Deep Learning for Early Detection of Pneumonia: Systematic Review

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Abstract - Pneumonia is a leading cause of illness and death worldwide, and early diagnosis is essential to improve patient outcomes. However, in many hospitals, the lack of advanced technology and the use of manual methods to detect the disease make accurate identification difficult. In this context, Deep Learning applied to the analysis of medical images, such as chest X-rays, is presented as a promising solution to improve both diagnostic speed and accuracy. This article reviews the literature on the use of Deep Learning models in early detection of pneumonia, showing that these models outperform or match the performance of expert radiologists. The PICOC methodology and the PRISMA diagram were used to select 30 relevant studies from the last five years. Although progress has been made, challenges remain, such as variable image quality and adaptation to different clinical contexts. The findings suggest that Deep Learning contributes to the reduction of diagnostic times and improves accuracy, but there are still areas to be improved for optimal integration into clinical practice. These tools are expected to become more adaptable and continue to improve their accuracy over time.

Keywords: Deep learning, Pneumonia, Early detection, X-rays

I. INTRODUCTION

Early detection of typical pneumonia remains a significant challenge in healthcare centers due to the lack of advanced equipment and the reliance on manual methods, which can lead to errors and delays in diagnosis [1]. The integration of **Deep Learning** techniques in the analysis of chest X-ray images has the potential to revolutionize this process by providing faster and more accurate diagnoses [2]. Deep Learning models can process large volumes of medical imaging data and detect subtle patterns that may not be visible to the human eye, enabling quicker and more precise identification of pneumonia [3]. Recent studies have shown that these models can achieve accuracy rates exceeding 90% in pneumonia detection, matching or even surpassing the performance of expert radiologists and significantly reducing the time required to reach a diagnosis [2], [3].

Despite advances in the implementation of Deep Learning for pneumonia detection, significant challenges remain to be addressed. Current models often struggle to adapt to variations in image quality and different clinical contexts, which can limit their performance in real-world scenarios [4]. Moreover, most models are not optimized to provide real-time diagnoses, which is crucial in situations where timely diagnosis can directly impact patient treatment [3].

These discrepancies and knowledge gaps highlight the need for a comprehensive review that explores the current capabilities and limitations of Deep Learning methods in the early detection of pneumonia. Proper implementation of this technology can significantly improve the accuracy and speed of medical diagnoses [4]. Therefore, it is essential to conduct a detailed analysis of the progress and challenges in this field to establish a solid foundation for developing new solutions and improvements.

This review aims to understand the applications and advancements of Deep Learning in the context of disease identification through medical imaging. The objective of this paper is to identify how Deep Learning has enhanced the accuracy and efficiency of diagnosing respiratory diseases such as pneumonia using chest X-rays [5], [6]. Pneumonia is a global public health crisis that primarily affects children under five and older adults [7]. Deep Learning models have demonstrated high accuracy, sensitivity, and specificity, making them reliable tools for distinguishing bacterial pneumonia from other viral and fungal infections [7].

Accordingly, this document is structured as follows: The second section, titled Methodology, presents the approach used to carry out the systematic literature review (SLR), detailing the research questions posed and the procedures followed to select the material analyzed in this report. For this purpose, we employed the PRISMA diagram, defined key questions using the PICOC framework, and established inclusion and exclusion criteria. A thorough search was conducted in the Scopus and Web of Science repositories. Studies were selected through screening and full-text evaluation, with data extracted and analyzed to better understand what has been researched so far and to identify areas that remain underexplored.

II. METHODOLOGY

A. PICOC

The PICOC methodology was used to structure information searches that are both efficient and specific. The first essential step is to clearly define the research question. This methodology involves identifying five key components: the Problem, the Intervention to be analyzed, the Comparison, the Outcome, and optionally, the Context, which allows for more precise identification of relevant data [8].

The research question formulated using this methodology is: *How does Deep Learning technology contribute to pneumonia detection compared to manual interpretation of chest X-rays by medical specialists?*

Subsequently, the research question was broken down into sub-questions related to the PICOC components:

RQ1: What types of data (medical images, electronic health records) are used in Deep Learning models for the early detection of pneumonia?

RQ2: What Deep Learning techniques are applied for data analysis and processing in the early detection of pneumonia?

RQ3: How does the effectiveness of Deep Learning models compare to traditional methods for early pneumonia detection?

RQ4: What is the accuracy and sensitivity of Deep Learning models in the early detection of pneumonia?

RQ5: In what settings are Deep Learning models used (health centers, clinics, hospitals), and how does the context influence the outcomes?

The following table identifies the four main components:

Table 1: PICO Words

P	Patients with signs of pneumonia	“pneumonia”
I	Deep Learning for pneumonia detection	“Deep Learning”
C	Manual interpretation of X-rays by medical specialists	"X-ray"
O	Accuracy in early pneumonia detection	“early detection” OR “early diagnosis”
C	Healthcare centers	clinic* OR hospital* OR "health center*"

Consequently, the search equation used in the Scopus and Web of Science (WOS) databases is as follows:
(“Deep Learning”) AND (“Early detection” OR “Early diagnosis”) AND (“Pneumonia”) AND (“X-ray”)

B. PRISMA

The PRISMA method was employed to conduct an effective search for the Systematic Literature Review (SLR). Published in 2009, the PRISMA Statement aims to assist researchers in writing detailed reports of their systematic reviews by providing transparency regarding the rationale for the review, the methods used, and the articles identified by the authors [9].

Regarding the inclusion and exclusion criteria, the following were considered:

Table 2: Inclusion and Exclusion Criteria

Inclusion	Exclusion
Conference papers and scientific journal articles were included. Publications from Saudi Arabia, India, China, the United Kingdom, the United States, Turkey, and Canada were included. Publications in Spanish and English were included.	Documents without a DOI were discarded. Documents that were not open access were excluded. Duplicates that emerged during the search and selection process were removed. Publications prior to 2020 were excluded.

In the initial identification phase, a total of 178 articles were identified through the Scopus (96 articles) and Web of Science (WOS) (82 articles) databases. Of these, 13 articles were removed prior to screening: 12 due to duplication and 1 marked as ineligible for other reasons, resulting in 165 articles for the initial screening.

During the screening stage, out of the 165 articles assessed, 115 were excluded for various reasons, leaving 50 articles for full-text retrieval. Among these, 1 article could not be retrieved, resulting in 49 articles being evaluated for eligibility.

Of these reports, 19 were excluded for the following reasons: 1 for lacking a DOI, 5 for not being open access, and 13 because the journal did not align with the focus of the review. Finally, in the inclusion phase, 30 publications were determined to be relevant and suitable for the review.

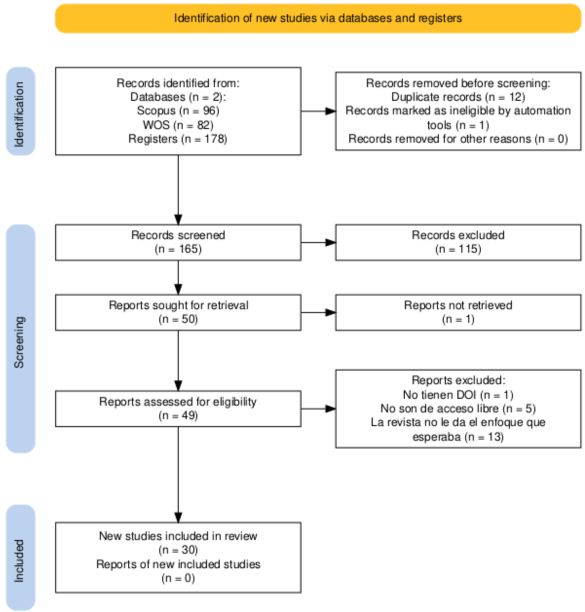

Figure 1: PRISMA Flow Diagram of the Selection Process

III. RESULTS

This section presents the findings derived from the analysis of the 30 selected articles. It begins with a description of the publication characteristics, quantifies the contribution of the articles to each research question, and finally, provides detailed answers to each of them.

The scientific production on this topic has shown sustained growth over the last five years, with a peak of 9 articles in 2024, reflecting a growing academic interest (see Fig. 2).

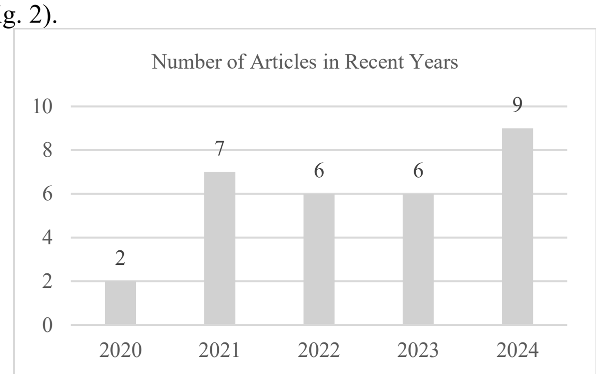

Figure 2: Number of Articles by Publication Year

Regarding the geographical distribution, India leads the research with 9 publications, followed by Saudi Arabia and Turkey. This international interest underscores the global relevance of artificial intelligence in the diagnosis of respiratory diseases (see Fig. 3).

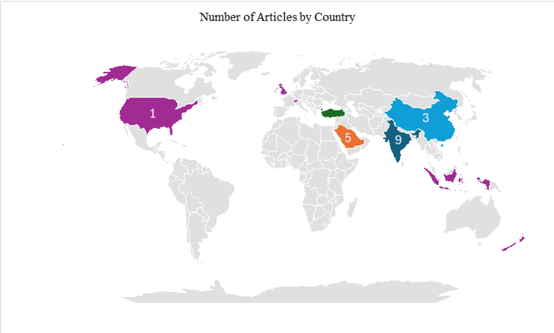

Figure 3: Number of Articles by Country

To identify the central concepts, the titles and keywords of the articles were processed, generating a word cloud. As shown in Fig. 4, prominent terms include “Deep Learning,” “Pneumonia,” and “X Ray,” confirming the focus of the research. (See Fig. 4).

Figure 4: Word Cloud of Keywords

To structure the findings, the number of articles that provided direct evidence to answer each research question was quantified, as summarized in the following table 3.

Table 3: Contribution of Articles to the Research Questions

Research Question	Number of Support Articles
RQ1: What types of data (medical images, electronic health records) are used in Deep Learning models for the early detection of pneumonia?	7
RQ2: What Deep Learning techniques are applied for data analysis and processing in the early detection of pneumonia?	16
RQ3: How does the effectiveness of Deep Learning models compare to traditional methods for early pneumonia detection?	9
RQ4: What is the accuracy and sensitivity of Deep Learning models in the early detection of pneumonia?	9
RQ5: In what settings are Deep Learning models used (health centers, clinics, hospitals), and how does the context influence the outcomes?	18

The analysis of the selected studies reveals consistent patterns in the application of Deep Learning for pneumonia detection. These patterns, ranging from performance metrics to preferred technological architectures, are summarized in the table below to provide a panoramic view of the current trends in the field. See Table 4.

Table 4. Summary of Patterns Found

Identified Pattern	Pattern Description	Key Evidence from the Review	Impact on Diagnosis
1. High-Accuracy Performance	There is a consensus that Deep Learning models achieve very high levels of accuracy and sensitivity, often exceeding 90%.	•Accuracy: Reported at 97% (ACNN-RF), 95.6% (VGG16), and 90.6% (Sharma et al.). •Sensitivity: Consistently reported as higher than 88%, indicating a strong capability to identify positive cases.	Increases the reliability of AI-assisted diagnosis, significantly reducing the rates of false negatives and false positives.
2. Dominance of Convolutional Neural Networks (CNNs)	The Convolutional Neural Network (CNN) architecture is the dominant and most effective technological approach for analyzing X-ray images.	•16 of the 30 articles (the majority) focus on CNN-based Deep Learning techniques. •Recurring mention of specific models such as VGG16, ResNet50, and MobileNet.	Establishes CNNs as the de facto standard for developing radiological diagnostic tools, demonstrating their superiority over older image analysis methods.
3. Superiority over Traditional Methods	AI models are not only accurate, but their effectiveness is consistently superior to that of conventional (non-expert) diagnostic methods.	•AI models are reported to exceed the specificity of traditional methods (which typically range from 80-90%). • Ability to detect subtle patterns that might be missed in an initial manual evaluation.	Accelerates the triage process and provides a near-instantaneous second opinion, optimizing specialists' time and reducing their workload.
4. Use of Transfer Learning	A recurring strategy is to adapt models pre-trained on large image databases (such as ImageNet) for the specific task of pneumonia detection.	•The study by Chouhan et al. (2020) explicitly focuses on transfer learning. •The use of well-known architectures like VGG16 and ResNet50 implies this technique.	Drastically reduces the development time and the amount of data required to train an effective model, thereby democratizing access to this technology.
5. Centrality of Chest X-Rays (CXR)	The primary and almost exclusive data source for training and validating the models is chest X-rays.	•The term "X Ray" is one of the most prominent in the keyword word cloud (Fig. 4). •RQ1 confirmed that CXRs are the main data type, mentioned in 7 key articles.	Ensures that AI solutions can be easily integrated into existing clinical workflows, which already rely heavily on chest X-rays.

This section will address the research questions based on the findings obtained from the reviewed articles.

RQ1: What types of data (medical images, electronic health records) are used in Deep Learning models for the early detection of pneumonia?

Deep Learning models for early pneumonia detection primarily use medical images, with chest X-rays (CXR) being the most common [1], [2], [7], [10], [11]. These images are essential for training and evaluating the models, as they allow the identification of patterns associated with pneumonia that may be difficult to detect with the naked eye. For example, models are trained using X-rays from patients diagnosed with pneumonia, and image enhancement techniques such as data augmentation are applied to optimize the classification process and increase the diversity of the training set [1], [2], [10].

In addition to X-rays, some studies also incorporate computed tomography (CT) scans as a complementary tool for detecting pulmonary abnormalities. These multimodal approaches enable more accurate and comprehensive evaluations, as CT images can provide a more detailed view of the internal lung structures, which is critical for diagnosing complex cases [11], [12], [13]. Figure 5 shows the proportion of use of Deep Learning models in pneumonia detection.

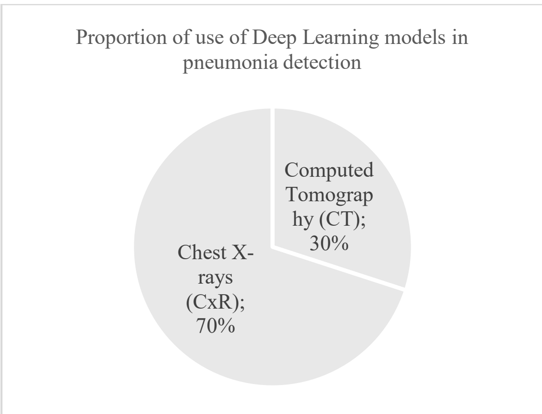

Figure 5: Frequency of Use of Data Types in Deep Learning Models for Pneumonia Detection

RQ2: What Deep Learning techniques are applied for data analysis and processing in the early detection of pneumonia?

Various Deep Learning techniques are applied in the early detection of pneumonia, with one of the most prominent being the use of Convolutional Neural Networks (CNNs) [1], [2], [3], [4], [7], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]. These networks are highly effective in processing and analyzing X-ray images due to their ability to identify patterns at different levels of abstraction. CNNs enable detailed feature extraction from chest radiographs, contributing to more accurate detection.

As detailed in Table 3, advanced architectures such as VGG16, ResNet50, and NASNet have been used in several studies, proving particularly useful due to their generalization capabilities and accuracy in image classification [14], [15], [17]. Additionally, some approaches combine CNNs with optimization and image enhancement techniques, such as data augmentation and normalization. These techniques help expand and balance datasets, making the models more robust to variability in images and clinical contexts, thereby improving overall model performance [16].

Table 5: Architectures of the CNN Technique

Architecture	Accuracy (%)	Additional Techniques	Dataset Size
VGG16	93.88	Data Augmentation	10000 Images
ResNet50	98.14	Normalization	15000 Images
NASNet	95.2	Data Augmentation and Normalization	20000 Images

RQ3: How does the effectiveness of Deep Learning models compare to traditional methods for early pneumonia detection?

Deep Learning models outperform traditional methods in the early detection of pneumonia [21], [22], [23], [24], [25], as shown in Figure 6, often achieving sensitivity and specificity levels above 88%, compared to traditional methods, which typically reach specificity levels between 80% and 90% [21], [22], [23], [26], [27], [28]. Moreover, techniques such as Grad-CAM enhance the interpretability of results, facilitating the diagnostic process [23], [29].

Examples like ACNN-RF and VGG16, known for their enhanced data analysis capabilities and high-detail image classification, demonstrate how these architectures can process complex patterns in chest X-ray images [24], [26]—something that is often difficult for traditional methods.

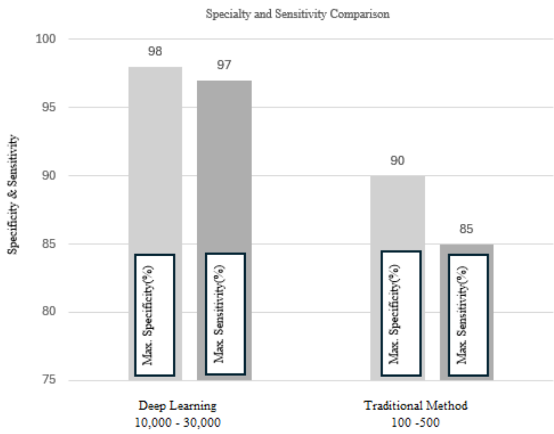

Figure 6: Comparison of Sensitivity and Specificity of Traditional Methods vs. Deep Learning

RQ4: What is the accuracy and sensitivity of Deep Learning models in the early detection of pneumonia?

The accuracy and sensitivity of various Deep Learning models and their derivatives are often higher than commonly expected [27], [28], [30], [31], [32]. Models such as ACNN-RF, which combines neural networks with advanced classification techniques, achieve up to 97% accuracy in identifying patterns in X-ray images, demonstrating their ability to detect subtle details that are typically imperceptible to the human eye [24]. Similarly, models like VGG16, which uses Grad-CAM to visualize and enhance result interpretability, have achieved 95.6% accuracy at their lowest performance point [23].

Both models stand out for their high sensitivity, exceeding 88%, and a margin of error between 1% and 5% [23], [24], indicating their effectiveness in correctly identifying both positive and negative pneumonia cases. Other models, such as MobileNet and ResNet50, optimized with data augmentation, can accurately and rapidly identify complex patterns in medical images, such as pneumonia indicators. MobileNet is specifically designed to perform well on low-resource devices, such as mobile phones, by reducing computational requirements [25], [27], [29]. Therefore, the implementation of Deep Learning models is highly valuable in healthcare, enabling accurate and accessible diagnoses across various settings.

RQ5: In what settings are Deep Learning models used (health centers, clinics, hospitals), and how does the context influence the results?

Deep Learning models are increasingly being used in health centers, clinics, and hospitals to make medical diagnoses faster and more accurate [5], [18], [21], [22], [23], [24]. These models are especially useful in fields such as radiology and medical image analysis, as they can identify complex patterns in X-rays, CT scans, and MRIs [3], [4], [6], [10], [14], [18], [19], [21], [29].

As shown in Figure 7, models like ACNN-RF, ResNet50, and VGG16 have demonstrated high accuracy in pneumonia detection, reaching between 93.88% and 98.14% [5], [27]. However, the effectiveness of these models depends heavily on the context in which they are applied. In environments with strong infrastructure, access to complete datasets, and trained personnel, the models can deliver excellent results—accelerating disease detection and improving patient care [3], [5], [7], [10], [12], [14], [19], [24], [26], [27], [28]

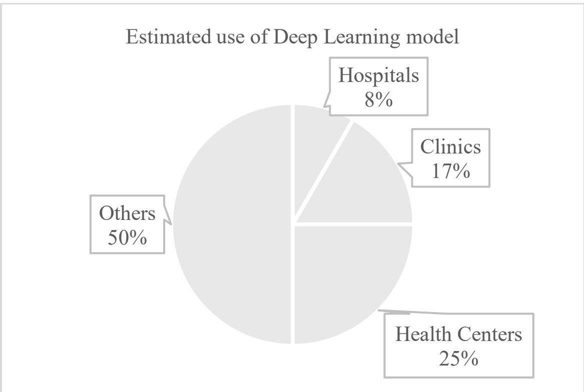

Figure 7: Number of Uses of the Deep Learning Method in Different Environments

A. How does deep learning technology contribute to pneumonia detection compared to manual X-ray interpretation by medical specialists?

Deep learning technology significantly enhances pneumonia detection, delivering faster and more accurate diagnoses compared to manual X-ray interpretation by medical specialists [6], [7], [10], [14]. By efficiently processing large datasets of medical images, deep learning models identify subtle patterns in chest X-rays that are often challenging for the human eye to discern. This capability stems from the ability of deep learning models, such as Convolutional Neural Networks (CNNs) and other advanced algorithms, to learn from diverse examples, achieving accuracies exceeding 90% in pneumonia detection and performing comparably to expert radiologists [10], [14]. See Fig. 8.

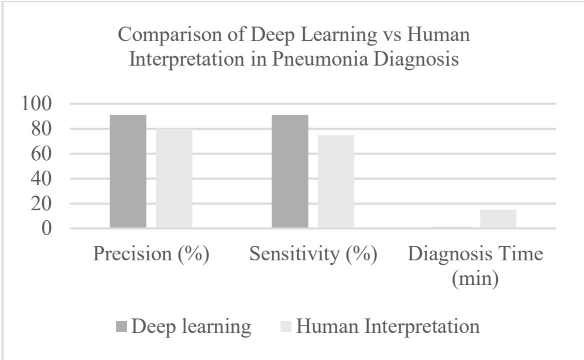

Figure 8: Comparison of Deep Learning vs. Manual Interpretation in Pneumonia Diagnosis

This advanced analytical capability directly impacts patient treatment, as rapid diagnosis is critical for initiating early interventions, particularly in severe cases or for high-risk groups such as children and older adults [1], [6], [7], [10]. Moreover, in regions with limited access to radiologists, such as rural communities or developing countries, deep learning models offer a viable and accessible solution to enhance healthcare delivery and reduce pneumonia-related mortality rates. This positions the integration of deep learning technology into clinical practice as a valuable tool for optimizing both diagnostic accuracy and speed [1], [6].

As further studies are conducted and models are refined, deep learning technology is expected to not only support but also complement the clinical decisions of specialists, reducing workload and minimizing error margins in the detection of pneumonia and other pulmonary diseases.

IV. DISCUSSIONS

This systematic literature review has highlighted that Deep Learning models are significantly transforming pneumonia diagnosis through the analysis of medical images. These models—particularly Convolutional Neural Networks (CNNs)—have demonstrated outstanding capabilities in processing and analyzing large volumes of imaging data, identifying complex patterns with accuracy rates exceeding 90% in various reviewed studies [7], [14], [21]. This high level of accuracy not only matches but, in some cases, surpasses the performance of expert radiologists, underscoring their relevance as complementary tools in clinical practice [10], [23].

The analysis of the studies reveals that advanced architectures such as ResNet50 and VGG16 are the most used due to their generalization capabilities and robustness in image classification. For instance, ResNet50 achieved an accuracy of 98.14%, while VGG16, when combined with techniques like Grad-CAM to enhance interpretability, reached 95.6% accuracy [23], [24]. Additionally, some approaches employed optimizations such as data augmentation and normalization, improving performance in contexts where image quality varies [15], [27]. However, technological limitations—such as the lack of real-time diagnostic optimization—were identified as factors affecting performance in critical clinical scenarios [14], [18].

On the other hand, the use of lightweight models like MobileNet, designed to operate on devices with limited resources, has facilitated the implementation of this technology in rural regions or areas with poor healthcare infrastructure [24], [25], [27]. This reinforces the potential of Deep Learning to reduce inequalities in access to advanced medical diagnostics, especially in developing countries or remote areas far from urban centers [6], [12]. The ability of these models to integrate into diverse environments positions Deep Learning as a scalable and complementary solution to address the pneumonia crisis, particularly among vulnerable populations such as children and the elderly [11], [14].
Nonetheless, important challenges remain. For example, the reliance on high-quality radiographic images limits applicability in healthcare centers lacking modern equipment. Likewise, variability in clinical data can lead to inconsistencies in results, especially when models are trained on datasets that do not adequately represent real patient conditions [3]. Despite these obstacles, the use of Deep Learning for early pneumonia detection has shown tangible benefits in optimizing diagnostic times and improving overall accuracy, significantly reducing the workload of healthcare professionals [21], [24].

Recommendations for Implementation and Future Research. Based on the patterns and challenges identified in the literature, transitioning Deep Learning models from research environments to effective, real-time clinical implementation requires addressing several technological obstacles. The following strategies and concrete recommendations are proposed to guide future research and development.
1. Detailed Strategies for Achieving Real-Time AI
Real-time diagnosis is critical for the tool to be useful in a high-demand clinical setting. A delay of several minutes per image would make its adoption unfeasible. See Table 6.

Table 6: Challenges of AI

Inference Model Optimization	•Lightweight Architectures: Instead of relying solely on heavy models like VGG16 or ResNet50, research should focus on adapting lighter architectures designed for efficiency, such as MobileNetV3, EfficientNet-Lite, or SqueezeNet. These models offer an excellent balance between accuracy and inference speed, making them ideal for rapid responses. •Quantization & Pruning: Applying post-training techniques such as quantization, which reduces the numerical precision of the model's weights, can accelerate inference by up to 3x with minimal loss of accuracy. Pruning removes redundant neural connections, reducing the model's size and computational load.
Hardware Acceleration and Edge AI	•GPU and TPU Inference: For fast, centralized processing, models must be optimized to run on Graphics Processing Units (GPUs) or Tensor Processing Units (TPUs), which can process multiple images in parallel. •Edge Devices: For healthcare centers with limited connectivity or requiring instantaneous responses, implementation on Edge AI devices (such as NVIDIA Jetson or Google Coral) is essential. This allows the analysis to be performed locally at the medical facility, eliminating network latency.
Data Pipeline Optimization	•An efficient image processing pipeline should be designed where loading, pre-processing (normalization, resizing), and model inference tasks run asynchronously and in parallel to prevent bottlenecks.

2. Overcoming Technological Obstacles with Tangible Recommendations
For AI to become a robust and reliable tool, it must overcome the following practical challenges. See Table 7.

Table 7: Specific recommendations

Technological Obstacle	Tangible Recommendations to Overcome It
1. Variability in Image Quality and Data Heterogeneity	•Adaptive Pre-processing Module: Implement a standardized pre-processing module that automatically applies techniques such as histogram equalization to normalize contrast and noise reduction filters to improve the quality of low-resolution images. •Realistic Data Augmentation: During training, use data augmentation techniques that simulate real-world imperfections: variations in brightness, slight rotations, image artifacts, and different exposure levels. This makes the model more robust.
2. Integration with Existing Clinical Systems (PACS, RIS, EMR)	•Standards-Based Development: Build the solution using medical interoperability standards such as DICOM for imaging and HL7/FHIR for integration with Electronic Medical Records (EMRs). •Creation of an Interoperable API: Encapsulate the AI model within a secure RESTful API that can be easily integrated by Picture Archiving and Communication Systems (PACS) and Radiology Information Systems (RIS). •"Human-in-the-Loop" Workflow: Propose a workflow where the AI does not replace the radiologist but acts as a triage tool. The system can automatically flag suspicious X-rays with a high degree of confidence and prioritize them in the specialist's worklist.
3. Model Generalizability and Hidden Biases	•External and Federated Validation: Train and validate models using data from multiple healthcare centers (different hospitals, countries, and demographics) to ensure the model generalizes well and is not biased toward a specific population or type of X-ray equipment. •Bias Auditing: Implement auditing tools (such as IBM's AI Fairness 360) to detect and mitigate biases related to patients' age, gender, or ethnicity throughout the model's lifecycle. •Continuous Monitoring and Retraining: Once deployed, the model's performance must be continuously monitored. A cycle of periodic retraining with new, verified data should be established to prevent model drift over time.

Implementing these strategies will not only enhance the technical feasibility of AI solutions for pneumonia detection but also accelerate their safe and effective adoption in real-world clinical settings.

V. CONCLUSIONS

The results of this systematic literature review, based on 30 selected articles, show that the use of Deep Learning, particularly through Convolutional Neural Networks (CNNs) and advanced architectures such as ResNet50, VGG16, and NASNet, is highly effective for the early detection of pneumonia in healthcare settings. These technologies have demonstrated accuracy rates exceeding 90% in interpreting chest X-rays, enabling fast and reliable diagnoses. Furthermore, their integration with data optimization techniques and classification algorithms makes them key tools for addressing diagnostic challenges in resource-limited environments.

Challenges in implementing these technologies in clinical settings include the required image quality, the lack of adequate technological infrastructure in some regions, and the initial costs involved. Variability in clinical data can also hinder the generalization of these models, affecting their performance in environments with limited technological standards. Despite these obstacles, the adoption of Deep Learning for improving medical diagnosis remains a promising option, as it can reduce diagnostic times and improve accuracy, even in low-resource areas.

The effective implementation of these technologies depends on overcoming the barriers by improving infrastructure, training, and adapting models to different clinical environments. Over time, these tools are expected to better adapt to diverse contexts and continue to improve in accuracy. This will allow their expansion to more healthcare centers, contributing to more efficient and equitable medical care, and significantly transforming the diagnosis and early detection of pneumonia on a global scale.

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