

# Multimodal Deep Learning Framework for PFT Estimation in Scoliosis Patients

Utilizing chest radiographs, radiographic measurements, and clinical information

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# Background, Clinical Need, and Study Objectives

## Clinical problem

- Scoliosis-related thoracic deformity can restrict lung expansion and reduce chest wall compliance.
- PFT remains the reference standard, but may be difficult in pediatric, neuromuscular, cognitive, or physically impaired patients.
- Routine standing PA chest radiographs may contain latent structure-function information.

## Study objectives

- Estimate continuous spirometric indices: FVC and FEV1.
- Identify restrictive ventilatory pattern using predicted FVC% (<80%).
- Quantify the incremental contribution of clinical variables, manual metrics, and raw CXR pixels.

**Key novelty: structure-driven pulmonary dysfunction in scoliosis**

Rather than treating pulmonary function prediction as a generic imaging task, this study isolates **how thoracic structural information contributes to FVC/FEV1 estimation in scoliosis.**

**Stepwise multimodal comparison**

**Clinical data**

**Manual metrics**

**Raw CXR pixels**

# Cohort Selection & Patient Characteristics

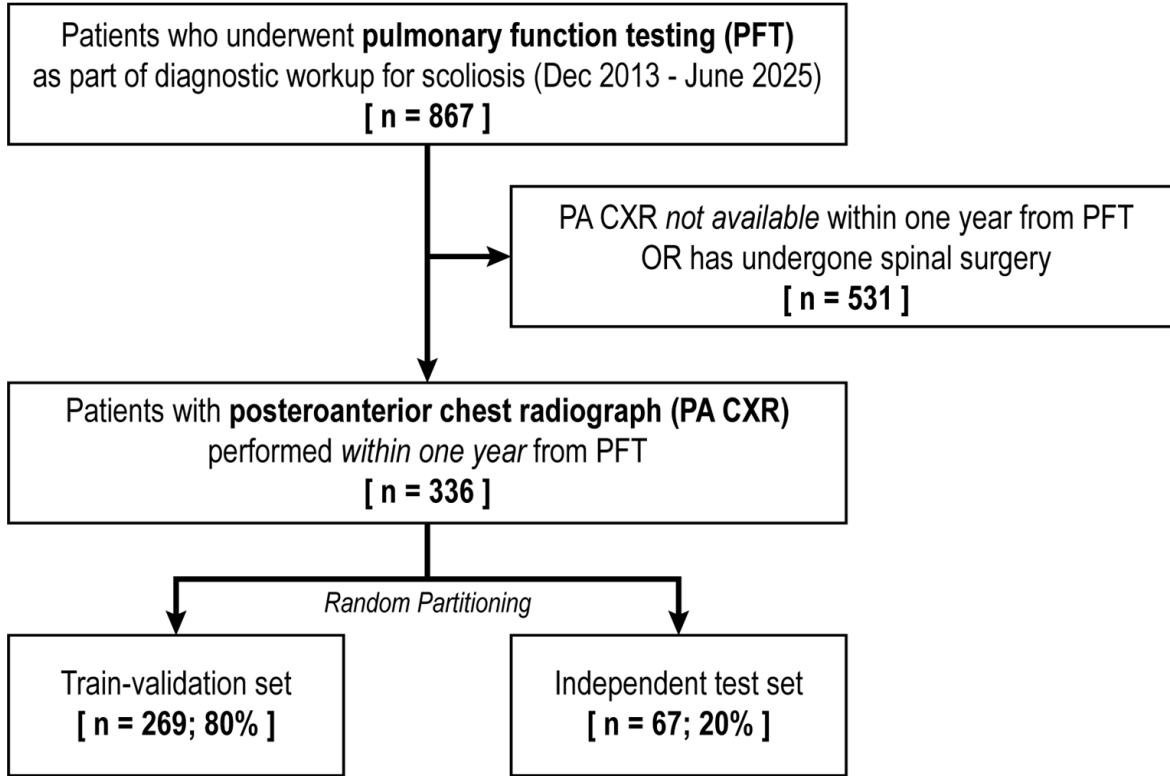


Figure 1. Cohort selection flowchart

## Study cohort

**867 screened → 336 included**

- Single tertiary care hospital
- December 2013 – June 2025
- Standing PA CXR within 1 year of PFT
- Prior spinal surgery excluded

## Final split

- Train-validation: n=269 (80%)
- Independent test set: n=67 (20%)

## Key Demographics (Train-Val / Test, p-value)

- Age: 31.1±24.1 / 30.9±24.3 yr (p=0.96)
- Height: 154.7±13.6 / 157.7±9.5 cm (p=0.09)
- FVC: 2.6±1.0 / 2.6±1.0 L (p=0.86) | Restrictive: 39.4% / 38.8%
- **Right lung area & height: significant group diff. (p<0.005)**

# Model Architecture Framework

Figure 2

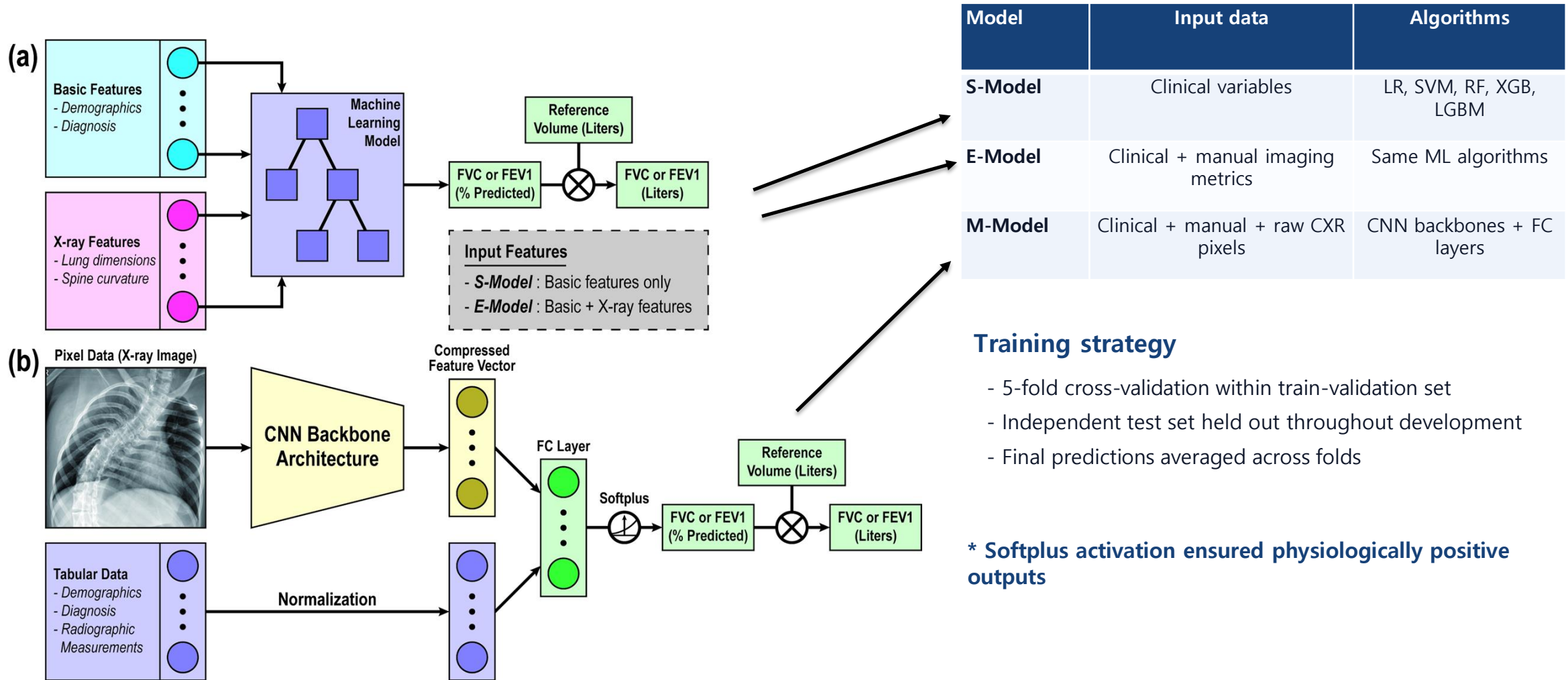
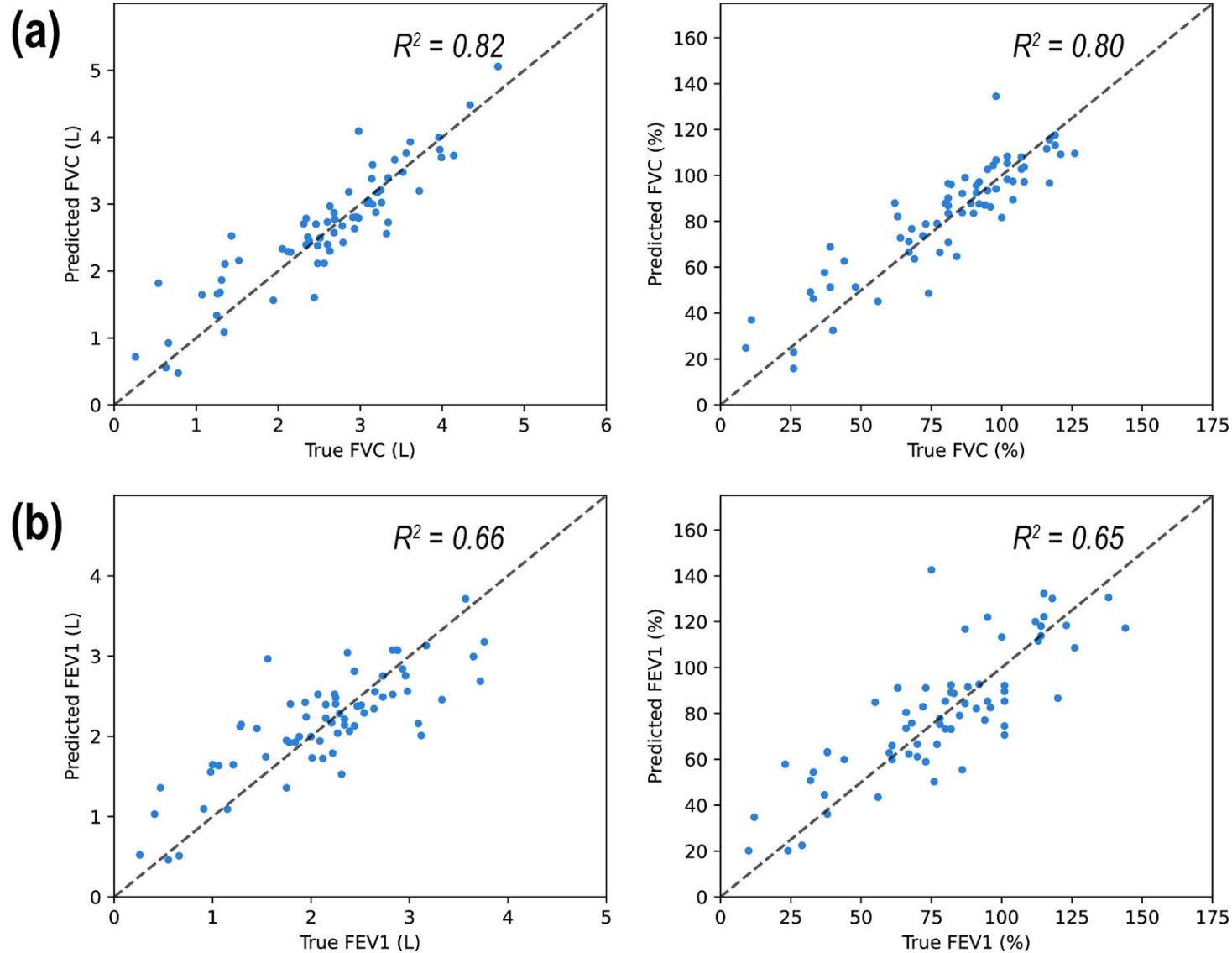


Figure 2. Schematic illustration of S-, E-, and M-model designs

# Regression Performance



## Key test-set results

**FVC: MAE 0.31 L  
RMSE 0.41 L,  $R^2$  0.82**

**FEV1: MAE 0.37 L  
RMSE 0.48 L,  $R^2$  0.66**

### Selected M-Model Performance

- **FVC (EfficientNetV2-B3)**  
MAE 0.31L | RMSE 0.41L |  $R^2$  0.82
- **FEV1 (EfficientNetV2-B0)**  
MAE 0.37L | RMSE 0.48L |  $R^2$  0.66

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- FVC: S→E→M Statically significant improvement ( $p=0.04$ ,  $p=0.002$ )
- FEV1: E vs M Not statistically significant

Figure 3. Scatter plots of FVC and FEV1 predictions on the independent test set

# Restrictive Ventilatory Pattern Classification

Classification based on predicted FVC% threshold <80%

Model	Accuracy	Sensitivity	Specificity	PPV	NPV	F1
S-Model (LGBM)	0.76	0.69	0.81	0.69	0.81	0.69
E-Model (LR)	0.85	0.81	0.88	0.81	0.88	0.81
M-Model (ResNet-34)	0.90	0.85	0.93	0.88	0.90	0.86

**Accuracy**  
**0.90**

**Specificity**  
**0.93**

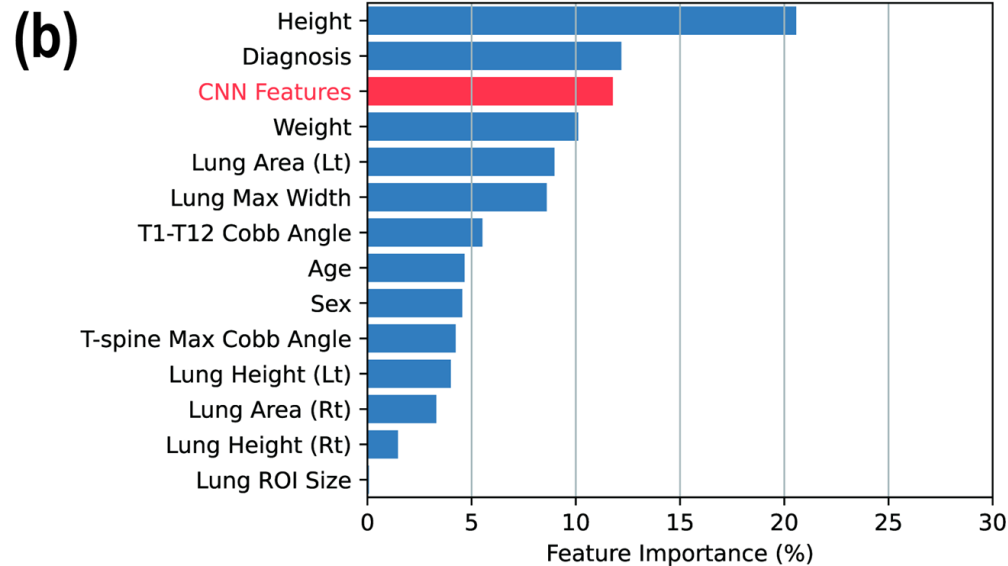
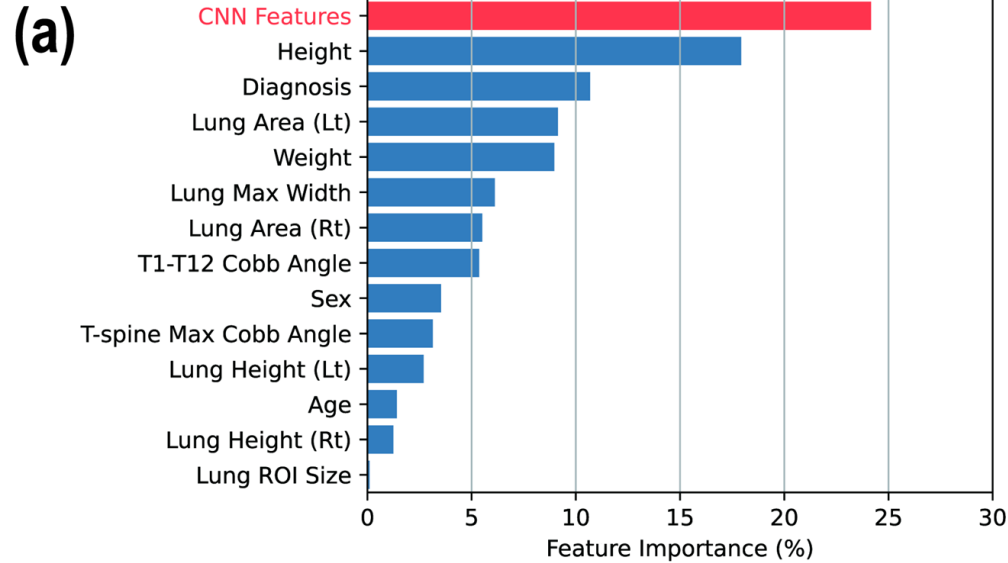
**F1-score**  
**0.86**

- M-Model improved specificity and F1-score compared with tabular-only model families.

- High specificity supports use as a conservative complementary screening adjunct to prioritize patients who may benefit from confirmatory PFT.

**Clinical emphasis: screening and risk stratification, not replacement of formal pulmonary function testing.**

# Model Interpretability: Feature Importance



## SHAP interpretation

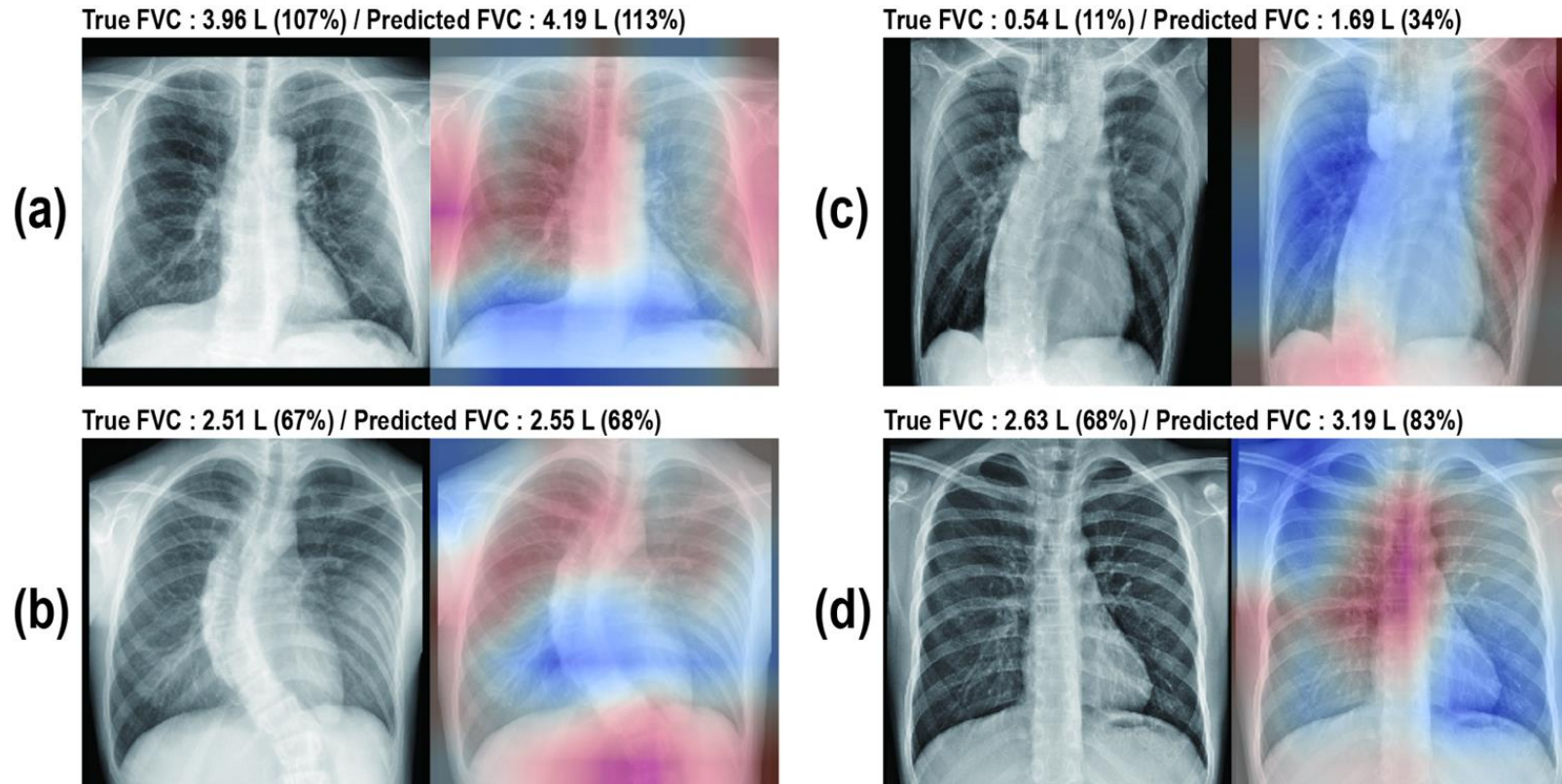
- For FVC prediction, CNN-derived image features accounted for approximately 25% of total contribution.
- Height, diagnosis, and lung area were also major contributors.
- For FEV1, height showed the largest contribution; CNN features contributed less than in FVC.

**Interpretation: raw pixels add structural information beyond manual measurements.**

The feature profile aligns with the clinical expectation that FVC is more directly tied to thoracic geometry, whereas FEV1 also reflects airway resistance, muscle strength, and patient effort.

Figure 4. SHAP-based feature importance for FVC and FEV1 prediction

# Grad-CAM Visualization: Where the Model Looks



## Visual activation

- Positive signals in preserved-function examples were observed along the thoracic spine and lung fields.
- Severe scoliosis showed strong negative activation near the curve apex.
- Diffuse lung-field signals suggest global thoracic structure-function learning.

**Error patterns highlight non-structural limits of radiograph-based estimation.**

Figure 5. Representative Grad-CAM visualizations for FVC prediction on selected test samples

These visualization patterns suggest that the model leverages thoracic curvature and lung-field information rather than a single focal anatomical landmark.

# Limitations and Future Work

## Current limitations

- Single-institution retrospective design: potential selection bias and temporal discordance between imaging and PFT.
- Standing PA CXR only: sagittal deformity and dynamic thoracic mechanics could not be assessed.
- Non-structural determinants of respiratory performance were not captured by static morphology.
- External validation has not yet been performed.

**This model is a complementary screening adjunct,  
not a replacement for confirmatory PFT.**

## Future work

- Multi-institutional external validation across diverse scoliosis populations.
- Longitudinal modeling to track pulmonary function change over time.
- Incorporation of lateral radiographs or 3D imaging to capture sagittal and rotational deformity.
- Evaluation as a preoperative risk stratification and follow-up monitoring tool.

**Pulmonary function in scoliosis patients can be estimated from routinely acquired CXR, manual radiographic measurements, and basic clinical information.**

## Clinical significance

- Non-invasive complementary screening when formal PFT is unavailable or impractical.
- Risk stratification for patients with structurally driven restrictive dysfunction.
- Potential support for preoperative assessment and longitudinal monitoring.

## Scientific implication

- Raw image features contributed meaningfully to FVC prediction.
- FEV1 showed weaker image-driven gains, reflecting non-structural physiological determinants.
- Grad-CAM supports global thoracic structure-function learning.

## Key metrics

**FVC MAE 0.31 L**

**Accuracy 0.90**

**Specificity 0.93**

**Thank you.**