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Recent Advances in Hybrid Deep Learning for Multi-Class Lung Disease Diagnosis from Radiological Images

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ABSTRACT:

Lung diseases such as pneumonia, tuberculosis, COVID-19, lung cancer, and chronic obstructive pulmonary disease (COPD) remain among the leading causes of morbidity and mortality worldwide. Effective clinical decision-making depends on early and precise diagnosis using radiological imaging modalities, such as computed tomography (CT) and chest X-rays. Although deep learning (DL) techniques have shown impressive results in automated lung disease detection in recent years, traditional deep models frequently have high computational complexity, large parameter sizes, and limited deployment feasibility in healthcare environments with limited resources. By mixing several learning paradigms and maximizing model efficiency, hybrid and lightweight deep learning systems have emerged as viable answers to these problems. Recent hybrid lightweight deep learning models created for multi-class lung disease diagnosis from radiological images are thoroughly examined in this article. The study systematically examines existing literature by categorizing approaches based on feature extraction strategies, hybrid model architectures, backbone networks, optimization techniques, and classification mechanisms. Performance metrics, datasets, preprocessing techniques, and validation strategies are critically discussed to highlight comparative strengths and limitations of current methods. This research also highlights how lightweight designs can improve computing efficiency without sacrificing diagnostic accuracy, which makes them appropriate for edge-based and real-time medical applications. The study concludes by outlining important research issues, such as clinical integration, interpretability, generalization across imaging modalities, and dataset imbalance. In order to construct robust, scalable, and clinically reliable hybrid lightweight deep learning frameworks for multi-class lung disease diagnosis, future research areas are described. The purpose of this review is to provide scholars and practitioners involved in medical image analysis and intelligent healthcare systems with a useful resource.

1. Introduction

Medical imaging, especially chest X-rays (CXR) and computed tomography (CT), is a crucial component of lung disease diagnosis because of its accessibility and non-invasive character, which helps clinicians make informed decisions. Image categorization tasks, such lung disease detection, have been successfully performed using deep learning (DL), particularly convolutional neural networks (CNNs). However, since traditional deep learning methods need large datasets and require large amount of processing power, it can be difficult to implement them in low-resource clinical environments or in real time. To overcome these problems, researchers are increasingly blending other models with deep learning to create hybrid models that improve performance, interpretability, and efficiency. In addition, lightweight architectures maximize model size and computation while preserving accuracy. From radiological images, this review explores the cutting edge of hybrid and lightweight deep learning methods for multiclass categorization of lung illnesses.

2. Literature Review

A. Hybrid and Lightweight Deep Learning Trends

Recent studies have shown that hybrid deep learning approaches, which merge deep feature extraction with either conventional machine learning classifiers or extra network modules, may increase performance in identifying multiclass lung disease while also optimizing computational needs. For example, hybrid models that combined support vector machines (SVM) with deep architectures (such as MobileNet) showed greater accuracy (approximately 97%) than standalone networks, demonstrating the promise of hybrid

techniques in achieving a balance between model efficiency and accuracy [1]. In a similar way, the synergy between traditional and learned features is demonstrated by the high performance (approximately 97% accuracy) attained by automatic pneumonia detection using a combination of hand-crafted feature extraction (e. g. , 2D discrete wavelet transform (DWT) and Gray-Level Co-occurrence Matrix (GLCM)) and deep networks like ResNet-50 and SVM classification[2].

B. Lightweight Architectures for Real-Time Deployment

The goal of creating lightweight deep learning models is to maintain high diagnostic accuracy while lowering the amount of trainable parameters, memory consumption, and computational complexity. This objective is particularly critical for real-time and resource-limited environments, such as mobile health platforms, telemedicine systems, and embedded or edge-based medical devices. Conventional deep learning architectures, although effective, are often computationally expensive and impractical for deployment in such constrained clinical settings. An extensive analysis of lightweight deep learning models for lung disease identification reports that models such as SqueezeNet, MobileNet, ShuffleNet, and EfficientNetV2 attain competitive classification performance with a substantially smaller number of parameters than traditional CNNs like VGG and ResNet. In particular, SqueezeNet, with approximately 0.57 million parameters, drastically reduces model size while achieving comparable accuracy, making it a incredibly effective method for automated lung disease detection tasks [3]. The use of architectural strategies such as fire modules, depthwise separable convolutions, and bottleneck layers enables these models to minimize computational overhead without compromising feature extraction capability.

Similarly, EfficientNetV2 employs a compound scaling approach that optimally balances network depth, width, and input resolution, resulting in faster training and improved inference efficiency. Studies indicate that EfficientNetV2-based lightweight models achieve high classification accuracy on multi-class lung disease datasets while significantly reducing floating-point operations (FLOPs), increasing their appropriateness for scalable and deployable medical imaging applications [3].

In addition to pretrained lightweight architectures, custom-designed lightweight CNN models have also demonstrated promising performance. A recent study proposed a redesigned lightweight CNN tailored specifically for chest X-ray image classification, achieving test accuracies exceeding 96% for COVID-19 and pneumonia detection. The model reduced computational cost by optimizing convolutional kernel sizes, minimizing network depth, and eliminating redundant layers, while still preserving discriminative feature learning [4]. These findings highlight the importance of task-specific architectural optimization in achieving an effective trade-off between accuracy and efficiency.

Overall, lightweight deep learning models are essential to the practical implementation of AI-based diagnostic tools in actual healthcare settings. By lowering processing requirements while preserving clinically acceptable performance, such models support large-scale screening, remote diagnosis, and real-time decision support, thereby bridging the gap between research-oriented deep learning solutions and practical clinical applications.

3. Cross-Dataset Integration and Explainable Artificial Intelligence for Lung Disease Diagnosis

To further enhance model generalizability and diagnostic reliability, The usage of hybrid datasets, which integrate radiological images from several publically available and institutional sources. The motivation behind this strategy is to mitigate domain bias, which arises due to variations in imaging protocols, device manufacturers, patient demographics, and acquisition settings across individual datasets. Models trained on a single dataset often exhibit reduced performance when tested on unseen data; therefore, hybrid datasets play a important role in improving robustness and cross-dataset generalization. Many researches have showed that leveraging merged and balanced datasets significantly improves multi-class lung disease classification performance. For example, a study utilizing a hybrid dataset composed of chest X-ray images collected from diverse sources reported classification accuracies higher using CNN-based architectures such as VGG16, Xception, and ResNet50V2. The results clearly show that data diversity

and balanced class distribution contribute substantially to improved feature learning and reduced overfitting, Consequently, deep learning models become more reliable in real-world clinical scenarios [5].

In addition to dataset fusion, Explainable Artificial Intelligence (XAI) approaches have grown in significance in medical imaging applications. Despite the high accuracy achieved by deep learning models, their black-box nature remains a major barrier to clinical acceptance. Recent studies integrating XAI with hybrid deep learning approaches have shown that explanation maps often correspond to clinically relevant lung regions, thereby increasing trust and transparency in AI-assisted diagnosis. In particular, LIME-based explanations have been effectively applied to chest X-ray classification models to validate that predictions are based on pathological regions rather than irrelevant background features [5]. Such explainability not only improves clinician confidence but also supports regulatory compliance and ethical deployment of AI systems in healthcare.

Overall, the combination of hybrid datasets and explainable AI techniques represents a critical advancement toward building robust, transparent, and clinically deployable deep learning systems for multi-class lung disease detection. Future research is expected to further explore standardized hybrid dataset construction and deeper integration of XAI methods to facilitate trustworthy and interpretable AI-driven diagnostic tools.

4. Comparative Performance and Model Enhancement Techniques

Comparative analyses across the literature indicate that while standalone deep learning models already outperform traditional machine learning approaches in lung disease detection from radiological images, their performance can be further enhanced through targeted model enhancement techniques. Studies reported on ScienceDirect show that hybrid and ensemble-based frameworks consistently achieve improved classification stability, sensitivity, and generalization compared to individual CNN models, particularly in multi-class lung disease scenarios. These enhancements are achieved by integrating complementary learning strategies such as CNN-based deep feature extraction combined with classical classifiers or ensemble decision mechanisms, which help mitigate overfitting and reduce variance across diverse datasets [6]. Furthermore, research published on SpringerLink emphasizes that hybrid feature fusion and model fusion approaches are especially effective in addressing persistent challenges such as class imbalance, inter-class similarity, and heterogeneous radiographic patterns. By leveraging the representational power of deep networks alongside the discriminative strengths of traditional learning algorithms, these enhanced models demonstrate more consistent performance across varied disease categories and imaging conditions, highlighting their suitability for real-world clinical deployment [7].

Reference	Imaging Modality	Model Type	Enhancement Strategy	Dataset Type	Key Observations
[6]	Chest X-ray	CNN Ensemble	Hybrid ensemble with voting & bagging	Single-source	Improved generalization and stability across multi-class tasks
[8]	Chest X-ray	CNN and SVM	Deep features + classical classifier	Single-source	Better handling of class imbalance and inter-class similarity
[9]	Chest X-ray	CNN and Feature Fusion	Hybrid deep + handcrafted features	Single-source	Enhanced discriminative capability and robustness to heterogeneous patterns
[10]	Chest X-ray	Lightweight CNN and Feature Fusion	Lightweight deep features combined with classical ML	Multi-source (Hybrid Dataset)	Efficient model with reduced computation and improved multi-class performance

5. Challenges and Limitations In Current Research

Despite significant advancements in deep learning–based lung disease detection from radiological images, several critical challenges and limitations continue to hinder the development of robust and clinically deployable systems. One of the most persistent issues is class imbalance, as most publicly available lung disease datasets exhibit skewed class distributions, with normal or common disease classes significantly outnumbering rare or severe conditions. This imbalance often biases model predictions toward dominant classes, leading to reduced sensitivity for minority disease categories. To address this issue, existing studies have explored techniques such as weighted loss functions, data augmentation, resampling strategies, and hybrid class balancing methods, yet achieving consistent performance across all classes remains an open research problem [11], [12].

Another major limitation is the lack of generalizability of trained models. Many deep learning frameworks demonstrate strong performance on the datasets they are trained on but experience notable performance degradation when evaluated on external or cross-institutional datasets. This limitation highlights the influence of dataset-specific biases, variations in imaging equipment, acquisition protocols, and patient demographics. Several studies have emphasized that models trained on single-source datasets often fail to generalize effectively across diverse clinical environments, underscoring the need for hybrid datasets, domain adaptation techniques, and multi-center training strategies [13], [14].

A significant clinical validation gap further restricts the translation of research findings into real-world healthcare applications. While the majority of existing studies rely on publicly available datasets such as ChestX-ray14 or COVIDx, relatively few works conduct prospective or multi-center clinical validation using real-world hospital data. The absence of extensive clinical trials and real-time validation limits the trustworthiness and regulatory acceptance of deep learning–based diagnostic systems, delaying their integration into routine clinical workflows [15].

Additionally, model interpretability remains a critical concern. Deep neural networks are often criticized for their “black-box” nature, which poses challenges for clinical adoption where transparency and explainability are essential. Although explainable AI (XAI) techniques such as Grad-CAM, LIME, and SHAP have been increasingly employed to visualize decision-relevant regions in radiological images, current interpretability methods are still limited in providing fully reliable, standardized, and clinically actionable explanations. Consequently, further research is required to develop robust and clinically aligned interpretability frameworks that can enhance clinician trust and support ethical AI deployment [16], [17].

Finally, computational resource constraints pose practical challenges, particularly for real-time and point-of-care applications. While lightweight and hybrid deep learning models aim to reduce computational complexity, many architectures still require careful optimization to meet the constraints of embedded systems, mobile health platforms, and resource-limited clinical environments. Achieving an optimal balance between accuracy, model complexity, inference time, and energy efficiency remains a key challenge, especially when deploying hybrid or ensemble-based frameworks in real-world settings [18].

6. Research Gaps and Future Directions

Although deep learning has achieved promising results in lung disease detection, several gaps remain. Most existing studies focus either on accuracy or efficiency, with limited exploration of hybrid lightweight architectures that balance both aspects. Additionally, the lack of cross-dataset and multi-center validation restricts model generalizability across diverse clinical settings [13]. Clinical translation is further hindered by insufficient real-world validation, as many models rely solely on public datasets [15]. While explainable AI techniques have been introduced, they are largely post hoc and lack standardized clinical interpretation, limiting trust and adoption [17]. Future research should prioritize hybrid lightweight model design, robust external validation, clinically driven explainability, and deployment-aware optimization to enable scalable and trustworthy AI-based lung disease diagnosis [18].

7. Conclusion

This review summarized recent progress in deep learning–based approaches for multi-class lung disease detection from radiological images, emphasizing hybrid

and lightweight model architectures. While deep learning techniques demonstrate superior performance over traditional methods, hybridization and model enhancement strategies improve robustness and generalization. However, challenges such as class imbalance, limited external validation, lack of clinical deployment, and insufficient interpretability remain unresolved. Additionally, balancing diagnostic accuracy with computational efficiency continues to be a key concern for real-time clinical applications. Future research should focus on hybrid lightweight model design, multi-center validation, explainable AI integration, and deployment-aware optimization to support reliable and scalable AI-assisted lung disease diagnosis in healthcare environments.

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