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Review

A Review of Early Detection of Lung Diseases based on Deep Learning Models

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Abstract

Earlier diagnosis of pulmonary disease is greatly significant in enhancing treatment impacts and lowering systems' medical workload. As increasingly more cases of pulmonary disease accumulate, methods of deep learning (DL) have increasingly become a viable option towards assisting physicians with diagnoses, particularly through the interpretation of chest X-ray (CXR) images. This paper presents the latest DL-based models and methods for early detection of lung diseases and evaluates their performance and accuracy of disease classification. It also demonstrates the power of ensemble learning methods, a combination of ResNet, EfficientNet, and Inception models, for enhancing the accuracy and reliability of diagnosis systems, especially in handling complicated patterns of diseases. The study seeks to introduce newer directions for research and explore the direction towards intelligent and scalable diagnosis solutions that can potentially make a critical contribution towards enhanced early detection and improving the quality of patient care.

Keywords: Lung Diseases; Pneumonia; CNN, Deep Learning; X-ray; Ensemble Learning.

1. Introduction

Pulmonary conditions such as pneumonia, chronic obstructive pulmonary disease (COPD), tuberculosis, lung cancer, etc., are found more frequently nowadays. These conditions are becoming increasingly harmful, making it more challenging to maintain a high quality of life for patients. Traditional diagnostic techniques primarily rely on X-ray imaging to detect structural damage in the lungs. However, these methods depend heavily on expert interpretation, which is subjective and difficult to standardize or disseminate.[1]. Recently, recent advances in DL models have revolutionized the medical imaging area by means of computerized, highly precise diagnostic techniques. In fact, using various architecture models in ensemble learning techniques is an effective method to improve the detection accuracy of X-ray based detection systems, making it possible to detect in advance a variety of lung diseases[2].Combining diverse DL architectures within a single model framework is one of the effective ways to capitalize on the power of DL towards lung disease detection. Researchers, for example, in UNet-Based Lung Segmentation and Ensemble Learning with CNN-Based Deep Features for Automatic COVID-19 Detection and Diagnosis of Lung Diseases Using Deep Learning Architecture from X-Ray Images," are leveraging ensemble models in an effective manner [3]. These ensemble models take the strengths of different CNN-based architectures and thus obtain complementary features from every model to improve performance. Apart from these, the techniques emphasize the superiority of ensemble learning for lung segmentation in complex and varying datasets, especially due

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to COVID-19 datasets[4].With this latter ensemble approach trend in methodologies, the research here develops an improvement on certain of the present DL models and, by doing that, provides a strong foundation for premature lung disease detection with the application of X-ray image diagnostics. Following inspiration from methodologies that incorporate stacked ensemble learning on deep multi-model CNN models to diagnose children's pneumonia, hence, this would offer more accurate and reliable methods of diagnosis and classification of lung diseases, thus enabling the augmentation of early diagnostic interventions. This study is expected to add to the continued advancement of increasingly emerging diagnostic approaches through DL, thus offering scalable, accurate diagnostic options that are easily accessible for the detection of lung diseases[5].

The aim of this article review studies using DL models to detect and classify lung disease, analyzing techniques, methodologies, and performance metrics. It discusses challenges, opportunities, and potential areas for further study in early detection of lung diseases.

The rest of this article is structured as follows: section 2 gives an overview of the background and theory, including DL models and Ensemble Learning. Also, challenges facing the process of early detection against lung diseases are presented in section 3. Section 4 provides an overview of related works conducted about previous studies. Findings from the literature are discussed in-depth in Section 5. Section 6 presents all the assessments and recommendations for lung disease detection. In addition to the future directions. Finally, Section 7 concludes the paper and summarizes the main ideas derived from the models used to detect and classify lung diseases.

2. Methodology

This is done in following well-established review procedures for ensuring greater transparency. A search is conducted in the following databases: PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar using Boolean-operated search strings like (“Deep Learning” OR “CNN”) AND (“Lung Disease” OR “Pneumonia”) AND (“Early Detection”).

The selection of the studies for the review included certain criteria, which included peer-reviewed English-language publications from January 2019 to December 2024, specifically targeting deep learning for the identification of lung disease. These criteria excluded editorials, as well as publications that only presented traditional machine learning concepts. The data that was retrieved was focused on the publication characteristics, deep learning model specifics, as well as the specified performance metrics, which have included figures such as accuracy, sensitivity, and specificity. This analysis qualitatively assists in an efficient synthesis of the existing literature, revealing insights regarding the role played by AI-based techniques in the diagnosis of pulmonary diseases.

3. Background Theory

The lung Diseases, including lung cancer, COPD, pneumonia, and tuberculosis, remain a serious public health issue worldwide. Early diagnosis is key to enhance outcomes for patients and to lower costs related to care [6]. Conventional methods of diagnosis include X-rays and CT scans, and MRIs, which often require the expertise of skilled radiologists, thus presenting delays and possible errors. Deep learning, a branch of a wide variety of methods termed artificial intelligence, has increasingly proved a formidable tool in the automation of medical image analysis. CNN and other sophisticated architectures such as ResNet, Inception, and EfficientNet have identified disease-related patterns in chest radiographs with a good record of performance. Ensemble models, which incorporated diffrent DL architectures, further enhanced detection accuracy by capturing an expanded range of features [7].

3.1 Deep Learning (DL)

Deep learning, a branch of artificial intelligence, has fundamentally transformed medical imaging by way of extracting complex features from big-picture datasets. CNNs, which are prevalent in deep learning architectures, express spatial hierarchies in images to discriminate between healthy and diseased tissue in chest radiographs [8],[9]. EfficientNet Inception,ResNet, and are a little sophisticated models that have broadened DL, enabling the net to learn different patterns in diverse lung diseases. Ensemble models, which combine the results of architectures of multiple deep learning, are meant to improve diagnostic accuracy, boost robustness, and reduce errors. Accurate classification of lung diseases like lung cancer, pneumonia, COPD, and TB, and quick detection by doctors, have improved patient outcomes. Deep learning has become a significant contributor to fighting respiratory diseases through constantly evolving models [10].

3.1.1 Convolutional Neural Networks (CNNs)

Medical image processing for early lung disease detection including lung cancer, pneumonia, and COPD depends critically on convolutional neural networks (CNNs). They extract hierarchical aspects from challenging data, therefore offering improved classification accuracy and powerful feature representation. Lung disease detection seems promising for advanced CNN designs like ResNet, Inception, and EfficientNet. By means of data augmentation and transfer learning, they may control tiny medical datasets and foster generalization. Combining CNNs with hybrid architectures and ensemble learning will help to increase early lung disease detection and diagnostic accuracy [11],[12].

3.1.1.1 ResNet

Using residual connections, ResNet a DL model created by Kaiming He and associates in 2015 solves the vanishing gradient challenge in extremely deep networks. This lets the network avoid several layers, hence allowing the building of rather deep networks like ResNet-50 and ResNet-101 free from performance loss. The model ResNet's design is very successful for challenging image processing problems like lung disease detection in chest X-rays. Its deep feature extraction powers help it to detect hierarchical patterns in photos, hence improving diagnosis accuracy. Data augmentation is crucial since ResNet's deep networks may overfit on limited samples and might be computationally taxing. ResNet's design is computationally intensive and may overfit on small datasets, hence data augmentation is crucial even if its high accuracy [13].

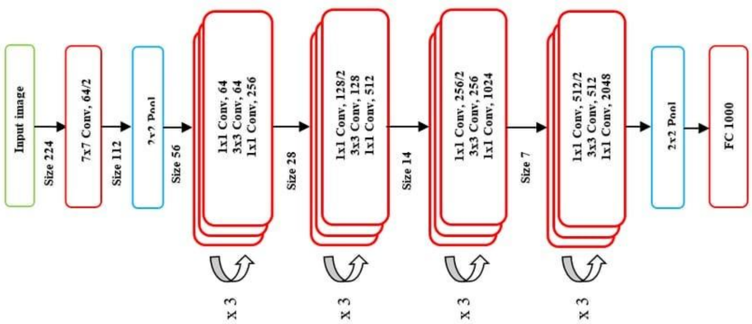

Figure 1. ResNet Model [13].

3.1.1.2 Inception (GoogLeNet)

Inception or GoogLeNet, in short, is one deep learning model proposed by Google for increasing the processing accuracy of photo classification systems along with efficiency. The module-based design enables it to convolve features with several filter sizes to gather information from a broad spectrum at different levels. This works well with complex applications, such as early lung disease detection, since different patterns can relate to different diseases like pneumonia, TB, and lung cancer. This design features 1×1 convolutions that reduce dimensionality, hence preserving efficiency by not piling up the processing burden. All this makes it scalable and available for use in medical imaging, for example. Chest X-rays can reveal complicated signs of lung diseases. Another advanced model, ELREI, combines Inception with ResNet and EfficientNet [14] to improve performance in classifying lung diseases.

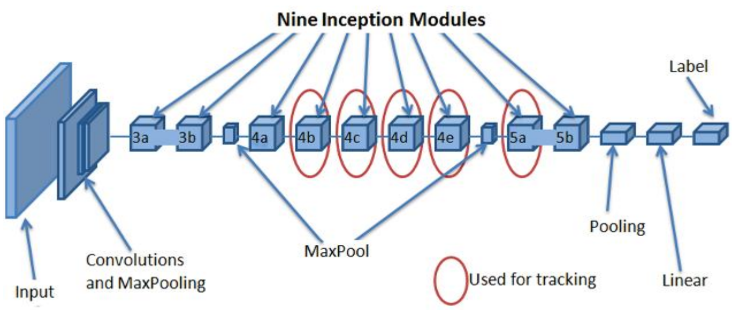

Figure 2. Inception (GoogLeNet) Model [14].

3.1.1.3 VGGNet

VGGNet, being a deep convolutional neural network, is popular for image classification, medical imaging, and lung disease diagnosis [15]. VGGNet uses very small 3x3 filters in convolutional layers to draw out high-level information that aids in the detection of faint patterns in chest X-rays such as indications of lung disease like malignancy, TB, and pneumonia. VGG-16 and VGG-19 models are composed of 16 and 19 layers, respectively, allowing them to differentiate between various lung diseases. VGGNet is appropriate for special medical data sets and will likely have cross-talks with transfer learning and fine-tuning methods. Its effective feature extraction capability makes it a useful tool for early and efficient diagnosis of lung disease from medical images due to its characteristic, stratified structure and large feature representation capability [16].

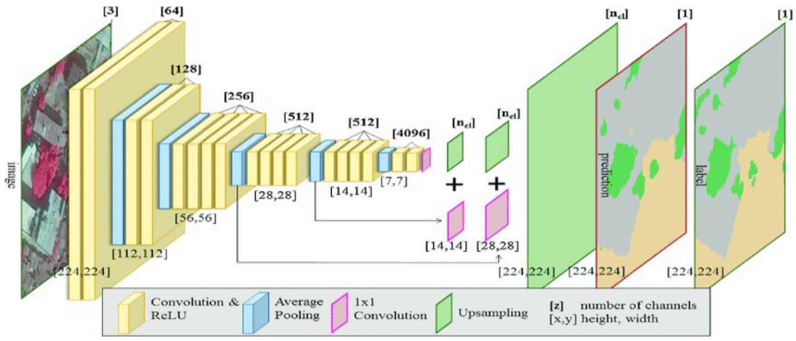

Figure 3. VGGNet Model [15].

3.1.1.4 MobileNet

Google developed a deep learning model called MobileNet, which intended to have high accuracy with reduced pro-cessing needs. As a result, it is suitable for mobile or embedded device applications such as medical image processing. This architecture based on depthwise separable convolutions decomposes the traditional convolution into two parts: first point-wise (1x1) convolution, which integrates the outputs, and then depthwise convolution, which applies a different filter to every input channel. Since this reduces the computing cost and model parameters without sacrificing performance, MobileNet is able to capture minute invariants from medical images while maintaining its lightweight nature. It facilitates identifying lung disorders in a resource-constrained setting, like general or rural areas with either mobile health service or scarce processing resources in clinics. Generally, MobileNet is adopted with transfer learning and fine-tuning on specialized medical data. It can be part of hybrid models and ensembles with complex models to enable earlier detection of lung diseases [17].

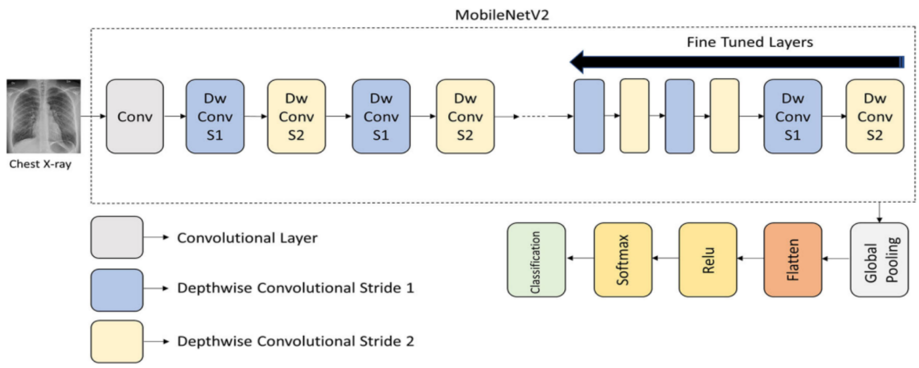

Figure 4. MobileNet Model [17].

3.1.2 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are deep learning models that are useful for early identification of pulmonary diseases. They can retain information from previous steps in the data sequence, enabling them to learn temporal dependencies essential for medical diagnostics. This is crucial for identifying lung diseases where progression can be monitored over time. RNNs can evaluate alterations and patterns within sequences of medical images or patient data.

Integrating RNNs with CNNs in lung disease detection improves the model's ability to capture spatial features and temporal features that may indicate disease progression [18]. This method may enhance the precision of early detection for diseases like pneumonia, tuberculosis, lung cancer and COPD, where timely intervention significantly influences treatment results. Thus, combine RNNs into a DL framework is a promising approach to improving early detection capabilities for lung disease diagnosis [19].

3.1.2.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory networks are an improved variant of RNN, showing their particular utility in applications with time-ordered information, including voice recognition, text processing, and medical time-series data. The goal is to capture long-term relationships in sequential data. Since LSTMs can consider imaging data over time, or respiratory signals, or patient health records, they make use of small patterns that point toward the onset of a disease. This allows the detection of lung problems much earlier than would otherwise be possible. Unlike other RNNs, LSTMs avoid the issues of vanishing and bursting gradients. They can maintain information for really long periods using memory cells and methods of gating that precisely regulate information flow. Application of LSTM in an advanced deep learning model for the detection of lung diseases can expose relevant trends in complicated temporal data, hence allowing early and accurate diagnosis [20].

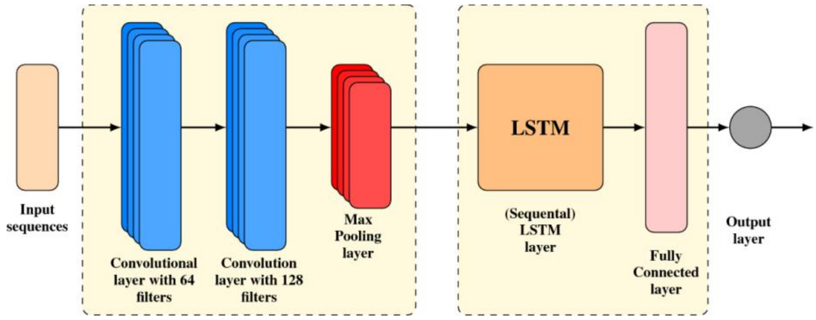

Figure 5. LSTM Model [20].

3.2 Ensemble Learning

In machine learning, ensemble learning is a powerful method that combines the predictions of several models to enhance robustness and overall performance [21]. Combining numerous algorithms in ensemble learning helps to reduce overfitting risk and improve generalization capacity of the model across several datasets. Therefore, combining the ideas taken from models that were trained to detect various disease patterns or traits may be particularly useful for early identification of lung diseases. Combining ResNet, EfficientNet, and Inception-v3, each model is allowed to play to its strengths: capturing complex hierarchical features for ResNet, economy of parameters for EfficientNet, and multi-scale processing capabilities for Inception. This cooperation, through the use of numerous techniques for identifying minute image traits, improves accuracy in detecting diseases such as lung cancer, pneumonia, COPD, and tuberculosis. Since the prediction dependability assures early and accurate diagnosis of lung disease, generally ensemble learning elevates the diagnostic models further [22].

3.2.1 Stacking

In ensemble learning, stacking is one of the techniques where simple learners make predictions that a meta-learner uses in making the final prediction. Early detection of lung diseases is based on this method since the diagnosing accuracy for deep learning models, such as CNNs, ResNet, and MobileNet, is boosted. The stacking involves combining predictions in order to generate a more complete model; hence, the reliability of these early detection systems increases, likely offering a more accurate diagnosis in the clinical setting [23]. This tiered approach is especially helpful in medical imaging.

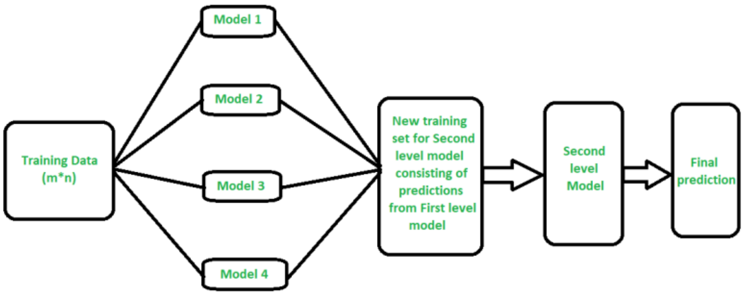

Figure 6. Stacking Technique [23].

3.2.2 Boosting

Boosting is a form of ensemble learning through which a set of weak learners is iteratively trained to correct mistakes made by each other at every subsequent step, hence further improving the model's performance. One strong, accurate model result from this iterative process that accumulates advantages of all students, hence decreasing variance and bias. Boosting highlights critical occurrences such as TB, pneumonia, and lung cancer, hence improving deep learning models used for chest X-ray classification in the early detection of lung conditions. This type of focused augmentation helps the diagnostic tool in terms of accuracy and reliability by facilitating the model in capturing the minor features and complicated patterns present in the medical images [24].

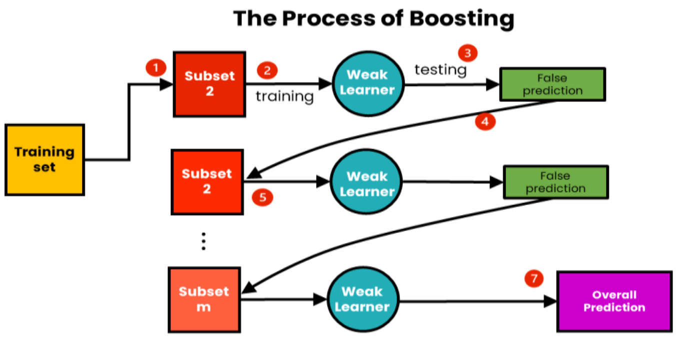

Figure 7. Boosting Technique [24].

3.2.3 Bagging (Boot Strap Aggregation)

The ensemble approach helps in training several models on random portions of the available data. The method is mostly known as bagging, and it improves model correctness and stability by doing bootstrap aggregation. With this approach, original training data for every model iteration is a guarantee, thus lowering overfitting and improving deep learning models in the early detection of lung disease. By averaging numerous model predictions through bagging, we improve the accuracy of spotting small symptoms in illnesses such as lung cancer, tuberculosis, and COPD. Because it mitigates impacts that may be brought by bias from a single model, it serves as a more reliable diagnostic tool [25].

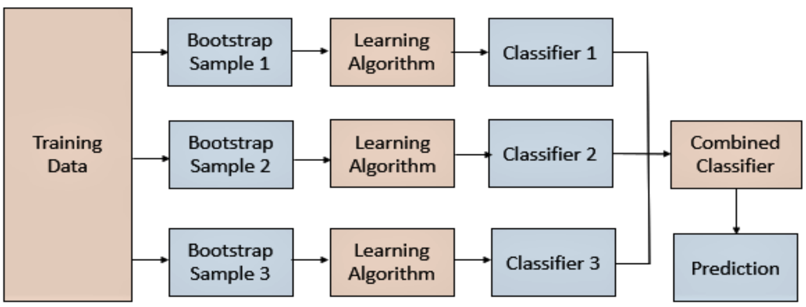

Figure 8. Bagging Technique [25].

4. Challenges of Deep Learning in lung Disease Detection

Data limitations and human variability are the major problems concerning DL for lung disease diagnosis. Insufficient datasets and information from imaging discourage the development of robust models. Since most lung disorders have a slow onset, monitoring the progression of such disorders is quite difficult. Patient characteristics like age and socioeconomic background affect disease presentation and model performance [26].

4.1 Dataset Collection and Complexity

The accurate diagnosis of lung diseases using deep learning is heavily dependent on the existence of large-scale, high-quality, well-annotated medical image datasets. Strict privacy policies, limited patient access, and the expensive price of expert annotations generally discourage the acquisition of such datasets, however. These limitations are part of the reasons why models trained on suboptimal or homogenous data are developed, hence limiting their generalisability to different patient populations and clinical environments. Furthermore, the intrinsic characteristic of medical images defined by fine patterns and integrating details requires high-level structures that are able to detect subtle visual cues, hence requiring large and varied datasets [27].

4.2 Growth and Progression of Disease

Pulmonary conditions often develop gradually and have mild radiographic appearances in the early stages. These beginnings are often not perceivable, even by expert radiologists; therefore, early diagnosis is particularly challenging. Although early intervention significantly improves patient outcomes, most deep learning models are developed to observe static, single-timepoint images and cannot follow the course of a disease over time. This limitation seriously hampers their capability of detecting faint temporal patterns and detracts from performance on early-stage detection and longitudinal monitoring. The challenge requires an approach involving temporal modeling using recurrent neural networks or transformer models able to learn sequential data across several imaging sessions [28].

4.3 Patient's Age and Socioeconomic Status

The generalizability of deep learning models in pulmonary diagnostics is significantly hindered by demographic and socioeconomic variables. In geriatric populations, multi-morbidity (e.g., congestive heart failure alongside pneumonia) and complex clinical profiles create overlapping radiographic shadows that obscure pathological features, leading to higher false-negative rates. Socioeconomic disparities introduce technical "domain shifts"; models trained on high-fidelity images from premier institutions often lose sensitivity when processing lower-resolution, "noisy" images common in resource-limited settings. Furthermore, reliance on homogeneous datasets primarily sourced from Western institutions encodes algorithmic bias, which degrades diagnostic accuracy for underrepresented groups and exacerbates health inequities. Consequently, incorporating demographic and technical diversity during training and multi-center validation is a critical technical necessity, not just a social goal. Achieving clinical fairness and ensuring model reliability across diverse, real-world populations requires a rigorous commitment to representative data to mitigate these systematic biases [29].

5. Literature Review

In the literature, recently, quite a lot of research has been presented in order to advance lung diseases through early detection and their prediction. This section reflects upon various methods applied regarding different types of lung disease detection, approaches toward data collection, challenges faced by researchers, problem domains, and techniques employed for problem-solving, and strategies adopted while developing a robust model on DL.

5.1 Synthesis by Imaging Modality and Task

The literature primarily bifurcates research based on the source of clinical data: Chest X-rays (CXR) and Computed Tomography (CT).

Chest X-ray (CXR) Analysis: CXR remains the most common modality due to its accessibility. Studies such as those by Reddy and Khanaa [34] and Bhattacharya et al. In [35] focus on multi-class classification (e.g., COVID-19, Pneumonia, and healthy states). While Reddy [34] reported a perfect 100% accuracy using the ACL model (CNN-LSTM-Attention), such results often indicate overfitting to specific dataset characteristics rather than clinical generalizability. Similarly, Manoharan et al. [45] achieved over 98% accuracy using an ensemble of ResNet and Inception-v3, though they noted that success remains highly dependent on image quality.

CT and HRCT Analysis: For more complex conditions like Interstitial Lung Disease (ILD) or localized nodules, CT scans are preferred. Li et al. [31] utilized High-Resolution CT (HRCT) with a hybrid U-Net++ for segmentation and MobileUNetV3 for classification. While reaching high precision, the computational cost and lack of dataset variety remain significant barriers to deployment. Pradeep and Rajesh [37] further demonstrated that Recurrent Residual U-Net (R2U-Net) outperforms traditional watershed algorithms for nodule detection in DICOM datasets.

5.2 Model Families: From CNNs to Hybrid Ensembles

Research has shifted from standard sequential models toward hybrid and ensemble architectures to capture both spatial features and long-range dependencies.

CNN and Lightweight Architectures: Standard CNNs continue to provide a baseline, but recent work emphasizes efficiency. Hasan et al. [41] proposed SqueezeNet-based lightweight architectures for real-time implementation, achieving 85.21% accuracy. While lower than some "heavy" models, these architectures offer better feasibility for resource-constrained clinical settings.

Hybrid and Attention Models: To improve feature extraction, researchers have integrated different network types. The CCDC-HNN [33] utilizes a 3D-CNN for feature extraction from CT scans, achieving 99.61% accuracy. Likewise, Abed et al. [52] proposed an F-RNN-LSTM model to handle the temporal and spatial complexities of differentiating COVID-19 from standard pneumonia.

Ensemble Learning: Multiple studies confirm that combining models (Ensemble) reduces the variance of individual learners. Siddiqui et al. While [47] fused EfficientNet variants (B0, B1, B2) to outperform single-model techniques in detecting TB and Pneumonia. Similarly, the PulDi-COVID [44] and ELREI [45] frameworks demonstrate that voting or stacking mechanisms provide more stable diagnostic outcomes than individual DCNNs.

Deep learning (DL) models have been promising to detect lung diseases but with certain limitations. First, they have to be trained with millions of parameters, hence are computationally expensive. Second, they were initially designed for binary classification; hence their performance is constrained when used in multi-class settings. Third, generalizability to diverse datasets is questionable because models work well on provided datasets but not when new or unseen data is presented to them. Fourth, performance on skewed datasets can lead to intrinsic underperformance on rare disease or underclass representation. Fifth, clinical integration and validation are necessary in that the models must be validated in real-world healthcare settings for validity and utility. Sixth, intrinsic model problems unique to an individual disease prevent the creation of generic universal solutions. Lastly, there is a tremendous shortage of standard metrics and benchmarking in the evaluation of model performance, which is critical in consistent benchmarking and comparison of different approaches to lung disease diagnosis. These loopholes must be filled to ensure effectiveness and usability of deep learning models in clinical diagnostics.

Table 1. Review of Lung Disease Detection Using Deep Learning Models.

Reference	Dataset	Model	Image samples	Performance Evaluation	No. of Classes	No. of Parameter	Dataset state
[30] 2024	**COVID-19 Image Data Collection, Actualmed-COVID-chestxray**	**DCNNs**	**16,435 chestxray**	**4 Class 94%, 3 Class 95%, 2 Class 99%, 2 Class 98%**	**Multi classification and Binary classification**	**does not include the specific architecture details**	**Imbalanced Dataset**
[31] 2024	**MedGIFT database**	**ResNet, MobileUNetV3**	**4000 HRCT slices**	**99.1%**	**Multi classification**	**8,045,347**	**Imbalanced Dataset**
[32] 2024	**(TCIA) and (TCGA)**	**ResNet, VGG,**	**MRI, CT scans, PET scan,X-rays**	**92.5 %,**	**binary classification**	**N/A**	**Imbalanced Dataset**
[33] 2023	**LIDC-IDRI database, the LUNA 16 dataset**	**Inception v3**	**1,463 CT scan**	**95%**	**binary classification**	**N/A**	**Imbalanced Dataset**

[34] 2023	Chest X-Ray Images (Pneumonia) ,	CNN models	1061 CX-R samples	96%.	Multi classification	N/A	Imbalanced Dataset
[35] 2023	COVID-19 chest xray Lungs Disease Dataset (4 types)	CNNs Models	502 CXR images	accuracy 98.2%	Multi classification	N/A	Imbalanced Dataset
[36] 2023	Tuberculosis Chest X-rays (Shenzhen), Chest X-Ray Images Pneumonia	ResNet50, ResNet101	(1814) Chest X-rays	98.43% for pneumonia, 99.4% for tuberculosis, and 99.9% for cancer detection	Multi classification	138000,000	Imbalanced Dataset
[37] 2023	(TCIA) repository	VGGNet, ResNet, and Inception	1000 CT scan images	DBN 93.50 SAE 96.25 CNN 94.65	binary classification	N/A	Imbalanced Dataset
[38] 2023	(PLCO, NLST) dataset	Inception v4, ResNet34.	147,497 x-ray images	N/A	binary classification	N/A	Imbalanced Dataset
[39] 2023	Not applicable	CNN models architecture	15,000 CT scans images	95%	binary classification	N/A	Imbalanced Dataset
[40] 2023	LUNA16 Database:	CNN architecture	888 CT scans	97%	binary classification	N/A	Imbalanced Dataset
[41] 2023	(LIDC-IDRI) dataset	ResNet, SqueezeNet, MobileNet	7556 CT scan	85.21%	binary classification	N/A	Imbalanced Dataset
[42] 2023	LUNA 16 Data set	ResNet	doesn't specify the exact number of CT scans	95%	binary classification	N/A	Imbalanced Dataset
[43] 2023	Not applicable	ResNet18, InceptionV3, DenseNet121, DenseNet169,	5856 chest X-ray images	DenseNet169 97.79%. DenseNet2097.7 90% MobileNet 97%, DenseNet 94%	binary classification	(MobileNet 2,665,473) (DenseNet121 4,632,897) (DenseNet169 8,544,833) (DenseNet201 12,741,185)	Imbalanced Dataset
[44] 2023	NIH ChestX-ray8, Chest X-ray Images	VGG16, ResNet50, ResNet152V2, MobileNet	10800 x-ray images images	99.70 %	Multi classification	N/A	Imbalanced Dataset
[45] 2023	COVID-19 Radiography Database	Inception-v3, ResNet, EfficientNet	21165 x-ray images images	99%	Multi classification	N/A	Imbalanced Dataset
[46] 2022	Montgomery County X-ray set, Shenzhen Hospital X-ray set	ResNet-101, ResNet-50, Vgg-19, SqueezeNet	800 X-ray images	98%.	binary classification	N/A	Imbalanced Dataset
[47] 2023	Chest X-ray Images	EfficientNet-B0, EfficientNet-B1 EfficientNet-B2	not explicitly mentioned	98%	Multi classification	N/A	Imbalanced Dataset
[48] 2022	covid-19-image-repository, chest-xray-pneumonia, RSNA	VGG-16, ResNet-50, and InceptionV3	80,000 X-ray images	96.48 %	Multi classification	24,622,470	Imbalanced Dataset

[49] 2022	**Pneumonia Detection Sapporo Medical University Hospital**	**CNNs Models**	**1159 chest radiograph images.**	**95%**	**binary classification**	**N/A**	**Imbalanced Dataset**
[50] 2022	**covid-chestx ray-dataset**	**CNNs Models**	**not mentioned**	**0.970936**	**Binary and Multi classification**	**N/A**	**Imbalanced Dataset**
[51] 2022	**NIH Chest X-rays, (OCT) and Chest X-Ray Images**	**ResNet, Efficientne**	**50,624 X-Ray Images**	**92.60%**	**Multi classification**	**N/A**	**Imbalanced Dataset**
[52] 2021	**(C19RD) (CXIP)**	**ResNet23, Inception_V2**	**C19RD (2905) samples CXIP (5856) samples**	**C19RD (95.04)**	**Multi classification**	**N/A**	**Imbalanced Dataset**

6. Discussion

The studies' comparison in Table 1 shows the higher maturity and performance of deep learning techniques in the classification of pulmonary disease from medical images. PulmoNet [30], MobileUNetV3 [31], and MFDNN [32] models achieved high accuracy (92.5% to 99.1%) for multi-class and binary classification. The experiments demonstrate the potential of DL models in handling complex medical features. Interestingly, the CNN-sequential model [36] registered superlative performance levels at 99.9% cancer detection, supporting the credibility of deep CNN architectures for implementation in real diagnosis use. In spite of the persisting success of the majority of models, the analysis exposes fundamental limitations. Most research is conducted on unbalanced datasets and yet achieves astonishing results e.g., 99% accuracy for ELREI [45], 99.7% for PulDi-COVID [44], which indicates that existing architectures, especially ensemble and hybrid models, can in some way counterbalance unbalanced data distribution. However, there are limited papers that even report model complexity, i.e., CNN-sequential with over 138 million parameters [36] and VGG19+CNN with 24.6 million parameters [48], which makes reproducibility and transparency difficult. Most submissions have "not explicitly stated" in the architecture details, and computational efficiency and scalability comparison becomes impossible. Furthermore, X-ray images are the undisputed gold standard modality, logically so since they are easily obtained and cheap, with CT, MRI, and PET images languishing in their unused potential, although they possess greater resolution or functional imaging capacity. This trend, seen on datasets such as NIH ChestX-ray8 [44] and COVID-19 Radiography Database [45], challenges the overall generalizability of the models to more advanced types of images. Another key trend is the growing usage of ensemble models (e.g., ELREI [45], Deep ensemble CNN [42]) and multi-architecture systems like MobileNet + DenseNet [43], which are more resilient. These findings confirm the theoretical advantages of averaging various feature extractors for improved generalization. Architectural strengths propel the strong performance of models such as EfficientNet, which applies balanced scaling to achieve the refinement needed for pathology, and Ensembles (ELREI), which integrate ResNet’s deep extraction and Inception’s multi-scale analysis.

Although these models have a near-perfect success rate, they still have challenges in being implemented. It should be noted that these models require a lot of computing power, thus warranting the applicability of models such as MobileNets in resource-limited areas. Furthermore, the black-box approach in ensembles acts as a barrier to acceptance in the healthcare setting. Relevant studies should, therefore, focus on improving the applicability of these models. Yet, real-world deployment is discouraged by lack of adequate standardization of reporting and a lack of rigorous investigation of interpretability methods, which are fundamental to medical trust. Further, even though accuracy is a widely used measure, not much research fully reports other performance metrics like sensitivity, specificity, or F1-score, which are critical in evaluating medical diagnostic systems.

6.1 Analysis of Trend, Issues and Future Directions of Lung Disease Detection Using Deep Learning

In this section, the overall review of the work available is given, which is the final contribution explained in this paper. Trend analysis of every attribute explained in the previous section is defined, wherein the intention is to point out the works progress and how the researchers are trending over the past five years. The indicated trend may be helpful to indicate the direction of the literature in this field. Section 5.1.1 presents the trend of the articles considered. The issues and the future work to be undertaken in rectifying the problems found are detailed in Section 5.1.2

6.1.1 Trend Analysis of the Image Type Used

Fig 9, shows the trend of types of medical images (X-ray, CT, MRI) used in deep learning-based studies for detecting lung disease between 2021 and 2024. The X-ray type is the most commonly used type and has a steep spike in 2022 and 2023. CT also increases in the year 2023 but is less used than X-rays in aggregate. MRI was used to a very small extent, and moderate expansion alone happened in the year 2024. The pie chart shows that X-ray contributes 56.4% of examinations, CT scans contribute 38.2%, and MRI and PET are used to a very small extent and contribute only 3.6% and 1.8%, respectively.

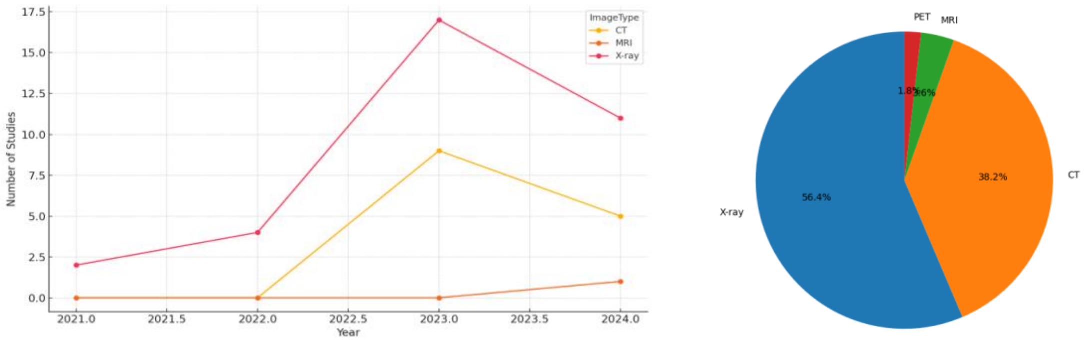

Figure 9. (a) The trend of the usage of image types in lung disease detection works in recent years; and (b) the distribution of the image type used in deep learning aided lung disease detection in recent years.

6.1.2 Compares the performance of the models

Fig. 10 compares plotting deep learning models for diagnosing lung disease, with CNN-Sequential, PulDi-COVID, and ELREI being the highest-scoring classification accuracy among all of them, with accuracy greater or nearly equal to 99%. Such models reflect the potential of ensemble and hybrid-based models towards improved diagnostic performance. Lightweight DNN shows reduced accuracy at the cost of complexity and computational efficiency. Pre-trained models like DenseNet and MobileNet have shown uniform performance across different datasets. This contrast also indicates the strengths and weaknesses of each model and calls for more exploration into ensemble learning algorithms to produce the best diagnostic performance.

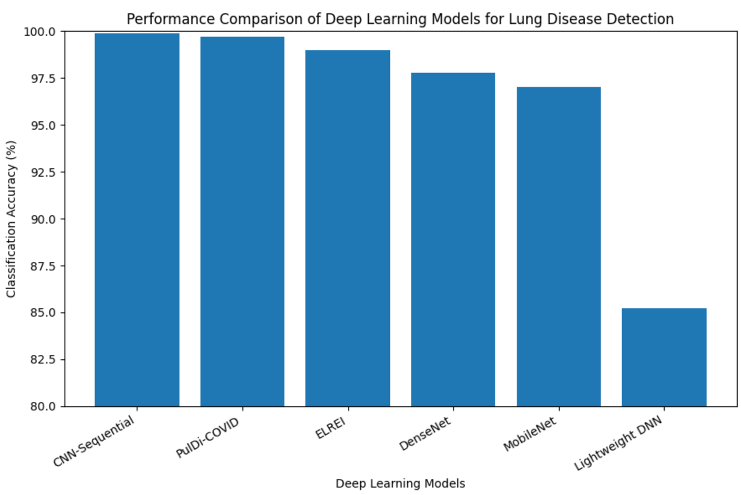

Figure 10. Compares the performance of the models.

7. Practical Implications for Clinical Integration

Deep learning algorithms like ResNet, EfficientNet, and Inception can potentially revolutionize clinical practice [53]. Their embedding in Picture Archiving and Communication Systems (PACS) is capable of enabling real-time radiologist decision-making in scenarios where there exists a shortage of skills or high levels of patient throughput. Diagnostic time can be minimized, errors avoided, and earlier intervention enabled in the treatment of progressive lung disease. Effective models like MobileNet can also be viable on embedded or mobile devices, facilitating AI-based diagnosis in resource-scarce and distant areas [54]. It can provide more access to health care, equalize equality of lung disease diagnosis, boost individualized treatment protocols, improved prognosis, and reduced healthcare cost.

8. Recommendation and Future Direction

Therefore, future studies should emphasize how pre-trained models can be improved by embedding the two giant pillars of ensemble learning techniques and designing customized DL architecture models to further increase the integration within the ambit of lung diseases detection [55,56]. Other models, including ResNet, EfficientNet, and Inception-v3, are bound to be fine-tuned on larger and more heterogeneous datasets that would improve their generalization capability and diagnostic accuracy on various clinical settings. The rich diagnostic context and manifold effectiveness are created in DL models by the representation of medical imaging with its combination with patient clinical records [57]. This would go a long way in helping to solve those complex cases where diagnosis cannot be afforded purely on imaging. Addressing dataset availability requires collaboration between institutions. These types of collaborations will promote access to a range of representative datasets that can be used in training DL models with images representative of the global variability in the presentation of lung disease. This will be the main step toward the development of models that can perform robustly across a wide range of clinical scenarios and patient populations [58,59].

In the future, pulmonary disease detection with deep learning will be done through refinement of ensemble learning techniques and further optimization of pre-trained models. Ensemble learning boosts the performance and robustness of predictions by integrating various models such as ResNet, EfficientNet, and Inception-v3, in terms of imaging efficacy. Future research should focus on fine-tuning these models with larger, more diverse datasets to capture global disease variability. In addition, adding data augmentation and multimodal learning will improve accuracy and sensitivity in early diagnosis and treatment. The area where the most progress is expected to be made in the coming years is in the application of Explainable AI (XAI) using tools such as Grad-CAM in order to provide visual explanations for the diagnosis made. In addition to this, the area that will greatly benefit from this changing landscape is the application of Temporal Modeling and the adoption of scalable architectures.

9. Conclusion

The pre-trained deep learning architecture holds much promise for the early detection of lung diseases. Powerfully promising models include ResNet, EfficientNet, and Inception-v3, since they are quite prominent in the identification of complicated patterns from chest X-rays and CT scans and thus serve well in conditions such as the diagnosis of lung cancer, COPD, and tuberculosis. Fine-tuning of such models assists in specific tasks, improving diagnostic accuracy with economized computational costs. Ensemble methods that combine such diverse models pretrained on different datasets further improve performance by capturing complementary features and subtle markers of disease. This advance enables early interventions and hence better outcomes for patients. Fully realizing the potential of these models clinically requires further refinement of high-quality datasets, appropriate transfer learning methodologies, and model interpretability techniques.

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