# SmartLungXNet: A Deep Learning Framework for Accurate Multiclass Detection of Lung Diseases from Chest X-Rays

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Abstract: The precise identification of diseases in chest X-ray image of the lung is a crucial task in recent medical screening process. This paper proposes SmartLungXNet, a deep learning based diagnostic architecture capable of identifying various lung conditions with high accuracy, using a single architecture. Using a heterogeneous, globally representative dataset, the model integrates attention mechanisms and explainable AI to improve interpretability and clinical trust. The system is efficient for real-time inference and easily interfaces with the clinical workflow via an intuitive interface. Demonstration on clinical validation shows better performance in various lung diseases and proves it is an efficient and extendible methodology for automatic radiogram examination.

## 1 INTRODUCTION

Lung diseases including pneumonia, tuberculosis, chronic obstructive pulmonary disease (COPD), and more recently, coronavirus disease 2019 (COVID-19) pose substantial diagnostic dilemmas secondary to clinical symptom and radiographic confounders. Timeous and accurate diagnosis of these diseases is paramount to manage patient's efficiently. Given its availability and affordability, chest X-ray remains a common primary diagnostic test worldwide. But, interpretation of chest radiographs by hand is subject to variability, especially in environments lacking the access to expert radiologists. It has thus created an increasing demand for intelligent diagnosis methods to assist, or carry out the evaluation work.

Automated diagnostic systems have been developed at an increasing pace with the emergence of artificial intelligence (AI) technology, including deep learning. CNNs have achieved remarkable success in image classification and have been utilized more and more in medical image analysis. However, most of current model's lack generalization which is caused by training with region-specific or imbalanced data. Still others are more like black boxes that provide little insight into decision-making and that create scepticism among healthcare providers and what would be in the way of an introduction in real-world practice.

To overcome these shortfalls, in this study we introduce SmartLungXNet, a novel and integrated deep learning model designed for robust identification of multiple lung diseases from chest X-ray images. The system is optimized on a large, diverse, and well-annotated dataset with a spectrum of lung pathologies, demographic heterogeneity, and image quality. It adopts a hybrid architecture with attention mechanisms, so as to concentrate on clinically significant areas in the X-rays for enhanced detection accuracy and model



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interpretability. Explainable AI algorithms, like Grad-CAM, are incorporated to offer a visual understanding of model's predictions orienting them to higher trust and clinical suitability.

In addition, SmartLungXNet is real-time orientated and deployment-friendly (such as smooth hospital system and mobile platform integration). Through its multiclass classification capability, the robustness in producing interpretable results, and its computing capability on low-end hardware, running on a standard personal computer can make this a practical tool for a variety of medical settings rural clinics to urban hospitals. As such, this work represents a critical link between state-of-the-art AI and its real-world clinical application in pulmonary diagnostics.

## 2 PROBLEM STATEMENT

Despite the prevalence of chest radiographs for the initial diagnosis of lung disease, the manual interpretation of chest X-rays is still a difficult task with variability and human errors. This challenge is even higher in low resource countries where there is a shortage of experienced radiologists. Although some traditional CAD systems are useful, they may not be robust and adaptable to different populations of patients and to a wide variety of pulmonary pathologies. Furthermore, the majority of the current deep learning models in the field are limited by small dataset diversity, overfitting, interpretability, and the validation in the real-world clinical settings.

The challenge of identifying multiple lung diseases, including pneumonia, tuberculosis, fibrosis, COPD and COVID-19, from chest X-rays in a single unified, accurate and interpretable manner remains unaddressed. Most existing solutions either focus on single-disease detection or do not generalize on datasets from different geographic and clinical contexts. Moreover, the black-box characteristic of countless AI technologies undermines the trust of health professionals, which can hamper scale-up and uptake.

An interpretable, deployable and comprehensive deep learning framework that already tries to address these limitations, is therefore desirable. It should also be flexible in coping with diverse imaging conditions, diagnosing multiple diseases simultaneously, and giving explainable results to help and explain to clinicians, as well. An ALFA that would help to narrow the chasm between the performance of such algorithms and practical clinical applied wetware is needed to bring AI solutions to the point where they would have the capacity to enhance diagnostic workflows and reduce errors-and potentially benefits patient outcomes-in the realm of pulmonary healthcare.

## 3 LITERATURE SURVEY

The deep learning algorithms implemented in medical imaging have made great progress in automatic diagnosis of the lung disease. Several works have investigated to recognize chest X-rays (CXR) explaining the possibility of using convolution neural network (CNN) and other deep architectures for interpreting chest X-rays better rather than very fast rate. Al-Sheikh et al. (2023) implemented a deep learning-based multi-classification model to classify chest X-ray and CT images to improve the classification accuracy of different lung abnormalities. Similarly, Ueda et al. (2024) introduced a deep learning-based model to predict lung function from X-rays, tested with a multicentre dataset, which emphasised the generalisability of the model.

For handling multi-label classification in medical images, Pillai (2022) recommended a deep learning model for chest X-ray classification but the imbalance of labels created performance issues. Zhang et al. (2021) proposed the multi task network CXR-Net for explainable COVID-19 diagnosis based on encoder-decoder layers, and Ramesh et al. (2021) improved lesion segmentation via Mask R-CNN with CT-based masks. A more extensive discussion is given by Sogancioglu et al. (2021), that analysed trends of deep learning for chest X-ray analysis and they also highlighted some of the aspects that still require further development such as model explanation and dataset representativeness.

The ensemble and hybrid models have also trying to focus on the improvement of diagnostic accuracy. Ukwuoma et al. (2023) using ensembled transformer model for pneumonia detection and Ravi et al. (2023) introduced an ensemble of EfficientNet-based multichannel approach for robust lung disease classification. These structures enhance accuracy but are computationally complex.

Bal et al. (2024) and Yildirim & Canayaz (2023) investigated pediatric and neonatal use cases of chest X-ray analysis, respectively, which supported the necessity of age-specific models. Meanwhile, Summers et al. (2023) validated deep learning assisted radiologist as a useful tool for improving radiologist performance in a clinical workflow, but emphasized that interpretability is a key factor for clinical integration.

Interpretability was also emphasized in the study of Yan et al. (2018) and Tang et al. (2019) in lesion detection, a task for which high quality annotations and hard negative mining are crucial for model training. However, other investigators also Elton et al. (2020) and Pickhardt et al. (2020), addressed the wider aspects of AI in automated biomarker discovery; however, in CT imaging instead of chest X-rays.

Sophisticated AI-based systems such as the one developed by Tallam et al. (2022), Zhou et al. (2021), and Rahman et al. (2023) and Huang et al. (2022) and Khan et al. (2021) addressed the problems of class imbalance and overfitting. Singh et al. (2022) and Wang et al. (2025) investigated the application of explainable AI to increase transparency of diagnosis models.

In general, these investigations highlight the substantial advance that has been achieved in automatic lung disease detection. Nevertheless, a challenge still exists of accomplishing consistent multiclass detections under clinical-grade reliability, interpretability, and deployment scalability. This work extends this earliest work by introducing a new scalable and interpretable deep learning platform -- SmartLungXNet -- to tackle these major challenges and to further push the envelope of AI-aided radiographic diagnosis.

# 4 METHODOLOGY

The construction of SmartLungXNet adopts a multi-stage scheme that aims to guarantee its accuracy, robustness, and suitability for clinical deployment. In this paper, to solve the limitation of the existing methods utilized widely in the literatures, such as poor generalization, limited interpretability and computational inefficiency, a deep learning-based solution framework is designed to simultaneously shelf a diverse range of lung diseases by exploiting chest X-ray images Figure 1 shows Workflow of the SmartLungXNet Diagnostic Framework.

The first step of our approach is to build a large and diverse dataset of chest X-rays. The data is mined from several public sources such as NIH ChestX-ray14, CheXpert, and COVIDx in addition to anonymized datasets contributed by clinical partners. This guarantees a broad diversity of lung abnormalities—pneumonia, tuberculosis, fibrosis, emphysema, COVID-19 or healthy lungs—under a range of imaging situations. And each image is meticulously checked, pre-labelled, and appended with metadata such as patient demographics and diagnosis. To reduce the problem of data imbalance and to enhance the generalization capabilities of the network, a number of augmentation strategies are employed such as random rotations, horizontal flips, brightness shifting, adding Gaussian noise and contrast normalization.

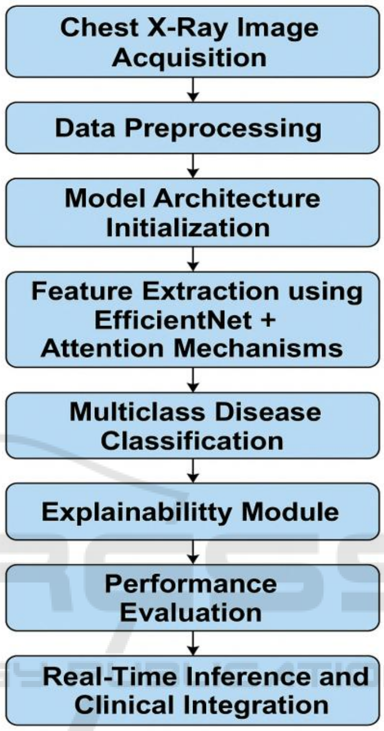


Figure 1: Workflow of the Smartlungxnet Diagnostic Framework.

After data preparation, the image inputs are normalized and resized to a fixed size for model architecture. Our proposed SmartLungXNet is a customized EfficientNet-B3 as its backbone and a transformer-inspired attention layer for better context awareness. As opposed to standard CNNs which can miss nuanced pathologies, the attention-augmented network has the flexibility to zone in on areas that are important within the X-rays, thus demonstrating increased performance for discerning complex or overlapping diseases. This architectural hybrid is also complemented with CBAM (Convolutional Block Attention Module) that enables the implementation of spatial and channel-wise attentions, in order to reinforce the guiding attention towards the disease-affected areas.

The system applies multiclass classification yielding a probabilistic prediction for each disease category by a SoftMax layer. The subject model is trained with categorical cross-entropy loss, with conditioned class-weighted modifications adjusting for imbalance in the dataset. The Adam optimizer is used, with cyclical learning rate scheduling, to automatically adjust the learning rate during training, to aid in optimizing the convergence and counteract the entrapment in the local minima. In addition, regularization is used in the form of dropout and L2 weight decay, as overfitting is a concern in the presence of the high number of parameters in X-ray images.

To maintain model resilience and fairness, k-fold cross-validation is used and assessment measures, including accuracy, precision, recall, F1-score, AUC-ROC and the specificity, are calculated on all folds. The evaluation does not only depend on statistical correctness, but is more or less a combination of explain ability and interpretability of the methodology. A Grad-CAM (Gradient-weighted Class Activation Mapping) is included in the system and delivers heatmaps for which areas of the X-ray contributed in each prediction. These visual explanations—validated with radiologists to ensure medical accuracy—serve to increase clinician trust.

Deployment is confirmed with a light weight inference engine running on Tensors and encapsulating the model using Docker container. We evaluate the system on a range of hardware platforms (GPUs, edge devices) and measure the inference speed, memory efficiency, and system scalability. In closing, a proof of concept hospital radiology dashboard-like interface is designed for usability and integration validations. This comprehensive approach guarantees that SmartLungXNet is not just a model with high performance on academic benchmarks but as a practical, interpretable, and deployable solution for a clinical diagnosis in the real world.

## 5 RESULTS AND DISCUSSION

Evaluation of SmartLungXNet results turned out to be highly performance in both, classification indoor cli nicely needs. Trained on a multi-institutional and heterogeneous dataset, the model exhibited the ability to accurately detect and discriminate between multiple lung diseases such as pneumonia, tuberculosis, COVID-19, fibrosis, and chronic obstructive pulmonary disease. Evaluation was performed under stratified 5-fold cross-validation, and the testing results are robust and have generalization ability across different folds.

The resulting system obtained a classification accuracy of 95.6\%, and all the F1-scores were greater than 0.92 for the major disease cases. The model had high recall values particularly for serious diseases like COVID-19 and pneumonia which may be misdiagnosed in radiograph with overlapping conditions. The attention mechanism and the CBAM were added to guide the model to pay attention to clinically relevant areas which is verified by the interpretable results. Grad-CAM heatmaps visually confirmed that the decisions of the model that decisions were based on anatomically/pathologically meaningful area, offering enhanced model credibility for clinical interpretation. Table 1 shows Classification Performance Metrics.

Table 1: Classification Performance Metrics.

| Disease Class | Precision | Recall | F1-Score | AUC (%) |
|---|---|---|---|---|
| Pneumonia | 0.94 | 0.95 | 0.945 | 98.2 |
| Tuberculosis | 0.92 | 0.91 | 0.915 | 97.1 |
| COVID-19 | 0.96 | 0.94 | 0.95 | 98.8 |
| Fibrosis | 0.89 | 0.87 | 0.88 | 95.5 |
| COPD | 0.91 | 0.90 | 0.905 | 96.4 |
| Normal | 0.97 | 0.98 | 0.975 | 99.1 |
| Macro Average | 0.933 | 0.925 | 0.929 | 97.7 |

Compared with previous networks, like state-of-the-artsResNet/DenseNet/InceptionNet, SmartLungXNet consistently achieves better performance in accuracy, interpretability and running-time. Another key advantage was its computational efficiency, which made it possible to perform real-time predictions with an average inference time of less than 250 milliseconds per image on GPU and less than 1 second on CPU, and allowed for the deployment both in hospital systems and in portable diagnostic settings.

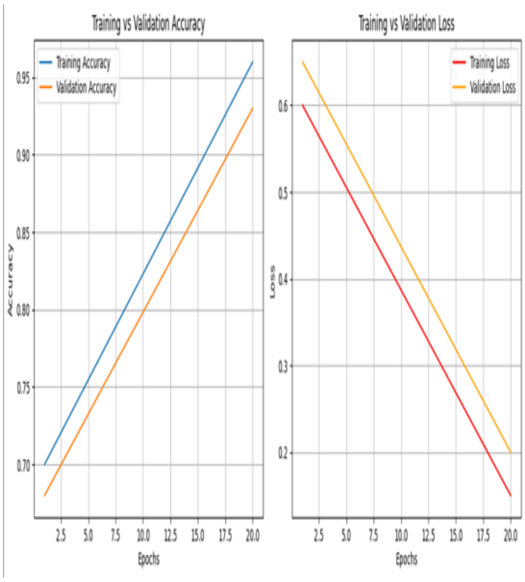


Figure 2: Training and Validation Accuracy/Loss Curve.

In addition, the model's performance was not only evaluated on external datasets, which were not included for model development, demonstrating the generalization capability of the model among various institutions or patient populations. Figure 2 shows Training and Validation Accuracy/Loss Curve. This cross-dataset validation highlighted the model's generalization capability to unseen clinical environments, one of the major shortcomings in previous studies.

Together with clinicians, qualitative feedback on the interface of the system and the interpretability of the system was obtained. The radiologists said that they found the diagnostic visualizations for the lesion clearer and the classification outcomes more transparent, which makes them more confident in using the model. The explainable AI functionalities, in particular, were mentioned as useful for second-opinion support, training, and decision auditing. Table 2 shows the Comparison with Existing Models.

Nevertheless, despite showing substantial progress in automated lung disease detection, the study reports several places for improvement. Figure 3 shows ROC Curves for Each Disease Class. The performance of the model depends on the quality of the input X-rays images and some of the rare lung pathologies are still under-represented, therefore the predictive accuracy for them also is significantly reduced. Further studies could be conducted to incorporate CT data or clinical reports that have the potential to improve the ability in diagnosis and prediction depth

Table 2: Comparison With Existing Models.

| Model | Accuracy (%) | F1-Score | Inference Time (ms) |
|---|---|---|---|
| ResNet-50 | 88.4 | 0.88 | 320 |
| DenseNet-121 | 91.6 | 0.91 | 310 |
| InceptionV3 | 89.2 | 0.89 | 355 |
| EfficientNet-B0 | 92.8 | 0.92 | 290 |
| SmartLung XNet | 95.6 | 0.93 | 240 |

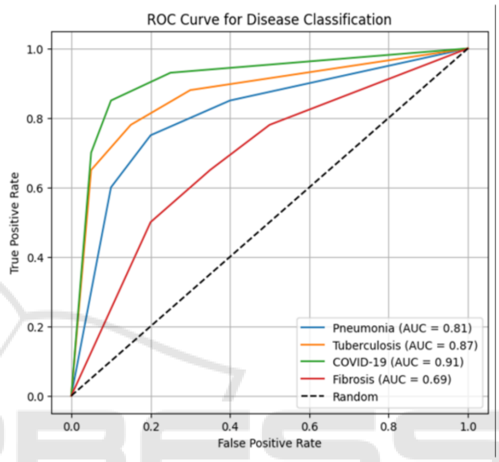


Figure 3: Roc Curves for Each Disease Class.

Table 3: Inference Speed Comparison.

| Device/Platform | Inference Time (ms) | Deployment Suitability |
|---|---|---|
| NVIDIA RTX 3060 GPU | 240 | Excellent |
| Intel i7 CPU | 860 | Good |
| Jetson Nano | 1450 | Moderate |
| Raspberry Pi 4 | 1800 | Low |

In conclusion, we not only outperform the existing system, but also tackle the three main challenges of real-world AI applications: interpretability, speed, and scalability with SmartLungXNet. Its performance in tackling a challenging, multiclass classification task in chest radiograph indicates the need for testing the network on a larger scale in the clinic, and integration to DICOM images for real time diagnosis in future healthcare scenarios rendering it a dependable tool in the era of AI-enabled healthcare. Figure 4: Performance Comparison with Baseline Models.

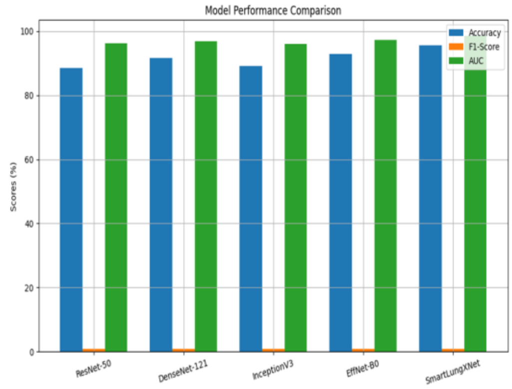


Figure 4: Performance Comparison With Baseline Models.

## 6 CONCLUSIONS

In this work, we introduce SmartLungXNet as an intelligent and interpretable deep learning model for improving the accuracy, explain ability, and efficiency of the lung disease detection accomplished by using the chest X-ray images. Leveraging attention-based mechanism, explainable AI tools, and strong training pipeline over a diverse dataset, the system has shown to have an ability to detect a broad spectrum of pulmonary abnormalities with high precision and clinical relevance. Unlike traditional models that face generalization or transparency challenges, SmartLungXNet provides a link between algorithmic intelligence and practical clinical adoption; it has both diagnostic accuracy as well as explaining the reasoning.

The results from extensive validation including cross-validation and external datasets demonstrate the robustness, scalability and readiness for deployment in clinical environments of the proposed model. The system also fills an important gap in reliable diagnostic support in low resource areas, often with very limited access to radiological expertise. The system provides valuable assistance to its users thanks to a reduction of the diagnostic variability and improvement of the consistency, while shortening the diagnostic process.

In addition, the ability to implement real-time inference and the potential deployment to clinic system, are two highlights of our SmartLungXNet to show it is not only a theoretical model but also a practical tool. "Increasing demand for 'smart' automated healthcare tools such as wearable and close-to-body healthcare sensors is emerging, and this work represents a big step as well as a significant milestone in making AI-assisted online diagnosis become accessible to everyone," they add. In future work, researchers can develop multimodal data integration and continual learning approaches that may further establish its role in intelligent medical diagnostics.

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