International Journal of Emerging Engineering and Technology (IJEET)
ISSN (e): 2958-3764
Volume: 4, Number: 2, Pages: 1- 9, Year: 2025

Artificial Intelligence–Driven Imaging Advances in Lung Fibrosis: A Comprehensive Review

Syeda Iqra Shakeel[1], Sidra Aslam[2], Hafiz Burhan Ul Haq[2,*], Sabir Abbas[2], Hafiz Muhammad Muneeb Akhtar[2], Saleem Abbas[3], Imran Khlaid[4]

[1]Department of Software Engineering, Faculty of Computer Sciences, Lahore Garrison University, Lahore, 54000, Pakistan
[2]Department of Information Technology, Faculty of Computer Sciences, Lahore Garrison University, Lahore, 54000, Pakistan
[3]Department of Computer Science, Imperial College of Business Studies, Lahore, 54000, Pakistan
[4]Department of Criminology and Forensic Science, Faculty of Social Sciences, Lahore Garrison University, Lahore, 54000, Pakistan

Corresponding author: Hafiz Burhan Ul Haq (Email: burhanhashmi64@lgu.edu.pk)

***Abstract*—Lung fibrosis is a chronic and progressive illness where there is pathologic tissue scarring, which affects lung architecture and respiratory organ functioning. It is caused by several factors, including idiopathic pulmonary fibrosis (IPF), radiation-related injury, tumour-related fibrosis, and post-COVID-19 complications, and all of them are associated with similar pathophysiology. This review investigates and summarises studies published from 2015 to 2025 on biological processes, clinical symptoms, and technological innovations in the diagnosis and monitoring of lung fibrosis. It emphasises the way that artificial intelligence (AI) and deep learning (DL) models, such as quantitative computed tomography (CT) and convolutional neural networks (CNNs), have enhanced the process of early detection, disease classification, and medical progression forecasting. The computational models, such as the agent-based and Monte Carlo simulations, which are used to study fibrotic dynamics, are also discussed in the review. In general, the combination of molecular knowledge, imaging, and AI-based systems can be considered a major next step in the creation of personalized diagnoses and better treatment outcomes in chronic fibrotic lung diseases.**

***Index Terms*— Lung Fibrosis, Idiopathic Pulmonary Fibro- sis, Artificial Intelligence, Deep Learning, Convolutional Neural Networks, Quantitative Computed Tomography, Post–COVID-19 Fibrosis.**

I. Introduction

World Lung Day highlights the international significance of respiratory health, and it aims to create awareness of the most significant airborne diseases like chronic obstructive pulmonary disease (COPD), asthma, tuberculosis, lung cancer, and the impacts of air pollution [1]. Lung fibrosis is a complicated and time-consuming diagnosis that requires clinical personnel to process a large number of high-resolution CT images to identify insidious fibrotic alterations. The non-uniform nature and large volumes of imaging data render manual interpretation challenging, and automated, intelligent solutions are in demand to precisely determine and measure fibrosis.

A. Background of Lung Fibrosis

Lung fibrosis is a chronic disease in which the lung tissue becomes thick and rigid, making breathing difficult andreducsing oxygen transport. The most severe form, idiopathic pulmonary fibrosis (IPF), typically occurs in individuals more than 60 years old, and in most cases, progressive difficulty in breathing occurs within a few years It occurs when the lungs are damaged repeatedly, and this may be occasioned by smoking or work exposures or infections. Genetics are also a cause of some people being more prone to lung diseases and less able to heal easily, which is caused by some inherited traits. Knowing these factors will support the prevention of the disease in its early stage and facilitate the development of individual strategies that will slow it down [2]. It occurs when the lungs are damaged repeatedly, and this may be occasioned by smoking or work exposures or infections. Genetics are also a cause of some people being more prone to lung diseases and less able to heal easily, which is caused by some inherited traits. Knowing these factors will support the prevention of the disease in its early stage and facilitate the development of individual strategies that will slow it down [2].

B. Causes and Pathological Variants

There are several etiologies of lung fibrosis, such as id-iopathic pulmonary fibrosis (IPF), radiation-induced lung fi-brosis (RILF), tumor-associated fibrosis, and post-COVID-19 fibrosis. Lung fibrosis caused by COVID-19 and radiation-induced pulmonary fibrosis (RIPF) both damage and scar tissue in similar ways. In both cases, inflammation hurts the lungs and sets off strange repair processes that make the lungs stiff and make it hard to breathe. The biological processes at play, such as the immune response and cellular stress pathways, seem to

be closely connected. Studying these common mechanisms may allow us to find strategies to protect lung tissue, reduce inflammation, and mitigate damage associated with radiation or viral infection [3].

C. Advances in Diagnostic Imaging and AI

Technological advances facilitate the detection and evaluation of lung fibrosis. Older imaging techniques like high-resolution computed tomography (HRCT) will soon be replaced and enhanced with tools like CT analysis and artificial intelligence (AI) models. Deep learning (DL) and convolutional neural networks (CNNs) have been very successful at detecting interstitial patterns, quantifying fibrotic areas, and forecasting disease progression. More recent publications have highlighted the value of AI and DL applied to CNNs on HRCTs for the recognition of lung fibrosis. CNN models recognize distinct patterns such as reticular and honeycomb, thus improving diagnostic efficiency and decreasing the need for biopsies; however, the use of small training datasets and segmentation problems still hinders overall applicability [4]. The conceptual framework of this research review on lung fibrosis, including important elements, methods of inquiry, and research design aspects, is presented in Fig 1.

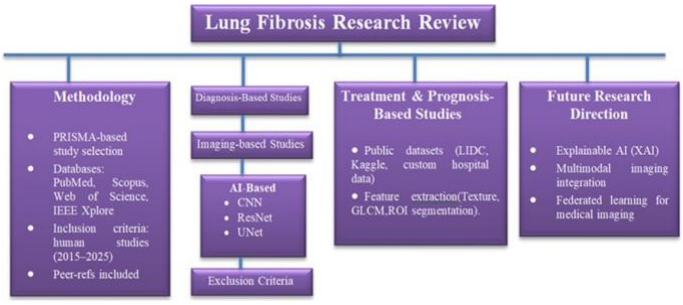

Fig. 1. Conceptual Structure of Lung Fibrosis Research Review.

II. Methodology

This review was conducted according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The purpose was to review and appraise clinical writings, images, and artificial intelligence studies, which pertain to the diagnosis and treatment of fibrotic lung dis- ease, including IPF and ILDs. The review protocol has been planned in accordance with the PRISMA 2020 standards and follows the earlier published medical imaging and computational diagnostics evidence synthesis frameworks.

A. Search Strategy

The literature search was conducted across the PubMed, Scopus, Web of Science, and IEEE Xplore databases to identify research on lung fibrosis published between 2015 and 2025. The selection of these databases was intended to cover both clinical and technological research positions related to pulmonary fibrosis. Also, imaging protocols. All the chosen works were peer- reviewed articles. Reference lists and grey literature sources (institutional repositories, preprints, and theses) were manually.

B. Inclusion Criteria

The inclusion criteria were established to identify articles that presented clinical or technological information on lung fibrosis. The inclusion criteria included the works having clinical or pathological data, such as characterization of the disease, biomarkers, or treatment outcome. The use of AI-based diagnostic structures, including image segmentation, classification, or prognosis prediction with the use of CT, HRCT, or histopathology data, was also incorporated in the studies. The included studies were those that involved human subjects and were published no earlier than 2015. Quantitative or qualitative measures of diagnostic performance, model performance, and data characteristics had to be reported in articles to ensure that the evidence reviewed was methodologically sound and applicable to modern AI-based research in lung fibrosis.

C. Exclusion Criteria

This implies that only credible and comprehensive researches were used in the review. Animal-based research, laboratory experiments or theoretical studies were not factored in because the studies were about the clinical aspects of human beings. The review also managed to exclude short or informal publications, such as conference papers, editorials, or opinions, that do not present the entire research methods or results. The research that lacked informational content, extremely small samples (less than 20 individuals), or lacked a report of their findings in the customary manner was also excluded. Lastly, only articles in English were included, and any overlaps across databases were eliminated to maintain accurate data. Table I outlines the study selection process, as guided by PRISMA 2020.

TABLE I
SUMMARY OF STUDY SELECTION PROCESS BASED ON PRISMA GUIDELINES

PRISMA Stage	Records(n)	Notes
Records identified through database searching	480	PubMed, Scopus, IEEE, Web of Science
Additional records identified through other sources	25	Manual search & grey literature
Total records identified	**505**	
Records after duplicates removed	420	85 duplicates removed
Records screened (title/abstract)	420	-
Records excluded	330	Irrelevant, outside scope
Full-text articles assessed	90	-
Full-text articles excluded	59	Small sample size, animal/preclinical, simulation-only, case reports.
Studies included in the qualitative synthesis	31	Included in review
Studies included in quantitative synthesis (meta-analysis)	0	Not performed

III. Literature Review

Batah et al. [5] illustrated how deep learning-based AI models can be used to analyze the HRCT lung images and classify and detect fibrotic patterns (such as honeycombing and ground-glass opacities) automatically. By employing Convolutional Neural Networks alongside quantitative features of CT images, it achieved an 85% accuracy. Among its many automated features, precise outputs remain one of this research's highlights. However, dataset bias and small sample sizes remain critical weaknesses. Valand et al. [6] investigated a study at Neuro computing presented an artificial intelligence-driven deep- learning architecture to the early detection of lung fibrosis based on the computed tomography (CT) imaging data. The model used convolutional neural networks (CNNs) and transfer learning to improve the accuracy of fibrotic pattern classification. Automation and precision were listed as strengths, but the lack of balance in the dataset, limited diversity, and the possibility of overfitting limit its clinical application. Yang et al. [7] studied developments in computational lung ultrasonography (LUS) for the diagnosis of respiratory conditions such as ARDS and COVID-19. For artefact detection and segmentation, the study contrasted deep learning (CNN, U-Net) with model-based techniques (e.g., Radon transform, ADMM). Real-time, explainable imaging is one of its strengths; generalisation problems, noise sensitivity, and a lack of annotated data are its drawbacks. Colombi et al. [8] explained the use of high-resolution computed tomography (HRCT) in AI-driven assessment of interstitial lung diseases (ILDs). For pattern classification, segmentation, and prognosis prediction, the study emphasises machine learning and deep learning (CNNs). Human-level accuracy and objective quantification are among its strong points; dataset heterogeneity, small sample sizes, and the requirement for standardized multicenter validation are among its weaknesses. Zhang et al. [9] studied 50 patients with solitary fibrous tumors of the chest (33 pleural, 17 pulmonary) were retrospectively examined to evaluate malignancy indicators, diagnosis, and treatment. Histopathological validation and CT confirmation were obtained for every case, and immunohistochemistry revealed positive results for CD34, Vimentin, Bcl-2, STAT6, and CD99. The results of surgery or radiofrequency ablation were positive, and the main indicators of malignancy were high Ki-67, CT necrosis, chest tightness, and advanced age. Limited therapy comparisons and a small single-center sample were among the limitations. Marchioni et al. [10] Examine how mechanical forces and stretching in the lungs can exacerbate fibrosis. Particularly in IPF, stiff and fragile lungs are more susceptible to dinjury wleadingto excess tissue accumulation and inadequate repair. The review explains how these forces impact lung cells and tissue using research on both humans. Its ability to relate lung mechanics to treatment concepts is one of its strong points; its main drawbacks are that it mostly depends on laboratory research and lacks solid evidence from human trials. Shepelkova et al. [11] compared TB patients with and without previous COVID-19 infection. They discovered that patients with TB after COVID-19 had higher levels of passive and active inflammatory molecules than those without TB after COVID-19, altered expression of key inflammatory miRNAs in blood and lung tissues, and more severe lung inflammation. The changes were assessed using tissue and blood laboratory tests. Although the study design was limited to a small, single-centre study and lacked long-term follow-up, the study interweaving tissue, molecular, and miRNA data integrated a design that illustrated enduring inflammation. Kumar et al. [12] discuss the use of Machine Learning (ML) to identify COVID-19, and more serious lung diseases like pneumonia and lung cancer from medical images. They indicated positive correlation predictive value in previous literature, and summarized the imaging and datasets (X-ray, CT, MRI, PET) with different ML techniques (CNN, transfer and ensemble learning) during a given research period. Reliance on previous research, dataset bias, and overlooking of rare or atypical diseases, were some of the limitations. Thoroughness and coverage of the topic, and emerging recommendations were the key strengths. Dorosti et al. [13] examined the use of Convolutional Neural Networks (CNNs) for the computerised detection of Chronic Obstructive Pulmonary Disease (COPD) from CT scans and the comparative influence of manual and automated window settings on processing speed. Using 7,194 images, they found that manual adjustments provided the greatest improvement in accuracy (AUC 0.86). This study's strengths include improvement in detection, relevance to the clinical methodology, automation, and method validation. However, the study is limited due to the single-center data, the scope of COPD, and the lack of external validation. Larici et al. [14] discuss the use of imaging techniques to study fibrotic lung diseases, underscoring the utility of high-resolution CT for diagnosing, monitoring, and assessing complications of progressive fibrosis. The authors concatenate imaging guide-lines, honing in on assisting radiologists in pattern detection and imaging for best practices in subsequent follow-ups. The review is especially strong in providing practical and clear suggestions. On the other hand, lacthe review suffers from a void of resubmission, a lack of new data, limited quantitative data, and gaps in the expert opinion. Giordani et al. [15] examined the fibrous zeolites erionite and offretite along with lung fluid simulants and atomic force microscopy. They observed that erionite is corrosive in acidic environments but expands in neutral and basic conditions, which explains why it is much more toxic and therefore more strongly associated with mesothelioma. The primary contribution of the study is impactful nanoscale, real-time observations and insights into toxicity, and the primary limitations of the paper are the use of non-fibrous crystals, a shortexperimentalf duration, and some unclear particle composition. Shah [16] analyses machine learning methods for lung cancer detection using CT, MRI, and X-ray images is analyzed. Data-driven algorithms like DNN, KNN, and SVM yield strong accuracy scores of 95%, yet biased datasets, narrow scope images, and processing complexities are factors on why these approaches still aren't ideal. The authors summarize progress of effective models and proposed hybrid methods for improved prompting. Abidi et al. [17] describe how oil from Pistacia lentiscus defends rats against the pulmonary toxicity and oxidative stress caused by bleomycin. In those

researchers' next work, they describe how fibrous mordenite from Northern Italy contains very fine, respirable and possibly health damaging fibers. These studies describe the natural protective resources and the minerals which are hazardous. Baratella, et al. [18] describe the use of high-resolution CT scans for evaluating the progression of pulmonary fibrosis in interstitial lung diseases. The researchers describe visual scoring and suggest more collaborative, multidisciplinary approaches in the technical protocols for identifying candidates for antifibrotic therapy. The strengths are practical and clear guidance but rely on expert opinion without original data and potential variability of observers are shortcomings. Li et al. [19] studied fibrous interstitial lung abnormalities (ILA) and used quantitative CT to predict lung function decline. They found that airway measurements such as wall thickness and luminal area, in conjunction with age and gender, can predict reduced pulmonary function with an AUC of 0.84. They identified non-invasive CT biomarkers for early detection of reduced pulmonary function, though the study was limited by single-centre data, a small sample size, and a lack of long-term follow-up. Buccardi et al. [20] demonstrated an automated method using micro-CT and deep learning was developed to track lung fibrosis in mice. It outperforms manual analysis by a factor of 45, correlates with tissue analysis, and evaluates disease progression and reversal on Nintedanib. Time efficiency, precision, fewer animals needed, and longitudinal studies are major strengths. Limitations are small sample size, sole focus on bleomycin damage, and untested applicability to other models, or to people. Harr et al. [21] focused on the PEG-FUD fibronectin-targeting probe for early detection of lung fibrosis in mice. Damaged lungs showed increased uptake demonstrating the probe's correlation with disease severity. This implies the probe may be capable of non-invasive detection in the early stages of the disease. In terms of accuracy, the potential for clinical use in the future, and the non-invasive nature of the probe highlight its strengths, while the limitations include focusing on only mice, the short-term nature of the assessment, and small sample size. Chen and Slater.[22] analyzed solitary fibrous tumors of the liver (SFTL) which state most are benign; however, about 18% can be malignant. They describe a case of a 61-year-old man with malignant SFTL with recurrence and metastasis six years after surgery. Strengths include a comprehensive review and detailed insights into the case; weaknesses include the rarity of the tumour, reliance on retrospective accounts, and vague imaging results. Cao et al. [23] utilized computer modelling to forecast potential lung damage caused by metal nanoparticles. They identified particle and cellular haracteristicls that best indicate damage and confirmed this in cellular and murine studies. Identifying critical safety indicators and adopting a trustworthy paradigm stand out as strengths, while the drawbacks include focusing on a single class of nanoparticles, limited cell-type testing, and the need for additional human validation. Wu et al. [24] reported a rare case of a 25-year-old male with a malignant solitary fibrous tumour in the brain that recurred aggressively and metastasised to the lungs and bones. The researcher described diagnosis via imaging and tissue sample analysis. Detailed tumour analysis and improved awareness of aggressive behaviour are strengths of this study. Limitations include a lack of generalizability due to the single case and a brief follow-up. Ajouz et al. [25] reviewed solitary fibrous tumours of the pleura and noted that any kind of surgical removal, whether open, VATS, or robotic, must be complete to eliminate recurrence risk. The reviewers have pointed out a real lack of source material when it comes to case studies, especially with a focus on long-term implications. They also noted a lack of original source materialforo practical recommendations on surgical guidance and minimally invasive techniques. However, a significant body of literature is available on the NAB2-STAT6 gene marker and imaging studies. They also recognized the utility of case studies, especially with a focus on implementing surgical recommendations. Ichiki et al. [26] document a rare case involving a lung solitary fibrous tumoru in a 68-year-old woman, which was successfully removed via minimally invasive VATS. The study also discusses tumor characteristics and the surgical approach taken. The case report's strengths are the thoroughness of the pathology and surgical descriptions while its limitations pertain to the single case nature of the study and the short follow-up period with which the findings may be generalized. Sturgil et al. [27] analysed data from 94 pneumonia-related ARDS cases, focusing on COVID-19 versus non-COVID cases. CT scans of COVID-19 survivors showed greater lung scarring, but the COVID-19-positive patients and the non-COVID patients exhibited similar physical functioning. Overall, both groups exhibited comparable outstanding mental health issues. A direct comparison of COVID versus non-COVID cases, and the attention to post-ICU recovery difficulties, are substantial. However, the study is limited by the small number of patients, a single centre approach, and a retrospective design. Hasan [28] generated two humanised mouse models to investigate lung fibrosis and test drugs, such as Nintedanib. The HSC model was stable, safe, and better approximated human immune responses. Strong points include testing human-specific therapies and achieving consistent results, while drawbacks include potential side effects from the PBMC model, a focus on a single drug, a small sample size, and the need for human validation. Nowak et al. [29]. The two computer tools were tested in this study, which quantified the extent of lung scarring in CT scans of 45 patients with idiopathic pulmonary fibrosis (IPF). One of them will examine the nature of the scar (ground-glass, small lines, honeycomb-like sites), and the other will merely categorise the lung tissue as normal or abnormal. The simple tool was twice as quick; both tools provided nearly identical results, and their 3-year survival predictions were also similar. This demonstrates that, despite being fast and easy, there are other approaches that doctors can rely on. Nonetheless, the sample was small, applied the data of one hospital, and it has to be tested on a larger group of patients. Cogno et al. [30-36] researchers demonstrated created a new computer model to study lung scarring caused by radiotherapy for cancer. By combining two advanced simulation methods, the model tracks cell damage over time and compares different radiation plans. It shows that splitting radiation doses and using even proton doses reduces lung damage compared to traditional

photon methods, offering a better prediction tool than older models. However, it simulates only a small lung section and relies on computer-based assumptions rather than real patient data, so further testing is needed to confirm its use in humans. The summary of key studies is shown in Table II.

TABLE II
SUMMARY OF KEY STUDIES ON LUNG FIBROSIS (2015–2025)

Author(s)	Journal / Conference	Objective	Method / Approach	Key Findings	Limitations
Batah et al. [5]	Respiratory Medicine	Identify fibrotic patterns in HRCT lung images using AI.	Convolutional Neural Networks (CNNs) with quantitative CT features.	85% accuracy in detecting honeycombing and ground-glass opacities.	Dataset bias, small sample size.
Valand et al. [6]	Neurocomputing	Early detection of lung fibrosis from CT using deep learning.	CNN with transfer learning.	Improved accuracy in fibrotic pattern classification.	Imbalanced dataset, overfitting risk, limited clinical validation.
Yang et al. [7]	IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control	Computational lung ultrasound for ARDS/COVID-19 diagnosis.	Deep learning (CNN, U-Net) vs. model-based methods.	Real-time, explainable imaging; effective artifact segmentation.	Generalization issues, noise sensitivity, lack of annotated data.
Colombi et al. [8]	Diagnostics	AI-driven HRCT Assessment of Interstitial lung diseases (ILDs).	Machine learning and deep learning (CNNs).	Human-level accuracy in pattern classification and prognosis prediction.	Dataset heterogeneity, small samples; needs multicenter validation.
Zhang et al. [9]	Frontiers in Oncology	Evaluate malignancy indicators in solitary fibrous tumors of the chest.	Histopathology and CT imaging validation.	High Ki-67, CT necrosis, chest tightness, advanced age as malignancy markers.	Single-center, small sample, limited therapy comparison.
Marchioni et al. [10]	IJMS	Study mechanical forces in lung fibrosis exacerbation.	Review of human and laboratory studies.	Links lung mechanics to fibrosis progression; suggests therapeutic targets.	Relies on lab studies, lacks human trial evidence.
Shepelkova et al. [11]	IJMS	Compare TB patients with/without prior COVID-19 infection.	Tissue and blood miRNA analysis.	Post-COVID TB patients show more severe inflammation and altered miRNA expression.	Single-center, small sample, no long-term follow- up.
Kumar et al. [12]	BMC Medical Imaging	Review ML methods for lung dis- ease detection from medical images.	Systematic review of CNN, transfer learning, and ensemble methods.	Summarizes imaging datasets and ML techniques; highlights emerging recommendations.	Dataset bias, over-looks rare diseases, reliance on prior studies.
Dorosti et al. [13]	Computers in Biology and Medicine	Optimize CNN for COPD detection from CT.	Manual vs. automated window setting comparison.	Manual adjustment improvedaccuracy (AUC 0.86).	Single centre data, limited to COPD, no external validation.
Larici et al. [14]	European Radiology	Imaging guidelines for fibrotic lung diseases.	Narrative review with expert opinion.	Practical imaging recommendations for diagnosis and monitoring	Lacks new data, quantitative evidence, and expertconsensus gaps
Buccardi et al [20]	Respiratory Research	Automated micro-CT deep learning for fibrosis tracking in mice.	Micro-CT + deep learning vs. manual analysis.	45× faster than manual, correlates with tissue analysis, tracks disease progression/reversal.	Small sample, bleomycin model only, not tested on humans.
Nowak et al. [29]	Scientific Reports	Compare two AI tools for IPF scarring quantification.	Texture analysis vs. binary classification.	Both tools showed similar 3-year survival prediction; simple tool was faster.	Small single-center dataset, needs larger validation.
Cogno et al. [30]	Communications Medicine	Develop a mechanistic model of radiotherapy-induced lung fibrosis.	Agent-based + Monte Carlo simulation.	Shows proton therapy and dose splitting reduce lung damage; better than older models.	Simulates small lung section, uses assumptions, needs human validation.

A. Domain-Based Analysis For Ai And Imaging Techniques in Lung Fibrosis

This research discusses various AI-driven diagnostic and imaging techniques applicable to different clinical and pathological domains of lung fibrosis. These domains employ distinct artificial intelligence methodologies and advanced imaging techniques tailored to their specific features and clinical needs. A concise analysis categorizes these domains into distinct classifications. The categorizstion of these domains according to their attributes, causative factors, imaging patterns, and utilizsd methodologies is encapsulated in the table below, emphasising the most pertinent and commonly employed AI and quantitative imaging techniques for each domain. Classification of Lung Fibrosis Domains with Associated AI-Driven Summarizstion Techniques is highlighted in Table III.

TABLE III
CLASSIFICATION OF LUNG FIBROSIS DOMAINS WITH ASSOCIATED AI-DRIVEN SUMMARIZATION TECHNIQUES

Domain / Disease Type	Useful/Desired AI & Imaging Approaches	Worked in Literature (References)
Idiopathic Pulmonary Idiopathic Pulmonary	CNN-based HRCT classification, Quantitative CT, Deep learning segmentation, Progression prediction, Visual scoring	[4-6], [8],[10],[14],[18-21],[27],[28],[29]
Post-COVID-19 Lung Fibrosis	CNN for ARDS/fibrotic pattern detection, Ground-glass & honeycombing analysis, Quantitative CT, Prognostic modeling	[5],[7],[11],[12],[27],[30]
Radiation-Induced Lung Fibrosis (RILF)	Quantitative CT, Mechanistic modeling (Agent-based + Monte Carlo), CNN-based fibrosis quantification, Proton vs Photon comparison	[3],[8],[18],[30]
Interstitial Lung Diseases (ILDs)	AI-driven HRCT evaluation, CNN segmentation & classification, Visual scoring protocols, Multidisciplinary antifibrotic guidance	[8],[14],[18],[19],[20],[21],[27],[29]
Progressive Pulmonary Fibrosis	HRCT visual scoring, Quantitative CT biomarkers, Deep learning prognosis models, Therapy response assessment	[14],[18],[19],[20],[21],[27],[29]
Preclinical / Animal Models	Automated micro-CT + Deep learning, Bleomycin mouse model analysis, Longitudinal tracking, Therapy response (Nintedanib)	[20],[21],[28]
General Lung Fibrosis & Fibrotic ILA	General Lung Fibrosis & Fibrotic ILA	[4],[5],[6],[7],[8],[9],[12],[13],[16],[19], [23],[27],[29],[30]

IV. LUNG SCARRING: THEMATIC REVIEW FACTORS, IMAGING, AND AI-BASED ASSESSMENT

A. Causes / Risk Factors

The damage to the lungs occurs as a result of harmful particles constantly penetrating the airways and being improperly removed by the body. Lung tissue becomes stiffer and less pliable due to factors such as cigarette smoke, a polluted environment, factory dust, and exposure to chemicals, which are slowly causing it to become harder and less flexible. There are also some infections that have long-term effects, making the lungs less healthy. The aging process also impairs the repair mechanism of the body, and scar-like tissues are produced instead of healthy replacement cells. All in all, poor defence mechanisms and exposure to the environment accelerate the progression of this condition.

B. Imaging Technique

Today, detailed body scans are the most widespread method for detecting stiff and damaged lung areas. These scans reveal distinctive patterns that help specialists gauge the extent of the condition's progression. Other equipment, such as ultrasound, might be useful in emergency cases, and simple X-rays can only provide general details. Nevertheless, the experience of an imaging expert usually determines the final assessment, leading to differences in accuracy. This highlights the increasing demand for more standardised technology-based systems. Figure 2 shows the most prominent imaging approaches that will be used to study lung fibrosis during 2015-2025.

• *AI Models & Performance*: The AI technologies assist in decreasing the human error in decoding body images. Deep learning models can notice the smallest abnormalities, which could have been overlooked in case a manual check is conducted. The level of scarring is also determined in these systems through analysis of texture and lung alterations, providing a more precise assessment of damage. Other researchers indicate that AI is capable of alleviating invasive tests by giving credible early warnings. As times move on, AI is becoming better at monitoring and assisting in the formation of better treatment plans.

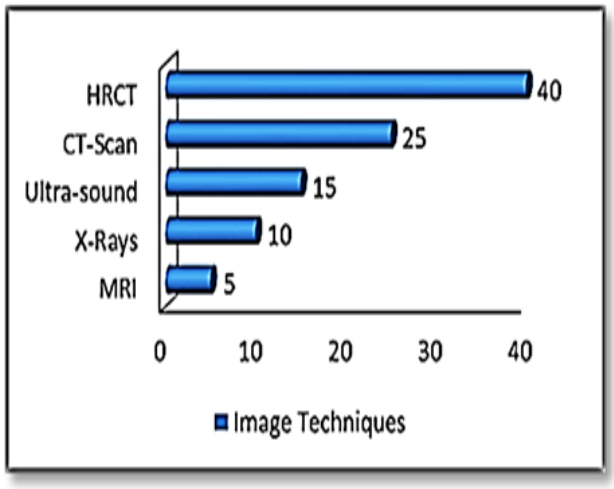

Fig. 2. Imaging techniques used in lung fibrosis research (2015–2025)

• *Treatment Advances:* The use of modern technology is enhancing the process of making decisions in treatment. Digital scoring and AI-based monitoring will facilitate estimating whether a patient's condition is increasing or decreasing gradually. The priority in the future is direct care, where an individual is given a treatment regimen tailored to their specific lung damage pattern. Because of the advancements in artificial intelligence, the ability to provide better and more innovative options for treatment and recovery will increase significantly. Table IV summarises the key applications of AI in the study of pulmonary fibrosis.

TABLE IV
AI BASED APPLICATIONS IN PULMONARY FIBROSIS

Applications	Pros	Cons	Key Results
AI-based diagnosis of pulmonary fibrosis on CT.	Improves accuracy; reduces need for biopsy.	Small dataset; segmentation limits.	Enhanced detection of fibrosis patterns.
AI analysis of COVID-19 ARDS lung images	High accuracy (85%); precise outputs.	Small sample; biased.	Successfully identifies fibrotic patterns.
Genetic & epigenetic data integration for fibrosis prediction.	Early detection support.	Dataset diversity issues; over-fitting risk.	Epigenetic changes improve predictive modelling.
Computational lung ultrasonography for ARDS/COVID-19.	Real-time detection; explainable; non-invasive.	Generalisation issues; limited labels.	Effective segmentation of abnormalities.
AI-driven HRCT evaluation of interstitial lung disease	Human-level accuracy; prognosis support.	Small dataset; heterogeneity.	Accurate quantification of fibrotic regions.
AI-based diagnosis of pulmonary fibrosis on CT.	Improves accuracy; reduces need for biopsy.	Small dataset; segmentation limits.	Enhanced detection of fibrosis patterns.

V. RELATED WORK

The table 5 clearly illustrates the key features of several studies spanning a variety of AI-assisted diagnostic domains. In contrast to previous studies that primarily examine single domain approaches, this review expands to include more advanced components such as the integration of HRCT-AI, quantitative analysis of CT data, and mechanistic modeling, along with micro-CT deep learning, genomics, explainable AI, and therapy-response prediction. The comparison illustrates the fully integrated, cross-domain breadth of this review that clearly distinguishes it from the other, disorganized approaches. The list comparison factor is described as below: F1: Multi-Domain Coverage, F2: AI + HRCT Integration, F3: Quantitative CT F4: Mechanistic Modelling (ABM/Monte-Carlo) F5: Post-COVID Fibrosis F6: Preclinical Micro-CT + DL F7: Genomic/Epigenetic Integration F8: Explainable AI F9: Therapy Response Prediction F10: Combined Classification Table V.

TABLE V
AI BASED APPLICATIONS IN PULMONARY FIBROSIS

Authors	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
Christe [4]	✗	✓	✓	✗	✗	✗	✗	✗	✗	✗
Batah [5]	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗
Valand [6]	✗	✓	✗	✗	✗	✗	✓	✗	✗	✗
Yang [7]	✗	✗	✗	✗	✓	✗	✗	✓	✗	✗
Colombi [8]	✗	✓	✓	✗	✗	✗	✗	✗	✗	✗
Dorosti [13]	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗
Shah [16]	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗
Baratella [18]	✗	✓	✗	✗	✗	✗	✗	✗	✓	✗
Li [19]	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗
Buccardi [20]	✗	✗	✗	✗	✗	✓	✗	✗	✓	✗
Harr [21]	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗
Sturgil [27]	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗

VI. FUTURE DIRECTIONS

AI-assisted imaging captures more intricate details than standard imaging techniques, making it easier to identify slungscarring. This technology lessens the need for human oversight, and the ability to quickly identify small changes in lung tissue could improve treatment options. The studies, however, are limited in scope. This is caused by small sample sizes, unregulated imaging techniques, and the black-box nature of the AI in use. Currently, the best AI systems work in conjunction with human specialists, and even in the future, the gold standard of medical imaging will be human evaluation. For future studies to be more valuable and used more widely in clinical practice, one hopes for the use of large, multicenter datasets, greater data transparency, and AI explainability for clinical integration. Figure 3 compares the precision of AI-based solutions and traditional manual techniques.

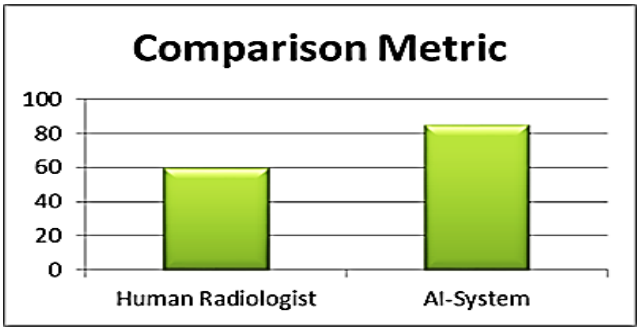

Fig. 3. Comparison Chart: AI vs. Manual Accuracy

Table V clearly illustrates the key features that several future investigations should concentrate on building large, diverse image datasets to boost the generalisation of AI models across different demographics and imaging devices. Fully addressing explainable AI is needed to improve acceptance of automated predictions in decision support. There is an opportunity for integrated imaging to personalise risk predictions and achieve earlier interventions by adding genetic and biomarker data. Furthermore, CT and ultrasound real-time monitoring systems need to be enhanced to safely and accurately manage the progressive stages of disease with minimal radiation. To confidently move these technologies from the research phase to everyday, practised solutions, close partnerships among engineers, radiologists, and clinical decision-makers will be essential. Stiffened, deteriorating lungs, improvements in data, transparency, and clinical testing must be made. The key potential research directions in the diagnosis and analysis methods of lung fibrosis are outlined in Fig 4.

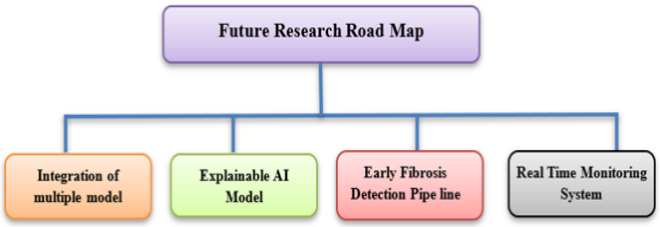

Fig. 4: Future research directions in lung fibrosis detection and analysis

VII. Conclusion

Lung fibrosis is a complicated type of lung disease that is very deadly, with almost no treatment options available. Things like radiation, pulmonary fibrosis, and even COVID-19 can all cause lung fibrosis. From 2015 to 2025, artificial intelligence has advanced significantly and played a major role in lung disease management. A systematic review of 30 studies found that A.I. has matched and even outperformed expert radiologists in early detection, predicting disease progression, recognising disease patterns, and quantifying lung disease. A.I makes prognosis and therapy tracking less invasive by providing objective measures, while saving time that can be spent considering the prognosis and therapy response. Fibrogenesis A.I. enhanced, and computational models, preclinical micro-CT automated analysis and lung ultrasounds also show promise.

Having an accurate lung disease A.I. prediction system with quantification capabilities moves this field towards personalized, proactive treatment. That being said, there is a longer road ahead. From a clinical perspective, larger, more diverse samples, along with multi-centre collaborations, need to be obtained. From the review, it is evident that, among the reviewed technologies, integrated imaging has made the greatest progress to date. This technology will enable fibrosis and lung disease management to operate around early interventions that human disease management has never experienced.

FUNDING STATEMENT

The author(s) received no specific funding for this study.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest to report regarding the present study.

AUTHOR CONTRIBUTIONS

Conceptualization, Syeda Iqra Shakeel and Hafiz Burhan Ul Haq; methodology, Syeda Iqra Shakeel and Sidra Aslam; software, Sabir Abbas. and Hafiz Muneeb.; validation, Hafiz Burhan ul Haq and Saleem Abbas; writing original draft preparation, Syeda Iqra Shakeel.; writing review and editing, Imran Khalid.

FUNDING STATEMENT

This research received no external funding.

INSTITUTIONAL REVIEW BOARD STATEMENT

Not applicable.

INFORMED CONSENT STATEMENT

Not applicable.

DATA AVAILABILITY STATEMENT

Data is available on reasonable request.

References

[1] C. Nardiello and R. E. Morty, “World health observances in September 2020: Sepsis, the lung and heart, and pulmonary fi- brosis in focus,” American Journal of Physiology – Lung Cellular and Molecular Physiology, vol. 319, no. 3, pp. L514–L517, 2020, doi: 10.1152/ajplung.00375.2020.

[2] A. Kaur, S. K. Mathai, and D. A. Schwartz, “Genet- ics in idiopathic pulmonary fibrosis pathogenesis, prognosis, and treatment,” Frontiers in Medicine, vol. 4, 2017, doi: 10.3389/fmed.2017.00154.

[3] P. Wang, Z. Yan, P. K. Zhou, and Y. Gu, “The promising therapeutic approaches for radiation-induced pulmonary fibrosis,” International Journal of Molecular Sciences, vol. 23, no. 23, 2022, doi: 10.3390/ijms232315014.

[4] [4] A. Christe et al., “Computer-aided diagnosis of pulmonary fibrosis using deep learning and CT images,” Investiga- tive Radiology, vol. 54, no. 10, pp. 627–632, 2019, doi: 10.1097/RLI.0000000000000574.

[5] [5] S. S. Batah and A. T. Fabro, “Pulmonary pathology of ARDS in COVID-19: A pathological review for clini- cians,” Respiratory Medicine, vol. 176, p. 106239, 2021, doi: 10.1016/j.rmed.2020.106239.

[6] A. Valand, P. Rajasekar, L. V. Wain, and R. L. Clifford, “Interplay between genetics and epigenetics in lung fibrosis,” International Journal of Biochemistry and Cell Biology, vol. 180, p. 106739, 2025, doi: 10.1016/j.biocel.2025.106739.

[7] T. Yang, O. Karakus, N. Anantrasirichai, and A. Achim, “Current advances in computational lung ultrasound imaging: A review,” IEEE

Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, vol. 70, no. 1, pp. 2–15, 2023, doi: 10.1109/TUFFC.2022.3221682.

[8] D. Colombi et al., "Computer-aided evaluation of interstitial lung diseases," Diagnostics, vol. 15, no. 7, 2025, doi: 10.3390/diagnostics15070943.

[9] J. Zhang, J. Liu, Z. Zhang, and B. Tian, "Solitary fibrous tumors of the chest: An analysis of fifty patients," Frontiers in Oncology, vol. 11, 2021, doi: 10.3389/fonc.2021.697156.

[10] A. Marchioni et al., "Pulmonary stretch and lung mechanotrans- duction," International Journal of Molecular Sciences, vol. 22, no. 12, 2021, doi: 10.3390/ijms22126443.

[11] G. S. Shepelkova et al., "Lung inflammation signature in post- COVID-19 TB patients," International Journal of Molecular Sciences, vol. 24, no. 22, 2023, doi: 10.3390/ijms242216315.

[12] Naseer, Fawad, Abdullah Addas, Muhammad Tahir, Muhammad Nasir Khan, and Noreen Sattar. "Integrating generative adversarial networks with IoT for adaptive AI-powered personalized elderly care in smart homes." *Frontiers in Artificial Intelligence* 8: 1520592, 2025.

[13] Naseer, F., Khan, M. N., & Altalbe, A. "Intelligent time delay control of telepresence robots using novel deep reinforcement learning algorithm to interact with patients," *Applied Sciences*, *13*(4), 2462, 2023.

[14] Jamil, M., Khan, M. N., Rind, S. J., Awais, Q., & Uzair, M. "Neural network predictive control of vibrations in tall structure: An experimental controlled vision," *Computers & Electrical Engineering*, *89*, 106940, 2021.

[15] Khan, M., Hasnain, S. K., & Jamil, M. "*Digital Signal Processing: A Breadth-first Approach*." River Publishers, 2022.

[16] Naseer, F., Khan, M. N., Tahir, M., Addas, A., & Aejaz, S. H. "Integrating deep learning techniques for personalized learning pathways in higher education." *Heliyon*, *10*(11), 2024.

[17] Naseer, F., Khan, M. N., Addas, A., Awais, Q., & Ayub, N. (2025). Game Mechanics and Artificial Intelligence Personalization: A Framework for Adaptive Learning Systems. *Education Sciences*, *15*(3), 2025.

[18] [S. Kumar et al., "Imaging modalities to detection through machine learning paradigms in lung disease diagnosis," BMC Medical Imaging, vol. 24, no. 1, 2024, doi: 10.1186/s12880-024-01192-w.

[19] T. Dorosti et al., "Optimizing convolutional neural networks for COPD detection," Computers in Biology and Medicine, vol. 185, 2025, doi: 10.1016/j.compbiomed.2024.109533.

[20] M. Giordani et al., "Real-time observation of fibrous zeolites re- activity," Minerals, vol. 9, no. 2, 2019, doi: 10.3390/min9020083.

[21] S. N. A. Shah and R. Parveen, "Lung cancer diagnosis using machine learning techniques," Archives of Computational Meth- ods in Engineering, vol. 30, no. 8, pp. 4917–4930, 2023, doi: 10.1007/s11831-023-09964-3.

[22] A. Abidi et al., "Protective effect of Pistacia lentiscus oil," Nutrition and Cancer, vol. 69, no. 3, pp. 490–497, 2017, doi: 10.1080/01635581.2017.1283423.

[23] E. Baratella et al., "Quantification of progressive pulmonary fibrosis by HRCT," La Radiologia Medica, vol. 130, no. 6, pp. 965–977, 2025, doi: 10.1007/s11547-025-01985-1.

[24] D. Li et al., "Prediction of pulmonary function decline," BMC Medical Imaging, vol. 25, no. 1, 2025, doi: 10.1186/s12880-025- 01561-z.

[25] M. Buccardi et al., "Automated micro-CT deep learning ap- proach," Respiratory Research, vol. 24, no. 1, 2023, doi: 10.1186/s12931-023-02432-3.

[26] T. J. Harr et al., "Fibronectin-targeting imaging probe," Respi- ratory Research, vol. 26, no. 1, 2025, doi: 10.1186/s12931-025- 03107-x.

[27] N. Chen and K. Slater, "Solitary fibrous tumour of the liver," World Journal of Surgical Oncology, vol. 15, no. 1, 2017, doi: 10.1186/s12957-017-1102-y.

[28] J. Cao et al., "Nano-bio interface descriptors to predict lung fibrosis," Particle and Fibre Toxicology, vol. 22, no. 1, 2025, doi: 10.1186/s12989-024-00616-3.

[29] Z. Wu et al., "Malignant solitary fibrous tumor," Diagnostic Pathology, vol. 10, no. 1, 2015, doi: 10.1186/s13000-015-0318-9.

[30] H. Ajouz et al., "Surgical considerations in solitary fibrous tumors," Journal of Cardiothoracic Surgery, vol. 18, no. 1, 2023, doi: 10.1186/s13019-023-02168-7.

[31] Ichiki et al., "Solitary fibrous tumor of the lung: A case report," Surgical Case Reports, vol. 34, pp. 3–7, 2017, doi: 10.1186/s40792-016-0286-7.

[32] J. L. Sturgill et al., "Post-intensive care syndrome and pul- monary fibrosis," Scientific Reports, vol. 13, no. 1, 2023, doi: 10.1038/s41598-023-32699-x.

[33] M. N. Hasan et al., "Humanized mouse model of pulmonary fibro- sis," Scientific Reports, vol. 15, no. 1, 2025, doi: 10.1038/s41598- 025-18370-7.

[34] S. Nowak et al., "Multi-texture fibrosis analysis," Scientific Re- ports, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-85135-7.

[35] N. Cogno, R. Bauer, and M. Durante, "Mechanistic model of radiotherapy-induced lung fibrosis," Communications Medicine, vol. 4, no. 1, 2024, doi: 10.1038/s43856-024-00442-w.

[36] N. Cogno, R. Bauer, and M. Durante, "Mechanistic model of radiotherapy-induced lung fibrosis using coupled 3D agent-based and Monte Carlo simulations," Commun. Med., vol. 4, no. 1, pp. 1–14, 2024, doi: 10.1038/s43856-024-00442-w.