaboration with clinicians, can leverage the insights and recommendations provided by the AI tool to make well-informed clinical decisions. As with any AI tool, the performance of deep learning algorithms relies on the quality and diversity of the training data that they have been exposed to and, for these reasons, the continuous validation and refinement of these algorithms are critical to ensure their effectiveness and generalizability across different patient populations. In conclusion, AI software utilizing deep learning techniques serves as a valuable aid to radiologists in the study of ILDs. By functioning as a pattern classifier, it assists in the analysis and interpretation of HRCT scans, providing automated annotations, disease quantification, and diagnostic suggestions. However, it is essential to recognize that human expertise and judgment remain integral to the diagnosis and management of ILDs [21].

3.2. Convolutional Neural Network, Radiomics, and Lung Shrinkage

The introduction of CNNs has ushered in a new era of diagnostic precision in ILDs. Leveraging their ability to extract complex features from medical images, CNNs have redefined the landscape of ILD diagnostics. Concurrently, radiomics has empowered clinicians to delve deeper into the quantitative analysis of ILD radiographs, enabling a comprehensive characterization and classification of these complex diseases. Integrated algorithms incorporating clinical assessment, functional tests, and CT imaging, along with radiomics-based features, have shown promise in evaluating and predicting prognosis in patients with fibrotic ILDs. By extracting 26 radiomic features from routine chest CT scans, these algorithms provide valuable information for predicting progression-free survival in individuals with SSc-ILD. The integration of radiomics enhances prognostic evaluation and enables more informed treatment decisions for improved patient care [22].

CNNs in the field of thoracic imaging have proven to be a powerful tool for automated image analysis in ILDs. By leveraging their capacity to capture subtle patterns and textures within high-resolution radiographic data, CNNs surpass human visual perception, enabling a superior detection and classification of ILD subtypes [23][24]. From distinguishing IPF from other ILDs to predicting disease progression, CNNs offer a multifaceted approach that aids in both diagnosis and prognosis. Furthermore, the integration of transfer learning improves the CNN performance, underscoring their versatility in ILD research. Radiomics, an emerging field within medical imaging, complements CNNs by extracting an extensive array of quantitative imaging features from radiological images. These features encompass a wide range of morphological, textural, and statistical descriptors, providing a holistic representation of disease characteristics [25]. Leveraging advanced machine learning algorithms, radiomics models can stratify ILDs, differentiate between disease stages, and even predict treatment response [26]. By unraveling hidden imaging biomarkers, radiomics demonstrates its potential as a non-invasive and objective tool for ILD assessment. The integration of CNNs and radiomics represents a paradigm shift in the management of ILDs for both primary and secondary forms, such as connective tissue diseases [22][27]. Together, they offer a comprehensive and detailed understanding of ILDs, facilitating accurate diagnosis and personalized treatment plans. CNNs excel at extracting complex visual features from radiological or medical nuclear data, while radiomics enables a quantitative assessment of disease characteristics. The synergy between these two approaches empowers radiologists and

clinicians to uncover previously unrecognized patterns and correlations, leading to an improved diagnostic accuracy and prognostic capabilities. As CNNs and radiomics continue to evolve, their impact on ILD diagnosis and management is expected to grow exponentially. The development of large-scale, curated datasets will further enhance the performance and generalizability of CNN models. Moreover, the integration of multi-modal imaging data, such as computed tomography (CT) and positron emission tomography (PET), holds great promise in unraveling the complexities of ILDs [28][29].

Lastly, new additional methods of lung evaluation using advanced AI techniques have emerged as additional tools for integrating clinical and pulmonary functional data. One of these methods is the assessment of the so-called “lung shrinkage”, a key component of worsening lung fibrosis in ILD, which could be effectively assessed using advanced imaging techniques such as CT. The regional distribution of lung shrinkage in ILD typically starts in the lower peripheral regions of the lungs, gradually ascending to the upper apical regions. This pattern may be attributed to mechanical stress on the alveolar epithelium and the fibroproliferative response. For this reason, the measurement of lung shrinkage using elastic registration and deep learning classifiers provides spatial information about the deformation process, enhancing the understanding of disease progression. It may also assist in the early detection and monitoring of ILD. However, it is important to consider lung shrinkage in conjunction with other markers, such as changes in lung function parameters such as forced vital capacity (FVC) and the diffusing capacity of carbon monoxide (DLCO), to obtain a comprehensive assessment of disease severity and treatment response. By combining these approaches, including advanced imaging techniques, quantitative analysis, and the evaluation of lung function, a more holistic understanding of lung shrinkage in ILD can be achieved, enabling an improved monitoring and management of this complex condition [30].

References

1. Raghu, G.; Remy-Jardin, M.; Myers, J.L.; Richeldi, L.; Ryerson, C.J.; Lederer, D.J.; Behr, J.; Cottin, V.; Danoff, S.K.; Morell, F.; et al. Diagnosis of idiopathic pulmonary fibrosis. An official ATS/ERS/JRS/ALAT clinical practice guideline. Am. J. Respir. Crit. Care Med. 2018, 198, e44–e68.
2. Mueller-Mang, C.; Grosse, C.; Schmid, K.; Stiebellehner, L.; Bankier, A.A. What every radiologist should know about idiopathic interstitial pneumonias. Radiographics 2007, 27, 595–615.
3. Flaherty, K.R.; Andrei, A.-C.; King, T.E., Jr.; Raghu, G.; Colby, T.V.; Wells, A.; Bassily, N.; Brown, K.; Bois, R.D.; Flint, A.; et al. Idiopathic interstitial pneumonia: Do community and academic physicians agree on diagnosis? Am. J. Respir. Crit. Care Med. 2007, 175, 1054–1060.
4. Lynch, D.A.; Sverzellati, N.; Travis, W.D.; Brown, K.K.; Colby, T.V.; Galvin, J.R. Diagnostic criteria for idiopathic pulmonary fibrosis a Fleischner Society White Paper. Lancet Respir. Med. 2018, 6, 138–153.

5. Walsh, S.L.F.; Lederer, D.J.; Ryerson, C.J.; Kolb, M.; Maher, T.M.; Nusser, R. Diagnostic Likelihood Thresholds That Define a Working Diagnosis of Idiopathic Pulmonary Fibrosis. Am. J. Respir. Crit. Care Med. 2019, 200, 1146–1153.
6. Rea, G.; Bocchino, M. The challenge of diagnosing interstitial lung disease by HRCT: State of the art and future perspectives. J. Bras. De Pneumol. 2021, 47, e20210199.
7. Smith, M.L.; Hariri, L.P.; Mino-Kenudson, M.; Dacic, S.; Attanoos, R.; Borczuk, A.; Colby, T.V.; Cooper, W.; Jones, K.D.; Leslie, K.O.; et al. Histopathologic Assessment of Suspected Idiopathic Pulmonary Fibrosis: Where We Are and Where We Need to Go. Arch. Pathol. Lab. Med. 2020, 144, 1477–1489.
8. Walsh, S.L.F.; Wells, A.U.; Desai, S.R.; Poletti, V.; Piciucchi, S.; Dubini, A. Multicentre evaluation of multidisciplinary team meeting agreement on diagnosis in diffuse parenchymal lung disease a case-cohort study. Lancet Respir. Med. 2016, 4, 557–565.
9. Maldonado, F.; Moua, T.; Rajagopalan, S.; Karwoski, R.A.; Raghunath, S.; Decker, P.A.; Hartman, T.E.; Bartholmai, B.; Robb, R.A.; Ryu, J. Automated quantification of radiological patterns predicts survival in idiopathic pulmonary fibrosis. Eur. Respir. J. 2014, 43, 204–212.
10. Hoang-Thi, T.N.; Chassagnon, G.; Tran, H.D.; Le-Dong, N.N.; Dinh-Xuan, A.T.; Revel, M.P. How Artificial Intelligence in Imaging Can Better Serve Patients with Bronchial and Parenchymal Lung Diseases? J. Pers. Med. 2022, 12, 1429.
11. Chang, Y.; Lim, J.; Kim, N.; Seo, J.B.; Lynch, D.A. A support vector machine classifier reduces interscanner variation in the HRCT classification of regional disease pattern in diffuse lung disease: Comparison to a Bayesian classifier. Med. Phys. 2013, 40, 051912.
12. Shaish, H.; Ahmed, F.S.; Lederer, D.; D'Souza, B.; Armenta, P.; Salvatore, M.; Saqi, A.; Huang, S.; Jambawalikar, S.; Mutasa, S. Deep learning of computed tomography virtual wedge resection for prediction of histologic usual interstitial pneumonitis. Ann. Am. Thorac. Soc. 2021, 18, 51–59.
13. Bratt, A.; Williams, J.M.; Liu, G.; Panda, A.; Patel, P.P.; Walkoff, L.; Sykes, A.-M.G.; Tandon, Y.K.; Francois, C.J.; Blezek, D.J.; et al. Predicting usual interstitial pneumonia histopathology from chest CT with deep learning. Chest 2022, 162, 815–823.
14. Suman, G.; Koo, C.W. Recent Advancements in Computed Tomography Assessment of Fibrotic Interstitial Lung Diseases. J. Thorac. Imaging, 2023; ahead of print.
15. Walsh, S.L.F.; Calandriello, L.; Silva, M.; Sverzellati, N. Deep learning for classifying fibrotic lung disease on high-resolution computed tomography: A case-cohort study. Lancet Respir. Med. 2018, 6, 837–845.
16. Agarwala, S.; Kale, M.; Kumar, D.; Swaroop, R.; Kumar, A.; Dhara, A.K.; Thakur, S.B.; Sadhu, A.; Nandi, D. Deep learning for screening of interstitial lung disease patterns in high-resolution CT images. Clin. Radiol. 2020, 75, E1–E8.

17. Kim, G.B.; Jung, K.H.; Lee, Y.; Kim, H.J.; Kim, N.; Jun, S.; Seo, J.B.; Lynch, D.A. Comparison of Shallow and Deep Learning Methods on Classifying the Regional Pattern of Diffuse Lung Disease. J. Digit. Imaging 2018, 31, 415–424.
18. Choe, J.; Hwang, H.J.; Seo, J.B.; Lee, S.M.; Yun, J.; Kim, M.-J.; Jeong, J.; Lee, Y.; Jin, K.; Park, R.; et al. Content-based image retrieval by using deep learning for interstitial lung disease diagnosis with chest CT. Radiology 2022, 302, 187–197.
19. Lacedonia, D.; De Pace, C.C.; Rea, G.; Capitelli, L.; Gallo, C.; Scioscia, G.; Tondo, P.; Bocchino, M. Machine Learning and BMI Improve the Prognostic Value of GAP Index in Treated IPF Patients. Bioengineering 2023, 10, 251.
20. Barnes, H.; Humphries, S.M.; George, P.M.; Assayag, D.; Glaspole, I.; Mackintosh, J.A.; Corte, T.J.; Glassberg, M.; Johannson, K.A.; Calandriello, L.; et al. Machine learning in radiology: The new frontier in interstitial lung diseases. Lancet Digit. Health 2023, 5, e41–e50.
21. Chen, X.; Wang, X.; Zhang, K.; Fung, K.M.; Thai, T.C.; Moore, K.; Mannel, R.S.; Liu, H.; Zheng, B.; Qiu, Y. Recent advances and clinical applications of deep learning in medical image analysis. Med. Image Anal. 2022, 79, 102444.
22. Schniering, J.; Maciukiewicz, M.; Gabrys, H.S.; Brunner, M.; Blüthgen, C.; Meier, C.; Braga-Lagache, S.; Uldry, A.C.; Heller, M.; Guckenberger, M.; et al. Computed tomography-based radiomics decodes prognostic and molecular differences in interstitial lung disease related to systemic sclerosis. Eur. Respir. J. 2022, 59, 2004503.
23. Aliboni, L.; Dias, O.M.; Baldi, B.G.; Sawamura, M.V.Y.; Chate, R.C.; Carvalho, C.R.R.; de Albuquerque, A.L.P.; Aliverti, A.; Pennati, F. A convolutional neural network approach to quantify lung disease progression in patients with fibrotic hypersensitivity pneumonitis (HP). Acad. Radiol. 2022, 29, e149–e156.
24. Bermejo-Peláez, D.; Ash, S.Y.; Washko, G.R.; San José Estépar, R.; Ledesma-Carbayo, M.J. Classification of Interstitial Lung Abnormality Patterns with an Ensemble of Deep Convolutional Neural Networks. Sci. Rep. 2020, 10, 338.
25. Budzikowski, J.D.; Foy, J.J.; Rashid, A.A.; Chung, J.H.; Noth, I.; Armato, S.G., 3rd. Radiomics-based assessment of idiopathic pulmonary fibrosis is associated with genetic mutations and patient survival. J. Med. Imaging 2021, 8, 031903.
26. Stefano, A.; Gioè, M.; Russo, G.; Palmucci, S.; Torrisi, S.E.; Bignardi, S.; Basile, A.; Comelli, A.; Benfante, V.; Sambataro, G.; et al. Performance of Radiomics Features in the Quantification of Idiopathic Pulmonary Fibrosis from HRCT. Diagnostics 2020, 10, 306.
27. Martini, K.; Baessler, B.; Bogowicz, M.; Blüthgen, C.; Mannil, M.; Tanadini-Lang, S.; Schniering, J.; Maurer, B.; Frauenfelder, T. Applicability of radiomics in interstitial lung disease associated with systemic sclerosis: Proof of concept. Eur. Radiol. 2021, 31, 1987–1998.

28. Frix, A.N.; Cousin, F.; Refaee, T.; Bottari, F.; Vaidyanathan, A.; Desir, C.; Vos, W.; Walsh, S.; Occhipinti, M.; Lovinfosse, P.; et al. Radiomics in Lung Diseases Imaging: State-of-the-Art for Clinicians. J. Pers. Med. 2021, 11, 602.
29. Anan, N.; Zainon, R.; Tamal, M. A review on advances in 18F-FDG PET/CT radiomics standardization and application in lung disease management. Insights. Imaging 2022, 13, 22.
30. Chassagnon, G.; Vakalopoulou, M.; Régent, A.; Sahasrabudhe, M.; Marini, R.; Hoang-Thi, T.-N.; Dinh-Xuan, A.-T.; Dunogué, B.; Mouthon, L.; Paragios, N.; et al. Elastic registration-driven deep learning for longitudinal assessment of systemic sclerosis interstitial lung disease at CT. Radiology 2021, 298, 189–198.