ISSN: 2581-3404 (Online) IF: 5.86 (SJIF)
IJIRTM, Volume-9, Issue-5, October-2025

# An Overview of Deep Learning Techniques for Interstitial Lung Disease (ILD) Diagnosis and Prediction

Sameer Dubey[1], Dr. Gourav Shrivastava[2]
[1]Research Scholar, Sanjeev Agrawal Global Educational University, Bhopal
[2]Professor, Sanjeev Agrawal Global Educational University, Bhopal
[1]dubeysameer83@gmail.com, [2]gourav.s@sageuniversity.edu.in

**Abstract.** *The broad category of pulmonary conditions known as interstitial lung disease (ILD), which is marked by fibrosis and inflammation, makes early diagnosis and categorization extremely difficult. Deep Learning (DL) and Machine Learning (ML), two recent developments in artificial intelligence (AI), have demonstrated impressive promise in improving ILD detection, segmentation, and prognosis. The performance of state-of-the-art techniques in ILD pattern recognition and clinical relevance are highlighted in this survey paper, which includes a thorough analysis of convolutional neural networks (CNNs), Vision Transformers, U-Net variants, hybrid radiomics approaches, and semi-supervised segmentation frameworks. Preprocessing, segmentation, and classification—three crucial phases in ILD image analysis—are rigorously analyzed using methods such Contrast Limited Adaptive Histogram Equalization (CLAHE), adaptive filtering, Fuzzy C-Means clustering, and feature extraction discussed in detail. The study also examines issues such the lack of annotated datasets, variations in lung anatomy, acquisition problems, and the requirement for models that are both clinically deployable and explicable. The survey also indicates research shortcomings, such as inadequate large-scale validation, integration of multimodal clinical data, and understudied forms of ILD following COVID-19. This review offers a thorough viewpoint on AI-driven ILD analysis by combining recent research, highlighting the potential for reliable, comprehensible, and scalable solutions for precise diagnosis, prognosis, and early intervention in clinical practice.*

***Keywords:*** Interstitial Lung Disease (ILD), Deep Learning, Convolutional Neural Networks, Medical Image Analysis, Image Segmentation, Feature Extraction, Machine Learning.

## Introduction

The term interstitial lung disease (ILD) describes a collection of lung conditions that result in inflammation and fibrosis, or scarring, in the lung tissues, particularly in the areas around the alveoli, or air sacs [1]. The causes, signs, severity, and results of these illnesses vary [2]. While Idiopathic Pulmonary Fibrosis (IPF) and non-IPF progressive fibrosing ILDs continue to worsen over time, causing breathing difficulties and even early death despite medical care, other types of ILD can recover on their own without treatment [3]. Because of its accuracy and non-invasiveness, digital imaging has emerged as the go-to method for identifying serious illnesses [4]. Imaging offers comprehensive insights into internal anatomy in the investigation of lung diseases, increasing the precision of diagnosis and treatment [5]. However, despite research linking vaccination and other factors to elevated risks of ILD, routine lung exams slowed during the pandemic due to inadequate resources [6]. ILD is common in India, and correctly classifying disease is extremely difficult because to its intricate and varied lung patterns. This emphasizes the necessity of sophisticated, automated techniques for early diagnosis and detection [7]. To classify ILDs effectively, deep learning is used to create algorithms that can recognize different ILD subtypes from high-resolution computed tomography (HRCT) scans [8]. CNNs are very well-suited for these kinds of image-based classification jobs. A thorough labeled dataset of HRCT pictures representing various ILD patterns is necessary for the development of this system [9]. Classification accuracy can be further increased by incorporating clinical information and patient history. The algorithm should also be tuned for accuracy and computing efficiency so that it can analyze medical images on a big scale. To guarantee clinical dependability, the model must be validated by comparing its diagnosis with those of skilled radiologists [10]. Since precise segmentation determines the Region of Interest (ROI) and has a major impact on classification performance, lung image segmentation is an essential stage in this procedure [11]. However, segmentation continues to be a significant difficulty because of the lungs' intricate structure and diversity [12]. The goal of this study is to provide effective techniques for ILD image segmentation and classification by utilizing enriched feature sets and fuzzy segmentation. In order to support accurate and timely disease diagnosis, the objective is to increase pattern recognition accuracy for a variety of ILD types. The three main phases of the entire framework are ILD image enhancement, segmentation, and classification [13].

## Challenges And Issues of ILD Images

Feature extraction via picture segmentation is the main method for diagnosing ILD diseases [14]. The efficiency of ILD segmentation can still be increased despite current techniques. Given the many alterations in lung patterns seen throughout the COVID-19 epidemic, identification is essential [15]. This section provides a systematic description of some difficult ILD segmentation problems. Interstitial lung disease (ILD) picture quality and interpretation can be greatly impacted by ILD image capture artifacts. During the imaging process, these abnormalities might originate from a number of sources, such as respiratory movements, patient movement, or equipment malfunctions. Motion blur, streaking, and beam hardening are examples of common aberrations that can mask significant lung structures or produce erroneous patterns that resemble ILD characteristics [16]. Advanced reconstruction algorithms and respiratory gating techniques are frequently used to reduce these artifacts. Their existence can still make picture analysis more difficult, nevertheless, and could result in misunderstandings or worse accuracy in automated classification systems [17]. To achieve correct diagnosis and prevent misdiagnosis of ILD patterns, radiologists and computer-aided diagnostic tools need to be aware of these artifacts [18].

A hexagonal layout describing the difficulties in classifying ILD images is shown in Figure 1. Among these difficulties are:

a) Pre-processing- Challenges in getting the pictures ready for analysis.

b) The Effects of Aging- Age-related changes' effects on how images are interpreted

c) Acquisition Artefacts- Problems resulting from the process of acquiring images

d) Structural Heterogeneity- Variability in lung structures that makes consistent classification more difficult

e) Classifier and Feature Vector Selection- Difficulties in selecting relevant image features and suitable classification algorithms.

f) Clustering Accuracy and Speed- Restrictions on the analysis-related clustering approaches' accuracy and speed.

The complex nature of the difficulties in correctly classifying ILD from medical images is illustrated in figure 1. The overall complexity of creating strong and trustworthy categorization systems is increased by each difficulty.

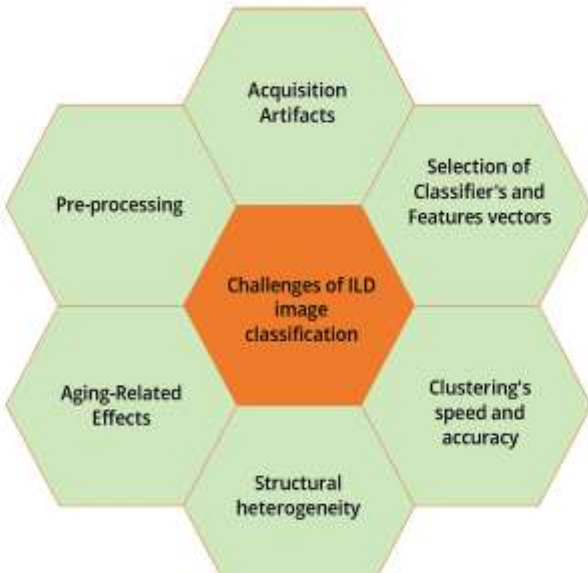


**Figure 1:** Challenges of ILD classification.

## Literature Review

A major breakthrough in improving disease categorization and patient care was taken when Jayalakshmi Ramachandran Nair et al. [1] proposed the MufiNet-DCGAN framework to improve medical picture quality for ILD diagnosis, with 98.75% accuracy with good precision, recall, and F1-score. A trustworthy reference for clinical practice, PMFF-Net was created by Ming-wei Xu et al. [2] to classify UIP, NSIP, OP, and normal HRCT scans from 180 patients. It achieved 92.84% accuracy and outperformed doctors at different seniority levels. Using quantitative metrics such as lung volume, mean lung density, and high attenuation areas, Kai Yang et al. [3] examined CT scans of patients with PM/DM-ILD. With an accuracy of 0.778 and an AUC of 0.843, their Random Forest model showed excellent diagnostic efficacy in identifying ILD using quantitative CT. A hybrid DenseNet169–Vision Transformer (ViT-ILD) model was presented by Sanjib Saha et al. [4] for the classification of lung diseases. The approach obtained 82.75% accuracy, 100% precision, and an F1-score of 82.35% on the ILD MedGift dataset by utilizing self-attention and positional encoding; however, additional refinement is required for clinical implementation. A dual strategy incorporating radiomic and deep learning characteristics from CT images was proposed by S. Kumarganesh et al. [5]. Deep learning classification was handled by an attention-based CNN, while radiomic features were tested with RBFNN and optimized using Particle Swarm Optimization. When both were combined, performance improved and classification accuracy increased by 5% compared to ensemble approaches. When taken as a whole, this research demonstrates how deep learning, transformers, and hybrid models greatly improve ILD diagnosis by providing reliable, effective, and practically applicable solutions. Deep learning-based CT quantification in ILD was assessed by Seok

Young Koh et al. [6], who correlated fibrosis and the overall amount of ILD with radiologist evaluations and the loss in forced vital capacity (FVC). Fibrosis growth was a strong predictor of poor survival (HR up to 2.9) in 468 individuals, validating quantification as a separate prognostic factor. In their assessment of 26 ML research on ILD, Geran Maule et al. [7] focused on prognostic modeling, biomarker discovery, and diagnostic imaging. ML models, particularly CNNs and transformers, frequently performed on par with or better than experts; however, validation, interpretability, and workflow integration are necessary for clinical adoption. VGG16 and VGG19 were used by Hüseyin Alper Kiziloğlu et al. [8] to categorize ILD patterns (UIP, NSIP, normal lung). VGG16 and VGG19 demonstrated a significant ability to distinguish between ILD subtypes using HRCT images, with 95.02% and 98.05% accuracy, respectively. Imbio Lung Texture Analysis was used by Theodoros Karampitsakos et al. [9] to study post-COVID-19 ILD. ML-based radiography models were useful in identifying fibrotic-like alterations early on, which could help direct antifibrotic treatment in patients with post-acute sequelae. In order to classify ILD, Ethan Dack et al. [10] examined AI-driven diagnostic methods that integrated CT, pulmonary function testing, demographics, and histology. They highlighted the value of multimodal data, the shortcomings of current models, and the necessity of comprehensive systems for predicting prognosis and progression. Xueyan Mei et al. [11] classified five types of ILD and predicted 3-year survival using a transformer model using RadImageNet pretrained models with multimodal data. Their technology offers dynamic clinical decision support for diagnosis, categorization, and prognosis. Using HRCT images, Vanita Dnyandev Jadhav et al. [12] suggested a two-phase deep learning method for diagnosing ILD. The lung was segmented using a c-GAN, and ResNet50 features were then categorized into seven ILD classes using SVM. With an accuracy of 94.65% for normal class and 84.12% for consolidation, this approach outperformed patch- and whole-image-based algorithms and did away with the necessity for ROI extraction. To predict UIP on chest CT scans, Jonathan H. Chung et al. [13] created an automated AI algorithm. The model, which was trained on 2,907 CTs, demonstrated 81% in a multicenter ILD cohort and 93% sensitivity and 86% specificity in the performance set. Although real-world validation is required, the results showed potential for clinical adoption and were in line with radiologist visual UIP classifications and survival outcomes. A lung graph-based machine learning approach was presented by Haishuang Sun et al. [14] in order to detect f-ILD from 417 HRCTs. A Weighted Ensemble model made use of radiomic information encoded into lung graphs. With a patient-level accuracy of 0.986 compared to 0.918, 0.822, and 0.904, the system outperformed three radiologists, demonstrating its usefulness for objective ILD diagnosis. Using 629 patient HRCTs, Jingping Zhang et al. [15] created a deep learning model for the classification of IIM-ILD imaging patterns. The model's accuracies were 0.724 and 0.795, and its AUCs were 0.885 (internal test) and 0.835 (external validation). It showed promise as a trustworthy tool for radiological decision support. ESSegILD, a semi-supervised segmentation technique based on HRNet and iterative pseudo-label re-training, was introduced by Guang-Wei Cai et al. [16]. The model outperformed state-of-the-art segmentation techniques in ILD pattern recognition by incorporating self-training and consistency regularization. For ILD screening, Surendra Reddy Vinta et al. [17] suggested a hybrid deep learning network. RAPNet extracted features, MobileUNetV3 classified five ILD classes, and an enhanced U-Net++ segmented lungs. Improvements made step-by-step resulted in improved ILD database performance. In their review of DL applications in ILD classification and prognosis, Yisong Wang et al. [18] highlighted ensemble learning as a promising avenue to address data imbalance, decrease training time, and increase accuracy. For wider clinical adoption, they called for development into explainable and deployable DL architectures, highlighting interpretability issues.

**Table 1: Summary of AI and ML Approaches for Interstitial Lung Disease (ILD) Diagnosis and Prognosis.**

| Ref. & Authors | Approach / Model | Dataset / Target | Key Results | Remarks |
|---|---|---|---|---|
| [1] Jayalakshmi R. Nair et al. | MufiNet-DCGAN | ILD HRCT images | 98.75% accuracy, high precision/recall/F1 | Enhances medical image quality, improves classification |
| [2] Ming-wei Xu et al. | PMFF-Net | 180 HRCT scans (UIP, NSIP, OP, normal) | 92.84% accuracy, outperformed physicians | Reliable for clinical practice |
| [3] Kai Yang et al. | Random Forest + Quantitative CT | PM/DM-ILD CT data | AUC = 0.843, Accuracy = 0.778 | Strong diagnostic efficiency |
| [4] Sanjib Saha et al. | DenseNet169 + Vision Transformer (ViT-ILD) | ILD MedGift dataset | 82.75% accuracy, 100% precision | Needs optimization for clinical use |
| [5] S. Kumarganesh et al. | Hybrid (Radiomics + Attention CNN) | CT scans | 5% higher accuracy vs. ensembles | Dual approach improves robustness |
| [6] Seok Young Koh et al. | Deep learning CT quantification | 468 ILD patients | Fibrosis extent predicted survival (HR up to 2.9) | Independent prognostic factor |
| [7] Geran Maule et al. | Review (26 ML studies) | ILD diagnosis/prognosis | CNNs/Transformers matched experts | Emphasis on validation & interpretability |
| [8] H.A. Kiziloğlu et al. | VGG16 & VGG19 | HRCT scans | VGG16: 95.02%, VGG19: 98.05% | Effective ILD subtype classification |
| [9] T. Karampitsakos et al. | Imbio Lung Texture Analysis | Post-COVID-19 ILD | Early detection of fibrotic changes | Guides antifibrotic therapy |
| [10] Ethan Dack et al. | Review of AI tools | CT, PFTs, demographics, histology | Highlighted strengths & weaknesses | Need for multimodal/holistic systems |
| [11] Xueyan Mei et al. | RadImageNet + Transformer | 5 ILD types | Classification + 3-year survival prediction | Supports diagnosis, classification, prognosis |
| [12] Vanita D. Jadhav et al. | c-GAN + ResNet50 + SVM | HRCT (7 ILD classes) | 94.65% (normal), 84.12% (consolidation) | No ROI needed, better than patch-based |

| | | | | |
|---|---|---|---|---|
| [13] J.H. Chung et al. | AI for UIP detection | 2,907 CTs | Sens. 93%, Spec. 86% (perf. set); 81/77% (multi-center) | Matches radiologists, needs validation |
| [14] Haishuang Sun et al. | Lung graph-based ML + Ensemble | 417 HRCTs | Accuracy 0.986 vs. radiologists (0.918/0.822/0.904) | Outperforms experts |
| [15] Jingping Zhang et al. | DL for IIM-ILD patterns | 629 HRCTs | AUC: 0.885 (internal), 0.835 (external) | Reliable diagnostic tool |
| [16] Guang-Wei Cai et al. | ESSegILD (HRNet + pseudo-labels) | HRCT | Improved ILD segmentation | Outperformed state-of-art methods |
| [17] S.R. Vinta et al. | Hybrid (U-Net++, RAPNet, MobileUNetV3) | ILD database | Effective 5-class ILD classification | Stage-wise improvements boost results |
| [18] Yisong Wang et al. | Review of DL + ensemble | ILD classification/ prognosis | Ensemble learning improves performance | Calls for explainable, deployable models |

Significant studies using ML, AI, and DL for ILD detection, classification, and prediction are compiled in Table 1. High accuracies (82–99%) were attained using models including CNNs, Vision Transformers, U-Net++, and semi-supervised frameworks, frequently outperforming radiologists. Robustness, interpretability, and diagnostic efficiency were enhanced by hybrid techniques that combined radiomics and attention-based networks; lung graph-based machine learning, for example, achieved an accuracy of 0.986. AI also showed promise in post-COVID ILD identification, survival prediction, and fibrosis quantification. The need for explainable, verified, and clinically deployable AI solutions for ILD treatment is highlighted by the difficulties that still exist despite these advancements, such as a lack of interpretability, data imbalance, and insufficient clinical validation.

***Research Gaps-*** Although deep learning has made considerable progress in ILD classification and prognosis, several research obstacles still remain. The majority of current models have not been extensively evaluated in actual clinical situations, across a range of populations and imaging modalities, despite their strong performance on test datasets. Doctors find it difficult to trust deep learning systems because many of them behave like "black boxes," providing no context for their predictions. Large, well-labeled, and balanced datasets are also lacking, and the majority of studies only combine imaging data without incorporating additional pertinent information such as genetic data, patient history, or pulmonary function tests. Results from different studies are hard to compare and replicate when there are no common benchmarks. Furthermore, there is currently no study on forecasting long-term results, therapy response, and illness progression. High processing demands, restricted scalability, and inadequate clinical system integration are further difficulties. Furthermore, research on post-COVID-19 ILD instances is still lacking, and promising techniques like federated learning and ensemble learning are still not widely applied in this area.

**Overview of Deep Learning in Medical Imaging And ILD Diagnosis**

A significant subgroup of artificial intelligence (AI) is machine learning (ML), which allows computer systems to learn particular tasks on their own using data-driven experience rather than explicit programming, as seen in figure 2. Multi-layer neural network designs are used in DL, a sophisticated subfield of machine learning, to automatically learn hierarchical data representations. Because each layer in these topologies processes the input in a nonlinear way, the network is able to extract features that are more complicated and abstract. One of DL's main advantages is that it can effectively execute parallel calculations and learn on its own without human assistance, which makes it ideal for jobs involving language, speech, and image recognition.

The Neocognitron model (1980), a pattern recognition architecture with neurophysiological inspiration, served as the early basis for DL. A significant turning point was the 1989 development of the backpropagation technique, which allowed networks to learn through mistake correction and produced innovations like the recognition of handwritten digits. Later, CNNs transformed computer vision, especially AlexNet (2012), which achieved state-of-the-art performance in large-scale image categorization after being trained on 1.2 million images. CNNs are perfect for medical imaging applications because of their exceptional ability to derive spatial hierarchies from 2D and 3D data.

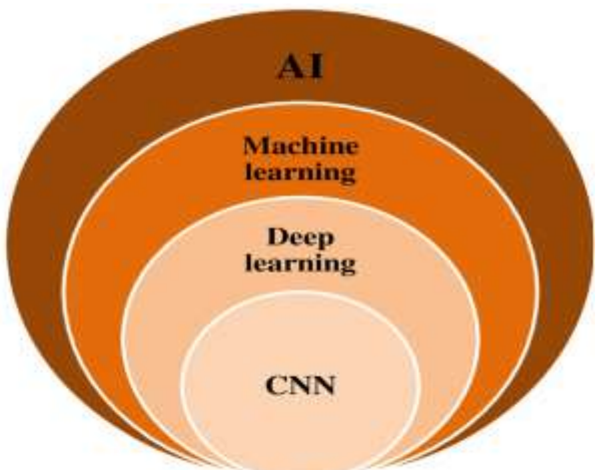


**Figure 2:** Artificial intelligence progression diagram.

Deep Learning has become a potent tool for feature extraction, classification, and quantitative pattern analysis in the medical field. Significant progress has been achieved across a variety of imaging modalities thanks to developments in GPU and CPU architectures, more data availability, and innovative DL methods. However, big and balanced datasets are necessary for the effective application of DL in healthcare, which presents a significant problem given that medical data is frequently expensive, limited, and requires expert annotation. These restrictions impair the performance and generalization of the model. Two methods of data encoding are frequently employed in medical imaging: 2D/3D pixel data for convolutional networks and vector-based features for multi-layer perceptrons. This study uses HRCT scans to categorize ILD from several subtypes using a compact CNN architecture, which is a variation of VGGNet. ILD is a complicated collection of lung conditions marked by fibrosis and inflammation, which results in decreased gas exchange, aberrant lung function, and increasing dyspnea. Malignancies like lymphangitic carcinomatosis, pulmonary edema, and bacterial pneumonia are examples of differential diagnoses. A thorough patient history, occupational exposure, and medication assessment are frequently required for clinical diagnosis. Radiological evaluation and, in rare instances, surgical or transbronchial lung biopsies follow.

Invasive procedures like open chest biopsies carry a significant risk, and clinical diagnosis accuracy for ILD is still less than 20% despite these diagnostic techniques. DL-powered computer-assisted diagnostic instruments are therefore crucial for enhancing non-invasive assessment, accuracy, and efficiency. However, there are still issues with obtaining high-quality annotated datasets, guaranteeing an adequate amount of data, and meeting computational requirements.

Transfer learning, which uses pretrained CNN models (such as AlexNet, GoogLeNet, and VGGNet) trained on big natural image datasets and fine-tunes them for medical imaging applications, has become popular as a solution to data shortage. Low-level characteristics like gradients and texture descriptors are shared by both natural and medical images, despite their differences in color and structure. Additional tools for segmentation and detection include the Scale-Invariant Feature Transform (SIFT) and the Histogram of Oriented Gradients (HOG). As a result, combining DL with transfer learning approaches offers a viable path toward efficient ILD diagnosis and classification with sparse medical data.

**Basic Architecture of ILD Patterns Detection**

The key image processing steps in ILD are shown in Figure 3. To improve the visual quality of ILD images, a pre-processing step is first conducted to increase contrast and eliminate noise. After this improvement, the desired components are separated using an image segmentation technique. The goal of the iterative segmentation procedure is to find the best answer.

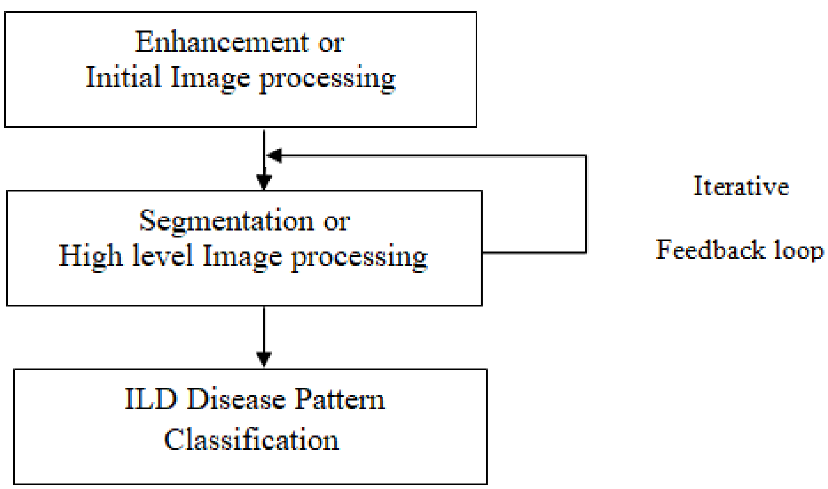


**Figure 3:** Basic processing step for ILD patterns detection.

Segmentation is frequently used in high-level image processing applications. By modifying the image utilizing the feedback path that exists between intermediary steps, segmentation is achieved. An ILD image's features are taken out in the third and last step. Both the accuracy and precision of the segmentation step and the effectiveness of the augmentation stage determine how well a classification works. Therefore, enhancing techniques must be used to improve the intended image's quality before segmenting it. Figure 4 displays the sequential steps of the block diagram for ILD pattern classification in the suggested methodology.

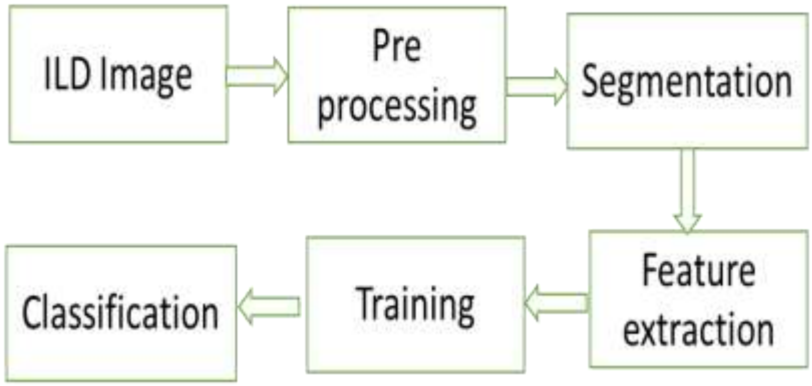


**Figure 4:** Block Diagram of Proposed Method.

To classify ILD images, segmented outputs are used to extract features. The features required for categorization are extracted from these segmented images. ILD pattern classification is a challenging task. Although the majority of current classification techniques are time-efficient because they employ supervised learning models, creating an easy-to-use system for efficient pattern classification with unsupervised algorithms is still very difficult.

***Segmentation and Pre-processing Methodologies-*** Preprocessing is essential for improving ILD photos since it reduces noise and boosts contrast. Compared to standard histogram equalization, Contrast Limited Adaptive Histogram Equalization (CLAHE) is a useful technique for improving medical images, increasing detail visibility, and possibly highlighting ILD features. Medical picture denoising also benefits from adaptive filters; adaptive fuzzy filters, for example, have demonstrated excellent efficacy in reducing impulsive noise. Segmentation techniques such as thresholding, region growing, level set methods, and fuzzy C-Means (FCM) clustering are frequently used for ILD classification. Because it can deal with tissue boundary uncertainty, FCM is one of these that is frequently used for medical image segmentation. Deep learning-based methods and enhanced FCM variants offer potential for ILD, despite not being widely used in this field. All things considered, a sequential and combined image processing framework that guarantees high accuracy at each step—preprocessing, segmentation, and classification—is still required.

***Classifier Steps for ML-Based Classification-*** The first step in creating a basic deep learning classifier for ILD image classification is to collect a wide range of data that covers different ILD patterns and severity levels. Preprocessing should then be carried out, including noise or artifact reduction, image scaling, and intensity normalization. employ texture and shape-based features for feature extraction, or employ CNNs that have already been trained to capture deep representations. Start with basic classifiers like SVM or Random Forest when choosing a model, then move on to CNNs for more complex categorization. Apply cross-validation, separate the dataset into training, validation, and testing subsets, and employ data augmentation to increase variety when training the model. Lastly, to guarantee robustness and dependability, assess model performance using metrics like accuracy, precision, recall, and F1-score.

***Support Vector Machine (SVM) Based Classification for ILD-*** There are various advantages to using SVM-based classification for ILD. SVMs are ideal for complex medical image analysis because of their exceptional performance with high-dimensional data. They lower the chance of overfitting by skillfully managing the trade-off between generalization and model complexity. Different kernel functions can be used into SVMs, allowing for non-linear decision boundaries that capture complex ILD patterns. They increase robustness and classification accuracy by optimizing the margin between classes. SVMs can also handle imbalanced datasets, which is a common problem in medical imaging. Insights into the most pertinent ILD characteristics for categorization can be gained by feature importance analysis, which is made possible by their interpretability.

## Conclusion

Because of its varied lung patterns, overlapping clinical symptoms, and the shortcomings of traditional imaging and biopsy techniques, ILD poses a challenging diagnostic problem. Recent research shows that AI-driven methods, especially DL and ML models, provide notable enhancements in ILD image processing, including prognosis prediction, segmentation, feature extraction, and classification. In addition to demonstrating the promise for early disease identification and individualized patient care, techniques including CNNs, Vision Transformers, U-Net variations, and hybrid radiomics models have achieved excellent accuracy, frequently outperforming human expert performance. Notwithstanding these developments, there are still a number of significant gaps, such as the absence of multimodal data integration, the lack of balanced and annotated datasets, the restricted interpretability of AI models, and the lack of extensive clinical validation. In order to address post-COVID-19 ILD and guarantee generalizability across a range of populations, future research should concentrate on creating strong, explicable, and clinically deployable frameworks that incorporate imaging, clinical, and patient-specific data. All things considered, AI and DL have enormous potential to transform ILD diagnosis and treatment, opening the door to more precise, effective, and patient-centered medical treatments.

## References

[1] Nair, Jayalakshmi Ramachandran, Sumathy Pichai Pillai, and Rajkumar Narayanan. "Enhanced visual insights and diagnosis of interstitial lung diseases via Mufinet-DCGAN framework." Engineering and Applied Science Research 52, no. 4 (2025): 352-363.

[2] Xu, Ming-wei, Zheng-hua Zhang, Xiao Wang, Chun-tao Li, Hui-yun Yang, Ze-hua Liao, and Jian-qing Zhang. "PMFF-Net: A deep learning-based image classification model for UIP, NSIP, and OP." Computers in Biology and Medicine 195 (2025): 110618.

[3] Yang, Kai, Yanrong Chen, Liyu He, Yadan Sheng, He Hei, Jingping Zhang, and Chenwang Jin. "Application of Quantitative CT and Machine Learning in the Evaluation and Diagnosis of Polymyositis/Dermatomyositis-Associated Interstitial Lung Disease." Academic Radiology (2025).

[4] Saha, Sanjib, Abhishek Kumar, and Debashis Nandi. "ViT-ILD: a vision transformer-based neural network for detection of interstitial lung disease from CT images." Procedia Computer Science 235 (2024): 779-788.

[5] Kumarganesh, S., K. V. M. Shree, P. Rishabavarthani, C. Ganesh, S. Anthoniraj, B. Thiyaneswaran, Lam Dang, K. Martin Sagayam, Linh Dinh, and Hien Dang. "Aggregated approach for

interstitial lung diseases classification using attention-based CNN and radial basis function neural network." Systems and Soft Computing 7 (2025): 200228.

[6] Koh, Seok Young, Jong Hyuk Lee, Hyungin Park, and Jin Mo Goo. "Value of CT quantification in progressive fibrosing interstitial lung disease: a deep learning approach." European Radiology 34, no. 7 (2024): 4195-4205.

[7] Maule, Geran, Joseph Ayim Zamora, Aseed Mestarihi, Akil Augustus, Kyle Da Silva, John Rickards, Mohammad Khraisat, and Jon Beacher. "AI-Enhanced Approaches to Interstitial Lung Disease: A Review of Machine Learning Advances." EMJ Respir. 2025; https://doi.org/10.33590/emjrespir/MDKO8232

[8] Kiziloğlu, Hüseyin Alper, Emrah Çevik, and Kenan Zengin. "Evaluation of Interstitial Lung Diseases with Deep Learning Method of Two Major Computed Tomography Patterns." Current Medical Imaging 20, no. 1 (2024): e15734056279295.

[9] Karampitsakos, Theodoros, Vasilina Sotiropoulou, Matthaios Katsaras, Panagiota Tsiri, Vasiliki E. Georgakopoulou, Ilias C. Papanikolaou, Eleni Bibaki et al. "Post-COVID-19 interstitial lung disease: Insights from a machine learning radiographic model." Frontiers in medicine 9 (2023): 1083264.

[10] Dack, Ethan, Andreas Christe, Matthias Fontanellaz, Lorenzo Brigato, Johannes T. Heverhagen, Alan A. Peters, Adrian T. Huber, Hanno Hoppe, Stavroula Mougiakakou, and Lukas Ebner. "Artificial intelligence and interstitial lung disease: diagnosis and prognosis." Investigative radiology 58, no. 8 (2023): 602-609.

[11] Mei, Xueyan, Zelong Liu, Ayushi Singh, Marcia Lange, Priyanka Boddu, Jingqi QX Gong, Justine Lee et al. "Interstitial lung disease diagnosis and prognosis using an AI system integrating longitudinal data." Nature communications 14, no. 1 (2023): 2272.

[12] Jadhav, Vanita Dnyandev, and Lalit Vasantrao Patil. "Interstitial Lung Diseases Classification in the Context of Pharmaceutical Education and Research: A Two-Level Deep Learning Approach." Indian Journal of Pharmaceutical Education and Research, 58, no. 3s (2024): s787-s795.

[13] Chung, Jonathan H., Lydia Chelala, Janelle Vu Pugashetti, Jennifer M. Wang, Ayodeji Adegunsoye, Alexander W. Matyga, Lauren Keith et al. "A deep learning-based radiomic classifier for usual interstitial pneumonia." Chest 165, no. 2 (2024): 371-380.

[14] Sun, Haishuang, Min Liu, Anqi Liu, Mei Deng, Xiaoyan Yang, Han Kang, Ling Zhao et al. "Developing the lung graph-based machine learning model for identification of fibrotic interstitial lung diseases." Journal of Imaging Informatics in Medicine 37, no. 1 (2024): 268-279.

[15] Zhang, Jingping, Liyu He, Ying Wei, Jiayin Tong, Kai Yang, Jiaojiao Wu, Youmin Guo, Feng Shi, and Chenwang Jin. "Deep learning for classifying imaging patterns of interstitial lung disease associated with idiopathic inflammatory myopathies." Scientific Reports 15, no. 1 (2025): 31655.

[16] Cai, Guang-Wei, Yun-Bi Liu, Qian-Jin Feng, Rui-Hong Liang, Qing-Si Zeng, Yu Deng, and Wei Yang. "Semi-supervised segmentation of interstitial lung disease patterns from CT images via self-training with selective re-training." Bioengineering 10, no. 7 (2023): 830.

[17] Vinta, Surendra Reddy, B. Lakshmi, M. Aruna Safali, and G. Sai Chaitanya Kumar. "Segmentation and classification of interstitial lung diseases based on hybrid deep learning network model." IEEE Access 12 (2024): 50444-50458.

[18] Wang, Yisong, Youlan Shang, Jiaqi Yao, Hao Li, Xiaoyan Kui, Wei Zhao, and Jun Liu. "Deep learning in interstitial lung disease: classification and prognostic insights." Radiology Science 3, no. 01 (2024): 41-49.