Deep Learning Innovations for Lung Disease Diagnosis and Severity Evaluation: A Comprehensive Review

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Abstract

The lung diseases like lung cancer, COVID-19, interstitial lung disease (ILD) and pneumonia still remain one of the leading causes of death in the world. There is a need for quick and precise diagnostic tools to overcome the existing disease diagnosis challenges. Despite the deep learning providing advances to traditional computer-aided diagnostics (CAD), still the issues such as computational complexity, lack of data, and explainability remain unaddressed. This review will present an overview of the recent research advances in the area of deep learning, where the hybrid architecture of convolutional neural networks with transformers is used to solve the problem. This study will discuss about the advances in improving practical clinical deployment through lightweight architectures such as GANs, solving the problem of data imbalance and the use of multimodal images including X-ray, CT, and histopathological images. The use of Explainable AI (XAI) includes visual heat maps like Grad-CAM and Bayesian uncertainty quantification, which solves the problems associated with medical trust. The importance of multi-center validation is highlighted in order to properly integrate efficient diagnostic assistants.

Keywords: Deep Learning, Hybrid Architecture, Feature Extraction, Segmentation, Classification, Localization, Explainable AI (XAI).

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1. Introduction

Lung diseases have been one of the primary causes of disease and death across the world, having an effect on millions of individuals from different ages. Hence, early diagnosis and proper management play a significant role. This disease is the third most common cause of death globally and contributes to about 10% of all deaths as reported by the World Health Organization (WHO). Deaths associated with lung diseases result due to delayed diagnosis of the diseases since they are usually hard to detect in their early stages with the use of established medical tests [1], [8].

Early detection will ensure better management of the pulmonary diseases and might help reduce the burden of disease and hence increase the survival rate. Traditional diagnostic methods largely rely on the manual interpretation of medical images. Hence, these methods are not only laborious but also prone to errors especially due to the complex and varied presentations of lung disease [2]. Traditional methods rely mostly on radiographic imaging methods such as chest x-rays, CT scans, MRI scans and HRCT scans that might be limited by the quality of images, experience of the radiologist and the subjective interpretation of the images. Hence, there is need for better and more efficient method of detecting lung diseases [3].

Visualization techniques in the area of artificial intelligence (AI) and deep learning (DL) have greatly advanced the field of medicine in recent years. In specific terms, deep learning algorithms work well in detecting complex patterns within the vast medical datasets. There are fascinating solutions of AI to the problems of lung disease detection in the fields of machine learning and deep learning. Machine learning algorithms are created to aid physicians in disease diagnosis through data analysis, pattern recognition, and prediction [4]. Through a number of patient dataset including demographics, history, and immunology results, these algorithms help in detecting subtle signs of lung disease [5].

The main goal of this literature review is to systematically analyze new developments within the fields of deep learning and artificial intelligence related to detection, segmentation, classification, and severity assessment of respiratory diseases like lung cancer, coronavirus infection, interstitial lung diseases, and pneumonia. The goal of this literature review is to explore how the latest technological advances like hybrid models (convolutional neural network + vision transformer), multimodal analysis, and XAI (explainable artificial intelligence) overcome some of the existing barriers like computational complexity, data limitations, and opacity of AI, thus bringing computational studies closer to clinical reality.

2. Literature Review

The application of AI and DL for the diagnosis of lung diseases has witnessed a significant progress due to the increasing availability of medical image databases and the development of computer vision technologies. Recent works have explored automatic detection, classification, segmentation, localization, and severity scoring of pulmonary lesions using CXR, CT, HRCT, and histopathological images. This trend is driven by the challenges associated with traditional image analysis techniques that tend to be lengthy and largely based on the expertise of healthcare professionals. The research reviewed in this study shows a steady shift from traditional machine-learning and CNN models to hybrid CNN-Transformer models, attention models, lightweight neural networks, multi-task learning, and explainable AI (XAI).

2.1 Deep Learning for Lung Disease Classification

Classification continues to be one of the most studied topics in lung disease detection using AI. Traditional methods usually involve the use of CNNs to directly extract hierarchical visual information from medical imaging data. The growing complexity of lung problems has led scientists to explore models that can extract features from different spatial resolutions and represent relationships between distant regions in the image.

The Attention-Based Inception-ResNet architecture was proposed by Hosny et al. [1], for detecting and classifying patients of lung cancer and pneumonia from different medical images, which include CXR, CT, and histopathological images. The network is comprised of a Hierarchical Feature Extraction (HFE) block to extract information from the multiple receptive fields, after which, the Inception-ResNet module is used to extract multi-scale spatial features. ECA is used for recalibrating discriminative regions. Alongside the classification task, the Grad-CAM heat maps have been utilized to provide visualization explanations for the predicted outputs of the model.

Also, Ozdemir et al. [3] explored the application of hybrid feature learning for lung cancer recognition in CT scans. In their Attention-Enhanced InceptionNeXt model, the authors have proposed CNN for local features extraction combined with ViT for capturing global dependencies. Multi-axis grid attention and multi-axis block attention are used for improving the ability to represent malignant areas. The high accuracy of 99.54% with just 18.1 million parameters shows that good performance is attainable without solely relying on large models. The interpretability of the model is provided by Grad-CAM and attention mechanisms.

Meeradevi et al. [4], on the other hand, have applied a novel technique where deep learning and traditional machine-learning algorithms were used together in order to classify lung diseases based on chest X-ray images. The deep learning model used in this technique is InceptionV3 while texture features such as GLCM and LBP are extracted from the preprocessed images. Subsequently, SVM, KNN, and Naïve Bayes classifiers are evaluated using TOPSIS, which is a multiple attribute decision-making technique. The classification accuracy of 97.05% proves that manually created texture data can provide additional useful information in combination with deep feature data.

Faizi et al. [7] proposed the DCSwinB architecture for classifying benign and malignant lung nodules using CT images. The architecture uses patch merging for downsampling the feature maps, a Conv-MLP layer for enhancing local interaction, and a dual-path network consisting of CNN and Swin Transformer for acquiring three-dimensional dependencies at both local and distant levels. The achieved accuracy rate of 90.96% along with the 24.4% decrease in FLOPs clearly show that it is an effort to optimize the trade-off between performance and efficiency.

CTXNET is an algorithm proposed by Hasan et al. [11] to detect lung anomalies using CXR and CT images. The technique makes use of a combination of DCGAN-based data augmentation along with morphological opening and CLAHE pre-processing followed by classification using Compact Convolutional Transformer (CCT). The use of Grad-CAM is made to visualize the model decisions by correlating them with the image regions. The model attained a claimed accuracy of 99.77% within a training time of 10-12 seconds per epoch.

2.2 Hybrid CNN–Transformer Architectures

A major trend across recent studies is the is the combination of CNNs and Vision Transformers. While CNNs are good at learning local spatial features like edges, textures, boundaries, and small anatomical structures, they might not be able to capture long-range relationships. Unlike that, Transformers utilize the self-attention mechanism for modeling relationships between image patches and are capable of capturing broader contexts but might have high computational needs.

The architectures discussed in this study try to make use of the complementary nature of these two types of architectures. Attention-Enhanced InceptionNeXt [3] architecture uses both CNNs to learn local representations and ViT for long-range dependency modeling. Similar approach was taken in DCSwinB [7], which uses CNN and Swin Transformer branches for local and long-range 3D dependencies.

The Cancer Nexus Synergy (CanNS) system proposed by Durgam et al. [2] is yet another example of the application of a transformer-based architecture in a complete segmentation and classification pipeline. The pipeline includes the Swin-Transformer U-Net (SwiNet) model for segmentation on a pixel level and the Xception-LSTM-GAN (XLG) CancerNet model for feature extraction and classification. Dynamic learning rate optimization is conducted using the Devilish Levy Optimization (DevLO). The F1-score of 98.99% and AUC of 99% show the high accuracy achieved by the research.

While hybrid architectures enable a better capture of local and global data, they tend to add complexity to architecture as well. Therefore, the usage of transformers must be analyzed with respect to computational costs, memory demands, and training difficulty.

2.3 Segmentation and Localization of Pulmonary Abnormalities

Segmentation plays an important role in computer-aided lung disease diagnosis due to the importance of accurate segmentation of the anatomical structures or lesions for subsequent classification and measurement tasks. Compared to image-level classification, segmentation tasks are much harder because the model must identify the relevant regions on the pixel level.

Durgam et al. [2] attempted to solve both problems simultaneously in a single method, that is, CanNS. SwiNet does pixel-wise segmentation, whereas XLG CancerNet does feature extraction and classification. Such architecture can be seen as an example of solving segmentation and classification together and getting more details on lung cancer regions.

Another segmentation and classification system that has been proposed in order to solve the problem of interstitial lung disease with the help of HRCT images is the one by Vinta et al.

[5]. In this case, there is an initial stage of lung region segmentation with the use of an enhanced U-Net++ and a special loss function. Then there is an extraction of multi-scale features using RAPNet which makes use of deformable and atrous convolutions. At last, there is a lightweight classification model – MobileUNetV3. The results were the accuracy of 99.10%.

Interactive lung nodule segmentation in CT images was the emphasis of Fernandes et al. [6]. The two-stage framework of their U-Net cascade includes Light U-Net for the creation of the initial segmentation mask and a Shallow U-Net for the refinement of the result, where the guidance of a user clicks and deep features extracted in the previous step is utilized. They managed to obtain 91.12% in the Dice score and demonstrated robustness to mistakes made by the user. In contrast to the completely automatic frameworks, this one includes user interaction.

2.4 Lightweight and Computationally Efficient Models

Computational efficiency is one of the significant concerns in recent times along with the increasing complexity of deep learning frameworks. Large ensembles of CNN and Transformer architectures require a considerable amount of memory, computational power, and training time, which would be rather problematic during the implementation in hospitals with limited computational capacity.

Vinta et al. [5] resolved this problem by introducing MobileUNetV3 into the classification stage of their ILD framework. The described framework is referred to as memory-efficient while maintaining 99.10% accuracy.

Faizi et al. [7] explicitly evaluate computational efficiency in terms of decreasing FLOPs by 24.4% while maintaining 90.96% accuracy. It means that decrease in computational complexity is not synonymous with rejection of hybrid CNN-Transformer representations.

Model complexity is the main focus of CNN-O-ELMNet [8]. Hierarchical features are extracted by using EfficientNetV2L, while the number of trainable parameters is decreased by applying imperialistic competitive algorithm. Classification is performed by Optimized Extreme Learning Machine (OELM). The framework includes 2,438 trainable parameters and provides cross-modality performance.

The problem of computational efficiency is also solved in CTXNET [11] since training time equals 10-12 seconds per epoch in addition to 99.77% accuracy.

2.5 Data Augmentation and Medical Dataset Limitations

The scarcity of large, adequately annotated datasets in the medical field is one of the key limitations in applying deep learning. Medical images require a high cost of acquisition and annotation, and an imbalanced class distribution may lead to lack of representation of the minority classes. As such, data augmentation and generation techniques become increasingly employed in analyzing diseases in lungs.

CanNS [2] involves the usage of GAN elements in the classification network, and CTXNET [11] uses DCGAN augmentation for balancing the dataset. The MViTReg-IP [9] study employs a combination of online and offline augmentation of lung replacement in chest x-ray images.

The application of data augmentation in these works shows the existence of two important goals – augmenting the diversity of data for training and solving the problem of class imbalance. Nonetheless, data augmentation cannot be used as a substitution for diverse datasets that were independently collected in a clinical setting. The model will be less generalized in case of application to images acquired in different clinical conditions.

2.6 Multi-Modal Lung Disease Analysis

Use of multi-modal imaging techniques is yet another promising avenue in contemporary research. Each modality reflects a different aspect of the pulmonary condition under study. CXR allows rapid and readily available 2D imaging, while CT allows detailed 3D anatomical information. Histopathological images can provide cellular information necessary for cancer detection.

Incorporation of CXR, CT, and histopathological images in multi-modal framework is made explicit in [1]. Also, the datasets reviewed here indicate use of CXR and CT for various pulmonary diseases such as lung cancer, pneumonia, COVID-19, pneumothorax, tuberculosis, and abnormalities of lungs. [8] explicitly shows cross-modality performance using CXR and CT images. [11] also employs CXR and CT images.

There is potential in use of multi-modal learning since it would allow use of complementary data to increase robustness of the diagnostic process. At the same time, there are many aspects that should be considered while integrating different modalities including but not limited to differences in resolution, acquisition process, anatomical representations, and annotation practices.

2.7 Severity Assessment of Lung Disease

While classification focuses on the presence or categorization of the disease, severity assessment provides clinical insights into the magnitude of pulmonary involvement. Recent studies have thus gone beyond classification tasks involving binary or multiple classes to estimate the severity of disease quantitatively.

CNN-O-ELMNet [8] takes up the challenge to classify the lung disease and estimate its severity. The lightweight nature of this architecture, along with the cross-modality approach adopted, is indicative of extending diagnostic prediction in an efficient way computationally.

Slika et al. [9] designed the MViTReg-IP framework specifically to predict severity scores from chest X-ray images in a multi-score setting. The approach involves the use of two encoders based on Vision Transformers, feature concatenation and fusion using ResBlocks, and dual regression using MLPs to predict both geographic extent and lung opacity simultaneously. A mixed online-offline augmentation strategy has also been used in the process. MAE and Pearson Correlation (PC) have been used as performance metrics.

These researches reveal an interesting development from disease detection to clinical quantification. The issue with severity prediction is that the scores can be subjective, difficult to annotate, and inconsistent among different clinicians. As such, validation and standardized scoring are important considerations.

2.8 Explainable Artificial Intelligence

The black-box nature of deep learning poses a big problem for its adoption in clinical settings. Accuracy of the model might not be enough if the clinicians cannot interpret the part of the image the model bases its prediction upon. Therefore, recent studies on lung diseases have been applying techniques from XAI.

Hosny et al. [1] applied Grad-CAM heatmaps along with ECA attention mechanism for providing visual explanation of predictions. [3] applies Grad-CAM along with grid/block attention, and Hasan et al. [11] applied Grad-CAM for final decision visualization. These approaches may help identify the image parts that influence the decisions of the models and help clinicians to verify if the model focuses on the right image parts.

Prado et al. [10] proposed another approach to explaining models through Bayesian uncertainty calculation. The method consists of combining object detection with one of the detectors, such as YOLOv8, Cascade R-CNN, or RetinaNet, and a Bayesian Neural Network for the task of classifying diseases and uncertainty calculations. Such an approach allows providing predictive confidence alongside diagnostic information, making the screening process more user-oriented.

Attention, however, cannot automatically be taken for full explainability in the clinical context. While attention is capable of highlighting features that the model pays more attention to, mechanisms like Grad-CAM allow for visualizing localizations post-hoc, and Bayesian uncertainty calculations provide uncertainty information.

3. Comparative Analysis of the Reviewed Approaches

In order to compare the datasets used in the recent research on lung diseases, Table 1 summarizes the major datasets considered in the reviewed literature.

Table 1. Comparative overview of datasets in recent deep learning-based lung disease analysis

Ref	Dataset Name	Modality	No. of Images	Diseases	No. of Classes	Annotation Type
[1]	Guangzhou Pediatric CXR, Chest CT-Scan, Lung & Colon Histopathological, Mega Dataset	CXR, CT, Histopathology	5,856 CXRs, 1,000 CTs, 25,000 Histopath, 31,768 overall	Pneumonia, Lung Cancer, Colon Cancer	Binary & Multi-class	Image-level
[2]	Kaggle Lung CT Image Dataset	CT	1,190 images from 110 cases	Lung cancer	Multi-class (Normal, Benign, Malignant)	Pixel-level (SwiNet), Image-level (XLG)

[3]	IQ-OTH/NCCD, Kaggle Chest CT	CT	1,197 scans (IQ-OTH), 1,000 scans (Chest CT)	Lung cancer	Multi-class (3 classes for IQ-OTH, 4 classes for Chest CT)	Image-level
[4]	NIH Chest X-ray Dataset	CXR	8,000 images (3,000 benign, 5,000 malignant)	Atelectasis, Infiltration, Nodule, Pneumonia	Binary & Multi-class (4 disease types)	Image-level
[5]	MedGIFT database	HRCT (High-Resolution CT)	1,946 ROIs from 108 series (4,000 slices with augmentation)	Interstitial Lung Diseases (ILD)	Multi-class (6 classes: Consolidation, Micronodules, etc.)	Pixel-level (Segmentation) Image-level (Classification)
[6]	LIDC-IDRI, LNDb	CT	1,018 cases / 2,625 nodules (LIDC), 294 scans (LNDb)	Lung nodules (Lung cancer)	Binary (Benign vs Malignant)	Pixel-level (segmentation mask), Bounding box and click points
[7]	LUNA16, LUNA16-K (derived from LIDC-IDRI)	CT	1,004 nodules	Lung nodules (Lung cancer)	Binary (Benign vs Malignant)	Image-level, Nodule-level (coordinates, malignancy ratings)

[8]	SIIM-ACR, NLM/Belarus /RSNA, LIDC-IDRI, Brixia COVID-19	CXR, CT	12,051 CXRs, 7,000 CXRs, 894 CTs, 4,707 CXRs	Pneumothorax, Tuberculosis, Lung Cancer, COVID-19	Binary & Multi-class (Severity levels)	Image-level (Disease labels, severity scores)
[9]	RALO (Radiographic Assessment of Lung Opacity Score)	CXR	2,373 images (augmented to 5,634)	COVID-19 / Pneumonia	Regression and Multi-score (Geographic Extent 0-8, Lung Opacity 0-8)	Image-level (scalar numerical severity scores)
[10]	Multiple (SIRM, Radiopaedia, Coronacases, MOSMED, RICORD, CC-CCII, COVID-CT-MD)	CT	90,000 images (slices)	Pneumonia (COVID-19, CAP)	Multi-class (3 classes: HC, CAP, COVID-19)	Bounding box (derived from pixel-level masks), Image-level
[11]	COVIDx CT Dataset, COVID-19 Radiography Dataset	CXR, CT	194,919 CT images, 21,149 CXR images	Lung abnormalities (COVID-19, Pneumonia, Lung Opacity)	Multi-class (3 classes for CT, 4 classes for CXR)	Image-level

The deep learning architectures are compared based on several parameters such as framework, model/architecture, input imaging modality, task, and explainability or main result obtained in Table 2.

Table 2. Comparative overview of the methodologies used for specific task in lung disease analysis

Ref.	Framework	Model / Architecture	Input / Modality	Task Covered	Explainability / Reported Outcome
[1]	Attention-Based Inception-ResNet	Hybrid Inception-ResNet with HFE, Inception-ResNet and ECA	CXR, CT, histopathology	Classification; detection	Grad-CAM + ECA attention; improved transparency with high diagnostic performance.
[2]	Cancer Nexus Synergy (CanNS)	SwiNet (Swin-Transformer U-Net) + XLG CancerNet (Xception- LSTM-GAN) + DevLO	High-resolution CT	Segmentation; classification	Swin-Transformer self-attention; F1-score 98.99%, AUC 99%.
[3]	Attention-Enhanced InceptionNeXt	Hybrid CNN + ViT with multi-axis grid and block attention	Raw lung CT	Classification; detection	Grad-CAM + grid/block attention; 99.54% accuracy with only 18.1M parameters.
[4]	ML Classifiers + TOPSIS	Inception V3 + GLCM/LBP + SVM/KNN/Naïve Bayes + TOPSIS	Lung X-ray images	Binary and multi-class classification	No XAI reported; 97.05% accuracy.
[5]	Hybrid Network: Improved U-Net++ + MobileUNetV3	Improved U-Net++ + RAPNet + MobileUNetV3	HRCT	Segmentation; classification	RAPNet attention; 99.10% accuracy with a memory-efficient architecture.

[6]	Interactive U-Net Framework	Two-stage cascade: Light U-Net + Shallow U-Net	Raw CT scans + clinician/user click	Interactive lung-nodule segmentation	No XAI reported; Dice score 91.12%, robust to annotation errors.
[7]	DCSwinB	Dual-branch CNN + Swin-Transformer with Conv-MLP	CT images	Benign vs malignant nodule classification	No XAI reported; 90.96% accuracy with 24.4% FLOPs reduction.
[8]	CNN-O-ELMNet	EfficientNetV2L + Imperialistic Competitive Algorithm + Optimized ELM	CXR and CT	Lung-disease classification; severity assessment	No XAI reported; 2,438 trainable parameters with strong cross-modality performance.
[9]	MViTReg-IP	Multi-task ViT regression with two ViTReg-IP encoders, ResBlock fusion and dual MLP regressors	Chest X-ray images	Severity quantification / multi-score regression	No XAI reported; accurate multi-score severity prediction with low MAE and high Pearson correlation.
[10]	Bayesian Automatic Screening	YOLOv8 / Cascade R-CNN / RetinaNet + Bayesian Neural Network	CT scans	Pneumonia screening/ classification; lesion localization	Bayesian uncertainty quantification; high diagnostic performance with predictive confidence measures.

[11]	CTXNET	Compact Convolutional Transformer (CCT) with DCGAN augmentation, morphological opening and CLAHE	CXR and CT	Lung-abnormality classification	Grad-CAM; 99.77% accuracy with 10–12 s/epoch training time.

4. Issues to be Addressed

- There are many structural trade-offs within AI architectures. The Convolutional Neural Networks (CNNs) face problems in capturing global context, while the Vision Transformers segment the images into fixed-size patches which may affect local feature capturing thus making it difficult to detect tiny lung nodules.
- Collecting large medical datasets is very difficult and expensive. These datasets have class imbalances and this will result in bias or poor performances for the minority disease classes.
- The deep learning algorithms are opaque black-boxes which make it extremely difficult to determine the logic behind the particular diagnosis made by the algorithm. It is therefore difficult to gain trust of clinicians in such situations.
- There are very high computational costs involved in using the self-attention mechanism in transformers, and therefore it is extremely impractical to use in the clinical setting.

5. Discussion

The use of the lightweight architecture such as MobileNetV2 is made possible by the use of the depthwise separable convolutions instead of computationally heavy standard convolutions together with the use of GAP layer, making it possible for the model to reduce feature dimensions and memory usage. Contrary to the need for more parameters in larger ensembles, this demonstrated the necessity of efficient resource networks, which are required for deployment in clinical environments. Moreover, a hybrid approach was used in order to effectively deal with the ongoing challenge of lack of data in the field of medical imaging through the use of transfer learning with pre-trained ImageNet weights and robust geometric data augmentation for dynamic increase of structural diversity.

6. Conclusion

Deep learning has been identified as a promising tool for improving the diagnosis of lung diseases, including detecting, classifying, segmenting, localizing, and assessing the severity of the disease. The above studies show that hybrid CNN and Transformer architectures are capable of integrating local feature extraction with global contextual representation, whereas lightweight architectures provide options for clinical implementation in an efficient manner. The analysis of multiple types of images like CXRs, CTs, and histopathological images can also provide complementary data for a better diagnosis. While data augmentation and transfer learning can overcome the problems of small and unbalanced medical data, they cannot replace clinical data gathered from diverse sources. Explainable AI tools like Grad-CAM, attention mechanism, and Bayesian uncertainty estimation can be used to make these algorithms more transparent for clinicians. However, the problem of computational complexity, lack of diverse datasets, poor generalizability, and standardization of the severity assessment should also be addressed in future research.

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