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Artificial Intelligence in Pulmonary Imaging: A Review of Techniques

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Abstract

Introduction and Purpose

The use of artificial intelligence (AI) in medical imaging has grown significantly in recent years, especially in the area of pulmonary imaging. AI systems have shown promising performance in a variety of thoracic imaging tasks, such as nodule detection, classification of interstitial lung diseases, and prognostic modeling. The purpose of this review is to provide a comprehensive overview of the current state of AI applications in pulmonary imaging, and to highlight clinical use cases, significant technological advancements.

Materials and Methods

This review is based on a comprehensive analysis of scientific literature from scientific databases (PubMed, Scopus, Web of Science, and IEEE Xplore), selected based on their citation impact, scientific quality, and relevance to the topic of AI in pulmonary imaging.

Results

An analysis of selected literature has revealed the rapid development of AI applications in pulmonary imaging in recent years. The identified studies cover a wide range of topics, from diagnostic support and automated lesion detection to segmentation of anatomical structures and prognostic modeling. The overwhelming majority of publications have demonstrated the high performance of algorithms for specific imaging tasks. Many have compared AI performance to that of radiologists, often indicating comparable or superior precision.

Conclusion

In pulmonary imaging, AI holds great promise for enhancing diagnostic precision, effectiveness, and decision support. The majority of models are still in the experimental stage, despite numerous studies reporting high performance, particularly in detection and classification tasks. Additional validation, standardization, and consideration of ethical issues are required to facilitate clinical adoption.

Keywords: artificial intelligence; pulmonary imaging; deep learning; radiology; medical image analysis; lung diseases; computer-aided diagnosis; thoracic imaging; clinical decision support.

Introduction:

Artificial intelligence (AI) has become a transformative force in modern medicine, unlocking new opportunities for data-driven diagnostics, prognostics, and clinical decision support. Over the past ten years, in particular, the application of AI to medical imaging has developed quickly, allowing for automated analysis, pattern recognition, and predictive modeling across a variety of imaging modalities [1]. Due to the prevalence of respiratory disorders worldwide and the growing need for quick and precise interpretation of different kinds of medical images, pulmonary imaging has become one of the most important application areas.

AI has been applied across a wide range of imaging modalities, including chest X-ray [2, 3,4], magnetic resonance imaging (MRI) [5, 6], computed tomography (CT) [7, 8], positron emission tomography (PET) [9], ultrasound [10], optical coherence tomography (OCT) [11], and histopathological imaging [1].

Most existing surveys on AI in pulmonary imaging do not reflect the rapid developments that have occurred in recent years [12, 1, 13, 14]. Many of these earlier reviews focused narrowly on selected applications, such as nodule detection and classification [15, 16, 17, 18] or on the surge of research related to COVID-19 imaging [19, 20]. Moreover, previous surveys have typically organized findings around model architectures, rather than from the perspective of clinical relevance or disease types. In contrast, the present review emphasizes a disease-centered classification - focusing on how AI techniques have been applied to specific pulmonary conditions, such as lung cancer, interstitial lung diseases (ILD), pneumonia, tuberculosis, and COVID-19 - regardless of the underlying model type. An important contribution of this review is an up-to-date overview of publicly available and widely used datasets in pulmonary imaging. In recent years, the number, diversity, and quality of these datasets have increased substantially, including multimodal collections that combine CT scans, chest X-rays, and associated clinical metadata. Noteworthy recent additions include expanded COVID-19 image repositories, large-scale annotated CT datasets for lung segmentation, and longitudinal datasets designed for modeling disease progression. These resources are now essential for benchmarking deep learning models, promoting reproducibility, and ensuring clinical relevance in pulmonary imaging research.

Artificial Intelligence

AI is a field of science that creates computer systems to perform tasks similar to those of ordinary human intelligence, such as pattern recognition, data analysis, or decision-making. The conceptual foundation of AI was introduced by Alan Turing in 1950 [21]. Machine learning (ML) is a fundamental element of modern AI and plays a key role in medical applications, including those related to emergencies. The term was coined by Arthur Samuel in 1959 [22]. Since then, machine learning has expanded beyond intensive evolution, encompassing the scope and techniques such as multilayer perceptron [23], backpropagation [24, 25], artificial neural networks [26, 27], support vector machines (SVMs) [28], random forests [29, 30] long short-term memory (LSTM) [31], dropout [32], batch normalization [33]. A major advancement came with the introduction of deep belief networks and hierarchical feature representations by Hinton et al. [34], which laid the groundwork for modern deep learning architectures.

One of the key moments in the development of deep learning was the introduction of graphics processing units (GPUs) for training large neural networks. As early as 2009, Raina, Madhavan, and Andrew Ng demonstrated the potential for significantly accelerating network training using GPUs. Andrew Ng's observation that larger models trained on larger datasets could yield greater benefits than algorithmic improvements alone, which formed the foundation of this concept [35]. The following year, record-breaking results were achieved on the MNIST dataset using a large convolutional neural network trained on GPUs [36]. One of the innovative aspects of this work was the extensive use of data augmentation, which effectively reduced overfitting.

A breakthrough in the development of AI in computer vision and image recognition was the development of AlexNet, a convolutional neural network (CNN) model capable of automatic feature extraction [37]. It achieved the highest performance in the ImageNet competition, outperforming existing machine learning methods. Since then, deep learning (DL) has become the dominant approach in image analysis, both for general and medical applications.

Although AlexNet is considered a breakthrough, the authors were not the first to use GPUs for this purpose. Earlier, in 2011, Hinton's team used GPUs to train a neural network for speech recognition, which significantly improved Microsoft's speech recognition system [38]. In 2017, Vaswani et al. proposed a groundbreaking neural network architecture known as the Transformer, which enables learning internal representations and global dependencies in sequential data [39]. This model, built on the concept of self-attention, was initially developed for natural language processing (NLP) tasks. Unlike traditional recurrent neural networks (RNNs), the Transformer processes the entire input sequence in parallel, allowing for a high degree of computational efficiency, faster training on large datasets, and improved learning performance. This approach has led to the development of several groundbreaking models, including BERT [40] and GPT [41], which were pre-trained on a vast corpus of text data and subsequently fine-tuned on smaller, task-specific datasets. These models have since redefined the state of the art in various NLP applications and have inspired adaptations of the Transformer architecture in other domains, including computer vision.

Machine learning is commonly categorized into two main types - supervised learning and unsupervised learning.

In supervised learning, models are trained on labeled data (e.g., medical images annotated with diagnostic labels), allowing them to perform tasks such as prediction, classification, or regression on new, unseen data. This approach is widely used in medical imaging - for example, in lesion detection, disease classification, and pattern recognition. In contrast, unsupervised learning involves analyzing unlabeled data to uncover hidden structures, identify clusters, or detect anomalies, which can be useful in medical data mining, where labeling is expensive or difficult. Both approaches are fundamental to the development of modern AI systems designed to support diagnostic imaging and clinical decision-making.

Table 1. Datasets that are utilized in deep learning applications for the analysis of pulmonary medical imaging.

Name	**Images Type**	**Classes**	**Description**
JSRT dataset [42]	CT, X-ray	Normal and Lung Nodules	93 normal and 154 nodule images, 2048 × 2048, with metadata
LIDC-IDRI [43]	CT	Lung Cancer	1018 images from 1010 patients, with metadata
Montgomery dataset [44]	X-ray	Tuberculosis and Normal	138 Tuberculosis and 80 normal images, 4020 × 4892 or 4892 × 4020, with metadata
Autofocus database [45]	Sputum Smear Microscopy	Tuberculosis	1200 images, 2816 × 2112
Shenzhen dataset [44]	X-ray	Tuberculosis and normal	662 frontal images, 326 Normal and 336 Tuberculosis with different size about 3000 × 3000
CPTAC-LUAD Dataset [46]	MRI, CT, X-ray	Lung Cancer	43,420 images
NCI Genomic Data Commons [47]	Histopathology	Lung Cancer	More than 575,000 images, 512 × 512
ChestX-ray8 [48]	X-ray	8 thoracic diseases and a normal case: Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, and Pneumothorax	108,948 images, 1024 × 1024, from 30,805 patients
ChestX-ray14 [48]	X-ray	14 thoracic diseases and a normal case: Edema, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Atelectasis, Hernia, Pleural thickening, Emphysema, Fibrosis, and Consolidation	112,120 images, 1024 × 1024, from 32,717 patients
Optical Coherence Tomography (OCT) and Chest X-ray Images [49]	CT, X-ray	Normal and Pneumonia (Bacterial, Viral, COVID-19 in one class)	5856 images - 1583 normal and 4273 pneumonia images with different images size
LDOCTCXR [50]	X-ray	Normal and Pneumonia	3883 Pneumonia and 1349 Normal images
FUMPE dataset [51]	CT (CTA)	Pulmonary Embolism	8792 3D images
ChestX-ray images - Pneumonia [49]	X-ray	Normal and Pneumonia	5232 chest X-ray images from children - 3883 pneumonia (2538 bacterial and 1345 Viral) and 1349 normal, from 5856 patients to train a model and test with 234 normal and 390 Pneumonia from 624 patients, with different size
RSNA Dataset [52]	X-ray	Pneumonia and Normal	5863 images with different images size
CheXpert [53]	X-ray	18 diseases: Atelectasis, Consolidation, Infiltration, Pneumothorax, Edema, Emphysema, Fibrosis, Effusion, Pneumonia, Pleural Thickening, Cardiomegaly, Nodule, Mass, Hernia, Lung Lesion, Fracture, Lung Opacity, and Enlarged Cardiomediastinum	224,316 images with different images size, from 65,240 patients with both frontal and lateral views
RIH-CXR [54]	X-ray	COVID-19	231 COVID-19 images with different images size, with metadata

Name	Images Type	Classes	Description
LC25000 Dataset [55]	Histopathology	Lung adenocarcinoma, Lung squamous cell carcinoma, and Normal lung tissue	25,000 images (with colon classes), 768 x 768, generated 750 images of lung tissue (250 benign lung tissue, 250 lung adenocarcinomas, and 250 lung squamous cell carcinomas), augmented to 25,000 images
MIMIC-CXR Dataset [56]	X-ray	Chest radiograph	377,110 chest radiographs with 227,835 radiology reports, around 3000 × 3000
ImageCLEF 2019 [57]	CT	Tuberculosis	335 images, 512 × 512, from 218 patients, with metadata
ImageCLEF 2020 [58]	CT	Tuberculosis	403 images, 512 × 512
Andrew's Kaggle Database [59]	CT, X-ray	COVID-19	16 CT and 79 X-ray images with different size of images
Chowdhury's Kaggle dataset [60]	X-ray	COVID-19, Pneumonia, and Normal	1341 Normal, 219 COVID-19, and 1345 Pneumonia
PadChest [61]	X-ray	16 diseases: Pulmonary Fibrosis, COPD signs, Pulmonary Hypertension, Pneumonia, Heart Insufficiency, Pulmonary Edema, Emphysema, Tuberculosis, Tuberculosis Sequelae, Lung Metastasis, Post Radiotherapy Changes, Atypical Pneumonia, Respiratory Distress, Asbestosis Signs, Lymphangitis Carcinomatosa, and Lepidic Adenocarcinoma	160,868 images with different images size from 67,625 patients and 206,222 reports
Covid Chest X-ray database [62]	X-ray	COVID-19	231 COVID-19 images with different images size, with metadata
Sajid's Kaggle database [63]	X-ray	Normal and COVID-19	28 Normal and 70 COVID-19 images with different images size
COVID-19 Image Data Collection [64]	X-ray	3 diseases and normal: COVID-19, Viral Pneumonia, Bacterial Pneumonia	306 images - 79 images for normal, 69 images for COVID-19, 79 images for Bacterial Pneumonia, and 79 images for Viral Pneumonia with different size, with metadata
COVIDx Dataset [65]	X-ray	Pneumonia, Normal, and COVID-19	5559 Pneumonia, 8066 Normal, and 573 COVID-19 images
Covid-19 Radiography Database [66]	X-ray	Normal, COVID-19, Lung Opacity, and Viral Pneumonia	10,200 Normal, 3616 COVID-19, 6012 Lung Opacity, and 1345 Viral Pneumonia, 299 × 299, with metadata
COVID-CT database [67]	CT	Normal and COVID-19	15,589 images for normal and 48260 images for COVID-19, 512×512 pixels
RadFusion [68]	CT	Normal and Pulmonary Embolism	1837 images from 1794 patients
VinDr-CXR [69]	X-ray	22 findings: Aortic enlargement, Atelectasis, Cardiomegaly, Calcification, Clavicle fracture, Consolidation, Edema, Emphysema, Enlarged PA, Interstitial lung disease (ILD), Infiltration, Lung cavity, Lung cyst, Lung opacity, Mediastinal shift, Nodule/Mass, Pulmonary fibrosis, Pneumothorax, Pleural thickening, Pleural effusion, Rib fracture, Other lesion, and 6 diseases: Lung tumor, Pneumonia, Tuberculosis, Other diseases, COPD, No finding	18,000 images, with metadata
PediCXR/VinDr-PCXR [70]	X-ray	36 findings, and 18 diseases	9125 images, posteroanterior view, children
LungHist700 [71]	Histopathology	Adenocarcinoma, Squamous cell carcinoma, and Normal	691 images, 1200×1600, from 45 patients
PedLUS dataset [72]	Ultrasound	Pneumonia	11,811 images - 4186 with subpleural consolidations, and 7625with segmental or lobar consolidations, from 57 patients
INSPECT [73]	CT	Normal and Pulmonary Embolism, Prognostic tasks: Pulmonary Hypertension, In-Hospital Mortality, Re-admission	23,248 images from 19,402 patients

Models for Pulmonary Imaging

Lung cancer (Pulmonary nodule)

Modern Computer-aided diagnosis (CAD) systems, which are made possible by advancements in CNN-based computer vision, allow for efficient detection, segmentation, and classification of pulmonary nodules, thereby improving the management of lung cancer, one of the most serious cancer types [74]. In lung nodule classification, much research focuses on the use of CAD systems, which provide radiologists with information about the nodule type (benign or malignant) and support the diagnostic process [75, 76]. CNNs are used to recognize various nodule types, such as solid, semi-solid, and ground-glass nodules [77]. Structures may be classified as nodules or non-nodules based on shape and texture features using SVM, and Pei et al. [78] used a 2D multiscale filter and geometrically constrained region growth to separate them. Various other approaches have been described in the literature, including classification using transfer learning with VGG-16, VGG-19, DenseNet-121, DenseNet-169, and ResNet to obtain good results with limited data [79], multi-task models [76], and 3D CNNs [80], achieving high accuracy.

Detecting pulmonary nodules is a challenging detection task, requiring 3D or 2.5D analysis due to the presence of lesions on multiple CT slices. High-performance detection systems require high sensitivity and precision, which is why many methods are based on a two-stage architecture: the first stage is responsible for candidate detection, and the second for reducing false positives. Various variants have been described in the literature, including models using 3D Faster R-CNN [81], 3D roto-translation group convolution (G-Convs) [82], 3D faster R-CNN with a U-net-like encoder-decoder structure for candidate detection and a gradient boosting machine with a 3D dual path network (DPN) [83], and Retina-UNet for candidate detection and SVM for features classification [84]. Class imbalance poses a challenge, leading to the use of strategies such as patch-based sampling [85], hard negative mining, and ensemble convolutions with an attention network [86]. Research also indicates that the effectiveness of models may depend on parameters such as radiation dose, patient age, and scanner type [87].

Segmentation of pulmonary nodules, once detected, is crucial for accurate measurement of their size and subsequent assessment of malignancy. U-Net architectures and unsupervised learning methods are commonly used for this purpose [88]. Due to the difficulty in obtaining accurate segmentation masks, weakly supervised methods are being developed, which enable accurate voxel-level segmentation using only image-level classification labels [89].

Pulmonary embolism (PE)

PE is a potentially fatal condition in which a blood clot blocks the pulmonary arteries. CT pulmonary angiography (CTPA) is the gold standard for diagnosis; however, interpretation is challenging and time-consuming because of the volume of images and the potential for artifacts. As a result, CAD was created to help radiologists identify PE while cutting down on analysis time and increasing precision. Using manually annotated reference data, Vainio et al. [90] created a 3D U-Net model in 2021 to segment hypoperfused lung regions that are specifically linked to chronic thromboembolic pulmonary hypertension (CTEPH). Proposed by Khan et al. DenseNet201-based classification model analyzes both acute and chronic PE cases using a large public dataset from the RSNA-Kaggle competition [91].

Similarly, Ma et al. [92] introduced a two-step approach combining 3D CNN feature extraction with sequential analysis for study-level PE prediction. In another study, Vainio et al. [93] utilized maximum intensity projection reconstructions and transfer learning to distinguish chronic PE from acute or negative cases using preprocessed CTPA images. A technique for automatically segmenting and quantifying hypoperfused lung volumes on dual-energy CTPA was presented by Bird et al. [94], which made it easier to determine the severity of CTEPH.

Pneumonia

Pneumonia is a lung infection that causes breathing difficulties by filling the alveoli in one or both lungs with pus and fluid. Recent studies on pneumonia detection have explored a variety of CNN-based approaches, often incorporating transfer learning and data augmentation. Tobias et al. [95] applied a straightforward CNN, while Stephen et al. [96] trained a CNN from scratch with extensive augmentation techniques. Several other works [97, 50, 98] leveraged pre-trained CNNs, with authors such as Rajpurkar et al. [99] and Ayan and Ünver [97] also using tailored augmentation methods to improve performance.

Hashmi et al. [100] combined CNNs with transfer learning, augmentation, and an ensemble approach. Acharya and Satapathy [101] presented a novel approach, using a Deep Siamese CNN to compare the symmetry of the left and right lungs for a more reliable classification. In order to address temporal dependencies in image sequences, Elshennawy and Ibrahim [102] combined CNN and LSTM. Jaiswal et al. [103] extended detection to include region-of-interest (ROI) localization using a Mask-RCNN model, while Hurt et al. [2] proposed probabilistic heatmaps over chest X-rays to assist radiologists in diagnosis. Reflecting a growing trend toward multimodal AI solutions, Antunes et al. introduced PneumoNet [104], an integrated system that combines an improved AlexNet-based CNN for pneumonia detection with the GPT-Neo language model to automatically generate diagnostic reports, demonstrating how visual and language models can be combined to enhance clinical interpretability.

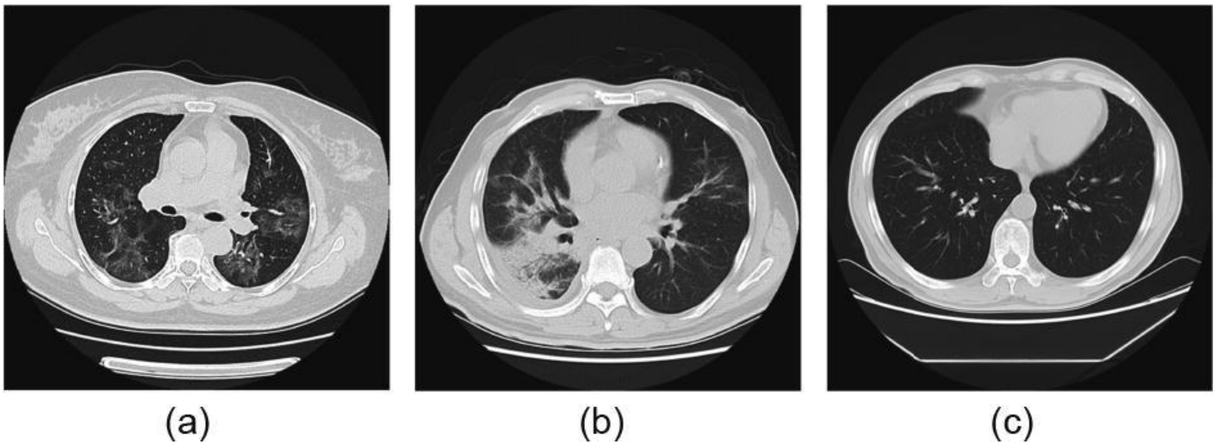
Tuberculosis (TB)

TB, caused by Mycobacterium tuberculosis, remains a major global health concern and is one of the ten leading causes of death worldwide. Various AI techniques have been developed to assist in TB detection, like CAD4TB [105], developed by Delft Imaging in collaboration with Radboud University and the Lung Institute in Cape Town. It provides automated heatmaps and abnormality scores from chest X-rays, achieving expert-level performance. Melendez et al. [106] combined clinical data with CAD4TB scores to further enhance diagnostic performance. For the classification of tuberculosis, numerous CNN-based models have also been put forth. According to Heo et al. [107], adding demographic factors like gender and age to CNNs increased their diagnostic precision. Pasa et al. [108] introduced a lightweight CNN that reduced computational cost without sacrificing performance. Other studies used region-based feature extraction and SVMs to improve TB recognition [109, 110]. Ul Abideen et al. [111] implemented a Bayesian CNN to handle model uncertainty, while Hwang et al. [112] and Lakhani and Sundaram [113] applied transfer learning from ImageNet using models like AlexNet and GoogLeNet. Further enhancements were achieved using ensemble methods. Islam et al. [114] combined outputs from multiple fine-tuned models, including ResNet-50, VGG16, and AlexNet.

Lopes and Valiati [115] introduced the Bag of CNN features approach, using ResNet, GoogLeNet, and VGGNet for feature extraction and SVM for classification. Other ensembles used voting [116], stacking [117], and feature-level fusion (RID network) combining DenseNet, ResNet, and Inception-ResNet [118]. Beyond X-rays, CT-based TB diagnosis has seen progress with models like AE-CNN, combining convolutional and autoencoding layers for feature extraction [119]. Depth-ResNet, a 3D ResNet variant incorporating depth information, was proposed for CT-based severity estimation [120]. Optical flow-based models treated CT sequences as video frames to detect motion patterns caused by TB lesions [121]. In sputum microscopy, CNNs have been trained to localize and classify TB bacilli in microscopic fields using RGB and binarised inputs [122, 123]. DBNs and segmentation techniques such as SURF and channel area thresholding have also been employed to distinguish bacilli from background artifacts [124]. Automated systems using motorised stages and models like Inception V3 have been developed for full-slide analysis and classification [125].

COVID-19

COVID-19, a contagious disease caused by a novel coronavirus, poses significant health risks, particularly for the elderly and individuals with pre-existing conditions [126]. Deep learning approaches, especially CNNs combined with transfer learning and data augmentation, have been widely employed for their detection. Studies such as Shibly et al. [127] and others [128, 129] used pre-trained models like InceptionV3 as feature extractors. Several works [130, 131] focused on three-class classification - distinguishing COVID-19, viral pneumonia, and normal cases, using CNNs trained from scratch or with transfer learning, often applying augmentations like rotation, scaling, and intensity shifts [60, 132]. Data augmentation has also been used to mitigate limited dataset size [133, 134] and, in some cases, to forecast pandemic trends [133]. Ensemble techniques have been explored to improve performance, including weighted averaging [135] and stacking [136]. Other methods include the use of VB-Net for segmentation and random forest classifiers trained on handcrafted features [137]. CT-based systems like that of Gozes et al. [138] integrate 2D and 3D subsystems for abnormality detection, volumetric analysis, and case scoring, using CNNs and Grad-CAM for localisation. Further innovations include the application of location-attention mechanisms (Figure 1) [139], differential evolution-optimised CNNs [140], hybrid CNN-LSTM architectures [141], MLP-CNN frameworks [142], and capsule networks with transfer learning [143].



Source: https://doi.org/10.1016/j.eng.2020.04.010

Figure 1. CT images: (a) COVID-19; (b) IAVP; and (c) no pneumonia manifestations used for application of location-attention mechanisms [139].

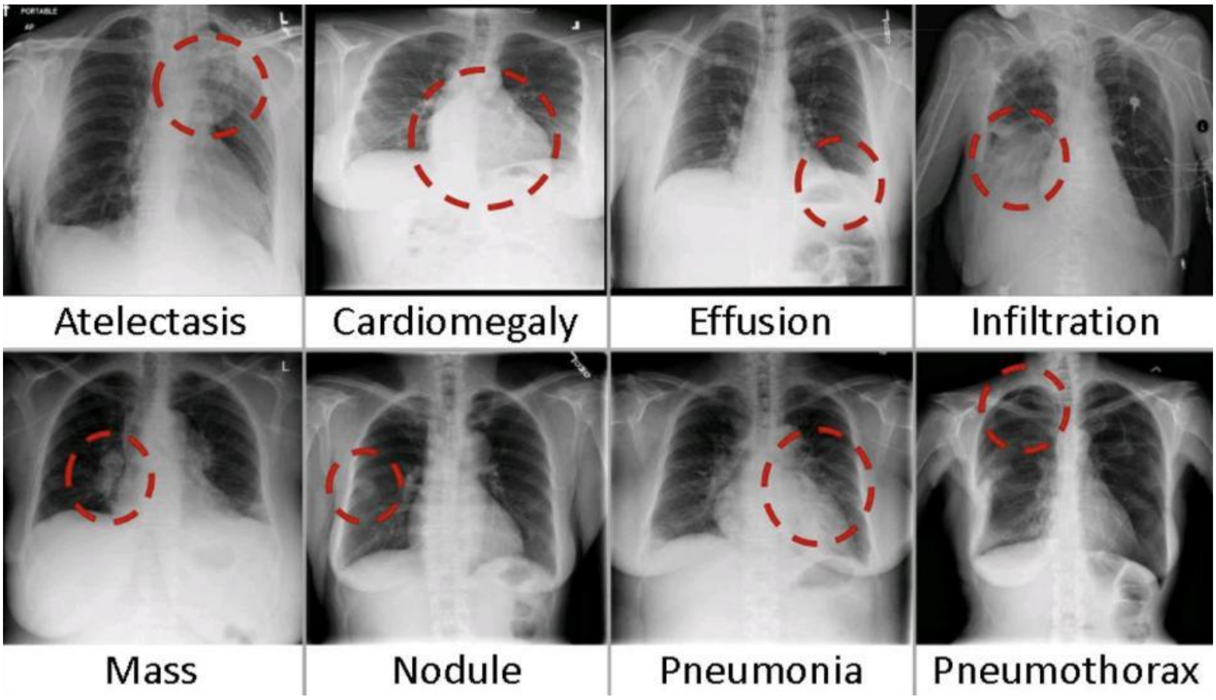
Interstitial lung disease (ILD)

ILD, also known as diffuse parenchymal lung disease (DPLD), encompasses a diverse group of non-infectious and non-neoplastic pulmonary disorders characterized by alveolar inflammation and interstitial fibrosis. Accurate identification of characteristic imaging patterns in CT scans is critical for clinical assessment and treatment planning. Consequently, several studies have explored deep learning-based CAD systems for ILD pattern classification. Anthimopoulos et al. [144] proposed a CNN-based method that segments the lungs, classifies local regions by texture, and generates quantification maps to assist in diagnosis. Simonyan and Zisserman [145] introduced a CNN capable of categorizing lung tissue into patterns such as normal, ground-glass opacity (GGO), reticulation, and honeycombing. Unsupervised feature extraction was investigated by Li et al. [146], who achieved promising results by leveraging multiscale image representations. In further work, Li et al. [147] introduced a shallow CNN tailored to ILD classification. To address the challenge of pattern co-occurrence in ILD, Gao et al. [148] developed multi-label CNN architectures, while Christodoulidis et al. [149] explored the use of transfer learning and knowledge maps, integrating domain-specific structural insights into the model training. A three-channel input strategy was later proposed by Gao et al. [150], where CT images were rescaled to focus on low, high, and normal attenuation ranges, enhancing the model's ability to visually distinguish between multiple ILD categories. These studies collectively demonstrate the growing capabilities of CNNs in automating ILD diagnosis from thoracic imaging.

Multi-Class Prediction Models

In recent years, deep learning models have increasingly been adapted to handle multi-class classification tasks in pulmonary imaging, reflecting the clinical reality where multiple disease patterns may co-exist or require simultaneous differentiation. Unlike binary classification, which focuses on distinguishing between two categories (e.g., healthy vs. diseased), multi-class models aim to classify images into three or more categories. Many modern models use the ChestX-ray14 dataset as a training or validation database for multi-label classification and lesion localization tasks (Figure 2) [48].

An example is CheXNet [99], a 121-layer DenseNet-based network that was trained directly on ChestX-ray14 and achieved performance comparable to that of radiologists in detecting pneumonia. Other approaches also use this dataset, such as one based on dense localization-aware networks (DNetLoc) [151], which takes into account both high-resolution image data and spatial information to classify abnormalities, or the Zero-Shot Learning approach [152]. In addition, several studies have adopted the CheXpert dataset - CheXbert [153] using a pretrained BERT model, or CheXzero [154], a zero-shot method using a fully self-supervised-learning procedure that was also checked with the MIMIC-CXR dataset. Many models use a combination of multiple datasets or are tested on more than one dataset [155, 156], also using Large Language Models (LLMs) [157, 158].



Source: https://nihcc.app.box.com/v/ChestXray-NIHCC
Figure 2. ChestX-ray14 dataset’s classes [48].

Future Directions and Challenges in AI for Pulmonary Imaging

Although pulmonary imaging has greatly benefited from deep learning, a number of issues still need to be resolved to improve model performance, generalizability, and clinical integration. The reliance on sizable, annotated datasets is a significant drawback. Labeling medical images takes a lot of time and effort and calls for skilled radiologists. Reproducibility and external validation are limited by the fact that many of the models in use today rely on private institutional data. Model robustness and wider collaboration would be made possible by de-identifying patient data to establish public repositories. Moreover, incorporating cloud computing solutions can aid in the management of massive image data, facilitating more rapid model training and more affordable experimentation with multiple GPUs.

Beyond data availability, future studies should explore a wider variety of input features beyond those extracted automatically by CNNs. Ensemble learning itself is also a promising direction - combining different deep learning architectures or feature types can improve performance and mitigate individual model weaknesses. However, this must be balanced with the need for interpretability. Deep learning models often function as "black boxes", a significant barrier to clinical trust and regulatory acceptance. Thus, improving model transparency and explainability is essential for widespread deployment in healthcare.

Future research should also look into how susceptible neural networks are to adversarial examples and how limited their ability is to generalize to inputs that are visually similar but slightly different. For safe clinical deployment, research into robust learning methods and adversarial training will be essential. Lastly, while supervised learning is the foundation of the majority of existing models, alternative paradigms like unsupervised or self-supervised learning provide scalable solutions, especially in medical imaging environments that are label-scarce but data-rich.

Conclusion

Artificial intelligence, particularly deep learning, is rapidly transforming pulmonary imaging by enabling faster, more accurate, and more scalable disease detection and classification. This review has presented a comprehensive overview of the current techniques applied across a wide spectrum of pulmonary conditions, including pneumonia, tuberculosis, pulmonary nodules, interstitial lung diseases, pulmonary embolism, and COVID-19. CNNs, along with their variants and ensemble strategies, dominate the landscape due to their ability to learn complex imaging features and support multi-label and multi-class classification tasks.

To better organize the key contributions in this rapidly evolving field, a conceptual taxonomy of AI-based pulmonary imaging studies can be established, categorizing methods by disease type, learning paradigm (supervised, unsupervised, or hybrid), data modality (X-ray, CT, ultrasound), and integration level (standalone imaging models versus multimodal AI systems incorporating clinical metadata or report generation tools such as GPT-based models). Analysis of these trends reveals an increasing reliance on transfer learning, multimodal data fusion, and model interpretability tools, reflecting the field's maturing focus on clinical applicability and transparency.

Despite significant progress, four persistent challenges were identified: limited access to annotated datasets, large image sizes that require significant computational resources, data imbalance, and high error correlation in ensemble models. Correspondingly, future directions include open data sharing with appropriate patient de-identification, cloud-based training solutions, development of new handcrafted and learned features, and robust ensemble techniques with error decorrelation strategies.

Moreover, the importance of explainability and model transparency has grown, as clinical integration increasingly demands not only high accuracy but also interpretability and regulatory compliance. Bridging the gap between experimental success and real-world deployment will require closer collaboration between AI researchers, radiologists, data engineers, and healthcare institutions.

In conclusion, AI has demonstrated strong potential to enhance diagnostic accuracy, reduce interpretation time, and support clinical decision-making in pulmonary care. However, realizing its full impact requires addressing current limitations, adopting interdisciplinary strategies, and focusing on clinically relevant, explainable, and scalable AI solutions. This review aims to support researchers and clinicians in navigating the evolving landscape and guiding future innovations in AI-powered pulmonary imaging.

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Author's contribution

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