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A Systematic Literature Review of Deep Learning-Based Disease Detection and Classification for Chest X-Ray Imaging

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Abstract

Conventional chest X-ray (CXR) interpretation is often constrained by inter-observer variability, high workload, and time-consuming diagnostic processes. This study aims to consolidate and analyze recent research trends, methodologies, dataset characteristics, and performance outcomes of deep learning (DL) in CXR-based disease detection published between 2021 and 2025. The methodology employs a Systematic Literature Review (SLR), involving research question formulation, comprehensive database searches, and study selection based on predefined inclusion criteria. Results indicate that CNN-based and transfer learning approaches dominate the field, with a significant shift toward multi-disease screening frameworks and the adoption of hybrid or lightweight architectures. The discussion highlights that while models achieve high accuracy, substantial variability in datasets and evaluation protocols hinders direct comparison and clinical generalizability. In conclusion, deep learning has become the prevailing methodology for CXR analysis, but establishing standardized evaluation frameworks and diverse clinical datasets is essential to bridge the gap between methodological development and real-world clinical implementation, and to provide representative quantitative comparisons that highlight performance variability across model architectures and disease scopes.

Keywords: Chest X-Ray, Classification, Deep Learning, Disease Detection, Systematic Literature Review

1. INTRODUCTION

Chest X-ray (CXR) imaging remains one of the most fundamental, cost-effective, and widely accessible radiological modalities for the screening and diagnosis of pulmonary diseases worldwide. It plays a crucial role in the early identification of respiratory conditions such as pneumonia, tuberculosis (TB), and COVID-19, particularly in low- and middle-income regions where advanced imaging modalities and expert radiologists are limited. Despite its clinical importance, conventional CXR interpretation relies heavily on human expertise, which is often constrained by inter-observer variability, high workload, and time-consuming diagnostic processes. These limitations may lead to delayed diagnosis and inconsistent clinical decision-making. In response to these challenges, a growing body of research published between 2021 and 2025 has explored the application of deep learning (DL) techniques for automated disease detection and classification using chest X-ray images. Among these techniques, convolutional neural networks (CNNs) have emerged as the dominant approach due to their strong ability to learn hierarchical visual representations from medical images. Several studies have demonstrated that CNN-based models can effectively classify CXR images into multiple disease categories, including pneumonia, TB, and COVID-19, achieving high diagnostic accuracy and highlighting their potential for multi-disease screening applications [1].

Beyond single-disease detection, recent studies increasingly address multi-class and multi-label chest disease classification, where a single CXR image may present overlapping pathological patterns. This task is inherently challenging due to class imbalance, subtle inter-class visual similarities, and heterogeneous imaging conditions across datasets. To overcome these challenges, researchers have employed strategies such as transfer learning from large-scale pretrained models, hybrid deep learning architectures, and ensemble learning techniques to improve robustness and generalization performance [2]

In addition, advancements in model design have focused on improving both performance and clinical usability. Lightweight and computationally efficient architectures have been proposed to facilitate real-time or near real-time deployment in clinical environments with limited computational resources [3]. Furthermore, the integration of explainable artificial intelligence (XAI) techniques, such as attention mechanisms and gradient-based visualization methods, has gained increasing attention to enhance model interpretability and support clinician trust in automated diagnostic systems.

Hybrid approaches that combine segmentation and classification have also been explored to enhance localization of pathological regions and improve feature extraction, particularly for disease severity assessment in COVID-19 cases [4]. By isolating lung regions prior to classification, these methods aim to reduce background noise and improve diagnostic precision. However, despite the promising results reported across these studies, the literature remains fragmented, with substantial variability in model architectures, dataset composition, evaluation metrics, and experimental protocols.

Given the rapid expansion of deep learning methodologies, diverse experimental designs, and heterogeneous reporting practices, a comprehensive and systematic synthesis of existing research is required. Therefore, this systematic literature review aims to consolidate and analyze recent studies on deep learning-based disease detection and classification using chest X-ray imaging, published between 2021 and 2025, in order to summarize dominant research trends, methodological approaches, dataset characteristics, and reported performance outcomes.

2. RELATED WORK

This section reviews recent studies on deep learning-based analysis of chest X-ray images for pulmonary disease detection and classification, with a particular focus on pneumonia, tuberculosis (TB), and COVID-19. The reviewed literature primarily explores convolutional neural network (CNN)-based architectures, transfer learning strategies, and hybrid deep learning frameworks to address challenges such as visual similarity among diseases, class imbalance, and limited annotated medical data. Rather than summarizing individual studies, this section synthesizes prior work by grouping existing approaches according to disease focus, learning task formulation, and methodological characteristics, thereby providing contextual grounding for the comparative analysis presented in this systematic literature review.

The study conducted [2] a comprehensive survey of 140 peer-reviewed papers to analyze deep learning techniques for pneumonia detection from chest X-ray images, with emphasis on the COVID-19 period. The review categorized existing approaches into custom CNNs, transfer learning, hybrid, and ensemble models, and examined datasets, evaluation metrics, and research trends. The results showed that CNN-based and transfer learning approaches dominate the literature, while hybrid and ensemble models offer performance improvements, and highlighted challenges including dataset bias, class imbalance, lack of standardized evaluation, and limited interpretability.

The study proposed [3] a knowledge distillation–based deep learning framework using a teacher–student architecture to efficiently classify chest X-ray images into COVID-19, pneumonia, tuberculosis, and normal categories. Evaluated on public datasets under multi-class scenarios, the lightweight student model achieved an accuracy of up to 96.08%, with 94% precision and 97% recall, while significantly reducing model complexity, demonstrating the effectiveness of knowledge distillation for efficient multi-disease chest X-ray classification in resource-constrained settings.

The study proposed [1] a CNN-based multi-class classification model using DenseNet121 with transfer learning to classify chest X-ray images into pneumonia, tuberculosis (TB), COVID-19, and normal categories. Trained on 7,135 public CXR images, the model addressed data imbalance through preprocessing and augmentation. The experimental results achieved an overall accuracy of 78%, with high recall for pneumonia (0.99), TB (0.93), and COVID-19 (0.92), demonstrating the effectiveness of deep learning for multi-disease chest X-ray screening.

The study proposed [5] a lightweight hybrid deep learning model for tuberculosis detection from chest X-ray images by integrating GhostNet and MobileViT through feature-level fusion. The study aimed to achieve high diagnostic accuracy while maintaining low computational cost for deployment in resource-constrained settings. Evaluated on two public CXR datasets, the proposed model achieved 99.52% and 99.17% accuracy, outperforming individual CNN and transformer baselines while using only 7.73M parameters and 282.11M FLOPs, demonstrating an effective balance between performance and efficiency.

The study proposed [6] a deep learning–based framework using ResNet50 and VGG16 architectures to detect COVID-19, tuberculosis, and normal lung conditions from chest X-ray images. The study aimed to enhance automated radiological diagnosis through data augmentation and class balancing. Experimental results showed that ResNet50 outperformed VGG16, achieving near-perfect precision, recall, and F1-scores (≈0.97–0.99) with AUC values close to 1.00, demonstrating strong potential for accurate multi-disease chest X-ray classification in clinical settings.

Although various deep learning models have demonstrated strong performance for chest X-ray–based detection and classification of pneumonia, tuberculosis, and COVID-19, existing studies largely address these problems in isolation or under heterogeneous experimental settings. Differences in disease scope, model architecture, dataset composition, and evaluation protocols make direct comparison across studies difficult. Moreover, while recent works explore efficient and lightweight models, issues related to dataset bias, class imbalance, inconsistent evaluation metrics, and limited interpretability remain insufficiently synthesized. These limitations highlight the need for a systematic literature review that organizes and compares deep learning-based chest X-ray studies within a unified framework, particularly for multi-disease screening during the 2021–2025 period.

3. MATERIALS AND METHOD

This study employs a Systematic Literature Review (SLR) approach to comprehensively examine the application of deep learning methods for detecting and classifying chest diseases based on X-ray imaging. The SLR process was conducted through several main stages, including formulation of research questions, literature search strategy, study selection and screening, and data extraction and analysis. The literature search was carried out using reputable scientific databases such as Scopus, IEEE Xplore, Web of Science, and PubMed, with Google Scholar utilized as a complementary search engine to identify additional relevant studies. The search was limited to articles published between 2021 and 2025.

Keywords used in the search included “chest X-ray”, “deep learning”, “disease detection”, “classification”, “pneumonia”, “tuberculosis”, and “COVID-19”. The retrieved studies were then selected based on predefined inclusion and exclusion criteria, focusing on topic relevance, the use of chest X-ray images, and the implementation of deep learning models. The selected studies were analyzed to identify types of detected diseases, deep learning approaches applied, learning tasks, datasets, and performance evaluation metrics, such as accuracy, precision, recall, F1-score, and AUC. The results are presented in tabular form and supported by narrative discussion to highlight research trends and potential directions for future studies. he methodological framework of this systematic literature review is presented in Figure 1.

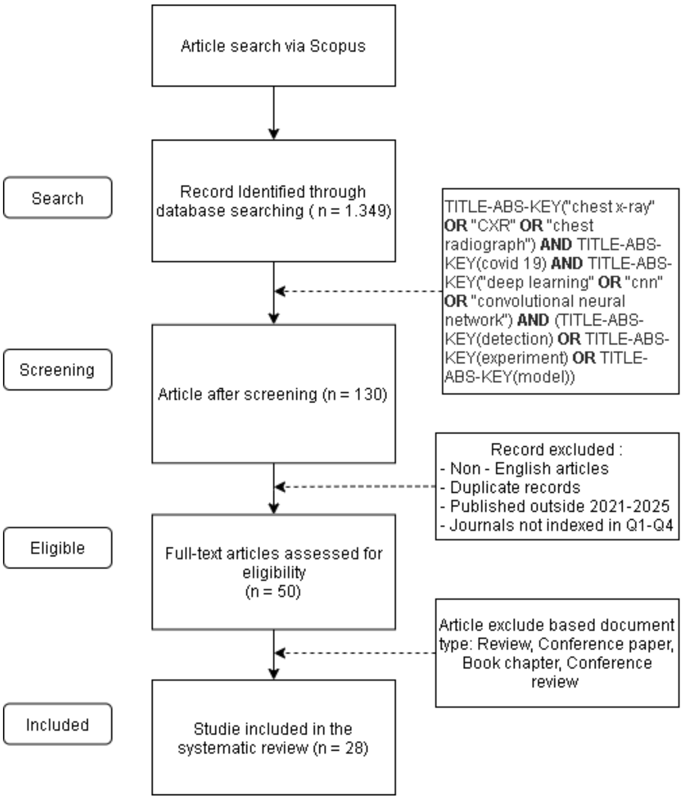

Figure 1. Research Methodology

3. RESULTS AND DISCUSSION

Figure X presents the keyword co-occurrence network generated using VOSviewer, highlighting the main research themes in deep learning-based chest X-ray analysis. The visualization reveals three closely connected clusters representing methodological approaches, disease focus, and clinical evaluation. Keywords such as deep learning, convolutional neural network, image classification, and transfer learning form the core methodological cluster, indicating the dominant use of deep learning techniques for automated chest X-ray analysis. Disease-related terms, including pneumonia, COVID-19, and tuberculosis, are strongly linked to this cluster, reflecting the primary clinical targets addressed in the reviewed studies. In addition, evaluation-oriented terms such as diagnostic accuracy and clinical study suggest a consistent emphasis on performance assessment and clinical applicability. Overall, the strong interconnections among these themes demonstrate an integrated research landscape that aligns with the focus of this systematic literature review. Visually maps occurrence network can be seen in Figure 2.

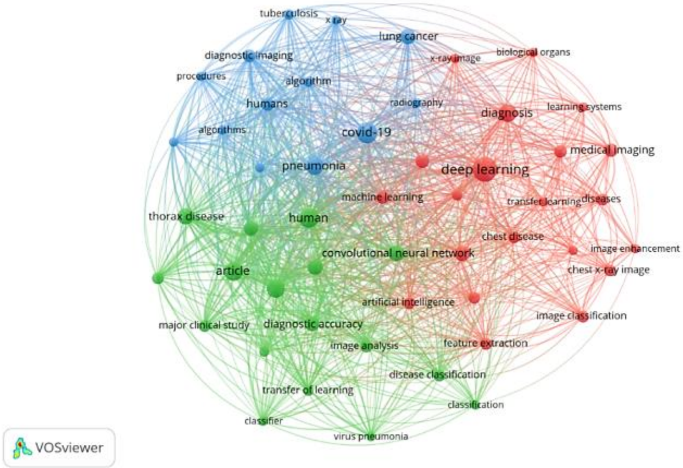

Figure 2. Visually Maps Occurrence Network

This section presents and discusses the findings of the systematic literature review based on the selected studies published between 2021 and 2025 that focus on deep learning-based disease detection and classification using chest X-ray imaging. The results are synthesized to highlight dominant research trends, commonly investigated diseases, learning tasks, model architectures, dataset characteristics, and evaluation practices reported in the literature. Rather than evaluating individual studies in isolation, this section provides a comparative analysis to identify recurring patterns and shared methodological directions across the reviewed works. The discussion further interprets these findings in the context of current research practices and clinical relevance, offering a comprehensive overview of the state-of-the-art in deep learning applications for chest disease analysis.

Based on the Table 1, it can be observed that research on chest X-ray–based lung disease classification and detection using deep learning is predominantly published in high-quality journals, particularly those ranked in Quartile 1 (Q1) and Quartile 2 (Q2). Most Q1 publications emphasize advanced deep learning architectures, such as optimized CNN models, hybrid approaches (CNN–Transformer, CoAtNet, EfficientDet), attention mechanisms, and the integration of explainable artificial intelligence (XAI) to improve diagnostic accuracy and model reliability for diseases including COVID-19, pneumonia, and tuberculosis.

Meanwhile, studies published in Q2 journals generally focus on segmentation–classification pipelines, multi-class classification frameworks, and the application of transfer learning to address limited or imbalanced medical datasets. In contrast, articles published in Q4 journals tend to employ more basic CNN architectures, few-shot learning, or simpler optimization techniques, which, although methodologically relevant, show relatively lower scientific impact. Overall, the distribution of journal rankings indicates that chest X-ray–based lung disease analysis is a well-established and competitive research area, with a clear trend toward more sophisticated methodologies and dissemination in higher-ranked journals.

Table 2 summarizes the distribution of the reviewed studies based on disease type, highlighting the primary pulmonary conditions addressed in deep learning–based chest X-ray research. The results show that a substantial number of studies focus on COVID-19, reflecting the rapid surge of research during the pandemic period and the urgent need for automated screening solutions. Pneumonia-related studies also constitute a significant portion of the literature, emphasizing its long-standing clinical relevance and the suitability of chest X-ray imaging for early detection. In contrast, tuberculosis-focused research appears less frequently, despite TB remaining a major global health concern, particularly in low- and middle-income countries. Notably, an increasing number of studies address multi-disease scenarios, where a single model is designed to classify more than two pulmonary conditions simultaneously. This trend indicates a shift toward more clinically realistic screening systems that aim to support comprehensive diagnosis rather than disease-specific detection.

Table 1. Results from Journal Ranking

Title	Journal Ranking	Citation
COVID-19 Classification on Chest X-ray Images Using Deep Learning Methods	Q1	[7]
Few-shot pneumonia detection using Siamese networks and transfer learning on chest X-ray images	Q4	[8]
Explainable AI hybrid CNN-transformer models for enhanced COVID-19 detection in chest X-rays	Q2	[9]

Title	Journal Ranking	Citation
CNN-Based Classification of Infectious Lung Diseases using Thorax X-Ray Analysis	Q4	[10]
Advanced chest X-ray image classification for early detection and treatment monitoring of respiratory conditions	Q2	[11]
A deep learning segmentation-classification pipeline for X-ray-based COVID-19 diagnosis	Q2	[12]
A multiclass deep learning algorithm for healthy lung, Covid-19 and pneumonia disease detection from chest X-ray images	Q2	[13]
Classification of COVID-19 chest X-Ray and CT images using a type of dynamic CNN modification method	Q1	[14]
Improving COVID-19 chest X-ray classification via attention based learning and fuzzy-augmented data diversity	Q4	[15]
EffiCOVID-net: A highly efficient convolutional neural network for COVID-19 diagnosis using chest X-ray imaging	Q1	[16]
A Hybrid Deep Learning CNN model for COVID-19 detection from chest X-rays	Q2	[17]
Optimized multi-dimensional attention spiking neural network for pneumonia detection in chest x-ray images	Q1	[18]
An experimental comparison of deep learning models for pneumonia classification from chest X-ray images	Q1	[19]
Pneumonia Detection from Chest X-ray Images Using Firefly Optimization Algorithm and Ensemble Deep Learning Models	Q4	[20]
Efficient Pneumonia Detection in Chest Xray Images Using Deep Transfer Learning	Q1	[21]
Pneumonia Detection from Chest X-Ray Images Using Deep Learning and Transfer Learning for Imbalanced Datasets	Q2	[22]
Deep Learning Models for Accurate Detection of COVID-19 Pneumonia from Chest X-Ray Images	Q2	[23]
Enhanced CoAtNet based hybrid deep learning architecture for automated tuberculosis detection in human chest X-rays	Q1	[24]
Tuberculosis chest X-ray detection using CNN-based hybrid segmentation and classification approach	Q1	[25]
Tuberculosis detection using deep and hybrid learning techniques using X-ray images	Q2	[26]
Classification of X-Ray Images Using Convolutional Neural Network and Automatic Hyper-Parameter Selection to Detect Tuberculosis (TB)	Q4	[27]
Deep Learning Classification of Tuberculosis Chest X-rays	Q4	[28]
OView-AI Supporter for Classifying Pneumonia, Pneumothorax, Tuberculosis, Lung Cancer Chest X-ray Images Using Multi-Stage Superpixels Classification	Q1	[29]
CXray-EffDet: Chest Disease Detection and Classification from X-ray Images Using the EfficientDet Model	Q1	[30]
Explanatory classification of CXR images into COVID-19, Pneumonia, and Tuberculosis using deeplearning and XAI	Q1	[31]
Deep learning improves physician accuracy in the comprehensive detection of abnormalities on chest X-rays	Q2	[32]
Deep Learning in Multi-Class Lung Diseases' Classification on Chest X-ray Images	Q1	[33]

Table 2. Disease Scope

Disease Type	Citation
Covid-19	[7], [9], [12], [14], [15], [16], [17], [23]
Pnemonia	[8], [18], [19], [20], [21], [22]
Tuberculocis	[24], [25], [26], [28]
MultiDisease (>2)	[13], [29], [30], [31], [33]

Table 3. Learning Task Formulation

Learning Task	Citation
Binary / Multi-Class Classification	[7], [13], [30], [33]
Few-Shot / Low-Data Learning	[8]
Segmentation + Classification Pipelines	[12], [25]
Efficiency-Oriented / Lightweight Models	[16], [24]
Esemble / Optimization Based	[20], [27]
Explainable AI (XAI)	[9], [31]
Clinical Decision Support	[29], [32]

Table 3 categorizes the reviewed studies based on model and algorithmic approaches for chest X-ray analysis. Most studies formulate disease detection as binary or multi-class classification, while a smaller number address data scarcity through few-shot learning. Segmentation-assisted classification and lightweight models are increasingly explored to improve feature focus and deployment efficiency. In addition, recent works incorporate explainable AI (XAI) and clinical decision support mechanisms, indicating a shift toward models that emphasize interpretability and practical clinical use.

Table 4. Model Architecture

Model/ Algorithm	Citation
Standard CNN (VGG, ResNet, DenseNet)	[7], [17], [21], [23]
Transfer Learning–Based CNN	[8], [11], [13], [22]
Hybrid CNN–Transformer	[9], [24]
Lightweight / Efficient Networks	[16]
Segmentation + Classification Pipelines	[12], [25]
Attention-Based / Optimization-Oriented Models	[15], [20]
Ensemble / Comparative Architectures	[10], [19]
Explainable AI (XAI)-Integrated Models	[9], [31]

Table 4 summarizes the reviewed studies according to their model architectures. Most works rely on standard CNN architectures such as VGG, ResNet, and DenseNet, often enhanced through transfer learning to improve performance on limited medical datasets. Recent studies increasingly explore hybrid CNN–Transformer models and lightweight architectures to balance accuracy and computational efficiency. In addition, segmentation-assisted pipelines, attention-based or optimization-oriented methods, and ensemble approaches are employed to enhance feature representation and robustness. The growing integration of explainable AI (XAI) further indicates a shift toward improving model transparency and clinical trust.

Table 5. Clinical Aspect

Clinical Aspect	Citation
Automated Screening / Triage	[7], [16]
Early Detection	[11], [22]
Treatment Monitoring / Severity	[11]
Clinical Decision Support	[29], [32]
Interpretability & Trust (XAI)	[9], [31]
Deployment in Resource-Limited Settings	[5], [16], [21]

Table 5 groups the reviewed studies based on their clinical aspects and application objectives. Most studies focus on automated screening and triage, aiming to accelerate initial diagnosis and reduce radiologist workload. Several works emphasize early disease detection, particularly for pneumonia, tuberculosis, and COVID-19, where timely intervention is critical. A smaller subset addresses treatment monitoring and disease severity assessment, mainly through enhanced feature localization and segmentation-based approaches. In addition, increasing attention is given to clinical decision support systems and interpretability through explainable AI (XAI) to improve clinician trust. Finally, the development of lightweight and efficient models highlights the importance of deployment in resource-limited settings, aligning with real-world clinical constraints.

Table 6. Quantitative Comparison of Representative Deep Learning Approaches for Chest X-ray–Based Disease Detection

Study	Disease Scope	Model Architecture	Dataset Characteristics	Reported Performance
[1]	Multi-disease (Pneumonia, TB, COVID-19)	DenseNet121 with Transfer Learning	Public dataset (7,135 images)	Accuracy: 78%; Recall: Pneumonia 0.99, TB 0.93, COVID-19 0.92
[3]	Multi-disease	Knowledge Distillation–Based CNN	Public datasets	Accuracy: 96.08%; Precision: 94%; Recall: 97%
[5]	Tuberculosis	Hybrid GhostNet–MobileViT	Two public datasets	Accuracy: 99.52% and 99.17%
[6]	Multi-disease	ResNet50	Public datasets	Precision, Recall, and F1-score ≈ 0.97–0.99; AUC ≈ 1.00
[9]	COVID-19	Hybrid CNN–Transformer with XAI	Public datasets	High diagnostic accuracy with improved interpretability
[16]	COVID-19	Lightweight CNN (EffiCOVID-net)	Public datasets	Competitive accuracy with significantly reduced model complexity

The quantitative comparison presented in Table 6 reveals several consistent patterns across the reviewed studies. Transfer learning–based CNN architectures demonstrate robust performance, particularly in single-disease classification tasks, with reported accuracy values commonly exceeding 90%. However, when extended to multi-disease screening scenarios, model performance becomes more variable, with accuracy ranging from approximately 78% to over 96%, reflecting increased task complexity and dataset heterogeneity. Lightweight and efficiency-oriented approaches, including knowledge distillation–based and hybrid architectures, achieve competitive diagnostic performance while substantially reducing computational complexity, underscoring their suitability for deployment in resource-constrained clinical environments. Meanwhile, hybrid CNN-Transformer and explainable AI-integrated models place greater emphasis on interpretability and clinical transparency, which may introduce additional computational overhead. Overall, these findings highlight an inherent trade-off between predictive performance, computational efficiency, and interpretability, thereby reinforcing the importance of standardized evaluation frameworks to facilitate fair, reproducible, and clinically meaningful comparisons across future studies.

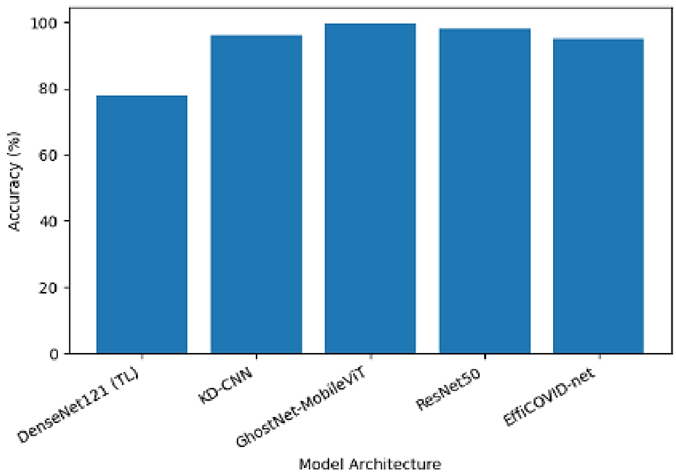

Figure 3. Comparison of Reported Accuracy Across Resresentive

As shown in Figure 3, lightweight and hybrid deep learning architectures generally achieve higher reported accuracy compared to conventional CNN-based multi-disease models. DenseNet121 with transfer learning exhibits relatively lower accuracy due to the increased complexity of multi-disease classification tasks. In contrast, knowledge distillation–based CNNs, hybrid GhostNet–MobileViT, and ResNet50 demonstrate superior performance, highlighting the effectiveness of architectural optimization and efficiency-oriented design. However, these performance differences should be interpreted cautiously, as variations in dataset size, disease scope, and evaluation protocols limit direct comparability across studies.

Overall, the findings of this review indicate that deep learning has become the prevailing approach for chest X-ray–based analysis of pulmonary diseases, particularly pneumonia, tuberculosis, and COVID-19. Most studies conceptualize disease detection as a classification task, with a growing emphasis on multi-disease screening frameworks that better reflect real clinical scenarios. These approaches are predominantly supported by CNN-based and transfer learning architectures, while recent research increasingly explores hybrid, lightweight, and segmentation-assisted models to address challenges related to data imbalance, computational efficiency, and deployment constraints. From a clinical perspective, the literature primarily focuses on automated screening and early detection, alongside rising attention to model interpretability through explainable AI and the development of clinical decision-support systems. Nevertheless, substantial variability in dataset selection, evaluation protocols, and limited clinical validation across studies underscores the need for more standardized and clinically oriented research, reinforcing the importance of systematic evidence synthesis in this domain.

4. CONCLUSION

This systematic literature review examined recent studies published between 2021 and 2025 that apply deep learning techniques to chest X-ray imaging for the detection and classification of pulmonary diseases, with a primary focus on pneumonia, tuberculosis, and COVID-19. The review confirms that deep learning particularly CNN-based and transfer learning approaches has become the dominant methodology for automated chest X-ray analysis due to its effectiveness in learning complex visual patterns. A clear shift toward multi-disease screening frameworks was observed, reflecting increasing alignment with real-world clinical diagnostic needs.

To address challenges such as class imbalance, limited annotated data, and heterogeneous imaging conditions, many studies have adopted hybrid architectures, lightweight models, and segmentation-assisted pipelines. In parallel, growing attention has been given to model efficiency and interpretability, highlighting the importance of explainable AI and clinical decision-support systems in facilitating practical deployment. However, this review also identifies substantial variability in datasets, evaluation protocols, and validation strategies, which constrains direct comparison and limits the generalizability of reported results.

Future research should therefore focus on establishing standardized evaluation frameworks, expanding multi-institutional and clinically diverse datasets, and advancing multi-label and cross-disease learning approaches, particularly for underrepresented conditions such as tuberculosis. Moreover, the integration of quantitatively validated explainable AI methods, alongside prospective clinical evaluation and physician-in-the-loop studies, is essential to bridge the gap between methodological development and real-world implementation. Collectively, these directions are expected to strengthen the clinical relevance and reliability of deep learning–based chest X-ray analysis and support its translation into robust diagnostic decision-support tools. In addition, representative quantitative comparisons further reveal performance trade-offs between predictive performance, computational efficiency, and model interpretability across different deep learning architectures.

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