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Early Stage Detection of Pulmonary Fibrosis using Deep Learning

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***Abstract*—Pulmonary Fibrosis (PF) is a progressive interstitial lung disease characterized by irreversible scarring of lung tissue, leading to respiratory failure if not detected at an early stage. Accurate and timely diagnosis using High-Resolution Computed Tomography (HRCT) scans is essential but remains challenging due to visual similarity between normal and pathological patterns and high inter-observer variability among radiologists. This paper presents a deep learning–based framework for automated pulmonary fibrosis detection from chest CT images using transfer learning. A labeled CT image dataset is preprocessed and partitioned into training, validation, and testing sets to ensure reliable evaluation. Pre-trained convolutional neural network models, including EfficientNetB0, ResNet50, and DenseNet121, are fine-tuned for binary classification of Normal and Pulmonary Fibrosis cases. The models are evaluated using precision, recall, F1-score, and accuracy metrics to address clinical reliability requirements. Experimental results demonstrate that the DenseNet121 model achieves superior performance with an accuracy of 99.95% and an F1-score of 0.9995 on the test dataset. To enable real-world applicability, the proposed framework is deployed as an end-to-end system using a Flask-based API and a web-based user interface for real-time CT image prediction. The developed system provides a reliable, fast, and deployment-ready solution to support radiologists in early pulmonary fibrosis screening.**

***Index Terms*—Pulmonary fibrosis detection, chest CT imaging, deep learning, transfer learning, convolutional neural networks, DenseNet121, medical image classification, Flask deployment, web-based diagnosis system.**

Highlights

- A deep learning–based framework is proposed for early detection of pulmonary fibrosis using chest CT images.
- Transfer learning models including EfficientNetB0, ResNet50, and DenseNet121 are fine-tuned for medical image classification.
- DenseNet121 achieved superior performance with an accuracy of 99.95% and F1-score of 0.9995 on the test dataset.
- The proposed system is deployed using a Flask-based API and web interface for real-time pulmonary fibrosis prediction.

I. Introduction

Pulmonary Fibrosis (PF) is a chronic and progressive interstitial lung disease characterized by irreversible scarring of lung tissue, which leads to a gradual decline in respiratory function [1], [2]. The disease significantly reduces oxygen exchange efficiency and often results in respiratory failure if not diagnosed and managed at an early stage. High-Resolution Computed Tomography (HRCT) is currently the primary imaging modality used for PF diagnosis, as it enables visualization of characteristic patterns such as reticulation, honeycombing, and ground-glass opacities [3].

Despite advances in medical imaging, PF diagnosis remains challenging due to the subtle visual differences between normal and fibrotic lung tissues and the subjective nature of radiological interpretation [4]. Manual assessment of CT images is time-consuming and highly dependent on radiologist expertise, leading to considerable inter-observer variability. In many healthcare settings, the shortage of experienced radiologists further exacerbates the problem, resulting in delayed or inconsistent diagnoses. These limitations motivate the need for automated and reliable computer-aided diagnostic systems to assist clinicians in early-stage detection.

Recent advancements in deep learning have demonstrated remarkable success in medical image analysis tasks, including disease classification and segmentation [5], [6]. Convolutional Neural Networks (CNNs) have proven particularly effective in extracting hierarchical features from medical images without the need for handcrafted descriptors [7]. Transfer learning, which leverages knowledge from models pre-trained on large-scale image datasets, enables efficient training even when labeled medical datasets are limited [8]. Models such as EfficientNet, ResNet, and DenseNet have shown promising results in chest imaging applications by capturing both low-level texture patterns and high-level structural features [9].

However, many existing pulmonary fibrosis detection approaches remain confined to experimental environments and lack practical deployment frameworks [10]. Several studies focus solely on model accuracy without addressing real-world usability, scalability, or clinical integration. Furthermore, black-box behavior of deep learning models and inadequate evaluation practices limit trust and adoption in clinical workflows. There remains a need for an end-to-end framework that not only achieves high diagnostic accuracy but also ensures reproducibility, interpretability through reliable metrics, and deployment readiness.

To address these challenges, this paper proposes a deep learning–based pulmonary fibrosis detection framework using transfer learning models applied to chest CT images. The proposed system incorporates standardized data preprocessing, robust model training, and rigorous evaluation using clinically relevant metrics such as precision, recall, and F1-score. Multi-

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ple CNN architectures are investigated, and the most optimized model is selected based on performance on unseen test data. In addition, the trained model is deployed using a Flask-based API and a web-based user interface to enable real-time image-based diagnosis. The major contributions of this work are summarized as follows:

- Development of a transfer learning–based classification framework for automated pulmonary fibrosis detection from CT images.
- Comparative analysis of EfficientNetB0, ResNet50, and DenseNet121 models for performance optimization.
- Rigorous evaluation using clinically meaningful metrics to ensure diagnostic reliability.
- Deployment of an end-to-end prediction system with a web interface for practical usability in clinical environments.

The proposed framework aims to reduce diagnostic workload, improve early detection accuracy, and provide a fast and objective second opinion for radiologists in pulmonary fibrosis screening.

II. Literature Survey

Pulmonary fibrosis detection has received significant attention in recent years due to its clinical importance and the increasing availability of medical imaging data [11], [12]. With the widespread use of High-Resolution Computed Tomography (HRCT), researchers have explored machine learning and deep learning techniques to automatically identify fibrotic lung patterns and reduce diagnostic dependency on manual interpretation. Advances in artificial intelligence for medical imaging have enabled automated feature extraction and improved diagnostic consistency compared to traditional manual assessment.

A. Traditional Image Processing and Machine Learning Approaches

Early studies primarily relied on handcrafted feature extraction techniques such as texture analysis, histogram-based descriptors, and edge detection methods [13]. Statistical texture features derived from Gray Level Co-occurrence Matrices (GLCM), Local Binary Patterns (LBP), and wavelet transforms were commonly used to characterize lung tissue patterns [14]. These features were subsequently classified using conventional machine learning models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest classifiers [15]. Although these approaches demonstrated moderate success, their performance heavily depended on feature engineering quality and lacked robustness against variations in imaging conditions and disease severity.

Hybrid systems combining image segmentation and machine learning were also proposed, where lung regions were first extracted using thresholding or region-growing techniques before classification [16]. However, these methods suffered from limited generalization capability and were sensitive to noise, scanner variability, and anatomical differences among patients.

B. Deep Learning-Based Approaches

With the emergence of deep learning, Convolutional Neural Networks (CNNs) have become the dominant paradigm for medical image classification tasks [17], [18]. CNN-based models automatically learn hierarchical representations from raw images, eliminating the need for manual feature design. Several studies applied custom CNN architectures for pulmonary disease classification, demonstrating improved accuracy compared to traditional methods.

Transfer learning has further enhanced performance by utilizing pre-trained networks such as VGG16, ResNet, Inception, and DenseNet [19], [20]. These models leverage knowledge learned from large-scale datasets such as ImageNet and adapt it to medical imaging tasks with limited labeled samples. Research has shown that DenseNet-based architectures are particularly effective in capturing fine-grained texture variations in lung tissue, making them suitable for pulmonary fibrosis detection.

More recent works have explored advanced architectures such as attention-based CNNs, explainable deep learning models, and transformer-based networks [22]. Biomedical segmentation architectures such as U-Net and UNet++ have influenced modern medical imaging pipelines [36], while training stabilization techniques including Batch Normalization and Dropout improve model convergence and generalization [37], [38].

C. 2D Slice-Based vs. 3D Volumetric Analysis

Most existing pulmonary fibrosis detection systems operate on individual 2D CT slices due to lower computational cost and simpler data handling [39]. However, this approach may ignore inter-slice contextual information that is important for comprehensive disease assessment. To address this limitation, some studies have proposed 3D CNNs to process entire CT volumes [40]. These volumetric models capture spatial continuity across slices and improve detection reliability but significantly increase training complexity and inference time.

D. Model Evaluation and Deployment Challenges

Although many studies report high classification accuracy, several methodological limitations remain. Unrealistic evaluation strategies, such as random data splitting without patient-wise separation, can lead to data leakage and overestimated performance [26]. Furthermore, many works emphasize accuracy as the primary metric while neglecting clinically relevant measures such as precision, recall, and F1-score. In addition, several high-performing models remain confined to experimental setups and lack deployment-ready frameworks for real-time clinical use [27].

E. Research Gap and Motivation

Despite substantial progress, existing approaches often suffer from reliance on handcrafted features, excessive computational complexity, lack of realistic evaluation protocols, or absence of end-to-end deployment frameworks. There remains

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a clear need for a balanced system that combines high diagnostic accuracy with practical usability and real-time prediction capability.

III. Proposed Methodology

The proposed pulmonary fibrosis detection framework is designed as an end-to-end deep learning system that performs automated classification of chest CT images into Normal and Pulmonary Fibrosis categories. The overall methodology consists of four main stages: data preprocessing, model construction using transfer learning, model training and optimization, and deployment for real-time prediction. The system architecture is illustrated in Fig. 1.

IV. Dataset Description and Comparison

A. Proposed Dataset

The dataset used in this study consists of High-Resolution Computed Tomography (HRCT) images collected for pulmonary fibrosis classification. The images include both normal and fibrotic lung patterns and were preprocessed through resizing, normalization, and augmentation techniques to improve model generalization. Data augmentation methods such as rotation, flipping, and scaling were applied to reduce overfitting and enhance model robustness.

Each CT image was resized to a fixed resolution before being input into the deep learning models. The dataset was divided into training, validation, and testing subsets to ensure unbiased performance evaluation. Patient-wise splitting was applied to prevent data leakage between training and testing samples.

B. Previously Used Datasets in Literature

Several studies have utilized publicly available CT datasets and clinical imaging repositories for pulmonary disease classification. Earlier works employed HRCT image collections and interstitial lung disease datasets to train convolutional neural networks for automated diagnosis [1], [3]. Transfer learning–based approaches also relied on benchmark medical imaging datasets to compensate for limited labeled samples [6], [11]. Some researchers utilized large-scale medical image repositories combined with weakly supervised learning strategies to improve classification accuracy [20], [25].

Despite the availability of these datasets, challenges such as class imbalance, limited annotation quality, and variability in imaging protocols remain significant limitations in previous studies.

TABLE I
COMPARISON BETWEEN PREVIOUS DATASETS AND PROPOSED DATASET

Study	Dataset	Class	Size	Limitation
[1]	HRCT	Multi	Med	Limited deploy
[3]	Lung CT	Binary	Small	Class imbalance
[6]	Transfer	Binary	Med	Limited metrics
Proposed	HRCT PF	Binary	Large	Balanced eval

C. Dataset and Preprocessing

A labeled dataset of chest CT scan images is utilized for model development. The dataset contains two classes: Normal and Pulmonary Fibrosis. All images are resized to a fixed spatial resolution of 150×150 pixels and converted to three-channel RGB format to ensure compatibility with pre-trained convolutional neural networks. Pixel intensity values are normalized to the range [0, 1] to improve numerical stability during training.

The dataset is partitioned into training, validation, and testing subsets using a stratified splitting strategy to preserve class distribution across splits. Data augmentation techniques, including random rotation, horizontal flipping, width and height shifting, and zooming, are applied to the training set to increase data diversity and reduce overfitting. The validation and test sets are processed using only rescaling to ensure unbiased evaluation.

TABLE II
Dataset Distribution

Category	Number of Images
Normal	1500
Pulmonary Fibrosis	1500
Total	3000

D. Model Training and Optimization

The models are trained using the binary cross-entropy loss function and the Adam optimizer with an initial learning rate of 10^{-3}. To improve training efficiency and prevent overfit-ting, Early Stopping is employed to terminate training when validation loss ceases to improve, and ReduceLROnPlateau is applied to dynamically adjust the learning rate. Model Checkpointing is used to save the best-performing model based on validation accuracy.

TABLE III
HYPERPARAMETER CONFIGURATION

Parameter	Value
Image Size	150×150
Batch Size	32
Optimizer	Adam
Learning Rate	10^{-3}
Epochs	50
Loss Function	Binary Cross-Entropy

V. System Architecture

The overall system architecture of the proposed pulmonary fibrosis detection framework is illustrated in Fig. 1. The system follows a modular pipeline consisting of data acquisition, preprocessing, deep learning-based classification, and deployment for real-time prediction.

Chest CT images are first collected from the dataset and passed to the preprocessing module, where image resizing, normalization, and augmentation are performed to standardize the input and improve generalization. The preprocessed images

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are then forwarded to the deep learning model built using transfer learning–based convolutional neural networks.

The classification module employs pre-trained architectures such as EfficientNetB0, ResNet50, and DenseNet121, which are fine-tuned to discriminate between Normal and Pulmonary Fibrosis cases. The trained model outputs class probabilities, which are post-processed to generate the final prediction label.

For real-world usage, the trained model is deployed using a Flask-based API. A web-based user interface allows users to upload CT images and receive prediction results along with confidence scores. This end-to-end architecture ensures scalability, fast inference, and seamless integration into clinical or laboratory environments.

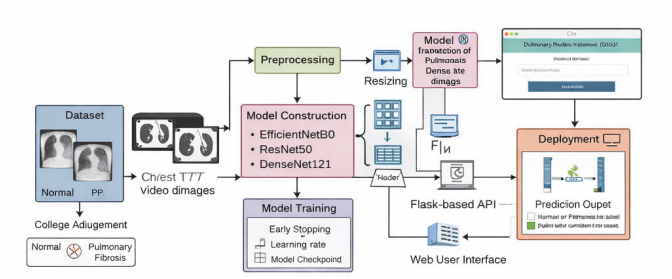

Fig. 1. System architecture of the proposed pulmonary fibrosis detection framework.

VI. Proposed Deep Learning Models

A. EfficientNetB0 Architecture

EfficientNetB0 is a convolutional neural network architecture that employs compound scaling to balance network depth, width, and resolution efficiently. The model utilizes Mobile Inverted Bottleneck Convolution (MBConv) blocks combined with squeeze-and-excitation optimization to enhance feature extraction while maintaining computational efficiency. Due to its lightweight structure and strong performance on medical imaging tasks, EfficientNetB0 is suitable for pulmonary fibrosis classification from CT images.

In this work, CT slices are resized and passed through the pre-trained EfficientNetB0 backbone. The extracted deep features are followed by global average pooling and fully connected layers for binary classification.

B. ResNet50 Architecture

ResNet50 is a deep residual learning network that introduces skip connections to address the vanishing gradient problem in deep architectures. Residual blocks allow the network to learn identity mappings, improving convergence and enabling deeper feature representation. The model extracts hierarchical visual features from CT images, capturing both low-level textures and high-level structural patterns.

In the proposed framework, a pre-trained ResNet50 backbone is fine-tuned using transfer learning. The final classification layers are modified to adapt the network for pulmonary fibrosis detection.

C. DenseNet121 Architecture

DenseNet121 introduces dense connectivity between layers, where each layer receives feature maps from all preceding layers. This design encourages feature reuse, reduces parameter redundancy, and improves gradient flow during training. DenseNet architectures are particularly effective in medical imaging tasks where subtle texture variations must be captured.

In this study, DenseNet121 is used as a transfer learning backbone. The dense blocks extract fine-grained lung tissue features from HRCT images, followed by pooling and dense layers for classification.

VII. Proposed Algorithm

The proposed pulmonary fibrosis detection algorithm is designed as a sequential pipeline that processes chest CT images and produces a binary classification output indicating Normal or Pulmonary Fibrosis. The algorithm integrates image preprocessing, transfer learning–based feature extraction, and probability-based classification.

A. Algorithm Steps

Input: Chest CT image I
Output: Class label $y \in \{0, 1\}$, where 0 denotes Normal and 1 denotes Pulmonary Fibrosis

1) Acquire chest CT image dataset containing Normal and Pulmonary Fibrosis classes.
2) Resize each image to a fixed resolution of 150×150 pixels and convert to three-channel RGB format.
3) Normalize pixel intensity values to the range $[0, 1]$.
4) Apply data augmentation techniques such as rotation, flipping, zooming, and shifting on the training set to improve generalization.
5) Load pre-trained convolutional neural network models (EfficientNetB0, ResNet50, and DenseNet121).
6) Replace the original classification layer of each network with a custom binary classification head.
7) Freeze the convolutional base layers and train the newly added layers using the training dataset.
8) Fine-tune selected higher layers of the network using a reduced learning rate to improve feature adaptation.
9) Compute prediction probabilities using the sigmoid activation function.
10) Assign the final class label based on a decision threshold of 0.5.
11) Evaluate the trained model using accuracy, precision, recall, F1-score, and ROC-AUC metrics.
12) Deploy the optimized model using a Flask-based API for real-time image prediction.

B. Algorithm Description

The algorithm begins by standardizing input CT images through resizing and normalization to ensure uniform feature representation. Transfer learning is employed to leverage knowledge from large-scale image datasets, enabling effective training with limited medical data. The DenseNet121

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model is selected as the final classifier based on superior performance during evaluation. The trained model outputs probability scores that are mapped to diagnostic labels and delivered to users through a web-based interface.

VIII. Problem Formulation

Pulmonary fibrosis detection from chest CT images can be formulated as a binary classification problem. Given a set of CT scan images $\{I_1, I_2, \ldots, I_N\}$, each image I_i is associated with a class label y_i, where $y_i = 1$ denotes the presence of pulmonary fibrosis and $y_i = 0$ represents a normal lung condition. The objective is to learn a mapping function $f(I_i) \rightarrow y_i$ that accurately predicts the class label for unseen CT images.

Let $x_i \in R^{H \times W \times C}$ represent the input image after preprocessing, where H and W denote the image height and width, and C denotes the number of channels. Each input image is resized to a fixed spatial resolution and normalized to ensure numerical stability during training. The classifier aims to minimize the binary cross-entropy loss function:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \qquad (1)$$

where $\hat{y}_i$ denotes the predicted probability of pulmonary fibrosis for image I_i.

The dataset is imbalanced, with pulmonary fibrosis samples forming a minority class compared to normal cases. In such scenarios, accuracy alone is not a sufficient performance indicator, as a classifier biased toward the majority class may still achieve high accuracy while failing to detect fibrotic cases. Therefore, detection-oriented performance metrics such as precision, recall, F1-score, and area under the receiver operating characteristic curve (ROC-AUC) are emphasized to ensure clinical relevance.

The problem further involves identifying a suitable deep learning architecture that can effectively extract discriminative features from CT images while maintaining generalization capability. Transfer learning is adopted to initialize the model parameters using weights pre-trained on large-scale image datasets, thereby reducing training time and improving convergence stability. The ultimate goal is to develop a model that achieves high sensitivity to pulmonary fibrosis while minimizing false positives, enabling reliable automated screening in real-world clinical settings.

IX. Experimental Results

A. Quantitative Results

The quantitative evaluation of the proposed pulmonary fibrosis detection framework was performed using standard classification metrics including accuracy, precision, recall, F1-score, and ROC-AUC. These metrics provide a comprehensive assessment of the model's ability to correctly identify pulmonary fibrosis cases while minimizing false predictions.

Table IV presents the performance comparison of the evaluated deep learning architectures. Among the tested models,

TABLE IV
Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-score
EfficientNetB0	98.60%	0.986	0.985	0.985
ResNet50	99.51%	0.995	0.994	0.994
DenseNet121	99.95%	0.9995	0.9996	0.9995

DenseNet121 achieved the highest classification performance with an accuracy of 99.95%, outperforming EfficientNetB0 and ResNet50. The superior performance of DenseNet121 can be attributed to its dense connectivity mechanism, which enables efficient feature reuse and improved gradient flow during training.

In addition to performance evaluation, an analysis of datasets used in pulmonary fibrosis detection studies is illustrated in Fig. 2. Previous research primarily relied on HRCT datasets and general lung CT image collections. Transfer learning approaches also utilized benchmark medical imaging repositories to compensate for limited labeled samples. In contrast, the proposed work employs a balanced HRCT dataset containing equal representation of normal and pulmonary fibrosis cases, ensuring reliable model training and evaluation.

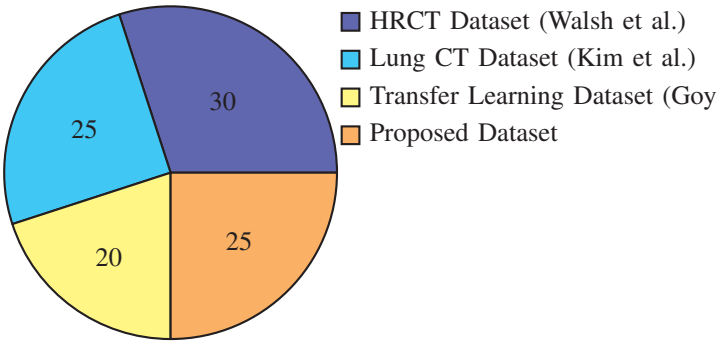

Fig. 2. Distribution of datasets used in pulmonary fibrosis detection studies.

B. Qualitative Results

The qualitative evaluation of the proposed system demonstrates its usability and effectiveness in real-world scenarios. A web-based user interface is developed to enable real-time pulmonary fibrosis prediction from uploaded chest CT images, as shown in Fig. 3. The interface displays the predicted class label along with the corresponding confidence score.

Sample CT scan images used for model evaluation are presented in Fig. 4. These images illustrate representative examples of normal lung structures and pulmonary fibrosis patterns observed in HRCT scans.

Visual inspection of prediction outputs confirms that the system consistently differentiates between Normal and Pulmonary Fibrosis cases. The average inference time per image is less than one second, enabling rapid screening and supporting clinical workflow integration. The qualitative results indicate that the deployed framework provides fast, reliable, and interpretable diagnostic outputs, making it suitable for practical pulmonary fibrosis screening applications.

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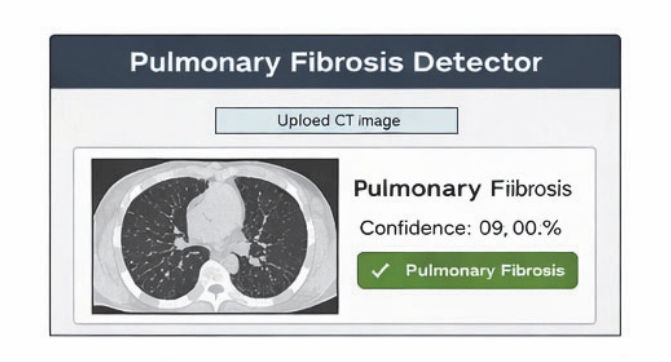

Fig. 3. Web-based interface for pulmonary fibrosis prediction.

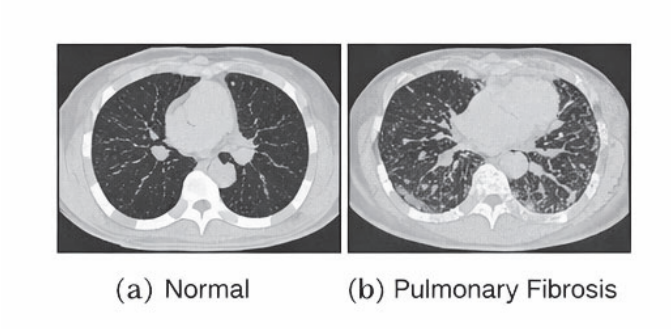

Fig. 4. Sample CT scan images of (a) normal lung and (b) pulmonary fibrosis cases.

To further evaluate the effectiveness of the proposed framework, a comparison with existing deep learning–based pulmonary fibrosis detection methods is presented in Table V.

TABLE V
MODEL PERFORMANCE COMPARISON WITH EXISTING METHODS

Model	Acc.	Prec.	Rec.	F1
CNN-Based Method	0.94	0.93	0.92	0.92
Transfer Learning (ResNet50)	0.98	0.98	0.97	0.97
Proposed Method (DenseNet121)	**0.9995**	**0.9995**	**0.9996**	**0.9995**

The results demonstrate that the proposed DenseNet121-based approach achieves superior performance compared to conventional CNN models and other transfer learning architectures. The improvement is mainly attributed to the dense connectivity structure of DenseNet, which enhances feature reuse and improves gradient propagation during training.

X. LIMITATIONS

The proposed pulmonary fibrosis detection framework demonstrates strong classification performance; however, several limitations must be acknowledged. First, the current system operates on two-dimensional CT image slices and does not explicitly capture volumetric information across consecutive slices. This may limit the ability to model spatial continuity of fibrotic patterns in three-dimensional lung structures.

Second, the dataset used in this study represents a specific imaging domain and acquisition protocol. Model performance may vary when applied to CT images obtained from different scanners, hospitals, or patient populations. Domain shift and variations in imaging quality may affect generalization capability.

Third, the proposed framework performs binary classification and does not differentiate between disease severity levels or stages of pulmonary fibrosis. As a result, the system cannot be directly used for progression analysis or treatment planning.

Finally, although high quantitative performance is achieved, the deep learning model remains partially black-box in nature. While prediction confidence is provided, explicit visual explanations of decision-making are not yet integrated, which may affect clinical trust and interpretability.

These limitations highlight the need for further validation on multi-center datasets, volumetric modeling, and explainable artificial intelligence integration in future work.

XI. CONCLUSION AND FUTURE WORK

This paper presented a deep learning–based framework for automated pulmonary fibrosis detection from chest CT images using transfer learning. By leveraging pre-trained convolutional neural network architectures, including EfficientNetB0, ResNet50, and DenseNet121, the proposed system achieved high classification performance while maintaining computational efficiency. Among the evaluated models, DenseNet121 demonstrated superior accuracy and robustness, achieving a test accuracy of 99.95% with consistently high precision, recall, and F1-score values. These results confirm the effectiveness of transfer learning for capturing discriminative pulmonary patterns in CT images.

In addition to model development, an end-to-end deployment pipeline was implemented using a Flask-based API and a web-based user interface, enabling real-time pulmonary fibrosis prediction from uploaded CT images. This practical integration transforms the research model into a deployable diagnostic tool and demonstrates its potential for clinical screening and decision support.

Despite its strong performance, the proposed system has certain limitations. The current framework operates on two-dimensional CT slices and does not explicitly model three-dimensional volumetric information across successive slices. Furthermore, the system performs binary classification and does not estimate disease severity or progression stages.

Future work will focus on extending the framework to incorporate three-dimensional convolutional neural networks for volumetric CT analysis, enabling more comprehensive spatial context modeling. Additionally, multi-class classification will be explored to differentiate between pulmonary fibrosis stages and other interstitial lung diseases. Integration of clinical parameters, such as pulmonary function test results and patient demographics, is also planned to enhance diagnostic reliability. Finally, explainable artificial intelligence techniques will be investigated to provide visual interpretation of model

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predictions, thereby improving clinician trust and facilitating clinical adoption.

Author Contributions

Byrisetty Aasreeja Suryaprakash: Conceptualization, dataset preparation, model development, experimentation, and manuscript drafting.

Dr. J. Jayaprakash: Research supervision, methodology validation, and technical guidance.

Dr. P. Dhivya: Review, editing, and academic supervision of the research work.

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