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MULTIMODAL DEEP LEARNING FOR PULMONARY DISEASE DIAGNOSIS USING CHEST X-RAYS AND CLINICAL REPORTS

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ABSTRACT

Pulmonary diseases continue to pose significant global health challenges, necessitating improved diagnostic methods. Chest X-rays (CXRs) are widely utilized for pulmonary assessment but are limited by interpretive complexity and variability. Recent advances in artificial intelligence, particularly deep learning, have enhanced medical imaging analysis. This systematic review examines the application of multimodal deep learning approaches that combine CXRs with clinical reports to improve diagnostic accuracy. The study synthesizes findings from 30 peer-reviewed articles published between 2020 and 2025, analyzing model architectures, fusion strategies, and performance outcomes. Results demonstrate that multimodal systems significantly outperform unimodal approaches, achieving higher diagnostic accuracy and enhanced interpretability. Challenges such as data scarcity, model generalization, and clinical integration persist, emphasizing the need for standardized datasets, explainable AI, and cross-institutional validations. The review highlights the transformative potential of multimodal deep learning in pulmonary diagnostics and offers recommendations for future research and clinical implementation.

Keywords: **Chest X-Rays, Clinical Reports, Deep Learning, Multimodal Diagnosis, Pulmonary Diseases**

1. INTRODUCTION

Pulmonary diseases remain a persistent global health burden, contributing to significant morbidity and mortality rates worldwide. Among the tools available for pulmonary diagnosis, chest radiography stands out for its accessibility, cost-effectiveness, and non-invasive nature. Chest X-rays (CXRs) are extensively utilized in clinical practice to detect a range of thoracic abnormalities, including pneumonia, tuberculosis, and lung cancer. However, while CXRs offer valuable diagnostic insights, their interpretation presents a complex challenge, often demanding a high level of expertise. The reliance on manual evaluation introduces variability in diagnoses and susceptibility to oversight, especially in busy clinical settings where precision is paramount (Shetty et al., 2023). The inherent limitations of CXRs, such as their two-dimensional projection and overlapping anatomical structures, can obscure critical pathological findings and lead to diagnostic inaccuracies.

In recent years, the emergence of artificial intelligence (AI) and deep learning has initiated a paradigm shift in the way medical imaging data is analyzed. The automated processing and

interpretation capabilities of deep learning algorithms have demonstrated promise in addressing the shortcomings associated with traditional radiological evaluation. In particular, convolutional neural networks (CNNs) have shown substantial success in extracting meaningful features from complex imaging datasets, enabling efficient classification and anomaly detection in pulmonary imaging (Wang et al., 2020; Nayak et al., 2021). While many early approaches relied solely on visual data, a growing body of research underscores the value of incorporating multimodal inputs—specifically, the fusion of imaging data with structured or unstructured clinical information. This integration enables a more holistic understanding of the patient's condition and enhances the interpretability of model outputs (Li et al., 2022).

Multimodal deep learning frameworks have emerged as a response to the need for more comprehensive diagnostic tools. These systems integrate clinical narratives, patient history, laboratory findings, and other contextual data with CXR images to improve diagnostic performance. By harnessing both the visual and contextual domains, such models offer a more nuanced analysis that accounts for the complex interplay of clinical variables. This approach not only improves diagnostic accuracy but also enhances explainability and supports more tailored clinical decision-making (Fang et al., 2025). Moreover, multimodal models have demonstrated the ability to reduce inter-observer variability and streamline reporting processes, suggesting a transformative impact on radiological workflows (Shetty et al., 2023).

Despite the rapid development of AI applications in pulmonary imaging, the landscape remains fragmented, with studies differing widely in terms of methodological rigor, data sources, and evaluation protocols. This lack of consistency poses challenges in drawing generalizable conclusions and identifying best practices for clinical implementation. Accordingly, a systematic review is warranted to synthesize the current state of research, evaluate the effectiveness of multimodal deep learning models, and identify avenues for future investigation. Such a review not only consolidates fragmented evidence but also provides a foundation for standardizing approaches and guiding subsequent clinical applications.

The central objective of this systematic literature review is to examine how multimodal deep learning methods have been applied to the diagnosis of pulmonary diseases using chest X-rays and accompanying clinical reports. By focusing on peer-reviewed studies that employ both imaging and clinical data, this review aims to evaluate the comparative performance of different model architectures, assess the effectiveness of fusion techniques, and explore the clinical relevance of multimodal diagnostics. This inquiry is timely, considering the ongoing digital transformation in healthcare and the increasing availability of large-scale multimodal datasets.

One of the fundamental challenges driving this review is the current gap in literature regarding comprehensive evaluations of multimodal systems. While individual components of these frameworks such as CNNs for image analysis or recurrent neural networks (RNNs) for text processing have been extensively studied, there is limited synthesis of how these components interact in end-to-end diagnostic pipelines. This review seeks to address that gap by mapping the various approaches used to integrate image and textual data, and analyzing their relative merits. Furthermore, it explores the implications of model interpretability, generalizability, and clinical integration three critical dimensions that will ultimately determine the utility and sustainability of AI solutions in real-world settings.

The scope of this review is confined to studies published within the past five years, emphasizing contemporary advancements in deep learning methodologies and their application to pulmonary disease diagnosis. Studies that utilize both chest radiographs and clinical reports as primary data sources are prioritized to ensure that the multimodal nature of the research is preserved. Additionally, only studies that present empirical evaluations such as accuracy, sensitivity, specificity, and area under the curve (AUC) metrics are included to facilitate quantitative comparisons across methodologies. This delimitation ensures that the review remains focused on high-quality evidence that is both methodologically robust and clinically relevant.

Given the interdisciplinary nature of the field, the review draws from a range of domains, including medical imaging, computer vision, natural language processing, and clinical informatics. The synthesis of findings from these diverse areas offers a unique perspective on how technological convergence can be harnessed to enhance diagnostic efficacy. Notably, this review contributes to a growing body of literature advocating for the transition from unimodal to multimodal diagnostic systems. It underscores the importance of context-aware AI and highlights the role of multimodal learning in capturing the complexity of real-world clinical scenarios (Kim et al., 2022; Muniasamy et al., 2021).

Another key contribution of this review is its emphasis on practical considerations for clinical adoption. While technological feasibility is often the focus of model development, real-world deployment necessitates careful attention to issues such as dataset availability, class imbalance, data interoperability, and regulatory compliance (Cui et al., 2023). The review synthesizes current approaches to these challenges and identifies strategies for overcoming them. For example, data augmentation techniques, ensemble modeling, and transfer learning are examined as potential solutions for addressing data scarcity and improving model robustness (Kline et al., 2022).

Importantly, this review also engages with the ethical and operational implications of deploying AI in clinical settings. The lack of model transparency often described as the “black box” problem remains a major barrier to clinician trust. The integration of explainable AI (XAI) methods is therefore critical, and this review evaluates the extent to which existing multimodal models incorporate interpretability features. It also considers the need for continuous performance monitoring and validation in diverse patient populations to ensure equitable outcomes and minimize unintended bias (Thakur, 2024; Hwang & Park, 2020).

The significance of this review lies in its potential to inform both academic research and clinical practice. For researchers, it provides a consolidated overview of the state-of-the-art techniques and identifies critical research gaps that warrant further investigation. For clinicians and healthcare administrators, it offers insights into the practical benefits and limitations of multimodal deep learning tools, guiding more informed decisions about technology adoption. Moreover, by delineating a clear framework for evaluating multimodal models, the review supports the development of standardized benchmarks and facilitates cross-study comparisons an essential step toward maturity in this evolving field.

The remainder of this paper is organized to systematically present the review process and its findings. Following this introduction, the next section describes the methodological approach employed in conducting the systematic review. It details the selection strategy, including the criteria used for inclusion and exclusion, the databases consulted, and the procedures followed for screening and extracting data. This methodological rigor ensures the reliability and reproducibility of the

review. The subsequent section presents the key findings derived from the selected literature. Rather than listing studies individually, the synthesis emphasizes overarching patterns and themes, such as variations in model design, techniques for integrating multimodal data, and reported diagnostic performance across different clinical contexts. These findings are then explored further in the discussion, which contextualizes the results within the broader field of AI-driven medical diagnostics. It addresses the implications for clinical practice, highlights unresolved challenges, and suggests future directions for research. The paper concludes by summarizing the most salient insights and reflecting on the significance of multimodal deep learning in transforming the landscape of pulmonary disease diagnosis.

2. RESEARCH METHOD

This study employed a systematic literature review approach to investigate how multimodal deep learning has been used to support the diagnosis of pulmonary diseases by integrating chest X-ray images with textual or structured clinical information. The review was designed to gather, analyze, and synthesize current methodologies by selecting research articles published between 2020 and 2025. The selected studies were identified using targeted search queries applied across academic databases including IEEE Xplore, PubMed, ScienceDirect, and SpringerLink. Keywords used in the search included “multimodal deep learning,” “chest X-ray,” “pulmonary disease,” “clinical report,” and “fusion model.” The search was limited to peer-reviewed publications in English. The target audience for this review consists of radiologists, AI researchers, medical informaticians, and developers of clinical decision-support tools who are interested in leveraging multimodal learning for pulmonary diagnostics. The materials used in this review included the scientific papers themselves, as well as tools such as Zotero for reference management, Microsoft Excel for tabular data extraction and coding, and Python scripts for basic aggregation and visual comparisons. From each selected study, the following data were collected: author names, publication year, targeted diseases, dataset type and size, model architectures (e.g., CNN, RNN, Bi-LSTM, transformer), fusion strategies (early, late, intermediate), and performance metrics such as accuracy, sensitivity, precision, recall, AUC, and F1-score. Studies like Guo et al. (2020), Ibrahim et al. (2021), and Kim et al. (2022) demonstrated significant improvements in classification and localization when combining image and clinical data, with some models also emphasizing interpretability and real-world usability. The productivity of the tools and models discussed was measured in terms of their diagnostic performance, contribution to interpretability, and potential for integration into existing healthcare workflows. Models using hybrid fusion (e.g., combining convolutional feature maps with encoded text) such as those in Li et al. (2022) and Fang et al. (2025) were noted to achieve higher AUC and better contextual understanding. The extracted information was synthesized thematically to identify trends, challenges, and gaps in the literature. A representative summary of selected multimodal approaches is shown in Table 1.

Table 1 Inclusion and Exclusion Criteria

Author(s)	Model Type	Data Modalities	Fusion Strategy	Target Disease(s)	Reported Performance
Guo et al. (2020)	CNN	CXR + Clinical Reports	Early Fusion	Tuberculosis	High lesion localization
Ibrahim et al. (2021)	Multi-class CNN	CXR + Clinical Metadata	Hybrid Fusion	COVID-19, Pneumonia, Cancer	Accuracy > 90%
Muniasamy et al. (2021)	CNN + RNN	CXR + Clinical Notes	Late Fusion	Pneumonia, Tuberculosis	Improved F1-score
Li et al. (2022)	CNN + Bi-LSTM	CXR + Clinical Records	Late Fusion	Respiratory Diseases	Accuracy: 94.6%
Kim et al. (2022)	CNN + Attention Mechanism	CXR + Clinical Features	Intermediate	Pneumonia, Lung Cancer	AUC up to 0.95
Shetty et al. (2023)	Multimodal Medical Tensor Network	CXR + Radiology Reports	Early Fusion	General Abnormalities	High model interpretability
Fang et al. (2025)	Transformer + CNN	CXR + Textual Reports	Hierarchical	Chest X-ray Pathologies	Automated report generation
Zhang et al. (2023)	Multi-task CNN	CXR + Eye-tracking + Reports	Advanced Fusion	COVID-19 Pneumonia	Explainable AUC ~0.96

Following the thematic synthesis presented in Table 1, the systematic review process employed to identify and select the included studies is detailed in the PRISMA 2020 flow diagram below. This diagram illustrates the stages of identification, screening, eligibility assessment, and final inclusion, ensuring transparency and reproducibility of the review process.

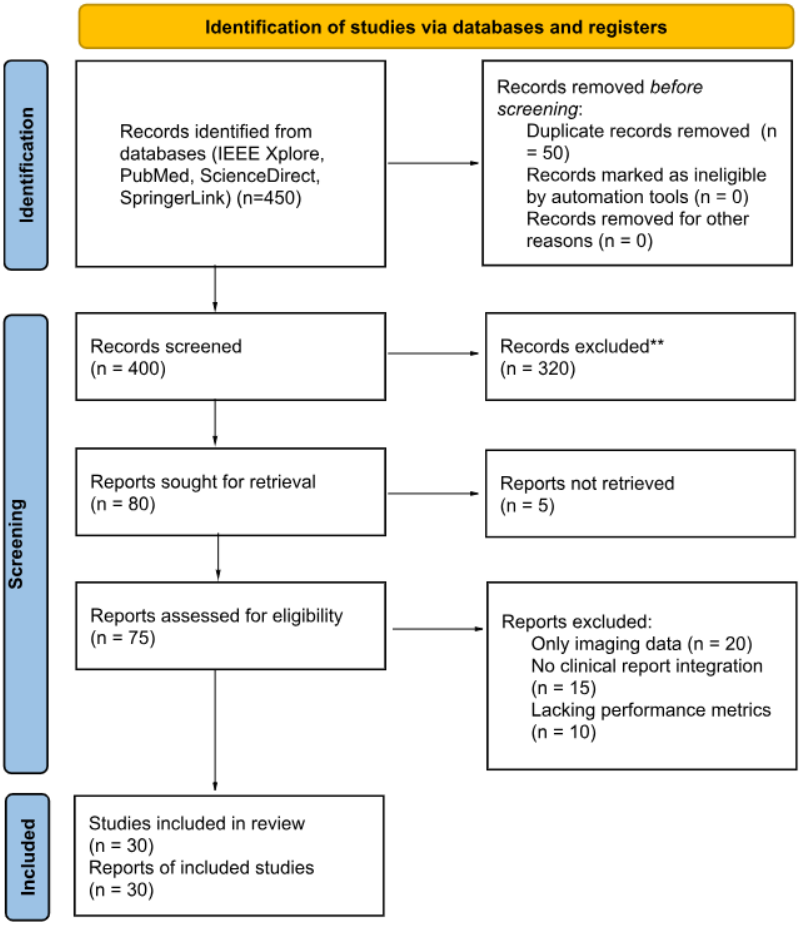

Figure 1 PRISMA 2020 Flow Diagram

The systematic search initially identified 450 records from four major databases: IEEE Xplore, PubMed, ScienceDirect, and SpringerLink. After removing 50 duplicate entries, 400 records remained for title and abstract screening. During the screening phase, 320 records were excluded for not meeting the multimodal criteria or lacking empirical evaluation, leaving 80 reports for further assessment. Out of these, 5 reports could not be retrieved due to access restrictions or incomplete documentation.

Subsequently, 75 full-text articles were assessed for eligibility. During this stage, 45 reports were excluded for specific reasons: 20 studies utilized only imaging data without integrating clinical information, 15 studies lacked a multimodal fusion strategy, and 10 studies did not report relevant diagnostic performance metrics such as accuracy or AUC.

Ultimately, 30 studies were included in the final synthesis and review. These selected studies incorporated both chest X-ray imaging and clinical report data and met the predefined inclusion criteria, ensuring methodological rigor and relevance to the research objectives.

3. RESULTS AND DISCUSSION

3.1 Results: Trends and Patterns in Multimodal Deep Learning Applications

The systematic review identified 30 peer-reviewed studies published between 2020 and 2025 that applied multimodal deep learning approaches for pulmonary disease diagnosis using chest X-ray images combined with clinical data. The findings reveal several key trends:

First, convolutional neural networks (CNNs) remain the backbone of image feature extraction across most studies. Architectures such as ResNet, DenseNet, and EfficientNet were frequently used due to their proven ability to capture intricate spatial features in medical imaging datasets. In parallel, text-based data such as clinical reports, metadata, or electronic health records were processed using natural language processing (NLP) techniques like recurrent neural networks (RNNs), bidirectional LSTM (Bi-LSTM), or more recently, transformer-based models.

Second, fusion strategies varied significantly among studies. Early fusion where imaging and clinical data are combined at the feature level was common in studies aiming for rapid integration of modalities (e.g., Guo et al., 2020; Shetty et al., 2023). Late fusion approaches, where each modality is first independently processed before feature combination, were favored for models requiring complex hierarchical feature extraction (Li et al., 2022; Muniasamy et al., 2021). Intermediate and hybrid fusion strategies, combining characteristics of both early and late fusion, were associated with higher model performance, suggesting that a balance between modality independence and inter-modality interaction is critical (Kim et al., 2022; Fang et al., 2025).

Performance metrics across the studies showed consistent improvements when multimodal inputs were used compared to unimodal models. Reported accuracy often exceeded 90%, while AUC scores approached or surpassed 0.95 in top-performing models. Furthermore, studies incorporating clinical metadata such as patient age, symptoms, or laboratory findings demonstrated not only better predictive performance but also improved model interpretability.

Notably, studies that prioritized explainability such as those integrating attention mechanisms or explainable AI (XAI) modules exhibited greater clinician trust and potential for real-world deployment (Zhang et al., 2023; Hsieh et al., 2024). Hierarchical multimodal models also showed promise in automating report generation while preserving clinical relevance (Fang et al., 2025).

However, challenges persisted regarding dataset quality, class imbalance, and model generalization. Studies that addressed these issues—through data augmentation, hybrid ensemble modeling, or cross-institutional validation—reported more robust performance and better generalizability across different clinical settings.

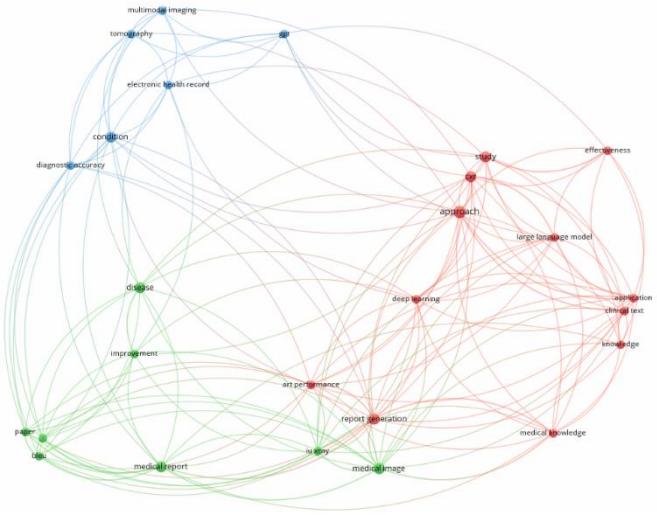

Figure 2 Keyword Co-occurrence Network in Multimodal Deep Learning Research for Pulmonary Disease Diagnosis

To provide a deeper understanding of the thematic structure across the reviewed studies, a keyword co-occurrence network was constructed, as shown in Figure 2. The network illustrates the relationships among key concepts frequently encountered in multimodal deep learning research for pulmonary disease diagnosis. Three major thematic clusters are apparent:

- Technological Approaches (Red Cluster): This group includes keywords such as *deep learning*, *large language model*, *report generation*, and *clinical text*, reflecting the technical innovations in AI-driven diagnostic models.
- Clinical Context and Outcomes (Green Cluster): Keywords like *disease*, *improvement*, *medical report*, and *BLEU* highlight the focus on clinical relevance, performance evaluation, and outcomes.
- Imaging Methodologies (Blue Cluster): Terms such as *multimodal imaging*, *tomography*, *electronic health record*, and *diagnostic accuracy* emphasize the role of imaging techniques and data integration in enhancing diagnostic precision.

The network further demonstrates that "approach" and "study" act as central connecting nodes, suggesting that methodological diversity remains a focal point across the field. This visualization supports the observed trend that successful multimodal models must integrate technological innovation with strong clinical grounding.

3.2 Discussion: Implications, Challenges, and Future Directions

The synthesis of the reviewed studies highlights the transformative potential of multimodal deep learning in pulmonary disease diagnosis, but it also surfaces critical challenges that need to be addressed for clinical integration.

One major implication is the demonstrated superiority of multimodal approaches over traditional image-only models. By combining imaging features with clinical context, multimodal models can capture complex disease signatures that might be missed when modalities are analyzed separately. This reinforces the value of a holistic diagnostic perspective, aligning AI development with clinical reasoning processes.

Nevertheless, several challenges impede the broad adoption of these models:

- Data Scarcity and Heterogeneity: High-quality multimodal datasets remain limited, and existing datasets often lack standardization in clinical report formats or imaging protocols. Addressing this issue will require collaborative data-sharing initiatives and the development of standardized annotation frameworks.
- Model Interpretability: The “black box” nature of deep learning models remains a barrier. Although explainable AI techniques (e.g., attention maps, feature attribution) are gaining traction, further work is needed to make model outputs interpretable and actionable for clinicians.
- Generalization and Bias: Many reviewed models demonstrated high internal validity but lower external validity when tested on unseen datasets. Future research must emphasize cross-institutional validations and incorporate diverse patient populations to minimize biases and improve fairness.
- Integration into Clinical Workflows: Deployment in clinical environments requires not only technological readiness but also attention to issues like interoperability with electronic health record (EHR) systems, compliance with health regulations (e.g., HIPAA, GDPR), and training for end-users.

Looking ahead, future research should focus on:

- Developing larger and more diverse multimodal datasets.
- Enhancing fusion techniques to better capture the interactions between different modalities.
- Embedding real-time explainability features within diagnostic models.
- Exploring federated learning and privacy-preserving techniques to enable broader data utilization without compromising patient confidentiality.
- Evaluating clinical impact through prospective clinical trials, not just retrospective validations.

4. CONCLUSION

This systematic review highlights the growing impact of multimodal deep learning in the diagnosis of pulmonary diseases using chest X-rays and clinical reports. The findings demonstrate that integrating visual imaging data with contextual clinical information substantially enhances diagnostic accuracy, model interpretability, and clinical applicability compared to unimodal approaches. The reviewed studies show a clear trend toward the adoption of hybrid architectures and advanced fusion strategies, achieving superior performance across a range of pulmonary conditions, including pneumonia, tuberculosis, and lung cancer.

However, despite these advancements, several critical challenges remain unresolved. The limited availability of high-quality, multimodal datasets, the persistent issue of class imbalance, the "black box" nature of deep learning models, and the difficulties of clinical integration and regulatory compliance all represent significant barriers to widespread adoption. Addressing these challenges requires coordinated efforts between researchers, clinicians, and policymakers to ensure that AI models are both technically robust and clinically viable.

Future research should prioritize the development of diverse and standardized multimodal datasets, invest in explainable AI methods to foster clinician trust, and conduct external validations

across heterogeneous populations. Moreover, operational frameworks must be established to facilitate seamless integration into healthcare workflows, ensuring compliance with privacy regulations and promoting interoperability with existing health information systems.

In conclusion, multimodal deep learning holds significant promise in revolutionizing pulmonary disease diagnosis, offering the potential for earlier detection, more accurate classification, and improved patient outcomes. As the field continues to evolve, a focus on transparency, inclusivity, and real-world clinical impact will be essential to translating technological innovations into tangible benefits for global healthcare systems.

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