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A Comprehensive Review: Advances in Deep Learning for Lung Disease Diagnosis Using Medical Imaging

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***Abstract*—Lung diseases with pneumonia, tuberculosis, chronic obstructive pulmonary disease, and lung cancer keep on major global health concerns, contributing to millions of deaths annually. Appropriate and precise diagnosis, primarily through medical imaging techniques such as chest X-rays and computed tomography, acting an essential role in effective treatment. Though, the shortage of expert radiologists and human limitations in interpretation complex images often lead to diagnostic delays and errors. The advancement in deep learning has extensively improved the capability of automated lung disease detection, leveraging architectures such as convolutional neural networks, vision transformers, and hybrid models. This broad review presents the evolution and impact of DL in lung disease diagnosis using medical imaging and analyzes performance across various architectures, explore benchmark datasets, and identifies persistent challenges such as data imbalance, model interpretability, and deployment barriers. The study underlines solutions including generative adversarial networks, explainable AI (XAI), and federated learning to deal with real-world boundaries. In addition, ethical considerations, case studies, and future directions are discussed to facilitate the development of transparent, fair, and reliable AI tools for global clinical use.**

Keywords—Deep learning, Lung disease, Medical imaging, CNN, Vision Transformer, Federated learning, Explainable AI, GAN

I. Introduction

A. Global Impact of Lung Diseases

Lung diseases are a major global health concern, accounting for millions of deaths annually. Among the most fatal respiratory conditions are lung cancer, tuberculosis (TB), chronic obstructive pulmonary disease (COPD), and pneumonia [1]. These illnesses not only pose serious health risks to individuals but also impose substantial economic and operational burdens on healthcare systems due to prolonged hospital stays, frequent clinical visits, and high treatment costs [2]. The prevalence of these diseases is amplified by various risk factors, with tobacco use, environmental pollution, occupational exposure to hazardous substances, and the spread of airborne pathogens such as Mycobacterium tuberculosis and the SARS-CoV-2 virus, responsible for COVID-19 [3]. Notably, chronic respiratory diseases are the third leading cause of death globally, with air pollution contributing to approximately 1.3 million deaths [4]. The burden is especially high in low- and middle-income countries, where underdeveloped healthcare infrastructure, limited access to diagnostic tools, and shortages of trained healthcare personnel hinder early detection and effective treatment [5]. Addressing this global health issue requires a broad approach, with public health awareness, early screening using advanced imaging systems, vaccination programs, environmental regulations, and important investment in healthcare systems [6], particularly in resource-limited settings [7].

B. Limitations of Conventional Diagnosis

Traditionally, diagnosis relies on expert interpretation of imaging modalities, supported by patient history and clinical examinations. Radiographs (X-rays) and CT scans are widely used [8], but their effectiveness depends on the experience and attention of the interpreting radiologist. Human factors such as fatigue, subjectivity, and inter-observer variability can result in diagnostic errors, especially in high-volume clinical settings. Moreover, many rural or underserved regions lack trained radiologists, making timely diagnosis nearly impossible.

C. Deep Learning in Medical Imaging

Deep learning, mainly with CNNs and transformer-based models, has allowed automated feature extraction, disease classification, and segmentation with extraordinary accuracy [9]. CNNs efficiently capture local spatial features, though transformers, through self-attention, model global relationships in images [10]. These models are Capable of analyzing thousands of images in minutes and Reduces subjective bias in interpretation.

II. Literature Review

This paper aims to provide an in-depth review of DL methods applied to lung disease diagnosis through medical imaging. Current improvements in deep learning have meaningfully enhanced the proficiencies of computer-aided diagnosis (CAD) systems for lung disease detection, particularly over medical imaging modalities such as CT scans and X-rays. Zhou et al. [11] applied deep learning methods to a smart IoT-based surveillance design, reaching an accuracy of 96.5% for multitarget detection using TensorFlow and PyTorch. Likewise, X. Zhou et.al [12] established a CNN-RNN hybrid model that supports pre-diagnosis verdicts in online medical consultations, achieving 94.8% accuracy. For early diagnosis of lung nodules, Pradhan [13] combined multiple classifiers, SVM, KNN, and Decision Tree into a hybrid framework, reaching 92% accuracy. Jain et al. [14] proposed a two-stage CNN model that achieved a detection accuracy of 97.3%. Traditional models also laid a strong foundation. Jaffar et al. [15] combined Genetic Algorithms for feature selection with SVM classification. Namin et al. [16] used 3D CT imaging for segmentation and classification, reporting accuracies of 89% and 85%, respectively. Modern deep neural networks have been particularly effective in segmentation tasks. Chen et al. [17] suggested a DNN for COVID-19 CT lung lesion segmentation, achieving a Dice score of 95%. Zhang et al. [18] optimized CNN hyperparameters using evolutionary algorithms, resulting in 93.4% accuracy. Innovations in U-Net architectures have further advanced segmentation. AWEU-Net by Banu et al. [19] incorporated attention mechanisms, achieving a 96.2% Dice score. Dutta [20] introduced DENSE R2UNET, reaching 95.6% Dice via dense residual and recurrent layers. More recently, Asha and Bhavani Shankar [21] adopted the Segment Anything Model (SAM) along with pretrained CNNs, achieving 94.28% accuracy for lung nodule detection and classification. Karla et al. [22] developed Infoline, a lightweight CNN, which achieved 96.2% accuracy with high specificity and sensitivity. The emergence of foundation models was highlighted by Kavitha et al. [23], who trained a model on large-scale CT datasets and reported an AUROC of 98.3%. Meanwhile, Md Asiful Islam et al. [24] benchmarked VGG, ResNet, and DenseNet, obtaining 92.5% classification accuracy. In a different direction, Syed Moshfeq [25] trained a custom CNN on spirometry-labeled data to diagnose COPD, achieving 90.3% accuracy. K.A. et al. [9] integrated CNN and LSTM networks in a hybrid framework, achieving 93.7% accuracy on CXR images. Bhosale et al. [1] proposed an RNN-based classification and prediction model, resulting in 91.5% accuracy. The reviewed works emphasize the trend of moving from traditional ML to hybrid and deep architectures. Models leveraging segmentation, attention, and historical learning show superior performance, indicating promising directions for future lung disease detection systems.

III. Imaging Modalities And Deep Learning Foundations

A. Imaging Modalities and Datasets

Chest X-rays (CXR): Cost-effective and widely used for initial screening. Mainly useful for detecting pneumonia, TB, and lung masses. Boundaries include low sensitivity in early disease stages. Computed Tomography (CT): Offers high-resolution, cross-sectional images. Essential for detecting pulmonary nodules, fibrosis, and COVID-19-related abnormalities [26]. Allows 3D reconstruction and volumetric analysis [27]. Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET): Used for functional and metabolic assessments, for example tumor metabolism in lung cancer, but less handy due to high costs and complexity [28].

Table 1: Summary of Public Lung Disease Datasets

Dataset	Modality	Images	Labels	Source
ChestX-ray14	X-ray	112,120	14 diseases	NIH
COVIDx	X-ray	16,352	COVID-19, Pneumonia	Open Access
LIDC-IDRI	CT	1,018	Lung nodules	TCIA
LUNA16	CT	888	Nodule detection	LIDC subset
MosMedData	CT	1,110	COVID severity	Open Access
CheXpert	X-ray	224,316	14 thoracic conditions	Stanford
PadChest	X-ray	160,000	193 findings	Spain (Open)
RSNA Pneumonia	X-ray	30,000+	Pneumonia (bbox)	Kaggle
COVID-CT	CT	746	COVID vs Non-COVID	Open Access
BIMCV-COVID19+	X-ray/CT	500,000+	COVID-19 confirmed	Spain (BIMCV)

B. Deep Learning Fundamentals

1) Convolutional Neural Networks:

Convolutional Neural Networks (CNNs) have become initial in medical image analysis due to their proficiency in inevitably extracting hierarchical features from raw pixel data. In lung disease diagnosis, CNNs are broadly used for responsibilities such as disease classification, nodule detection, and anatomical segmentation [29]. Their architecture comprises multiple convolutional layers that capture local spatial patterns, shadowed by pooling layers to diminish dimensionality, and fully connected layers for decision-making [30]. By leveraging shared weights and local receptive fields, CNNs achieve high computational efficiency and robustness to spatial variations. Their capability to detect subtle abnormalities in lung CT and X-ray scans makes them indispensable for early and accurate diagnosis in clinical workflows [31].

2) Vision Transformers (ViTs):

Vision Transformers signify a model shift in image analysis by treating images as sequences of fixed-size patches, alike to tokens in natural language processing. Unlike CNNs that focus on local receptive fields, ViTs use self-attention mechanisms to model worldwide relationships across the whole image. This competence allows them to capture long-range dependencies and holistic context, which is particularly advantageous in complex analytic tasks relating high-resolution lung images. The ViT design comprises patch embedding, positional encoding, and stacked transformer blocks, enabling effective feature representation without relying on convolution. Current studies have demonstrated the superior performance of ViTs in fine-grained classification and multi-label disease detection, especially when trained on large-scale annotated datasets [32].

3) Autoencoders:

Autoencoders are unsupervised neural networks designed to absorb packed together illustration of input data through a bottleneck architecture. Including an encoder and a decoder, these models aim to reconstruct input images from latent features though diminishing reconstruction error. In medical imaging, autoencoders have shown potential in detecting irregularities by learning the distribution of healthy lung scans and identifying abnormalities indicative of disease [33]. It is also employed for unsupervised feature extraction, serving as a pre-processing step for downstream classification tasks. Moreover, variants like denoising autoencoders contribute to image enhancement by removing noise and artifacts from low-quality scans, thereby improving diagnostic clarity and aiding in more accurate interpretation by clinicians [34].

4) Generative Adversarial Networks (GANs):

Generative Adversarial Networks have developed as powerful tools for creating high-fidelity synthetic images, addressing key challenges in medical imaging such for example data scarcity and class imbalance. A GAN contains of two competing neural networks a generator that synthesizes new data samples, and a discriminator that evaluates their authenticity [35]. In the area of lung disease diagnosis, GANs are expansively used for data augmentation, making diverse and accurate lung images that enhance the generalizability of classification models. Additionally, GANs facilitate super-resolution imaging, translating lower solution scans into high-quality counterparts. They also add to modality translation and segmentation refinement, making them highly versatile in improving both model performance and diagnostic outcomes [36]. As shown in Figure 1, hybrid models outperform individual CNN and ViT models, achieving higher sensitivity and overall accuracy.

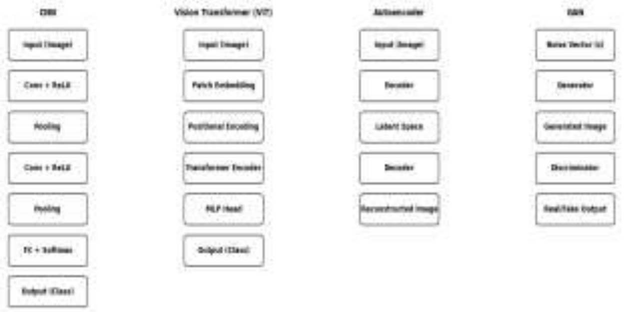

Fig. 1. Overview of DL model, CNN, ViT, Auto-encoders, and GAN,

C. Performance Comparison of DL Models

In this section, to evaluate the routine of numerous deep learning architectures for lung disease recognition using widely accessible datasets. The comparison includes CNN, ViT, ResNet, DenseNet, and hybrid models in terms of Accuracy, Sensitivity, and Specificity. As shown in Figure 2, hybrid models outperform individual CNN and ViT models, achieving higher sensitivity and overall accuracy.

IV. Deep Learning in Supervised Lung Disease Diagnosis

Supervised learning has determined significant progress in lung disease classification by training models on labeled datasets. The models acquire to associate imaging features with disease conclusions, using several architectures optimized for medical image analysis.

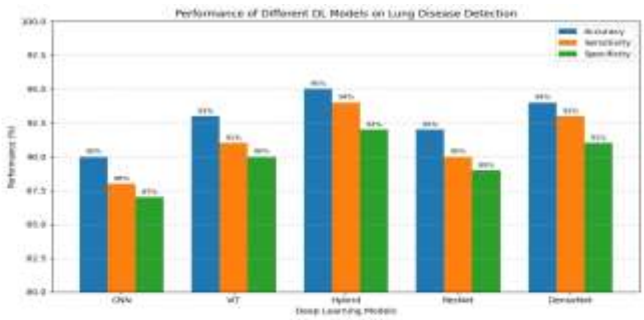

Fig. 2. Performance of Different DL Models on Lung Disease Detection

A. Hybrid and Ensemble Models

Hybrid architectures that integrate CNNs and ViTs purpose to exploit both local feature extraction and global context modeling. For instance, CNN-centered encoders can mine spatial patterns, whereas transformer decoders improve context-aware feature improvement. Similarly, CNN-SVM hybrids use CNNs for feature extraction and SVMs for classification, offering benefits in generalization and performance, mainly in binary classification problems [37]. Ensemble methods combined multiple base learners CNNs, ViTs, or hybrids to moderate overfitting and improve accuracy. These methods have been applied to distinguish between lung cancer subtypes (e.g., adenocarcinoma vs. squamous cell carcinoma) and recognize COVID-19-related anomalies from CT and X-ray images [3].

B. Performance Metrics

Model performance is evaluating by accuracy, precision, recall, F1-score, AUC-ROC, and confusion matrices. For segmentation tasks, Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) are common. The Benchmark datasets are ChestX-ray14, CheXpert [38], and COVIDx (for classification), LIDC-IDRI and NSCLC-Radio genomics (for nodule detection and cancer subtype analysis) [25]. These datasets offer a standardized root for comparison [39], while heterogeneity in annotations and disease prevalence remains a challenge.

V. Unsupervised and Semi-Supervised Learning Approaches

Although supervised learning has seen extraordinary achievement in medical imaging, it greatly relies on large, annotated datasets an expensive and time-intensive requirement in the healthcare domain [40]. Unsupervised and semi-supervised learning provide substitutions by leveraging unlabeled data, enabling broader scalability and adaptability in clinical applications.

A. Unsupervised Learning

Unsupervised learning algorithms learn data patterns without clear labels. In lung imaging, this methodology is used for tasks like clustering, anomaly detection, and feature extraction[41].

Clustering Algorithms: Methods like k-means and DBSCAN support in determining latent disease patterns, often used to stratify lung cancer patients or classify imaging phenotypes in COPD.

B. Semi-Supervised Learning

Semi-supervised learning pools a minor amount of labeled data with a large collection of unlabeled data. This pattern is especially convenient for rare lung diseases somewhere labeled examples are rare.

C. Pseudo-Labeling

This comprises producing artificial labels for unlabeled images using a model trained on labeled data. These pseudos labeled instances are then used to retrain the model, iteratively refining performance.

D. Applications and Benefits

Unsupervised and semi-supervised learning approaches are supportive when only a small quantity of labeled data is available. These methods can find hidden patterns and disease subtypes without needing manual labels [42]. They are principally useful for early identification and finding unusual areas in lung scans. Although challenges like label noise and model instability exist, these approaches show great prospective for refining lung disease detection in diverse clinical environments.

VI. Proposed Framework

As illustrated in Figure 3, the suggested framework initiates with lung image input, which is first process from beginning to end a 3D U-Net for segmentation. then, YOLO-v5 is working to detect possible lung nodules, followed by the classification stage by means of either a Vision Transformer (ViT) or a hybrid CNN-SVM model. This structured pipeline is considered to simplify the diagnostic workflow ranging from image preprocessing to final disease classification, while enhancing accuracy and flexibility across different lung conditions.

Fig. 3. End-to-End DL Framework for Lung Disease Diagnosis

VII. Challenges In Deep Learning For Lung

A. Imaging

Despite the advancements, several challenges persist in applying DL to lung imaging:

- **Data scarcity and imbalance:** High-quality annotated datasets are limited.
- **Interpretability:** Deep learning models are frequently considered black boxes, building clinical adoption difficult.
- **Deployment:** Large models require high computational resources, hindering deployment in low-resource settings.

VIII. Solutions And Future Directions

Here are several strategies have been proposed to address these challenges:

- **GANs:** Generative Adversarial Networks can generate synthetic medical images to augment datasets and address class imbalance.
- **Explainable AI (XAI):** Techniques like Grad-CAM, LIME, and SHAP provide visual explanation for model decision, attractive trust.
- **Federated Learning:** Enables collaborative model training across institutions without sharing patient data, preserving privacy.
- **Lightweight Models:** Models like Mobile Net and pruning strategies enable deployment on edge devices.

IX. Conclusion

Deep learning has transformed lung disease analysis using medical imaging by offering precise, scalable, and interpretable solutions. From CNNs and ViTs to hybrid and ensemble models, these technologies have outdone traditional diagnostic methods in frequent tasks. However, challenges continue mainly about labeled data insufficiency, class imbalance, and model transparency. Innovative techniques similar GAN-based data augmentation, explainable AI frameworks, and federated learning offer feasible solutions. Future research should focus on creating diverse, high-quality datasets; integrating multi-modal clinical data; refining real-time model organization; and ensuring ethical AI development through transparency, fairness, and clinical validation. With sustained interdisciplinary collaboration, deep learning models embrace great potential in democratizing access to expert-level diagnostics and dropping the global burden of lung disease

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