# Literature Survey

## 2025 : Predicting Risk of Pulmonary Fibrosis Formation in PASC Patients

Task Type: Binary Classification

- Categories: Positive (showing fibrosis signs) vs. Negative (no fibrosis)
- Labels: 156 positive cases, 191 negative cases from 347 total CT scans

Learning Type: Supervised Learning

- Expert radiologist with 8 years of experience manually labeled all scans
- Ground truth labels based on persistent imaging abnormalities (ground-glass opacities, consolidation, reticulation, traction bronchiectasis, honeycombing)
- Labels represent persistent findings at 2+ months post-COVID diagnosis

### 1. Data Collection & Preprocessing

What's happening: Collecting 347 chest CT scans from multiple hospitals (Pennsylvania and Turkey). The dataset contains 156 positive cases (showing fibrosis signs) and 191 negative cases.

Key steps:

- Expert radiologist labels all scans based on persistent abnormalities
- Extract representative 2D slices from 3D CT volumes focusing on lung tissue with potential fibrotic changes
- Multiple slices per patient ensure comprehensive lung representation

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### 2. Deep Learning Pipeline

What's happening: Training CNN models to automatically classify CT images as showing fibrosis risk or not.

Models tested:

- DenseNet-121 (best accuracy: 82.21%)
- ResNet-18 (best AUC: 85.46%)
- ResNet-34
- ResNeXt
- MobileNet V2

Training setup:

- 100 epochs with batch size of 2
- Learning rate: 0.01 with cosine annealing scheduler
- MixUp data augmentation to prevent overfitting
- 10% test split + 5-fold cross-validation on remaining 90%
- Trained on Nvidia A100 GPU

Why these models: DenseNet and ResNet architectures capture complex hierarchical features needed to identify subtle lung damage patterns.

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## 3. Radiomics Analysis

What's happening: Extracting 107 quantitative features from CT images to characterize tissue patterns mathematically.

Feature categories:

- First-order statistics (19 features): Overall tissue density patterns
- Shape features (26 features): 3D and 2D geometric properties
- Texture features (61 features): Spatial relationships captured through:
    - Gray Level Co-occurrence Matrix (24 features)
    - Gray Level Run Length Matrix (16 features)
    - Gray Level Size Zone Matrix (16 features)
    - Other texture matrices (10 features)

Machine learning models tested:

- LASSO (best performance: 67.42% accuracy, 72.54% AUC)
- XGBoost
- SVM
- Random Forest

Why radiomics: Provides clinically interpretable features that quantify specific imaging characteristics, complementing deep learning's pattern recognition.

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## 4. Model Interpretability (Grad-CAM)

What's happening: Visualizing which lung regions the deep learning models focus on when making predictions.

Purpose:

- Ensures the model looks at clinically relevant areas (ground-glass opacity, reticular patterns)
- Validates that model decisions align with radiologist expertise
- Builds trust for clinical deployment

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## Summary

Goal: Predict which Long COVID patients will develop permanent lung scarring using CT scans.

Approach: Dual methodology combining:

1. Deep learning (CNNs) for pattern recognition → 82.21% accuracy with DenseNet-121
2. Radiomics (quantitative features) for interpretable biomarkers → 67.42% accuracy with LASSO

Why it matters: Early identification enables timely interventions for a condition affecting 65+ million people worldwide, with $50+ billion annual economic impact in the US alone.

Key finding: This represents the first computational framework for PASC-related fibrosis prediction, demonstrating that AI can support early detection and risk assessment of Long COVID lung complications.

## Key Novel Contributions

1. Unique Multi-Center Dataset

- First specialized dataset curated for PASC-related fibrosis analysis
- 347 chest CT scans from two countries (USA and Turkey) with expert radiologist labels
- Captures persistent abnormalities at 2+ months post-COVID diagnosis
- Will be made freely available after peer review

2. Dual-Pathway Analytical Framework

- Deep learning approach: CNNs with Grad-CAM visualization for pattern recognition (achieving 82.21% accuracy)
- Radiomics approach: 107 quantitative features for clinically interpretable biomarkers (achieving 67.42% accuracy)
- This hybrid methodology provides both high performance and clinical explainability

## Limitations

## 1. Dataset Size and Generalizability

- While multi-center (347 scans), the dataset requires validation across additional healthcare systems and geographic regions to ensure broad applicability
- Current approach focuses primarily on imaging features without integrating other physiological data

## 2. Long-Term Follow-Up Needed

- Longer-term follow-up imaging is required to definitively classify findings as permanent rather than merely persistent
- Uncertainty remains about which early patterns reliably predict irreversible damage

## 3. Methodological Constraints

Training Strategy:

- Models trained from scratch rather than using transfer learning with pre-trained weights
- This avoided domain shift concerns between natural images and specialized CT imaging but may have limited performance
- Future work will explore transfer learning from large-scale chest CT datasets

Architecture Limitations:

- State-of-the-art architectures (Vision Transformers, foundation models, Mamba) not applicable due to dataset size
- These advanced models require massive datasets that weren't available for this specialized task

# 2025 : AI-Driven Early Prediction of Pulmonary Fibrosis Using Deep Learning

This project predicts pulmonary fibrosis (lung scarring disease) early using U-Net deep learning on High-Resolution Computed Tomography (HRCT) scans. The disease affects 13-20 per 100,000 people yearly and is linked to diabetes through inflammation and oxidative stress.

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DataSet : OSIC

Task Type: Image Segmentation (pixel-level classification)

- Primary task: Segment fibrotic regions from healthy lung tissue using U-Net
- Output: 388×388×2 binary segmentation map where each pixel is classified as fibrotic or healthy
- Secondary task: Regression - predicting FVC (Forced Vital Capacity) decline values over time

Learning Type: Supervised Learning

- Requires annotated segmentation masks showing fibrotic regions
- Ground truth labels for each pixel indicating tissue type
- FVC measurements at multiple time points (Week 0, follow-ups over 1-2 years)

## Code Sections in Simple Terms

## 1. Data Collection

- Dataset: ~200 patient HRCT scans tracking lung function decline over 1-2 years
- What's measured: Forced Vital Capacity (FVC) - amount of air a patient can forcefully exhale
- Data structure: Each patient gets a baseline scan at Week 0, then FVC measured at multiple follow-ups

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## 2. Image Preprocessing

Purpose: Clean and standardize HRCT images for neural network input

Data Augmentation: Create training variety through:

- Rotation, translation, scaling
- Flipping images
- Patch extraction from larger images

One-Hot Encoding: Convert each pixel's class label into binary vectors for multi-class segmentation

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## 3. U-Net Architecture

What it does: Deep learning model for image segmentation - identifying fibrotic lung regions pixel-by-pixel

Architecture components:

- Encoder (Contracting Path): Progressively reduces image size (572×572 → 30×30) while increasing feature channels to 1024, capturing high-level patterns
- Bottleneck: Creates compressed 30×30×1024 feature map at deepest layer
- Decoder (Expansive Path): Reconstructs original image size using upsampling layers
- Skip Connections: Connect encoder to decoder layers, preserving fine details and boundaries

Output: 388×388×2 binary segmentation map where each pixel indicates fibrotic or healthy tissue

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## 4. Model Training

Loss Function: Dice Coefficient - measures overlap between predicted and actual segmentation:

$$D=2|X\cap Y||X|+|Y|$$

$$D=\frac{2|X\cap Y|}{|X|+|Y|}$$

Optimizer: Adam (Adaptive Moment Estimation) - combines benefits of AdaGrad and RMSProp

- Maintains adaptive learning rates for each parameter
- Uses first moment (mean) and second moment (variance) of gradients

Hyperparameter Tuning:

- Learning rate: $10^{-1}$ to $10^{-5}$ (controls step size)
- Batch size: Powers of 2 (16, 32, 64, 128) - balances memory vs. gradient accuracy
- Tuned using grid search based on training stability

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## 5. Model Evaluation

Performance Metrics:

- Accuracy: Overall correct predictions
- Precision: Correct positive predictions / total positive predictions
- Recall: Correct positive predictions / actual positives
- F1-Score: Harmonic mean of precision and recall

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## Summary of Methods

Workflow:

1. Acquire HRCT lung scans + FVC measurements
2. Preprocess images (normalize, augment, resize)
3. Train U-Net segmentation model using Dice loss and Adam optimizer
4. Segment fibrotic regions in lung tissue
5. Predict FVC decline severity
6. Evaluate using accuracy, precision, recall, F1-score

Results Achieved: 96-98% across all metrics (accuracy: 0.98 test, 0.975 validation)

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## Novelty of This Project

## Key Innovations

1. U-Net for Fibrosis Segmentation

- Applies encoder-decoder architecture with skip connections specifically for pulmonary fibrosis detection
- Achieves precise pixel-level identification of fibrotic regions (ground-glass opacities, modules)

2. Non-Invasive Early Detection

- Overcomes limitations of invasive lung biopsies
- Uses HRCT's high resolution and thin slice thickness for precise visualization

3. Superior Performance

- Outperforms existing methods by 3-8% across metrics
- Compared to Li (94%), Zhu (91-94%), Cui (90-96%), Xu (79-94%), this method achieves 96-98%

4. Addresses Critical Clinical Gaps

- Current imaging (X-rays, CT) has limited predictive accuracy
- Existing biomarkers lack specificity/sensitivity
- Subjective interpretation introduces diagnostic variability

5. Diabetes-Fibrosis Connection

- Recognizes diabetes as indirect risk factor through inflammation, oxidative stress, and impaired immune function
- Integrates clinical laboratory tests with imaging data

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## Limitations

## 1. Dataset Constraints

- Small sample size: Only ~200 patient scans
- Generalizability: Limited to specific patient populations; needs validation across diverse demographics and healthcare settings
- Dataset not publicly available yet for independent validation

## 2. Follow-Up Period

- Short observation window: 1-2 years may be insufficient to confirm permanent fibrosis vs. reversible changes
- Needs longer longitudinal studies to validate long-term predictive accuracy

## 3. Methodological Limitations

Architecture constraints:

- U-Net designed for segmentation, not specifically optimized for fibrosis progression prediction
- No comparison with newer architectures (Vision Transformers, Attention U-Net)

Input limitations:

- Relies solely on imaging data
- Does not integrate comprehensive clinical data (lab results, patient history, comorbidities beyond diabetes)
- Missing genetic/biomarker information that could improve predictions

## 4. Clinical Translation Challenges

- Interpretability: While segmentation is visual, model decision-making process not explained
- Real-world validation: No prospective clinical trial data
- Cost-effectiveness: HRCT scans may not be accessible in resource-limited settings
- Radiologist workflow integration: Unclear how this fits into current diagnostic protocols

## 5. Technical Gaps

- No sensitivity analysis: How does performance change with image quality variations?
- Computational requirements: Training/inference time and hardware needs not specified
- Multi-modal fusion: Doesn't combine HRCT with other imaging modalities (PET, MRI)

## 6. Comparison Limitations

- Compared methods (Li, Zhu, Cui, Xu) use different datasets and evaluation protocols
- Performance differences may reflect dataset characteristics rather than algorithmic superiority

## 7. Disease Complexity

- Pulmonary fibrosis has multiple subtypes (IPF, diabetic fibrosis, post-COVID)
- Model may not generalize across different etiologies
- No discussion of handling edge cases or ambiguous presentations

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## Summary Table

| Aspect | Description |
|---|---|
| Goal | Early prediction of pulmonary fibrosis using HRCT scans |
| Method | U-Net segmentation + Adam optimization + Dice loss |
| Performance | 96-98% accuracy, precision, recall, F1-score |
| Novelty | First U-Net application for fibrosis; superior performance vs. existing methods; non-invasive detection |
| Main Limitation | Small dataset (~200 patients); short follow-up; lacks clinical data integration; needs real-world validation |

# 2025 : Predicting Pulmonary Fibrosis Progression Using EfficientNet-LSTM Model: A Hybrid Approach

## Task Type & Learning Approach

Task Type: Regression

- Predicts continuous FVC values (lung function measurement in mL)
- Not classification - outputs numerical predictions of lung capacity decline over time

Learning Type: Supervised Learning

- Requires labeled training data with ground truth FVC measurements
- Uses historical FVC values at multiple time points to predict future decline
- Time-series data transformed into supervised format using lag-based representations

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| Model | RMSE (mL) | $R^2$ Score |
|---|---|---|
| **Standalone CNN** | **192.45** | **0.87** |
| **Standalone EfficientNet** | **180.50** | **0.88** |
| **Standalone LSTM** | **185.58** | **0.85** |
| **EfficientNet-LSTM (Hybrid)** | **170.20** | **0.90** |

## Dataset Source

OSIC Pulmonary Fibrosis Progression Dataset (Kaggle)

Dataset Contents:

- DICOM CT scans: High-resolution chest computed tomography images showing structural lung damage
- Clinical CSV data: Patient demographics and measurements
    - Age, gender, smoking status
    - FVC values (forced vital capacity)
    - FVC percentage relative to expected values
    - Time information tracking patient progression across weeks

Dataset Structure:

- Training set: Baseline CT scan + complete FVC history
- Validation set: 15% of data
- Test set: 15% of data
- Data split: 70% training, 15% validation, 15% testing

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## Code Sections Explained Simply

## 1. Data Collection

What's happening: Loading multimodal medical data from Kaggle

Two data types:

- Imaging data: CT scans in DICOM format showing lung tissue scarring (fibrosis)
- Clinical data: Structured patient information (age, sex, smoking status, FVC measurements over time)

Purpose: Combining visual and numerical data provides comprehensive disease progression information

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## 2. Data Preprocessing

Image Preprocessing:

- Load DICOM files using pydicom library to extract pixel intensities
- Normalize pixel values using RescaleIntercept and RescaleSlope to standardize intensity variations across different CT scanners

- Resize images to 224×224 pixels for consistent input size
- Convert grayscale to RGB (CT scans are originally grayscale but models expect 3-channel images)
- Convert to PyTorch tensors for neural network compatibility

Clinical Data Preprocessing:

- Remove corrupted records that generate DICOM loading errors
- Label encoding: Convert categorical features (Sex, SmokingStatus) to numeric format
- Time-series transformation: Restructure patient records into supervised learning format using lag-based representations where past FVC values predict future values
- Patient ID encoding: Label-encode patient identifiers while preserving patient-specific information

Data Augmentation (for images):

- Random cropping, flipping, rotation of CT images
- Increases training data variety and prevents overfitting

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## 3. Model Architecture: EfficientNet-LSTM Hybrid

Component 1: EfficientNet-B3 (Image Processing)

What it does: Extracts spatial features from CT scans showing fibrotic patterns

Architecture details:

- Pre-trained weights: Starts with ImageNet pre-training for general feature extraction
- Input conversion layer: Convolutional layer (kernel size 3, stride 2, padding 1) converts grayscale 1-channel images to 3-channel format
- Batch normalization: Stabilizes training and improves generalization
- Modified classifier head: Replaced with fully connected layer (500 neurons) + ReLU activation
- Transfer learning strategy:
    - Freeze early convolutional layers to preserve low-level feature extraction (edges, textures)
    - Fine-tune later layers to learn fibrosis-specific patterns (scarring, tissue damage)

Why EfficientNet-B3: Efficient compound scaling balances depth, width, and resolution for optimal feature extraction without excessive computational cost

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Component 2: LSTM Network (Clinical Data Processing)

What it does: Captures temporal dependencies in disease progression from sequential FVC measurements

Architecture details:

- Input: 6 standardized clinical features (age, sex, smoking status, FVC, etc.)
- Two stacked LSTM layers: 32 hidden units each for hierarchical temporal learning
    - First layer: Captures short-term fluctuations
    - Second layer: Learns long-term disease progression trends
- Dropout 0.4: Between LSTM layers to prevent overfitting
- Output: Final hidden state representing compressed time-series features

Why LSTM: Unlike standard neural networks, LSTM maintains long-range dependencies in sequential data, essential for tracking FVC decline patterns over weeks/months

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Component 3: Fusion & Prediction

What's happening: Combining spatial (CT) and temporal (clinical) features

Process:

1. EfficientNet-B3 outputs 500-dimensional image feature vector
2. LSTM outputs 32-dimensional time-series feature vector
3. Concatenate both vectors into single combined representation
4. Feed through fully connected output layer
5. Output: Single continuous value = predicted FVC (in mL)

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# 4. Training Process

Loss Function: Mean Squared Error (MSE)

Why MSE: Penalizes larger prediction errors more heavily, appropriate for regression tasks

Optimizer: Adam

- Learning rate: 0.001
- Adaptive learning rates for each parameter
- Weight decay for regularization

Training Configuration:

- 30 epochs
- Batch size: 64
- Early stopping: Terminates if validation loss stops improving
- Regularization: Batch normalization + 0.4 dropout rate

Training Steps:

1. Forward propagation: EfficientNet extracts image features, LSTM learns sequential patterns
2. Loss calculation: Compute MSE between predicted and actual FVC
3. Backpropagation: Calculate gradients and update weights
4. Validation check: Monitor validation loss after each epoch

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## 5. Data Handling

Custom PyTorch Dataset classes:

- Process both image and time-series data simultaneously
- Ensure each batch contains matched CT scan + clinical data for same patient

DataLoader configuration:

- Batch loading for efficient GPU processing
- Stratified partitioning ensures even patient distribution across train/validation/test sets

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## 6. Model Evaluation

Performance Metrics:

- RMSE (Root Mean Squared Error): Average prediction error magnitude
- $R^2$ (Coefficient of Determination): Proportion of variance explained by model (0-1 scale)

Experimental Setup:

- Hardware: Kaggle GPU (NVIDIA Tesla T4), 16GB RAM
- Software: Python 3.9, PyTorch 1.9, CUDA

- Libraries: NumPy, Pandas, OpenCV, Matplotlib, Scikit-learn

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## Summary of Methods

Workflow:

1. Load OSIC dataset from Kaggle (CT scans + clinical CSV)
2. Preprocess images (normalize, resize, convert to RGB tensors)
3. Preprocess clinical data (encode categories, create time-series lags)
4. Train EfficientNet-B3 on CT images for spatial feature extraction
5. Train LSTM on sequential FVC measurements for temporal pattern learning
6. Fuse image and time-series features
7. Predict FVC values using combined representation
8. Evaluate using RMSE and $R^2$ metrics

Key Innovation: Multimodal learning combining spatial (imaging) and temporal (clinical) information

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## Results Achieved

| Model | RMSE | $R^2$ |
|---|---|---|
| Standalone CNN | 192.45 | 0.87 |
| Standalone EfficientNet | 180.50 | 0.88 |
| Standalone LSTM | 185.58 | 0.85 |
| EfficientNet-LSTM (Hybrid) | 170.20 | 0.90 |

**Novelty**

EfficientNet-LSTM hybrid model combining spatial (CT) and temporal (clinical) features achieving 90% $R^2$ and 170.20 mL RMSE—10-22 mL better than standalone models.

**Limitation**

Small dataset size; no external validation; missing uncertainty quantification; dataset-specific performance without cross-hospital testing; limited interpretability for clinical adoption

# 2025 Unraveling Pulmonary Fibrosis Deep Learning Transfer Learning for Diagnosis

## Overview

Goal: Automated diagnosis of pulmonary fibrosis from CT scans using deep learning feature extraction + machine learning classification, deployed as a Flask web application.

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## Task Type & Learning Approach

Task Type: Binary Classification

- Class 0: No Fibrosis
- Class 1: Pulmonary Fibrosis Present

Learning Type: Supervised Learning

- Labeled training data with ground truth fibrosis classifications
- Expert annotations on CT images

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## Dataset Source

Custom Pulmonary Fibrosis Dataset

Characteristics:

- CT scan images with binary labels (fibrosis/non-fibrosis)
- Total samples split into training/validation/test sets
- Support = 70 for class 0, 80 for class 1 (150 total test samples)

Note: Paper doesn't explicitly specify total dataset size or source institution

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## Code Sections Explained Simply

## 1. Data Preprocessing

Data Augmentation:

- Rotation, zooming, flipping, shifting of CT images
- Increases training data variety to prevent overfitting

Noise Reduction:

- Gaussian filtering or median filtering
- Removes artifacts from CT scans

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## 2. Feature Extraction (Deep Learning)

Three Pre-trained Models Used:

| **Model** | **Purpose** | **Key Feature** |
|---|---|---|
| Inception V3 | Captures multi-scale features | Inception modules extract complex hierarchical patterns |
| VGG16 | Extracts hierarchical spatial features | 19 layers capture detailed fibrosis patterns (honeycombing, reticulation) |
| MobileNetV2 | Lightweight efficient extraction | Depth-wise separable convolutions for real-time predictions |

Process:

1. Load pre-trained weights from ImageNet
2. Remove classifier head
3. Fine-tune on pulmonary fibrosis dataset
4. Extract feature vectors (flattened outputs before classification layer)

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## 3. Dimensionality Reduction

Methods Used:

- PCA (Principal Component Analysis): Reduces feature vector dimensions
- t-SNE (t-Distributed Stochastic Neighbor Embedding): Preserves important patterns

Purpose: Reduces computational load and focuses classifiers on significant features

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## 4. Classification (Machine Learning)

Two Classifiers Tested:

Random Forest:

- Ensemble of decision trees
- Handles non-linear patterns in fibrosis features
- Effective for complex, multi-scale tissue variations

Support Vector Machine (SVM):

- Uses RBF (Radial Basis Function) kernel for non-linear classification
- Separates linearly inseparable fibrosis patterns
- Maps features to higher-dimensional space for optimal separation

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## 5. Model Integration: Flask Web Application

Deployment Steps:

1. Save trained feature extractors (InceptionV3, VGG16, MobileNetV2)
2. Save trained classifiers (Random Forest, SVM)
3. Create Flask web interface for image upload
4. Preprocess uploaded CT images
5. Extract features using trained deep learning models
6. Classify using machine learning classifiers
7. Return predictions with confidence scores in real-time

User Flow:

- Medical professional uploads CT scan
- System processes image (seconds)
- Returns: Fibrosis classification + confidence score

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## Summary of Methods

Workflow:

1. Collect and label CT scans (fibrosis/non-fibrosis)
2. Data augmentation + noise reduction
3. Extract features using InceptionV3, VGG16, or MobileNetV2 (transfer learning)
4. Reduce dimensionality (PCA/t-SNE)
5. Train classifiers (Random Forest or SVM)
6. Evaluate using accuracy, precision, recall, F1-score
7. Deploy best model in Flask web application

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## Final Output Metrics as Benchmark

| **Model Combination** | **Accuracy** | **Precision (Class 0)** | **Recall (Class 0)** | **F1-Score (Class 0)** | **Precision (Class 1)** | **Recall (Class 1)** | **F1-Score (Class 1)** | **Macro Avg** | **Weighted Avg** |
|---|---|---|---|---|---|---|---|---|---|
| InceptionV3 + Random Forest | 75.33 % | 0.79 | 0.64 | 0.71 | 0.73 | 0.85 | 0.79 | 0.76 | 0.76 |
| VGG16 + SVM | 86.67 % | 0.89 | 0.81 | 0.85 | 0.85 | 0.91 | 0.88 | 0.87 | 0.87 |
| MobileNetV2 + Random Forest | 79.33 % | 0.83 | 0.70 | 0.76 | 0.77 | 0.88 | 0.82 | 0.79 | 0.79 |

Best Model: VGG16 + SVM with 86.67% accuracy

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## Novelty

Key Innovations:

- Hybrid transfer learning approach: Combines three pre-trained deep learning models (InceptionV3, VGG16, MobileNetV2) with machine learning classifiers (Random Forest, SVM)
- Systematic comparison: Tests multiple feature extraction + classification combinations to identify best performer
- Clinical deployment: First to integrate into Flask web application enabling real-time diagnosis by medical professionals
- Computational efficiency: MobileNetV2 option enables real-time predictions on resource-constrained environments

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## Limitations

Key Constraints:

- Dataset not specified: Paper doesn't state total dataset size or source institution
- No external validation: Single dataset validation; transferability unknown
- Limited interpretability: No explainability mechanisms (Grad-CAM, attention maps) showing which lung regions drive classifications
- No uncertainty quantification: Confidence scores not provided with predictions
- Architectural justification missing: Why these specific models chosen over alternatives unexplained
- Comparison gap: No direct comparison with other hybrid approaches or state-of-the-art methods
- Clinical integration untested: Web application functionality demonstrated but not validated in real clinical workflow

# 2025 High-Performance Detection of Pulmonary Diseases in CT Images Using PFC-DenseNet121 and Binary Robust Independent Elementary Features

This project uses an enhanced DenseNet121 model (PFC-DenseNet121) combined with BRIEF feature extraction for automated pulmonary fibrosis detection from CT scan images.

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## Task Type & Learning Style

- Classification task: Binary classification (Pulmonary Fibrosis vs. Normal)
- Supervised learning: Model trained with labeled CT images (ground truth: fibrosis or normal)

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## Dataset Used

- Source: Kaggle Pulmonary Fibrosis CT Image Dataset
- Size: 3,182 CT images
    - Training: 1,178 fibrosis, 1,050 normal (2,228 total)
    - Validation: 252 fibrosis, 225 normal
    - Testing: 252 fibrosis, 225 normal
- Preparation: Images resized to 224×224, pixel values normalized (0–1)

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## Methods & Code Sessions (Crisp Steps)

1. Preprocessing:
    - Resize images to 224×224 pixels
    - Normalize pixel intensity
    - Split data (train, validation, test)
2. Feature Extraction:
    - Apply BRIEF (keypoint detector) for fast, efficient structural feature capture
3. Model Architecture:
    - Use modified DenseNet121 (PFC-DenseNet121)

    - Added dense blocks, attention mechanisms, and small convolutions (3×3, 1×1)
    - Dropout applied to reduce overfitting
    - Channel-wise concatenation for efficient feature reuse and improved gradient flow
4. Classification:
    - Fully connected layers with sigmoid output for binary prediction (fibrosis/normal)
    - Output also includes localization of affected area (contour mapping)
5. Training & Evaluation:
    - Early stopping applied (best model at epoch 37)
    - Metrics: Accuracy, Recall, Precision, F1-score, Specificity measured on test set

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## Benchmark Metrics (Final Results)

| **Metric** | **Value** |
|---|---|
| Accuracy | 98.74% |
| Recall | 99.20% |
| Precision | 98.42% |
| F1-Score | 98.83% |
| Specificity | 98.22% |

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## Novelty (Crisp)

- Combines BRIEF keypoint descriptors with DenseNet for high-performance, low-complexity pulmonary fibrosis detection
- Modified DenseNet121 improves feature propagation, gradient flow, and localization by adding attention and new connections
- Outperforms baseline DenseNet121 and prior studies on accuracy and sensitivity
- Provides automatic identification and visualization (affected lung area) directly from CT images

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## Limitations (Crisp)

- Single, publicly available Kaggle dataset used—generalizability to other populations/hospitals not tested
- No external multi-center validation performed
- Limited interpretability: no visual explanation techniques (e.g., Grad-CAM)
- Current model only classifies disease presence, not severity
- Future work needed on larger, more diverse datasets and severity grading

# 2024 Elevating Cystic Fibrosis Detection in Lungs using HRCT Images with a Cutting-Edge CNN-Based Approach

This project aims to detect cystic fibrosis (CF) in lung CT images using a cutting-edge convolutional neural network (CNN) model that incorporates a modified PSP-Net architecture.

## Task Type and Dataset

- Task: Supervised binary classification — detecting presence of cystic fibrosis in lungs.
- Dataset: High-resolution CT (HRCT) scans — 312 images from hospital radiology department with detailed CF annotations, segmented into training and testing sets.

## Methods and Code Sessions

1. Data Preprocessing:
    - Images undergo normalization and enhancement to improve quality.
    - Images are segmented into lung regions, then further into different-sized patches for multiscale analysis.
2. Feature Extraction:
    - A multiscale CNN extracts hierarchical features (textures, edges, shapes) at different spatial resolutions (e.g., 2×2, 3×3, 6×6 areas).
    - Pyramid Scene Parsing Network (PSP-Net) is applied to capture global and local context with pyramid pooling modules enhancing the segmentation of cystic fibrosis lesions.
3. Model Architecture:
    - Input HRCT scans are processed by CNN layers, followed by pyramid pooling, feature upsampling, and concatenation to generate a composite multi-scale feature map.
    - Final convolutional layers produce predictions that identify cystic fibrosis and localize lung regions affected.
4. Training:
    - The network is trained with annotated HRCT scans; training and testing performance is evaluated.
5. Evaluation Metrics:

- Accuracy, precision, recall, F1-score, and error rate are calculated and compared with baseline methods (Decision Trees, Random Forests, Neural Networks, PSP-Net).
- Matthews Correlation Coefficient (MCC) and specificity are also computed.

## Final Output Metrics (Benchmark)

| **Metric** | **Proposed CNN Model** | **Compared Models Range** |
|---|---|---|
| Accuracy | 84% | 75% - 82% |
| Precision | 74% | 68% - 72% |
| Recall | 79% | 70% - 77% |
| F1-Score | 72% | 66% - 70% |
| Error Rate | 16% | Higher (Compared Models) |
| MCC | 71% | 63% - 67% |
| Specificity | 76% | 68% - 74% |

## Novelty

- Combines multiscale CNN processing with pyramid pooling (PSP-Net) tailored for cystic fibrosis lesion detection.
- Efficiently captures lung abnormalities at multiple spatial scales, improving recognition accuracy.
- Demonstrates better performance over traditional classifiers like Decision Trees and Random Forests.
- Provides detailed localization of pathological lung regions, aiding clinical interpretability.

## Limitations

- Limited dataset size (312 images) from a single hospital; generalizability to broader populations remains untested.
- Moderate classification accuracy (~84%) showing room for improvement.
- Lacks deeper validation on independent or multi-center datasets.
- No discussion of explainability techniques (e.g., Grad-CAM).
- Future work suggested for expanding dataset, improving model robustness, and extending applicability to other lung diseases.

In summary, this project develops a CNN + PSP-Net based supervised classification system for detecting cystic fibrosis in HRCT lung images with promising accuracy and localization capability, outperforming several classical machine learning methods but limited by dataset size and scope of validation.

# 2024 Prediction Of Pulmonary Fibrosis Disease

## *Neglect this into consideration look into this*

This project aims to predict pulmonary fibrosis (PF) and assess the risk of developing lung scarring using both imaging and clinical data, with a focus on improving early detection through machine learning and deep learning.

Task Type & Learning Approach
**Regression task:** Predicts the continuous variable "Forced Vital Capacity (FVC)" (a lung function metric).

Supervised learning: Models are trained with labeled examples (input features with known FVC values).

Dataset Source
OSIC Pulmonary Fibrosis Progression Dataset (from Kaggle)

Contains: 200 patients

Each patient: baseline CT scan, full history of FVC over time (for training); initial FVC only (for testing)

Link

Methods & Code Sessions (Crisp Summary)
1. Data Preprocessing:

Remove missing and duplicate values; normalize and clean tabular data

Extract and preprocess CT image data (segmentation, resizing, Hounsfield Unit conversion)

2. Feature Selection/Engineering:

For tabular models: select age, sex, smoking status, week, percent, baseline FVC, etc.

For LSTM: combine tabular clinical data with image features (when available)

3. Model Training:

Huber Regression: Robust regression for handling outliers, using only tabular data

Support Vector Regression (SVR): Non-linear regression using RBF kernel, tuned for best FVC prediction

Long Short-Term Memory (LSTM): Deep learning RNN for modeling time-series data by combining sequential tabular features and image-derived features

Each model is trained, tested, and performance is evaluated on held-out data

4. Model Evaluation:

Use Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) as key metrics

Compare actual vs. predicted FVC values on both training and testing

## Final Output Metrics (Benchmark)

| Model | MSE | MAE | RMSE |
|---|---|---|---|
| Huber Regression | 7.98 | 3.57 | 2.82 |
| LSTM | 0.94 | 1.07 | 1.39 |
| Support Vector Reg | 0.029 | 0.144 | 0.171 |

## Best performance: Support Vector Regression (SVR) with the lowest MSE (0.029) and RMSE (0.171) on test data.

Novelty (Crisp)
Compares three supervised regression models (SVR, Huber Regression, LSTM) for predicting FVC, using both tabular and imaging data.

First application of LSTM to incorporate both clinical time-series and imaging (CT scans) within this PF task.

Demonstrates SVR (with only tabular features) outperforms both deep learning (LSTM) and robust regression approaches on this dataset.

Provides practical evaluation with real-world PF longitudinal data.

Limitations (Crisp)
Dataset is moderate-sized (200 patients; risk of overfitting and limited generalizability)

No external (multi-institution) validation performed—tested only on the OSIC dataset

LSTM model did not outperform SVR in this application, possibly due to small sample size or insufficient imaging features

Only initial FVC and basic clinical features used—future work could include more comprehensive longitudinal data, external validation, and ensemble techniques.

# 2024 : FibroRegNet: A Regression Framework for the Pulmonary Fibrosis Prognosis Prediction Using a Convolutional Spatial Transformer Network

## Project Overview: FibroRegNet — IPF Prognosis Prediction

This project predicts the progression of Idiopathic Pulmonary Fibrosis (IPF) by forecasting Forced Vital Capacity (FVC) decline using a multimodal framework combining CT scans with demographic information.

---

## Task Type & Learning Approach

- Regression task: Predicts continuous FVC values (lung function metric) to track disease progression
- Supervised learning: Trained with labeled examples (CT images + demographics paired with FVC measurements)

---

## Dataset Source

- OSIC Pulmonary Fibrosis Progression Dataset (from Kaggle)
    - 176 CT scans, 33,026 slices, 1,549 FVC values
    - 200 patients with multiple FVC measurements across irregular weeks
    - Training (80%) / Testing (20%) split stratified by patient
    - 5-fold cross-validation used

---

## Methods & Code Sessions (Crisp Summary)

1. FVC Data Preprocessing:

- Convert FVC measurements into quadratic polynomial ridge regression coefficients (3 targets: a, b, c)
- Formula:
- $FVC(wi)=a\times wi2+b\times wi+c$

- $FVC(w$
- $i$
- $)=a\times w$
- $i$
- $2$
- $+b\times w$
- $i$
- $+c$

2. Demographic Data Preprocessing:
    - One-hot encoding for categorical features (Sex: 2 categories, SmokingStatus: 3 categories)
    - Keep continuous features (Age, Weeks, Percent)
3. Lung Volume Estimation:
    - Use pre-trained U-Net (R231) for lung segmentation
    - Calculate lung volume in milliliters from voxel counts
4. CT Feature Extraction:
    - Spatial Transformer Modules (STN): Learn spatially invariant features with rotation, scaling, translation abilities
    - Three parallel streams, each with two cascaded STN modules
    - Select 85% of slices for volume estimation; only 3 central slices for feature learning
5. Multimodal Fusion:
    - Combine demographic features (fDIE) + lung volume (fLV) + CT features (fCT)
    - Feed through dense layers to predict 3 regression coefficients
6. Training Strategy (Two Phases):
    - Phase 1 (40 epochs): Train ST modules on CT slices only
    - Phase 2 (20 epochs): Freeze ST modules, fine-tune dense layers with demographic + volume features

---

## Final Output Metrics (Benchmark)

| Metric | FibroRegNet | Best Previous |
|---|---|---|
| Modified Laplace Log-Likelihood (LLLm) | −6.64 | −6.41 (Yadav et al.) |
| RMSE | 172.35 ± 16.2 | 173+ (others) |
| Model Parameters | 22.4M | — |
| MACs | 0.63G | — |
| Inference Time | 0.81s | — |

Key Finding: FibroRegNet outperforms all recent methods on OSIC dataset with superior LLLm score.

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## Novelty (Crisp)

- First application of Spatial Transformer Networks (STN) in medical image analysis for IPF prognosis
- Quadratic polynomial ridge regression for FVC coefficients instead of linear regression or quantile regression
- Multimodal fusion (demographics + lung volume + ST-based CT features) in a unified end-to-end framework
- Two-phase training strategy: phase 1 learns spatial transformations; phase 2 integrates demographic context
- Best LLLm score (−6.64) compared to previous state-of-the-art methods on OSIC dataset

---

## Limitations (Crisp)

- Single CT scan per patient; irregular FVC measurement intervals complicate prediction
- Limited dataset size (200 patients): prevents use of deeper architectures or Vision Transformers
- High computational cost (22.4M parameters, 0.63G MACs, 0.81s inference) compared to simpler baselines
- Only 3 CT slices used for training due to variable slice counts across patients
- No external validation: tested only on OSIC Kaggle dataset
- Lacks uncertainty quantification and explainability mechanisms
- Future work needed: larger multi-center datasets, deeper architectures, and integration with clinical workflows

# 2024 Detection of Idiopathic Pulmonary Fibrosis Lesion Area Based on Transfer Learning

- This project detects IPF lesion regions in CT images using transfer learning with U-Net and attention mechanisms, addressing the challenge of limited labeled IPF data.

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## Task Type & Learning Approach

- Semantic Segmentation (pixel-level classification): Identifies and localizes IPF lesion areas in lung CT images
- Supervised Learning: Trained with labeled CT images paired with ground truth segmentation masks

---

## Dataset Source

- Two combined sources:
  - ILD-Database (Interstitial Lung Diseases): 371 fibrosis-labeled images
  - Sichuan Provincial People's Hospital (SPPH): 897 annotated CT images from 14 IPF patients
  - IPF-like Dataset (Transfer Learning): 99 image pairs from DTD and ALOT natural texture databases (bubbles, sponges, meshes resembling honeycomb/mesh shadows)
- Total: 1,268 real IPF CT images + synthetic IPF-like images for pre-training

---

## Methods & Code Sessions (Crisp Summary)

1. IPF-like Dataset Construction:
   - Analyzed IPF imaging features (honeycomb, mesh shadows, ground-glass opacity)
   - Selected similar natural textures from DTD (Describable Textures Database) and ALOT datasets
   - Manually annotated 99 image pairs as binary masks (lesion vs. healthy)
- 2. Network Architecture:
  - Backbone: VGG16 or ResNet50 (encoder with pre-trained ImageNet weights)
  - Decoder: U-Net upsampling path with skip connections
  - Attention Module: CBAM (Convolutional Block Attention Module) with:

        - Channel Attention (learns which channels matter)
        - Spatial Attention (learns which spatial regions matter)
    - Loss Function: Tversky Loss (balances precision and recall; handles data imbalance)
- 3. Two-Phase Training:
    - Phase 1 (50 epochs): Pre-train U-Net on IPF-like dataset (VGG16/ResNet50 frozen)
    - Phase 2 (50 epochs): Fine-tune entire network on real IPF data (7:3 train-validation split)
- 4. Inference:
    - Segment lesion regions from test CT scans
    - Output binary masks showing fibrotic lesion locations
-

---

# Final Output Metrics (Benchmark)

| **Metric** | **Proposed (Vgg16)** | **Proposed (ResNet50)** | **CPD Method (Previous)** |
|---|---|---|---|
| Dice Coefficient | 0.74 | 0.73 | 0.59 |
| Precision | 0.83 | 0.72 | 0.72 |
| Sensitivity | 0.87 | 0.87 | 0.85 |
| F-score | 0.85 | 0.78 | 0.78 |

| | | | |
|---|---|---|---|
| MIoU | 0.79 | 0.79 | — |

- Best Model: VGG16 backbone with Dice = 0.74, Precision = 0.83, Sensitivity = 0.87

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## Novelty (Crisp)

- First transfer learning approach for IPF lesion segmentation using natural texture pre-training to overcome scarce labeled data
- IPF-like dataset construction: Creatively maps natural textures (bubbles, sponges, meshes) to IPF imaging features for pre-training
- Attention mechanisms (CBAM): Improves detection of small lesions by learning channel and spatial importance
- Tversky Loss: Directly addresses medical imaging challenge of data imbalance (fewer lesion pixels than healthy pixels)
- Outperforms CPD baseline: 25% improvement in Dice coefficient (0.74 vs. 0.59)

---

## Limitations (Crisp)

- Small IPF dataset (1,268 images from 14 patients): Limited generalizability; risk of overfitting
- 2D segmentation only: Ignores 3D spatial context; future work should extend to 3D detection
- Single-institution validation: SPPH hospital data only; needs multi-center testing
- Synthetic pre-training: IPF-like dataset quality depends on manual texture selection; may not capture all disease variations

# 2024 Enhanced Pulmonary Pattern Classification in HRCT Images Using Advanced Data Augmentation Strategies and Fine-Tuned CNN Models

This project classifies seven pulmonary patterns in HRCT CT images using advanced deep learning with data augmentation to improve early diagnosis of various lung diseases.

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## Task Type & Learning Approach

- Classification task: Multi-class classification into 7 pulmonary patterns (ground-glass, fibrosis, micronodules, consolidation, healthy, reticulation, emphysema)
- Supervised learning: Trained with labeled HRCT images paired with pattern annotations

---

## Dataset Source

- HUG-Dataset (University Hospitals of Geneva - ILD Database)
    - Publicly available dataset for Interstitial Lung Diseases
    - 1,937 HRCT images from 128 patients
    - 12 different pathologic categories annotated
    - 7 primary patterns used in this study:
        - Ground Glass: 427 images
        - Fibrosis: 473 images
        - Micronodules: 297 images
        - Consolidation: 196 images
        - Healthy: 100 images
        - Reticulation: 131 images
        - Emphysema: 66 images

---

## Methods & Code Sessions (Crisp Summary)

1. Data Preprocessing:

- Convert images to PNG format
- Label images based on pulmonary patterns (not anatomical regions)
- Duplicate images containing multiple patterns with separate labels

2. Data Augmentation Strategies (Applied):

- Random Transformations: Width/height shifts (1%), random zoom (1%), shear (1%), horizontal flip
- Brightness Adjustment: Random brightness range [0.5, 1.5]
- Class Balancing: Duplicate underrepresented consolidation class to 390 samples (matching maximum class size)

3. Model Architectures (Transfer Learning):

- EfficientNet-B0: Compound scaling method balancing depth, width, and resolution
- Inception-ResNet-v2: Combines Inception modules with residual connections for faster training

4. Training Configuration:

- Optimizer: SGD with learning rate 0.005
- Epochs: 20
- Tasks: 5-class, 6-class, and 7-class classification

5. Performance Evaluation:

- Compare: Original data vs. Augmented data vs. Balanced data (with duplication)
- Metrics: Accuracy, Loss, F1-score

---

## Final Output Metrics (Benchmark)

| **Strategy** | **Model** | **Classes** | **Test Accuracy** | **F1-Score** |
|---|---|---|---|---|
| Original Data | EfficientNet | 5 | 0.918 | 0.92 |

| | | | | |
|---|---|---|---|---|
| Original Data | Inception | 5 | 0.91 | 0.90 |
| Augmented Data | EfficientNet | 5 | 0.91 | 0.91 |
| Augmented Data | EfficientNet | 7 | 0.91 | 0.90 |
| Balanced Data | EfficientNet | 5 | 0.90 | 0.90 |
| Balanced Data | EfficientNet | 6 | 0.90 | 0.90 |
| Balanced Data | EfficientNet | 7 | 0.90 | 0.89 |

Best Performance: EfficientNet with 5 classes on original data: 91.8% accuracy, 0.92 F1-score

---

## Novelty (Crisp)

- 7-class multi-pattern classification of HRCT images (expanded from previous 6-class approaches)
- Systematic comparison of three data handling strategies: original, augmented, balanced
- Advanced data augmentation (brightness adjustment, random transformations) improving generalization
- No segmentation required: Direct end-to-end pattern classification without lung region extraction
- EfficientNet compound scaling: Achieves high accuracy with optimized model efficiency

---

## Limitations (Crisp)

- Small dataset: 1,937 total images from 128 patients; risk of overfitting despite augmentation
- Imbalanced classes: Significant variation in class sizes (Emphysema: 66 images vs. Fibrosis: 473 images)
- No external validation: Tested only on HUG-Dataset; generalizability to other hospitals unknown
- Single-institution data: All images from one center; clinical applicability across diverse populations untested
- Modest improvements from augmentation: Marginal gains from data augmentation in some cases (0.91 → 0.86)
- Missing localization: Classifies patterns but doesn't indicate their anatomical location within lungs
- Future work needed: Larger multi-center datasets, determining intra-lung lesion positions, clinical workflow integration

# 2024 Accurate Prediction of Pulmonary Fibrosis Progression Using EfficientNet and Quantile Regression: A High Performing Approach

This project predicts FVC (lung function) decline in IPF patients by combining deep learning (EfficientNet) with quantile regression to estimate both predictions and confidence levels.

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## Task Type & Learning Approach

- Regression task: Predicts continuous FVC values and their uncertainty (confidence intervals)
- Supervised learning: Trained with labeled CT scans paired with FVC measurements over time

---

## Dataset Source

- OSIC Pulmonary Fibrosis Progression Dataset (Kaggle - Open-Source Imaging Consortium)
    - 176 unique patients
    - 2,270 data rows with 7 columns (CT scans + demographics + FVC measurements)
    - 200 patients in combined public/private test sets
    - 34,000 CT images (mostly 512×512 pixels)
    - Features: Age, Gender, Smoking Status, FVC values, Week measurements

---

## Methods & Code Sessions (Crisp Summary)

1. CT Image Preprocessing:

- Convert DICOM to Hounsfield Units (HU range: -1000 to ~3000)
- Normalize pixel spacing (critical for comparing across patients)
- Resize to 512×512 pixels
- Apply windowing to visualize clinically relevant HU ranges

2. Metadata Processing:

- One-hot encode categorical features (Gender: 2 categories, Smoking Status: 3 categories)
- Normalize numerical features (Age, Weeks, Percent)
- Add derived features: "start_week" (baseline week), "base_week" (relative to baseline)

3. Two-Stream Architecture:

Stream 1 (Image):

- EfficientNet-B0/B1/B2/B3/B4 (pre-trained ImageNet weights)
- Global Average Pooling 2D layer

Stream 2 (Metadata):

- Gaussian noise layer (improves robustness)
- Dense layers process categorical and numerical features
- Concatenate both streams → Dropout → Dense layer → Final prediction

4. Quantile Regression:

- Predict both FVC value and confidence (standard deviation σ)
- Allows uncertainty estimation crucial for medical applications

5. Training:

- Early stopping (prevent overfitting)
- Learning rate reduction on plateau (if no improvement after 20 epochs)
- 5-fold cross-validation
- Optimize using modified Laplace-Log-Likelihood metric

6. Evaluation Metric (Modified Laplace-Log-Likelihood):

$$\text{Metric}=-\Delta-\sigma_{\text{clipped}}-\ln(2\sigma_{\text{clipped}})$$

$$\text{Metric}=-$$

$\Delta$

$-\sigma$

clipped

$$-\ln($$

$$2$$

$$\sigma$$

$$\text{clipped}$$

$$)$$

Where: σ_clipped = max(σ, 70), Δ = min(|FVC_true − FVC_predicted|, 1000)

---

## Final Output Metrics (Benchmark)

| Model | Score | Status |
|---|---|---|
| EfficientNet B2 + Quantile Regression (Ours) | −6.64 | BEST |
| Fibro-CoSANet | −6.68 | Previous SOTA |
| Elastic Net Regression | −6.73 | Baseline |
| Kaggle 1st Place | −6.81 | Competition Winner |
| Kaggle 2nd Place | −6.83 | Competition |
| Multiple Quantile Regression | −6.92 | Older method |

Best Training Losses:

- EfficientNet B0 + QR: 3.6524
- EfficientNet B2 + QR: 3.8340
- EfficientNet B3 + QR: 3.6728

---

## Novelty (Crisp)

- First to combine EfficientNet with quantile regression for IPF FVC prediction with uncertainty quantification
- Outperforms Kaggle competition winners (−6.64 vs. −6.81)
- Better than previous state-of-the-art (Fibro-CoSANet, Fibrosis-Net) on OSIC dataset
- Multimodal fusion: Combines CT imaging with demographic metadata efficiently
- Confidence estimation: Quantile regression provides uncertainty bounds, critical for clinical deployment
- EfficientNet efficiency: Achieves superior performance with fewer parameters than ResNet50/VGG16

---

## Limitations (Crisp)

- Limited dataset: 176 patients; small for modern deep learning standards
- Risk of overfitting: ResNet50 and VGG16 showed overfitting tendencies; only EfficientNet variants remained stable
- No external validation: Tested only on OSIC Kaggle dataset; generalization to other institutions unknown
- Irregular FVC measurements: Patients have variable measurement intervals, complicating temporal modeling
- 2D image processing: Ignores 3D spatial context of CT volumes
- Missing interpretability: No visualization of which lung regions drive FVC predictions
- Clinical deployment uncertainty: No discussion of real-world integration or clinical workflow testing

# 2024 Identification of Molecular Biomarkers and Key Pathways among Idiopathic pulmonary fibrosis (IPF), Chronic Obstructive Pulmonary Disease (COPD) and Lung cancer

This project identifies shared molecular biomarkers and disease pathways connecting Idiopathic Pulmonary Fibrosis (IPF), Chronic Obstructive Pulmonary Disease (COPD), and lung cancer using genomic analysis.

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## Task Type & Learning Approach

- Unsupervised Learning (Bioinformatics/Systems Biology approach)
- Not classification/regression but biomarker discovery through differential gene expression analysis, network analysis, and pathway enrichment
- Uses R programming for computational genomics

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## Dataset Source

- Three public microarray datasets from GEO (Gene Expression Omnibus) database:

| Dataset | Disease | Samples | Platform |
|---|---|---|---|
| GSE24206 | IPF | 11 IPF + 6 controls = 17 | GPL570 |
| GSE18842 | Lung Cancer (NSCLC) | 45 controls + 46 cancers = 91 | GPL570 |
| GSE76925 | COPD | 40 nonsmokers + 111 COPD = 151 | GPL10558 |

---

## Methods & Code Sessions (Crisp Summary)

1. Differential Gene Expression (DEG) Analysis:

- Used R programming to identify DEGs in each dataset
- Threshold: |log fold change| > 1, Adjusted p-value < 0.05
- Result: 693 DEGs (IPF) + 2,338 DEGs (Lung Cancer) + 597 DEGs (COPD)
- Common genes: 8 shared DEGs across all three diseases

2. Venn Diagram Analysis:

- Identified overlap between DEG sets from all three datasets
- Visualized shared vs. disease-specific genes

3. Protein-Protein Interaction (PPI) Network Construction:

- Used STRING database and NetworkAnalyst tools
- Built PPI network from 8 common DEGs
- Network consists of: 344 nodes, 366 edges, 8 seed genes

4. Hub Gene Identification (Topological Analysis):

- Used CytoScape with cytoHubba plugin
- Ranked genes by network degree (connectivity)
- Identified top 8 hub genes: CFH, MSH2, SORD, NEDD9, CCNL1, RORA, ETS1, PMAIP1

5. KEGG Pathway Enrichment Analysis:

- Used Enrichr platform with KEGG database
- Analyzed biological pathways associated with common DEGs
- Found pathways related to colorectal cancer and cancer pathways

6. Drug Compound Identification:

- Used DSigDB (Drug Signature Database) via Enrichr
- Identified therapeutic drug candidates targeting the hub genes

---

## Final Output Metrics & Results

Top 5 Hub Genes (Network Properties):

| Hub Gene | Degree | Stress | Closeness Centrality | Betweenness Centrality |
|---|---|---|---|---|
| ETS1 | 133.0 | 39,372 | 204.17 | 72,812 |
| MSH2 | 95.0 | 305,904 | 176.67 | 51,293 |
| SORD | 35.0 | 49,354 | 136.67 | 20,606 |
| RORA | 34.0 | 59,786 | 137.65 | 19,531 |
| NEDD9 | 33.0 | 48,032 | 137.5 | 19,570 |

Top Drug Compounds (p-value < 0.0001):

| Drug | p-value | Adjusted p-value | Target Genes |
|---|---|---|---|
| Astemizole | 0.0000345 | 0.00951 | NEDD9, PMAIP1, CCNL1 |
| Calmidazolium | 0.0000401 | 0.00951 | NEDD9, PMAIP1, CCNL1 |
| Ivermectin | 0.0000926 | 0.00951 | NEDD9, PMAIP1 |

| | | | |
|---|---|---|---|
| Dichloromethane | 0.0001631 | 0.00951 | NEDD9, PMAIP1 |
| Ethylbenzene | 0.0001699 | 0.00951 | NEDD9, PMAIP1 |

---

## Novelty (Crisp)

- First transcriptome-wide systems biology study linking IPF, COPD, and lung cancer molecular mechanisms
- 8 shared DEGs discovered connecting three seemingly distinct diseases, revealing common pathophysiology
- ETS1 identified as primary hub gene with highest network connectivity (degree 133), suggesting central role in disease mechanisms
- Drug candidate prediction: Astemizole, calmidazolium, ivermectin proposed as therapeutic candidates targeting shared pathways
- Addresses critical gap: reveals why IPF/COPD patients have 3.34× higher lung cancer risk

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## Limitations (Crisp)

- Only 8 common genes: Limited overlap suggests diseases have largely distinct molecular pathways
- Small sample sizes: GSE24206 has only 11 IPF + 6 controls; limited statistical power
- Single analysis type: No machine learning classification; no validation on independent cohorts
- Microarray only: No RNA-seq data; microarray less sensitive for low-abundance transcripts
- Incomplete validation: Top 5 biomarkers (ETS1, MSH2, SORD, RORA, NEDD9) require functional validation via experiments
- Drug candidates not validated: Proposed drugs (astemizole, ivermectin) need in vitro/in vivo testing
- Future work needed: miRNA analysis, transcription factor analysis, gene ontology (GO) annotations, and module-level network analysis

# 2023 Domain Generalization for Diagnosis of Pulmonary Fibrosis Using Dose-Invariant Feature Selection

This project focuses on the diagnosis of pulmonary fibrosis from CT scan images. It addresses the challenge that the performance of deep-learning models for pulmonary fibrosis diagnosis often decreases when CT scans are taken at radiation doses different from those used in training. The main goal is to develop a method for domain generalization, ensuring that model representations and predictions remain invariant to CT radiation dose variations, even for unseen doses, without needing to retrain the entire network.

## Task type:

- It is a classification task that classifies CT scan slices into three fibrosis severity levels: absence (0), mild (1), and advanced fibrosis (2).
- This is a supervised learning problem, using labeled CT data with fibrosis severity.

## Dataset Used:

- An in-house dataset from the University Hospital of Zurich with 230 patients and 690 CT images.
- Each patient has CT scans obtained at multiple radiation doses, enabling dose-invariance training and testing.

## Methods Summary:

- Train a neural network comprising a feature extractor (ResNet50 or Vision Transformer) and a classifier on CT slices from two different radiation dose levels.
- Extract feature representations from the feature extractor for all samples in each dose group.
- A feature selection technique identifies features invariant to radiation dose by measuring similarity of feature distributions between doses using statistical tests (e.g., Kolmogorov-Smirnov, posterior agreement kernel).
- Retrain the classifier on only the dose-invariant selected features.

- This process ensures the classifier is minimally influenced by radiation dose variation.
- The pipeline avoids retraining the whole network, making it efficient.

## Code Sessions Explained Simply:

1. Network training on union of CT scans from two doses.
2. Feature extraction to obtain intermediate representations.
3. Compute dose-invariance similarity per feature and select top invariant features.
4. Retrain classifier on these invariant features.
5. Evaluate robustness on unseen radiation doses using F1-score.

## Final Output Metrics:

- Performance measured by F1-score, reporting robustness improvements of 6% to 15% on unseen doses over standard methods.
- Marginal (<2%) decrease in in-distribution F1 when applying dose-invariance feature selection.
- The method outperforms previous approaches significantly in domain generalization.

## Novelty:

- Introducing a novel dose-invariant feature selection method for domain generalization in medical imaging.
- Achieves stable and improved performance despite CT radiation dose shifts, a real-world variability source.
- Uses multiple statistical similarity functions, showing improved robustness beyond standard Pearson correlation.
- Avoids computationally expensive retraining by selecting invariant features post hoc.

## Limitations:

- Requires availability of CT scans from multiple radiation doses for training, which may not be widely accessible.
- Limited to 2D CT slices rather than full volumetric analysis.
- The in-house dataset used is relatively small (230 patients).
- The approach assumes availability of dose metadata and requires manual tuning of selected feature count.

- Generalization to other domain shifts beyond radiation dose remains to be tested.

## Summary:

This supervised classification study tackles pulmonary fibrosis diagnosis from CT images, emphasizing robust model performance across different CT radiation doses via dose-invariant feature selection. Using an in-house multi-dose CT dataset, it achieves notable gains in accuracy and robustness compared to traditional training, demonstrating an effective strategy for domain generalization in medical imaging.

# 2023 Lung Function Decline Predicting Using Improved EfficientNet

This project focuses on predicting lung function decline in pulmonary fibrosis patients using an improved EfficientNet deep learning model.

## What we are doing:

- Predicting Forced Vital Capacity (FVC)—a continuous lung function metric—using baseline CT scans and clinical data.
- Model output includes predicted FVC values and confidence via Laplace Log Likelihood metric.

## Task type:

- Regression task (predict continuous FVC)
- Supervised learning with labeled CT images plus longitudinal FVC measurements.

## Dataset source:

- OSIC Pulmonary Fibrosis Progression dataset (from Kaggle)
- Around 200 patients with baseline CT scans, follow-up visits across 1-2 years, FVC data.

## Code sessions (simple summary):

1. Preprocess CT images: normalize, resize to 512×512 pixels, convert to Hounsfield Units.
2. Process categorical and numerical clinical features with one-hot encoding and normalization.
3. Build two streams: EfficientNet (pre-trained on ImageNet) for CT features + dense layers for clinical data.
4. Fuse features, add dropout, fully connected layer to predict FVC and confidence.
5. Train with Adam optimizer, early stopping and learning rate schedule using Laplace Log Likelihood loss.
6. Evaluate with modified Laplace Log Likelihood metric to capture accuracy and uncertainty.

## Final output metrics benchmark:

| Model | Laplace Log Likelihood (higher better) |
|---|---|
| Improved EfficientNet (proposed) | -6.89 |
| ResNet34 | -7.12 |
| ResNet50 | -7.11 |
| Base EfficientNet | -7.04 |

## Novelty:

- Combines EfficientNet with uncertainty-aware quantile regression using Laplace Log Likelihood loss for accurate FVC prediction.
- Outperforms ResNet and baseline EfficientNet models on the OSIC dataset.
- Confidence quantification in predictions supports clinical trust.
- EfficientNet's compound scaling design balances depth, width, and resolution for improved feature extraction.
- Multi-modal fusion of imaging and clinical data.

## Limitations:

- Dataset moderate size (~200 patients), limiting deep model generalization.
- No external dataset validation beyond OSIC.
- Only 2D slice-based image processing; no volumetric modeling.
- No interpretable explanations or attention maps provided.
- Potential overfitting risks mitigated by early stopping but residual uncertainty remains.
- Clinical workflow integration not tested yet.

In sum, this supervised regression project uses improved EfficientNet plus quantile regression to predict pulmonary fibrosis progression with state-of-the-art accuracy and uncertainty modeling on a public dataset, pushing forward personalized diagnosis and prognosis for PF patients.

# 2022 A combined CNN-LSTM and LSTM-QRNN model for prediction of Idiopathic Pulmonary Fibrosis Progression using CT Scans and Clinical Data

This project develops a hybrid deep learning model combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architectures together with a Long Short-Term Memory Quantile Regression Neural Network (LSTM-QRNN) to predict the progression of Idiopathic Pulmonary Fibrosis (IPF) by forecasting Forced Vital Capacity (FVC) using CT scans and clinical data.

## Task type:

- Regression task: Predicts continuous FVC values over time to estimate lung function decline.
- Supervised learning: Trained on labeled CT images along with clinical metadata.

## Dataset source:

- OSIC Pulmonary Fibrosis Progression dataset from Kaggle, containing:
    - Baseline CT scans
    - Longitudinal clinical FVC measurements for around 200 patients

## Methods summary (simplified):

1. Data preprocessing:
    - Convert CT slices to Hounsfield Units
    - Normalize + resize images to 128×128 pixels
    - Normalize clinical metadata (age, sex, smoking status, FVC, weeks)
    - Remove outliers from clinical data using quartile method
2. Model architectures:
    - CNN-LSTM: EfficientNet pretrained CNN for spatial feature extraction from CT slices combined with LSTM to capture temporal dependencies across slices and clinical data.
    - LSTM-QRNN: Uses clinical metadata to predict FVC quantiles and uncertainties via Smooth Pinball loss.
3. Model training:

- Transfer learning and fine-tuning of CNN-LSTM with early stopping and learning rate scheduling.
- LSTM-QRNN trained with 10-fold cross-validation.

4. Ensemble fusion:
    - Simple dense neural network fuses CNN-LSTM regression with LSTM-QRNN uncertainty predictions.
5. Evaluation:
    - Metrics: Modified Laplace Log-Likelihood (mLLL), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE)
    - Model tested on Kaggle private dataset leaderboard.

## Final output metrics (benchmark):

| **Model** | **Private Dataset mLLL Score** |
|---|---|
| CNN-LSTM + LSTM-QRNN (transfer learning) | -6.8308 |
| CNN-LSTM + LSTM-QRNN (fine-tuning) | -6.8098 |
| CNN-LSTM (EfficientNet-B5) | -6.8209 |
| LSTM-QRNN | -6.8658 |
| Top Kaggle 1st place | -6.8305 |
| Fibrosis-Net (previous SOTA) | -6.8188 |

## Novelty:

- Hybrid model integrates deep spatial features (CNN-LSTM) and clinical temporal data (LSTM-QRNN) for improved IPF progression prediction
- Uses quantile regression to provide uncertainty bounds alongside predictions, enhancing clinical applicability
- Transfer learning from ImageNet pretrained EfficientNet improves feature extraction from limited CT data
- Achieves superior score on Kaggle OSIC private leaderboard over previous state-of-the-art models

## Limitations:

- Moderate dataset size (~200 patients), risking overfitting despite regularization
- Only 2D CT slice processing; no full 3D volume context
- No interpretability or explainability methods presented
- Dependence on quality longitudinal clinical data, which may have missing entries or noisy measurements
- Clinical real-world deployment and validation remain future work

In summary, this supervised regression project uses combined CNN-LSTM and LSTM-QRNN models on the OSIC dataset to predict IPF lung function decline with uncertainty measures, showing top leaderboard performance and promising clinical assist potential.

# 2022 Estimating Lung Capacity in Pulmonary Fibrosis Patients via Computerized Tomography (CT) Scan Data and Machine Learning

This project aims to estimate lung capacity (Forced Vital Capacity - FVC) in pulmonary fibrosis patients using computerized tomography (CT) scan data combined with machine learning models.

## Task type:

- Primarily regression task: predict continuous FVC percentage values from CT images.
- Uses unsupervised image detection for identifying lung tissue regions and supervised machine learning for regression of lung capacity.

## Dataset:

- 172 patients with CT scans and spirometry lung capacity results.
- CT images processed from DICOM files using Hounsfield Units to identify lung tissue.
- Training images constructed by combining CT slices into large images per patient for machine learning.

## Methods (Crisp Summary):

1. DICOM parsing: Read and order CT image slices by instance number.
2. Rescale adjustment: Adjust pixel values based on DICOM Rescale Slope and Intercept to normalize intensity.
3. Hounsfield Unit filtering: Filter pixel values between -700 and -500 HU to isolate lung tissue.
4. Image Processing & Filtering:
    - Otsu thresholding and morphological filtering (dilate, erode) applied to create binary masks of lung regions.

    - Contour detection to identify closed shapes matching lung tissue structures, e.g., honeycombing.
    - Calculate "Honeycomb rating" as a ratio of detected honeycomb contour area to total lung image area.
5. Machine Learning:
    - Use Orange3 platform for logistic regression and neural network models.
    - Train on categorized lung capacity percentage (discretized to increments).
6. Performance Evaluation:
    - Logistic regression and neural networks had low classification accuracy in small incremental categories.
    - Improved results in 10% increment categories but still limited (~10/51 accuracy).
    - Honeycomb rating showed poor correlation with actual lung capacity measurements.

## Final Output Metrics:

- Classification accuracy under 20% for fine-grained lung capacity categories.
- No strong correlation between honeycomb rating from image processing and lung capacity.

## Novelty:

- Uses combined CT image preprocessing and objective computer vision filtering to estimate lung tissue abnormalities.
- Aims to predict lung capacity without direct spirometry, reducing patient burden.
- Introduces a method combining Hounsfield Units and contour-based honeycomb detection for fibrosis quantification.

## Limitations:

- Poor machine learning classification performance due to imprecise lung tissue representation by Hounsfield Units.
- Honeycomb rating did not align well with actual lung function.
- Variable CT image resolutions and slice counts led to potential data loss and inconsistent representation.
- Small sample size (172 patients) limits generalizability.
- Spirometry itself has accuracy concerns, complicating ground truth reliability.
- Suggests exploring better image processing techniques and 3D modeling for future work.

In summary, this project uses CT scan processing and machine learning to predict lung capacity in fibrosis patients with a focus on reducing spirometry dependency but is limited by data representation quality and model performance.

# 2022 Analysis of Idiopathic Pulmonary Fibrosis through Machine Learning Techniques

This project analyzes Idiopathic Pulmonary Fibrosis (IPF) using machine learning techniques, focusing on predicting lung function decline through Forced Vital Capacity (FVC) values.

## Task Type and Learning Approach

- Regression task: Predicts continuous FVC values to assess lung function decline.
- Supervised learning: Models trained on labeled patient clinical data and CT images paired with FVC measurements.

## Dataset Used

- OSIC Pulmonary Fibrosis Progression Dataset (Kaggle)
    - 176 patients, 1,554 FVC records, and CT scans.
    - Patient demographics: 79% male, 21% female, ages 49 to 88.
    - Smoking status recorded: ex-smoker, never smoked, current smoker.

## Code Sessions and Methods (Simplified)

1. Data Preprocessing:
    - Convert categorical data (gender, smoking status) to numerical.
    - Merge train/test data for K-fold cross-validation.
    - Normalize and clean clinical data.
    - Use baseline (0th week) HRCT images aligned with FVC data.
2. Machine Learning Models:
    - Multiple Quantile Regression (MQR): CNN-based regression predicting multiple quantiles of FVC to model different levels of lung function.
    - Elastic Net Regression: Combines L1 and L2 regularization to handle data sparsity and multicollinearity.
    - CNN architecture: 4-layer CNN trained for 2000 epochs, batch size 128, optimizer Adam.
3. Training and Evaluation:
    - Validation via cross-validation.
    - Prediction accuracy measured by Laplace Log Likelihood loss.
    - Quantile regression approach outperforms elastic net.
4. Prediction Visualization:

- Predicted FVC quantiles plotted to assess confidence intervals.
- Summary of quantile predictions provided.

## Final Metrics as Benchmark

- Quantile Regression Model Accuracy: 92% (cross-validation)
- Elastic Net Regression Accuracy: Lower than MQR
- Laplace Log Likelihood Metric: -6.13 for MQR (better)

## Novelty

- First to apply multiple quantile regression with CNN on IPF FVC prediction.
- Provides probabilistic lung function estimates with confidence bounds.
- Improved accuracy and insight over traditional regression methods.
- The model can detect decline progression aiding early intervention.

## Limitations

- Dataset size moderate; only 176 patients.
- The model assumes patients already diagnosed with IPF.
- Future aims include direct detection of fibrosis from CT images without prior diagnosis.
- Uses 2D CNN on baseline images; volumetric context missing.
- No external datasets or real-world clinical validation done yet.
- Longer follow-up data needed to improve progression tracking.

---

This project produces a supervised regression model that predicts lung function decline in IPF using clinical data and CT images with advanced quantile regression providing more accurate, probabilistic lung capacity forecasts.

# Previous Work

## "Automated Pulmonary Fibrosis Progression Prediction using 3D CNNs" (IEEE TMI, 2023):

## 📘 Paper Overview

- **Goal**: Predict future pulmonary function decline (e.g., FVC) by leveraging longitudinal CT scans, clinical metadata, and temporal modeling.
- **Core Innovation**: Integrating **3D ResNet-50** for spatial features and **LSTM** for capturing temporal progression across multiple scans, along with demographic and other tabular data.

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## 🧬 Dataset Details

- **Population**: 1,284 patients diagnosed with fibrosing interstitial lung diseases (including NSIP, UIP/IPF).
- **Longitudinal CT Data**: Each patient has multiple CT scans taken at varying intervals (e.g., baseline, 6 months, 12 months).
- **Clinical Metadata**: Age, sex, smoking status, baseline FVC, and other lab values collected at each timepoint.
- **Preprocessing**:
    - CT volumes resampled to a common voxel size (e.g., 1 $mm^3$).
    - Lung segmentation applied to isolate lung parenchyma.
    - Intensity normalization and cropping/padding to fixed size (e.g., $128^3$ voxels).

---

## 🏗️ Model Architecture

1. **3D ResNet-50 Backbone**:
    - Processes each CT volume to extract spatial feature embeddings.
    - Output: A fixed-length feature vector per timepoint.
2. **Temporal Model (LSTM)**:
    - Inputs: Sequence of CT embeddings + corresponding clinical metadata concatenated per timepoint.
    - Captures progression trends across scans.
3. **Regression Head**:
    - Fully connected layers on LSTM output to predict future FVC values.
    - Loss: Mean Squared Error (MSE).

---

## ⚙️ Implementation Details

- **Training**:
    - Input sequences include $t_0$, $t_1$, …, $t$□ scans per patient.
    - Regularization via dropout, weight decay.
    - Optimizer: Adam with cosine learning rate scheduler.
- **Data Augmentation**: Random rotations, flips, intensity scaling applied per CT volume.
- **Validation**:
    - 5-fold cross-validation on patient-level splits.

---

## 📈 Performance Metrics

| Metric | Measured Value |
|---|---|
| MAE | 189 mL ± 23 |
| RMSE | 247 mL |
| $R^2$ Score | 0.79 |

These results indicate reliable predictive accuracy and consistency compared to baselines or single-timepoint models.

---

## 💡 Key Insights

- **Spatial + Temporal Fusion**: 3D features captured at each timepoint were effectively combined through LSTM to model progression dynamics.
- **Clinical Data Integration**: Performance improved when demographic and baseline lab values were included, highlighting multimodal fusion's importance.
- **Comparative Gain**: Model outperformed prior single-scan or simple regression models by a significant margin in MAE/RMSE.

---

## ✅ Strengths vs Limitations

### Strengths:

- **Robust longitudinal modeling** using multiple CT timepoints.
- **Strong clinical realism**, reflecting real-world disease progression.
- **Good generalization potential** across fibrotic ILD subtypes (NSIP, UIP).

### Limitations:

- Relies on **relatively high model complexity** (3D ResNet + LSTM).
- CT scan intervals varied—model might not generalize to extreme gaps.
- May require **significant GPU memory** for training with volumetric data.

---

## 📌 How This Informs Your Project

1. **DenseNet with Temporal Fusion**: Replace 3D ResNet with a **3D DenseNet121 + LSTM/Transformer** for improved parameter efficiency and effective spatial modeling.
2. **Self-supervised Pretraining**: Pretrain your DenseNet features using contrastive learning on unlabeled CT volumes to strengthen spatial embeddings.
3. **Multimodal Enhancements**: Fuse lung volume, demographics, labs, and CT embeddings with attention mechanisms.
4. **Uncertainty Estimation**: Move from MSE to **Laplace log-likelihood with uncertainty prediction** (mean + sigma outputs) to better reflect real-world risk modeling.
5. **Explainability**: Use **Grad-CAM++** for spatial insight and **SHAP** for tabular influence, improving clinical interpretability.

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By adopting and refining this architecture—with DenseNet, attention-based fusion, uncertainty modeling, and explainability—you position your work to surpass existing benchmarks (e.g., RMSE < 165 mL, Laplace < −6.60) and deliver a robust publication-ready model

**"Deep Transfer Learning Techniques-Based Automated Classification and Detection of Pulmonary Fibrosis from Chest CT Images"**, published in *Processes* (2023) (mdpi.com):

🩺🟢 Lung Fibrosis DICOM Image Preprocessing

GitHub Not sure : https://github.com/tabrejmsc/Deep-Transfer-Learning-Techniques-Based-Automated-Classification-and-Detection-of-Pulmonary-Fibrosis

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## 🩺 What's it about?

The authors developed an AI-powered method for diagnosing pulmonary fibrosis (PF)—a chronic, currently incurable lung disease—using chest CT scans. They evaluated six well-known deep learning models via transfer learning to see which best detects PF.

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## ⚙️ Methodology

- Gathered **2,299 CT scan images** (about 1,470 PF-positive and 829 normal).
- Preprocessed and split the dataset: **75% training**, **15% validation**, **10% test**.
- Fine-tuned six pre-trained CNNs (VGG-19, DenseNet121, Xception, InceptionResNetV2, ResNet50v2, plus another variant).
- Applied preprocessing steps: normalization, segmentation, masking, data augmentation (flips, rotations, zooms), dropout, and early stopping.
- Optimized hyperparameters like learning rate (~0.0000625) and number of epochs (26).

---

## 🎯 Top Performance

- **ResNet50v2** outperformed the other models.

    - Achieved **99.92% training accuracy**, **99.22% validation accuracy**.
    - On the test set, it reached **100%** on all major metrics: accuracy, precision, recall, F1-score, MCC, ROC-AUC, and PR-AUC (mdpi.com).
- They also used **Grad-CAM** to visually highlight fibrotic regions (scarring) identified by the model.

---

## ✅ Key Takeaways

- Fine-tuning ResNet50v2 with a well-optimized setup yields **near-perfect PF detection** from CT slices.
- The study underscores the effectiveness of transfer learning + augmentation for medical imaging.
- Grad-CAM adds interpretability by showing which lung regions influenced the model's decisions.

---

## 🧩 Why it matters

Early and accurate PF detection is critical because timely intervention can delay progression. This model demonstrates how AI can enhance diagnostic consistency and precision, potentially assisting radiologists and reducing delays in care.

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## 🔎 Ways to challenge their model:

1. **Cross-dataset testing**:
    - Validate their model on a **completely different PF dataset** (e.g., OSIC Pulmonary Fibrosis) to test generalizability.
2. **3D CT Volume Analysis**:
    - They used 2D slices; you can use **3D CNNs or hybrid models** (e.g., V-Net, 3D ResNet) for full volumetric context.

3. **Self-Supervised Pretraining**:
    - Use models like **SimCLR** or **DINOv2** to pretrain on unlabeled lung CT data for better representation learning.
4. **Ensemble Techniques**:
    - Combine multiple models (e.g., ResNet + DenseNet + ViT) for robust classification.
5. **Clinical Metadata Fusion**:
    - Combine **CT features with patient data** (age, smoking history, etc.) using multi-input networks.
6. **Explainability**:
    - Improve interpretability using **SHAP, Integrated Gradients**, or **better Grad-CAM** implementations.
7. **Data Leakage Check**:
    - Ensure no overlapping slices from same patients in train/test sets (many studies overlook this!).

# 📝 3. Future Scope Ideas (Based on the Paper + Current Trends)

## 🔬 Based on Their "6. Conclusions and Future Scope" (Paraphrased from Source):

- They suggest enhancing interpretability and exploring other imaging modalities (like X-rays).
- They mention testing with more diverse and real-world datasets.

## 🔥 Current ML Paper Trends (2025):

- **Multi-modal learning**: Image + text or image + tabular.

- **Lightweight models** for edge deployment (e.g., MobileNetV3, EfficientNetV2, quantized models).
- **Self-supervised learning** and **few-shot learning** are hot.
- **Explainability & fairness audits** in medical ML are crucial for acceptance.
- **Synthetic data generation** with GANs or diffusion for rare classes.

# Prediction of Pulmonary Fibrosis Progression using CNN and Regression

https://ieeexplore.ieee.org/abstract/document/9725730

Dateset: OSIC Pulmonary Fibrosis Progression Challenge

GitHub Code : https://github.com/darwinai/FibrosisNet/tree/main

the 1st place winning solution (OSIC, 2020) proposed a weighted ensemble between a deep convolutional neural network with a state-of-the-art EfficientNet-B5 network architecture design (Tan and Le, 2020) and a multiple quantile regressor to predict the lung function decline of a patient based on a patient's CT scans, initial spirometry measurement, and clinical metadata.

## 🏗️ Method Highlights

- Used **machine-driven architecture search** to create a lightweight yet effective CNN tailored for CT lung analysis PubMed.
- The model ingests CT images, initial FVC measurement, and metadata to predict FVC at future time points PubMed.
- Incorporated an **explainability-driven validation**, ensuring the model focuses on medically relevant CT patterns (e.g., honeycombing) using GSInquire, an interpretable saliency method PMC+1PubMed+1.

| Method | Laplace log likelihood |
| --- | --- |
| Kaggle 1st place (OSIC, 2020) | −6.8305 |

| | |
|---|---|
| Kaggle 2nd place (OSIC, 2020) | −6.8311 |
| Kaggle 3rd place (OSIC, 2020) | −6.8336 |
| Fibrosis-Net | −6.8188 |

## ✅ Goal

**Beat Fibrosis-Net's −6.8188 Laplace Log Likelihood** using a DenseNet-based or hybrid architecture by:

1. Improving model input (data)
2. Enhancing architecture (model)
3. Refining training + optimization (methods)
4. Deepening interpretability (explainability)
5. Validating generalization (testing)

---

## 🔧 1. Architecture: DenseNet as Base

**Why DenseNet?**

- High **parameter efficiency** (due to feature reuse).
- **Deep supervision** makes gradient flow easier.
- Already performs well in medical imaging tasks.

**How to Enhance DenseNet:**

- **Pre-trained 2D DenseNet121** → Fine-tune on lung CT slices.

Or, for better context: use **3D DenseNet** (or 2.5D approach):
python
CopyEdit

```
from monai.networks.nets import DenseNet121
# 3D DenseNet from MONAI for volumetric data
```

Fuse DenseNet features with **clinical data (age, sex, FVC, smoking history)**:
python

CopyEdit

```
# Create two inputs: (1) CT image, (2) tabular metadata
# Concatenate after FC layers
```

---

## 🧠 2. Temporal Modeling

Instead of just predicting FVC from one CT:

| Option | Approach |
|---|---|
| 🕓 RNN | Pass DenseNet features + tabular inputs into an LSTM/GRU to model temporal progression |
| 🔁 Transformer | Use a Time Series Transformer or TabTransformer on FVC sequence |
| 📊 Gaussian Process | Predict a distribution over FVC over time (like OSIC challenge did) |

---

## 🧪 3. Data Improvements

Use the **OSIC Pulmonary Fibrosis Dataset** (official Kaggle dataset). Structure:

- 176 unique patients
- CT scan series (DICOM), baseline FVC, week-wise progression data
- Tabular data: `FVC`, `Percent`, `Age`, `Sex`, `SmokingStatus`

**Suggestions:**

- Use **3D patches** or full lung volumes, not just 2D slices.
- Normalize FVC across age, sex (as relative decline).
- Apply **lung segmentation preprocessing** for better ROI focus.

---

## 🎯 4. Objective Function: Laplace Log Likelihood

Same as used in OSIC challenge.

For each week:

python
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```
# Assume predicted FVC mean and std
loss = np.mean( np.log(sigma) + 0.5 * ((FVC_true - FVC_pred) / sigma)**2 )
```

Optimize model to **predict both mean and uncertainty** (σ), not just FVC value.

---

## 🌐 5. Explainability: Go Beyond GSInquire

GSInquire was used in Fibrosis-Net. You can:

- Use **Grad-CAM++**, **Integrated Gradients**, or **SHAP (for tabular)**.
- Highlight fibrotic tissue regions more clearly.
- Show attention maps over time (if using a sequence model).

---

## 📊 6. Benchmarking + Validation

| Method | Laplace log likelihood |
|---|---|
| Kaggle 1st (OSIC) | −6.8305 |
| Fibrosis-Net | −6.8188 |

**Your Target** **< −6.8100**

📌 Also validate on:

- **Patient-level split**
- **Leave-one-out** or **k-fold**
- **External CT datasets** (e.g., LIDC-IDRI if labeled for fibrosis or other open-access dataset

## 🚀 To Get Started:

1. ✅ Use **DenseNet121 + tabular fusion**
2. ✅ Implement **FVC + uncertainty** prediction for Laplace loss
3. ✅ Try **temporal modeling** (LSTM or transformer)
4. ✅ Apply **Grad-CAM++** for CT attention and **SHAP** for tabular data
5. ✅ Tune for Laplace Log Likelihood on OSIC dataset

# FibroRegNet: A Regression Framework for the Pulmonary Fibrosis Prognosis Prediction Using a Convolutional Spatial Transformer Network → BEST SO FAR

Downloaded paper locally

Achieved:

- **Laplace Log Likelihood (LLLm)**: **−6.64**
- **RMSE**: ~172 ml

## 🔍 Ablation Insights

- **Polynomial regression > linear regression**:
  - More accurately captures nonlinear FVC trends
  - Validated using F-statistic and residual analysis
- **Encoding > Embedding for demographic data**:
  - Dataset too small, low-cardinality features → embeddings underperform
- **3-slice input with 3-stream STN** bested deeper/more complex CNNs

## ⚙️ Technical Details

- Framework: **PyTorch**
- Loss: **L1** for regression; **Laplace LL** for evaluation
- Optimization:

    - Adam optimizer
    - 2-phase training: CT-only training, then fusion-based fine-tuning
- Model:
    - ~22M parameters
    - ~0.63G MACs
    - ~0.81 sec inference per patient

## 🧩 Limitations

- Uses only **1 CT scan per patient**
- Performance sensitive to **slice selection**
- Not a time-series model — FVC is **modeled statically**, not predicted incrementally

📚 **Position vs Existing Works**

| Model | LLLm | Notes |
|---|---|---|
| **Kaggle 1st place** | **−6.8305** | **Ensemble + quantile regression** |
| **Kim et al. [25]** | **−6.68** | **Linear regression + CT + lung volume** |
| **Yadav et al.** | **−6.41** | **Honeycomb features + EfficientNet** |
| **FibroRegNet** | **−6.64** | **CT+Demographics+LungVol+STN+RidgeReg** |

## ✅ Summary of Novelty

- **First to apply cascaded STNs for pulmonary fibrosis prognosis**
- **Unique use of quadratic polynomial ridge regression**

- **Efficient multimodal fusion with only 3 slices per patient**

**How to beat this papers beanchmark**

# 1. Model Architecture: DenseNet Backbone

- **Base: Start with a pretrained DenseNet121 (2D) or MONAI's 3D DenseNet121 for volumetric CT input.**
- **Enhancements:**
  - **CBAM (Convolutional Block Attention Module): Wrap DenseNet's dense blocks with CBAM to add spatial + channel attention.**
  - **Squeeze-and-Excitation (SE) layers in each transition layer for lightweight attention.**
- **Hybrid Option: After DenseNet's final feature map, feed into a light Transformer encoder (e.g., 2 layers) to capture global context.**

---

# 2. Input Representation

- **2.5D Strategy: For each patient, stack 7 contiguous slices centered on the mid-lung, treat as a 3-channel input (groups of 3 slices) to DenseNet.**
- **Full 3D Option: Use MONAI's 3D DenseNet121 on entire lung volume (resampled to fixed 64-slice cubes).**
- **Learned Slice Selection: Precede DenseNet with a tiny CNN "scorer" that picks the top-N most informative slices per patient.**

---

# 3. Multimodal Fusion

- **Early Fusion:**
  1. **DenseNet features (after global pooling) → FC(256)**
  2. **Lung volume + demographic embeddings → FC(128)**
  3. **Concatenate → FC(256) → dropout**

- **Attention-based Fusion: Use a cross-modal attention block where DenseNet features attend to tabular features and vice versa.**

---

# 4. Target Design & Loss

- **Multi-output Regression:**
    - **Predict polynomial coefficients *(a, b, c)* and direct FVC at weeks [4, 12, 24, 52] to capture both curve shape and discrete predictions.**
- **Loss Function:**
    - **Laplace log-likelihood for the continuous outputs.**
    - **Quantile loss at the discrete weeks (e.g., 0.5 quantile) for robustness to outliers.**
    - **Total loss = 0.6·LaplaceLL + 0.4·QuantileLoss.**

---

# 5. Explainability

- **Grad-CAM++ on DenseNet feature maps to highlight fibrotic regions.**
- **SHAP for tabular (demographic + volume) contributions.**
- **Attention maps from CBAM/Transformer to visualize which slices/channels matter most.**

---

# 6. Training & Data Strategy

- **Data Augmentation (on CT slices):**
    - **Intensity window shifts (simulate different Hounsfield scales)**
    - **Elastic deformations, random rotations (±15°), flips, cut-patch (CutMix)**
- **Cross-Validation:**
    - **10-fold patient-level CV, plus a held-out external cohort if possible.**
- **Self-Supervised Pretraining:**
    - **Use SimCLR on all unlabeled CT slices before fine-tuning DenseNet.**

---

## 7. Efficiency & Benchmarking

| Metric | FibroRegNet | Your DenseNet Plan |
|---|---|---|
| LLLm | –6.64 | Target < –6.60 |
| RMSE | 172.35 ml | Target < 165 mlosic-pulmonary-fibrosis-progression |
| Params | 22 M | ~12–15 M (DenseNet121+CBAM) |
| Inference (per patient) | 0.81 s | ≤ 0.5 s |

**Prune & Quantize: After training, apply weight pruning (30%) and 8-bit quantization to hit the inference target.**

---

## 8. Paper & Publication Angle

- **Title: “DenseFusion-Net: CBAM-Enhanced DenseNet for Multimodal Pulmonary Fibrosis Prognosis”**
- **Novelty Claims:**
    1. **Attention-augmented DenseNet outperforms STN-based models.**
    2. **Multi-output regression capturing both continuous curves and discrete time-point predictions.**
    3. **Self-supervised pretraining on CT boosts low-data performance.**
- **Journals/Confs: IEEE JBHI, MICCAI, Frontiers in AI.**

# 🔍 Comparative Analysis: FibroRegNet vs 3D ResNet-50 + LSTM

## 1. Model Architecture

- **FibroRegNet**:
    - Uses **three 2D spatial transformer streams** with 3 CT slices each.
    - Lightweight (~22M params), uses quadratic ridge regression for FVC.
- **3D ResNet-50 + LSTM**:
    - Employs a **3D CNN** (spatial) + **LSTM** for temporal progression.
    - Larger model that processes full CT volumes across timepoints.
    - Better captures spatial and temporal disease patterns.

**Winner**: The 3D ResNet + LSTM captures progression more naturally, but is heavier and more resource-intensive.

---

## 2. Input Utilization

- **FibroRegNet**: Only **single-scan input** (3 slices).

- **3D ResNet + LSTM**: Uses **longitudinal data** (baseline + follow-up CT scans).

**Winner**: 3D + LSTM, due to temporal insight.

---

## 3. Dataset and Data Size

- **FibroRegNet**: Based on OSIC challenge (~176 patients, single-scan).
- **3D ResNet + LSTM**: Uses **1,284 patients** with multi-scan longitudinal CTs.

**Winner**: The latter — larger, more diverse data → better generalization.

---

## 4. Performance

- **FibroRegNet**: Reports Laplace log likelihood ~ –6.64, RMSE ~172 mL.
- **3D ResNet + LSTM**: Reports MAE 189 ±23 mL, RMSE 247 mL, $R^2 = 0.79$.

Converting metrics is tricky, but **FibroRegNet has lower RMSE**, while the 3D model captures broader progression ($R^2$ ~79% is impressive).

---

## 5. Explainability & Efficiency

- **FibroRegNet**: Grad-CAM–style STN-supported visualization, explainable but 2D-only.
- **3D ResNet + LSTM**: Likely no detailed explainability tracked; it's heavy and harder to interpret slice-level pathology.

---

## ✅ Bottom Line: Which Is Better?

- For **temporal progression and clinical realism**, the **3D ResNet + LSTM** is superior.

- For **efficiency, interpretability, and prediction accuracy per scan**, **FibroRegNet** excels.

- You can aim to **combine the best of both**: a lightweight 3D network (e.g., a trimmed DenseNet3D) + temporal modeling + explainability + uncertainty estimation (Laplace loss) to surpass both.