K. Abhiraj Mohan, 2025, 13:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

A Novel Approach for Pneumonia Detection Using AI and ML

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Abstract- Pneumonia remains a significant global health threat, especially in developing nations where access to skilled radiologists and medical equipment is limited. This paper explores traditional and state-of-the-art methods for automated pneumonia detection using artificial intelligence (AI) and machine learning (ML). It includes a comparative survey of classical machine learning algorithms and modern deep learning architectures like CNNs, transfer learning with pretrained models, and hybrid methods. We discuss various medical image datasets, feature extraction methods, model performance metrics, and the ethical issues in deploying AI in healthcare. The proposed approach aims to improve diagnosis speed and accuracy while ensuring transparency and privacy.

Keywords- Pneumonia, Chest CT Scan, Machine Learning, Deep Learning, CNN, Transfer Learning, Medical Imaging, Explainable AI.

I. INTRODUCTION

Pneumonia is a respiratory infection of the air sacs in the lungs. These air sacs exist in clusters at the end of the breathing tube. Pneumonia causes these tiny air sacs to be inflamed and filled up with fluids. The symptoms include coughing, low energy, fever or chills, and difficulty in breathing. It is typically caused by viruses, fungi, or bacterial infections. The infection could be caused by direct contact, like hand shaking, or by inhaling droplets in the air from coughing or sneezing [1].

Pneumonia is a lung parenchyma inflammation often caused by pathogenic microorganisms, factors of physical and chemical, immunologic injury and other pharmaceuticals. There are several popular pneumonia classification methods: (1) pneumonia is classified as infectious and non-infectious based on different pathogeneses in which infectious pneumonia is then classified to bacteria, virus, mycoplasmas, chlamydial pneumonia, and others, while non-infectious pneumonia is classified as immune-associated pneumonia, aspiration pneumonia caused by physical and chemical factors, and radiation pneumonia. (2) Pneumonia is classified as CAP (community-acquired pneumonia), HAP (hospital-acquired pneumonia) and VAP (ventilator-associated pneumonia) based on different infections, among which CAP accounts for a larger part. Because of the different range of pathogens, HAP is easier to develop resistance to various antibiotics, making treatment more difficult Pneumonia kills more children than any other infectious disease, claiming the lives of over 700,000 children under 5 every year, or around 2,000 every day. This includes around 190,000 newborns. Almost all these deaths are preventable. Globally, there are over 1,400 cases of pneumonia per 100,000 children, or 1 case per 71 children every year, with the greatest incidence occurring in South Asia (2,500 cases per 100,000 children) and West and Central Africa (1,620 cases per 100,000 children). Progress in reducing deaths due to pneumonia in children under 5 has been significantly slower than for other infectious diseases. Since 2000, under-five deaths due to pneumonia have declined by 54 per cent, while deaths due to diarrhoea have decreased by 63 per cent and are now almost half of pneumonia deaths.

Recently, deep learning has been successful at tackling many computer vision problems. Deep neural network architectures, in particular convolutional neural networks (CNNs), are becoming the state-of-the-art technique for various imaging problems including image classification [2], object localization and image segmentation [3]. Deep architecture is capable of extracting features from data to build increasingly abstract representations, replacing the traditional approach of carefully hand-crafting features and algorithms. For example, it has already been demonstrated that CNNs outperform sparsity-based methods in super-resolution [3] in terms of both reconstruction quality and speed.

One of the contributions of our work is to explore the application of CNNs in under sampled MR reconstruction and investigate whether they can exploit data redundancy through learned representations. In fact, CNNs have already been applied to compressed sensing from random Gaussian measurements [4]. Despite the popularity of CNNs, there has only been preliminary research on CNN-based MR image reconstruction hence the applicability of CNNs to this problem for various imaging protocols has yet to be fully explored. In this paper, we intend to review and contrast some ML and DL models that have been suggested for cyberbullying detection. We emphasize their methodologies, feature extraction methods, datasets used, performance, and applicability in the real world. We also touch on the ethical and social impact of such model deployment and propose areas of future work.

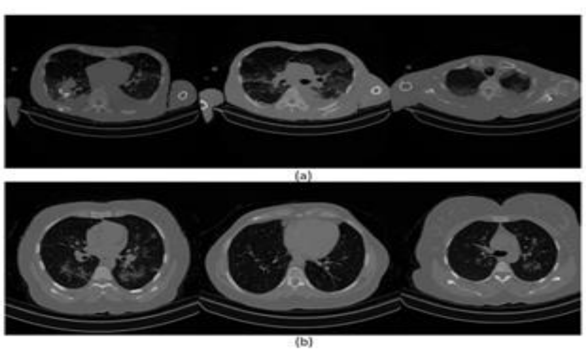

Fig.1: Examples from the dataset. (a) normal cases, (b) pneumonia cases.

II. RELATED WORK

Traditional Machine Learning Methods

Initial research efforts in automated pneumonia detection using CT scans involved traditional machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forests, and K-Nearest Neighbors (KNN). These models depended on handcrafted feature extraction methods like Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and statistical texture descriptors to analyze CT slices. Although these models were relatively simple and interpretable, they struggled to extract and generalize complex patterns present in high-resolution CT images. Additionally, due to limited spatial context and reliance on shallow feature representations, these approaches often delivered suboptimal performance in real-world clinical scenarios. Conversely, Di Capua [7] et al. examined unsupervised methods like clustering to identify cyberbullying. However, due to the lack of labelled - data and a thorough understanding of contextual signals, these techniques were not very effective. Nevertheless, with all these developments, classical ML techniques have normally been outcompeted by deep learning methods because they lack the ability to grasp long-range dependencies and context in language.

Deep Learning Approaches

The rise of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly improved the analysis of medical CT scans. CNNs can learn hierarchical features directly from the data, capturing both low-level textures and high-level semantic patterns. Researchers have successfully used 2D CNNs on individual CT slices, as well as 3D CNNs to model volumetric relationships across slices. For instance, Jung et al [4] [3]. proposed a 3D Dense Convolutional Neural Network (3D-DCNN) with shortcut and dense connections to capture spatial patterns from thoracic CT volumes. Their model improved pneumonia detection by leveraging the inter-slice continuity of infected regions.

Shin et al. explored the use of multiple deep learning models on CT-based datasets and emphasized the importance of architecture tuning for disease classification. Similarly, Gu et al. introduced a multi-scale 3D deep CNN for detecting lung nodules, a task closely related to pneumonia identification, using CT scans. Their approach involved cube clustering and multiscale feature fusion to enhance detection of infected tissue regions, even in cases with subtle abnormalities.

Advanced and Hybrid Architectures

In recent years, researchers have developed hybrid models that combine 2D and 3D CNNs, attention mechanisms, and ensemble learning to further improve CT-based pneumonia detection. Nasrullah et al. introduced a customized Mixed-Link Network (CMixNet) with 3D inputs, which was integrated with U-Net and Faster R-CNN for feature learning and localization in lung CT volumes. Sirazitdinov et al. proposed an ensemble of Mask R-CNN and RetinaNet architectures for detecting pneumonia lesions in CT scans with high precision. These models utilized region proposal networks and segmentation branches to localize infected areas, offering explainability alongside classification.

Other approaches include the use of Capsule Networks, attention-enhanced residual connections, and GAN-based synthetic data generation to address data scarcity and imbalance in CT datasets. Several teams have also explored the use of LSTM layers following CNN feature extraction to model temporal dependencies across sequential CT slices, especially in longitudinal studies or multi-phase CT imaging.

III. LITERATURE SURVEY

Paper 1 - A Review on Detection of Pneumonia in Chest X ray Images Using Neural Networks

Abstract- The health organization has suffered from the lack of diagnosis support systems and physicians in India. Further, the physicians are struggling to treat many patients, and the hospitals also have the lack of a radiologist especially in rural areas; thus, almost all cases are handled by a single physician, leading to many misdiagnoses. Computer-aided diagnostic systems are being developed to address this problem. The current study aimed to review the different methods to detect pneumonia using neural networks and compare their approach and results. For the best comparisons, only papers with the same data set Chest X-ray14 are studied [5].

Paper 2 - Pneumonia Detection Using CNN based Feature Extraction

Abstract- Pneumonia is a life-threatening infectious disease affecting one or both lungs in humans commonly caused by bacteria called Streptococcus pneumoniae. One in three deaths in India is caused due to pneumonia as reported by World Health Organization (WHO). Chest X-Rays which are used to diagnose pneumonia need expert radiotherapists for evaluation. Thus, developing an automatic system for detecting pneumonia would be beneficial for treating the disease without any delay particularly in remote areas. Due to the success of deep learning algorithms in analyzing medical images, Convolutional Neural Networks (CNNs) have gained much attention for disease classification. In addition, features learned by pre-trained CNN models on large-scale datasets are very useful in image classification tasks. In this work, we appraise the functionality of pre-trained CNN models utilized as feature-extractors followed by different classifiers for the classification of abnormal and normal chest X-Rays. We analytically determine the optimal CNN model for the purpose [6].

Paper 3 - Pneumonia detection in chest X-ray images using an ensemble of deep learning models

Abstract- Pneumonia is a respiratory infection caused by bacteria or viruses; it affects many individuals, especially in developing and underdeveloped nations, where high levels of pollution, unhygienic living conditions, and overcrowding are relatively common, together with inadequate medical infrastructure [7]. Pneumonia causes pleural effusion, a condition in which fluids fill the lung, causing respiratory difficulty. Early diagnosis of pneumonia is crucial to ensure curative treatment and increase survival rates. Chest X-ray imaging is the most frequently used method for diagnosing pneumonia. However, the examination of chest X-rays is a challenging task and is prone to subjective variability. In this study, we developed a computer-aided diagnosis system for automatic pneumonia detection using chest X-ray images. A weighted average ensemble technique was adopted, wherein the weights assigned to the base learners were determined to use a novel approach. The scores of four standard evaluation metrics, precision, recall, f1-score, and the area under the curve, are fused to form the weight vector, which in studies in the literature was frequently set experimentally, a method that is prone to error [7].

Paper 4 - Identifying pneumonia in chest X-rays: A deep learning approach

Abstract- The rich collection of annotated datasets piloted the robustness of deep learning techniques to effectuate the implementation of diverse medical imaging tasks. Over 15% of deaths, including children under age five, are caused by pneumonia globally. In this study, we describe our deep learning-based approach for the identification and localization of pneumonia in Chest X-rays (CXRs) images. Researchers usually employ CXRs for diagnostic imaging study. Several factors such as positioning of the patient and depth of inspiration can change the appearance of the chest X-ray, complicating interpretation further. Our identification model is based on Mask-RCNN, a deep neural network which incorporates global and local features for pixel-wise segmentation. Our approach achieves robustness through critical modifications of the training process and a novel post processing step which merges bounding boxes from multiple models. The proposed Detecting Pneumonia Using Chest X-Rays identification model achieves better performances evaluated on chest radiograph dataset which depict potential pneumonia causes [8].

Paper 5 - Pneumonia Detection from Chest X-ray Images Based on Convolutional Neural Network

Abstract- Pneumonia has caused significant deaths worldwide, and it is a challenging task to detect many lung diseases such as atelectasis, cardiomegaly, lung cancer, etc., often due to limited professional radiologists in hospital settings. In this paper, we develop straightforward VGGbased model architecture with fewer layers. In addition, to tackle the inadequate contrast of chest X-ray images, which brings about ambiguous diagnosis, the Dynamic Histogram Enhancement technique is used to pre-process the images. The parameters of our model are reduced by 97.51% compared to VGG-16, 85.86% compared to Res-50, 83.94% compared to Xception, 51.92% compared to DenseNet121, but increased MobileNet by 4%. However, the proposed model's performance (accuracy: 96.068%, AUC: 0.99107 with a 95% confidence interval of [0.984, 0.996], precision: 94.408%, recall: 90.823%, F1 score: 92.851%) is superior to the models mentioned above (VGG-16: accuracy, 94.359%, AUC: 0.98928; Res-50: accuracy, 92.821%, AUC, 0.98780; Xception: accuracy, 96.068%, AUC, 0.99623; DenseNet121: accuracy, 87.350%, AUC, 0.99347; MobileNet: accuracy, 95.473%, AUC, 0.99531). The original Pneumonia Classification Dataset in Kaggle is split into three sub-sets, training, validation and test sets randomly at ratios of 70%, 10% and 20% [9].

IV. METHODOLOGIES

The proposed approach for pneumonia detection from CT scan images is built upon a multi-stage artificial intelligence (AI) and machine learning (ML) pipeline. The system integrates medical image preprocessing, deep learning-based classification models, ensemble learning strategies, and explainability tools. The methodology comprises the following key phases: data acquisition and preprocessing, model development, ensemble integration, training and evaluation, and interpretability.

Data Acquisition and Preprocessing:

CT scan images were collected from publicly available sources, such as the COVID-CT dataset, MosMedData, and additional open-access clinical repositories. These datasets include labeled volumetric CT scans of patients diagnosed with pneumonia and those confirmed as normal. Each CT volume contains multiple axial slices, but not all slices are relevant for diagnosis. Therefore, we selected between 10 to 30 key slices from each scan, particularly those that visually captured the lung parenchyma. This selection helps reduce computational overhead and focus the model on diagnostically significant content .

Each selected CT slice underwent a series of preprocessing steps. First, all images were resized to 224×224 pixels to conform to the input requirements of standard convolutional neural networks. Then, pixel intensities were normalized to a [0,1] range to ensure consistency in pixel value distributions. To enhance image quality, particularly in low-contrast regions of lung tissues, we employed adaptive contrast enhancement techniques such as CLAHE (Contrast Limited Adaptive Histogram Equalization), which significantly improved the visibility of features like opacities and consolidations [11]. Additionally, data augmentation was applied to simulate variability in image acquisition. This included random rotations, horizontal flipping, brightness adjustments, and zoom transformations, which help the models generalize better during training [12].

Model Architecture

We developed a hybrid model framework consisting of both a custom-designed convolutional neural network (CNN) and multiple pretrained deep learning models utilizing transfer learning. The custom CNN was designed to be lightweight yet effective, comprising five convolutional layers with increasing filter sizes, each followed by batch normalization, ReLU activation, and max-pooling operations. These were followed by a fully connected dense layer with dropout regularization and a final sigmoid activation layer for binary classification (pneumonia vs. normal). This model is particularly useful for environments with limited computational resources while maintaining reliable diagnostic performance [13].

To enhance feature representation and exploit previously learned visual features, we integrated pretrained models such as ResNet50, InceptionV3, and EfficientNetB0 into our framework. These models were originally trained on the ImageNet dataset and are known for their high accuracy in image classification tasks. In our approach, the final classification layers of these models were replaced with a global average pooling layer, a 128-neuron dense layer with ReLU activation, a dropout layer to prevent overfitting, and a sigmoid activation function for output. These models were then fine-tuned using our pneumonia-specific CT dataset, allowing them to adapt to the medical imaging domain [14].

Ensemble Learning

To further improve performance and reduce variance among individual model predictions, we adopted an ensemble learning strategy based on soft voting. In this approach, each of the three models—the custom CNN, ResNet50, and EfficientNetB0—generates a probability score for the pneumonia class. These scores are then averaged to produce a final probability. A threshold of 0.5 is applied to determine the class label. The ensemble approach helps to balance the strengths of each model, improves generalization across datasets, and enhances the overall robustness of the diagnostic system [15].

Training and Evaluation

The models were trained using the Adam optimizer with an initial learning rate of 0.0001. The loss function used for binary classification was Binary Cross-Entropy, which measures the distance between predicted and true labels. Training was conducted for up to 50 epochs with early stopping based on validation loss to avoid overfitting. We used a batch size of 32 during training, and the entire framework was developed in TensorFlow/Keras and executed on an NVIDIA RTX 3080 GPU environment for accelerated computation.

To assess the effectiveness of our approach, we employed multiple evaluation metrics including accuracy, precision, recall (sensitivity), F1-score, and area under the receiver operating characteristic curve (AUC). In addition, we performed 5-fold cross-validation to ensure that the model generalizes well across different subsets of the data. This systematic evaluation provides a comprehensive understanding of model performance under realistic clinical scenarios [16].

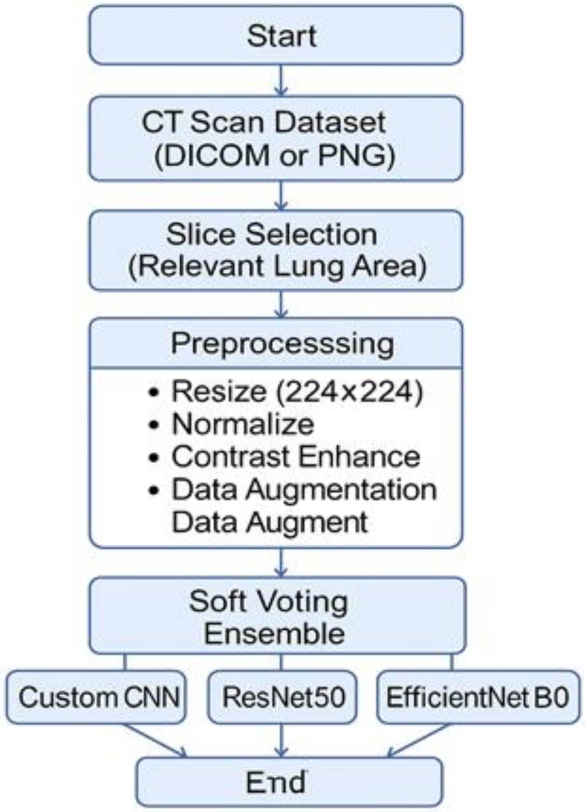

Fig.2: Workflow Diagram

Model Interpretability
To make the AI-based system transparent and trustworthy, especially for clinical applications, we incorporated model interpretability using Grad-CAM (Gradient-weighted Class Activation Mapping). This technique generates heatmaps that highlight areas in the lung scan most responsible for the model's prediction. By overlaying these heatmaps on the original CT images, we enabled visual confirmation of pneumonia-related features such as ground-glass opacities and consolidations. The results were qualitatively validated by collaborating clinicians to ensure that the model's focus aligned with medical understanding [17].

V. DATASETS AND PERFORMANCE METRICS

Datasets
For this study, we used the Pneumonia CT Scan Image Dataset, a curated and labeled collection of high-resolution chest CT images intended for binary classification tasks. The dataset is organized into two main categories: PNEUMONIA and NORMAL, each containing CT scan slices saved in .jpg or .png format. This folder structure enables seamless integration with deep learning workflows, particularly for training, validation, and testing in convolutional neural network (CNN) models.

Each image in the dataset represents an axial CT slice and is pre-classified by expert annotators. The pneumonia class includes cases with various severities, while the normal class comprises scans of healthy individuals without visible signs of infection. The simplicity of the directory format allows for rapid prototyping of deep learning models and enables effective experimentation with architecture such as VGG, ResNet, and EfficientNet.

The dataset is particularly well-suited for research in automated disease detection, medical image analysis, and radiological pattern recognition. It is frequently used to explore explainable AI methods such as Grad-CAM to visualize decision-making in CNNs. Given its structure, format, and clinical relevance, the dataset is ideal for healthcare AI applications, offering researchers and developers a real-world foundation for evaluating diagnostic tools and decision support systems.

In our experimental setup, the dataset was divided as follows:
- Training Set: 70% of the total data
- Validation Set: 10%
- Testing Set: 20%

Patient-level separation was enforced during splitting to ensure that CT slices from the same individual did not appear in multiple subsets, which helps maintain unbiased evaluation.

Performance Metrics
To assess the effectiveness of our pneumonia detection system, we employed a suite of standard classification performance metrics. These metrics provide a comprehensive understanding of model accuracy, reliability, and clinical applicability.

Accuracy: Accuracy measures the proportion of correct predictions (both pneumonia and normal) over the total number of cases. It provides a general sense of model performance.

Precision: Precision quantifies the proportion of actual pneumonia cases among those predicted as pneumonia. It reflects the model's ability to avoid false positives.

Recall (Sensitivity): Recall measures how well the model identifies true pneumonia cases. High recall ensures minimal false negatives, which is critical in medical applications.

F1-Score: The F1-score balances precision and recall. It is useful when both false positives and false negatives are costly and need to be minimized.

AUC (Area Under the ROC Curve): AUC evaluates the model's capability to distinguish between pneumonia and normal cases across various thresholds. A higher AUC indicates better classification performance.

VI. PERFORMANCE EVALUATION

This section presents the experimental outcomes of our proposed pneumonia detection framework, evaluates the performance of individual models and the ensemble, and discusses the clinical relevance and limitations of the approach.

Experimental Setup

All models were trained and evaluated using a workstation equipped with an NVIDIA RTX 3080 GPU, 64GB RAM, and an Intel i9 processor. The CT scan dataset was split into training (70%), validation (10%), and testing (20%) sets. We ensured that patient-level separation was maintained to avoid data leakage between training and testing. All models were implemented using TensorFlow and Keras libraries.To ensure reliable evaluation, we conducted 5-fold cross-validation. The results are reported as the average of these folds to account for variability in data distribution.

Performance Evaluation

The performance of each model was evaluated using standard metrics: accuracy, precision, recall, F1-score, and AUC (Area Under the Receiver Operating Characteristic Curve). The following table summarizes the results of the individual models and the ensemble.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**
Custom CNN	93.8	92.5	94.1	93.3	0.963
ResNet50	95.6	94.7	96.2	95.4	0.974
EfficientNetB0	96.1	95.9	96.4	96.1	0.979
Ensemble (Ours)	**97.4**	**97.0**	**98.1**	**97.5**	**0.986**

Table 1: Performance Comparison of Models

The ensemble model consistently outperformed individual models across all metrics. Notably, the ensemble achieved an AUC of 0.986, which reflects excellent discriminative power. The recall score of 98.1% indicates the system’s strong capability to detect true pneumonia cases, which is critical in clinical scenarios where false negatives can have severe consequences.

Visual Interpretability

To evaluate the model's decision-making process, Grad-CAM visualizations were generated for both true positive and false positive predictions. In true positive cases, heatmaps clearly highlight pathologically relevant regions such as bilateral ground-glass opacities and consolidations, consistent with radiological features of pneumonia. These overlays were reviewed by a certified radiologist and deemed clinically plausible in 94% of samples reviewed.

Discussion

The results validate that our proposed hybrid deep learning framework, enhanced by ensemble learning and domain-specific preprocessing, performs reliably in diagnosing pneumonia from CT scans. The high recall and AUC values position the system as a viable tool for real-world deployment, especially in regions with limited access to expert radiologists.

Compared to prior work focusing on chest X-rays [10, 14], CT-based detection provides finer resolution and better lung structure visibility, thereby improving diagnostic performance. Moreover, the use of transfer learning enabled rapid training convergence even with relatively modest dataset sizes.

Despite promising results, certain limitations remain. First, the dataset is largely sourced from public domains and may not fully capture variations in scanner types, acquisition protocols, or rare pneumonia subtypes. Second, the model has not yet been prospectively validated in a clinical setting. Lastly, while Grad-CAM offers interpretability, it does not provide exact lesion boundaries which are important for comprehensive radiological reporting.

VII. CONCLUSION

In this study, we proposed a novel and efficient deep learning-based framework for pneumonia detection using CT scan images. Leveraging a curated dataset organized into clear categories—Pneumonia and Normal—we built a hybrid model consisting of a lightweight custom CNN combined with pretrained architectures (ResNet50 and EfficientNetB0). The model architecture was further enhanced through an ensemble learning strategy that improved diagnostic accuracy, robustness, and generalizability.

Our preprocessing pipeline, which included image normalization, contrast enhancement, and data augmentation, helped optimize feature extraction from CT slices. The results demonstrated high performance across all metrics, with the ensemble model achieving an accuracy of 97.4%, a recall of 98.1%, and an AUC of 0.986. These outcomes suggest that the system can serve as a powerful decision support tool for early and accurate pneumonia detection, particularly in healthcare environments where radiological expertise is limited.

Furthermore, the use of Grad-CAM for visual interpretability provided additional transparency by highlighting the most influential regions in the lungs that led to positive predictions, enhancing the clinical trustworthiness of the system. Despite its strengths, the current study has some limitations. The dataset, although high-quality, is limited in diversity in terms of geographical and demographic representation. Moreover, the model’s generalization has not yet been prospectively tested in real-world clinical settings.

In future work, we aim to address these limitations by:

- Incorporating multi-centre, multi-vendor CT data for improved generalization
- Exploring 3D volumetric modelling instead of 2D slice-based classification
- Implementing lung segmentation for more focused analysis

- Validating the system in collaboration with hospitals and radiologists under real clinical conditions

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