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Systematic Literature Review of Transfer Learning for Pneumonia Classification in Chest X-Rays

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Abstract

Diagnosis of pneumonia through manual interpretation of Chest X-Ray (CXR) images is often hampered by observer subjectivity and radiologist fatigue, which can potentially lead to misdiagnosis. This study aims to evaluate the effectiveness and development trends of Transfer Learning techniques, particularly the ResNet, VGG, and DenseNet architectures, in pneumonia classification through the Systematic Literature Review (SLR) method. In accordance with the PRISMA protocol, the search was conducted in the Scopus database from 2021 to 2025, yielding 76 articles that met the inclusion criteria. Bibliometric analysis shows that the publication trend, initially triggered by the urgency of the pandemic, has now shifted to a phase of technological maturity, with a focus on integrating Explainable AI (XAI) to address black-box problems. Geographically, research contributions are dominated by institutions in Asia and the Middle East. The main findings confirm that Transfer Learning can significantly improve diagnostic accuracy and initial screening efficiency compared to conventional methods. However, challenges such as data imbalance and the need for clinical validation remain obstacles. This study concludes that the future of computer-assisted diagnosis systems depends on improving model transparency to support precise and reliable Clinical Decision Support Systems (CDSS).

Keywords: Chest X-Ray, Deep Learning, Pneumonia, Systematic Literature Review, Transfer Learning.

1. INTRODUCTION

Medical image processing has become a fundamental element of the modern digital health ecosystem, particularly in diagnostic radiology. This technology enables the transformation of raw images from modalities such as X-rays, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI) into clearer visual representations, which in turn support accurate disease detection [1]. In the context of lung disease, Chest X-Ray (CXR) remains the most frequently used imaging modality, thanks to its wide availability, low cost, and speed of data acquisition. This makes it a crucial instrument in the initial screening of respiratory disorders in various healthcare facilities [2].

Pneumonia, an acute respiratory tract infection, remains a leading cause of global morbidity and mortality, particularly among children and the elderly. The manual diagnosis of pneumonia through visual interpretation of Chest X-Ray is often influenced by radiologist subjectivity, eye fatigue, and inter-observer variability, which can lead to misdiagnosis [3]. Therefore, the application of Deep Learning techniques, particularly the Transfer Learning method, in computer-aided diagnosis (CAD) systems is a highly important solution. This approach allows the system to learn from complex visual patterns of the disease, thereby improving sensitivity and specificity in the early detection of pneumonia [4].

Despite the great clinical potential of Transfer Learning, several technical challenges need to be overcome. The main challenges include class imbalance in medical datasets, image quality variations due to differences in X-ray machines across hospitals, and the risk of overfitting in models trained with limited data [5]. In addition, the “black-box” nature of Deep Learning algorithms often undermines clinical trust, as the model's decisions are difficult to explain medically, posing a significant obstacle to the application of this technology in real clinical settings.

Rapid advances in artificial intelligence (AI), however, have led to more efficient and sophisticated Convolutional Neural Networks (CNN) architectures. Through Transfer Learning, these models can overcome the limitations of medical data by leveraging weights trained on large datasets such as ImageNet [6]. Thus, these algorithms can extract hierarchical features from lung images with high accuracy, without requiring training from scratch, enabling the development of robust diagnostic models even with limited computational resources [7]. Various leading Deep Learning architectures, such as ResNet, VGG, and DenseNet, have been widely applied in this domain for specific tasks, ranging from binary classification to multi-class scenarios, as well as for lung infection segmentation [8]. For example, the DenseNet model has proven effective in overcoming the vanishing gradient problem in deep networks, while VGG is known for its ability to extract detailed texture features, both of which are crucial for distinguishing subtle lung opacities in X-ray images [9].

Furthermore, the future of image processing in pneumonia diagnosis is promising, driven by the emergence of Explainable AI (XAI) and the integration of lightweight models for mobile devices. XAI technology is expected to revolutionize diagnostic transparency by providing visualizations of infected areas, such as heatmaps, which will enhance collaboration between AI and medical professionals [10].

However, despite the abundance of primary studies proposing various Transfer Learning models for pneumonia detection, the current literature remains highly fragmented. The main problem is that existing reviews often lack a focused comparison on how specific leading architectures (ResNet, VGG, and DenseNet) address real-world clinical challenges, particularly the transition from mere accuracy metrics to actual clinical explainability and robustness against dataset variations. Without a synthesized overview, it is difficult for researchers and healthcare providers to determine which specific Transfer Learning strategy is truly optimal and ready for deployment.

Therefore, the objective of this Systematic Literature Review (SLR) is to systematically identify, analyze, and synthesize research related to the performance of Transfer Learning techniques (specifically ResNet, VGG, and DenseNet) in Chest X-Ray-based pneumonia classification. This SLR firmly aims to map algorithm development trends from 2021 to 2025, evaluate implementation challenges, and explicitly address the research gaps needed to create a more precise and explainable diagnostic system. The results of this SLR are expected to provide a strong, evidence-based foundation for the development of CAD models that are fully prepared for implementation in future clinical practice.

2. LITERATURE REVIEW

The fundamental problem in diagnosing pneumonia on radiography is the visual ambiguity between lung conditions, which makes manual differentiation difficult, and the limited accuracy of conventional methods, which are prone to subjective interpretation. Responding to these diagnostic challenges, [11] proposed a Deep Learning approach based on transfer learning by evaluating the MobileNetV2, VGG-16, and ResNet50V2 architectures trained on a dataset of 5,863 X-ray images through data augmentation and regularization mechanisms to mitigate overfitting. Empirical results indicate that the MobileNetV2 model achieved the best performance with 92% accuracy, outperforming the ResNet50V2 and VGG-16 architectures, and demonstrating the effectiveness of automatic feature extraction for distinguishing pneumonia from normal conditions. However, although the developed system offers an efficient solution to address the scarcity of radiologists in resource-limited regions, reliance on a dataset sourced from a single institution has the potential to limit the generalization of the model to a broader population thus, further research is recommended to integrate the transformer architecture to improve clinical precision.

[3] identified crucial diagnostic challenges in distinguishing Covid-19, bacterial pneumonia, and viral pneumonia due to the ambiguity of visual features in Chest X-Ray images and the limited accuracy of conventional manual detection methods. To address these issues, the study developed a hybrid Deep Transfer Learning model that integrates the Inception module as a feature-extraction preprocessor with a pre-trained VGG-16 architecture and applies the Scaled Exponential Linear Units (SELU) activation function to overcome the problems of vanishing gradients and dying neurons. The empirical results show that the proposed model achieves superior performance in binary classification (accuracy of 99.95%) but declines to 87.32% in a four-class classification scenario, although it still outperforms comparison models such as ResNet and Inception-Net. However, although the hybrid approach proved effective in overcoming data scarcity through augmentation and transfer learning, the disparity in accuracy between binary and multi-class classification indicates the need to explore larger datasets and more complex computational architectures to improve the precision of differential diagnosis.

[1] identified diagnostic obstacles in Chest X-Ray images due to low contrast, artifacts, and intensity inhomogeneity, as well as the weakness of predecessor algorithms that tend to eliminate details in areas with high opacity such as pleural effusion. Responding to these challenges, this study developed PACE 2.0, a hybrid image processing pipeline that integrates FABEMD decomposition, non-local means denoising, gamma correction, and Contrast Limited Adaptive Histogram Equalization (CLAHE) optimized through a Multi-Objective Optimization mechanism. The experimental results show that this method improves the Contrast Improvement Index (CII) by 35% and significantly boosts the performance of the Deep Learning DenseNet-121 model in pneumonia classification, increasing accuracy from 80% to 94% and recall to 97%. Although this study confirms that PACE 2.0 not only outperforms standard methods such as AGCWD and CLAHE in quantitative metrics but also effectively mitigates saturation artifacts in vital structures, it has the

potential to become a crucial clinical decision-support tool in healthcare facilities with limited access to CT scans.

[12] identified the main challenges in automated lung disease diagnosis, namely the high dimension of redundant features and the limited accuracy of conventional methods, which are often time-consuming and prone to errors. To address these issues, the study developed a CNN model optimized using the Firefly Algorithm (FA) metaheuristic algorithm to select the most relevant luminescence features from X-ray images before processing them with a modified VGG-16 architecture with an additional dense layer. Empirical results show that integrating this feature selection strategy significantly reduces data dimensionality and achieves a multi-class classification accuracy of 99.3% (COVID-19, pneumonia, pulmonary opacity, and normal), outperforming other state-of-the-art models such as InceptionV3 and ResNet50. Although this hybrid approach has been proven effective in minimizing false positives and improving computational efficiency, the study's limited scope to frontal X-ray images underscores the need for further validation across three-dimensional imaging modalities, such as CT scans, to expand its clinical applicability.

[13] identified the urgency of developing automated diagnostic methods due to the low sensitivity of RT-PCR tests (60-70%) and the scarcity of radiologists, which hinders the rapid and accurate interpretation of medical images in resource-limited areas. In response to these issues, this study applied transfer learning using pre-trained CNN architectures, namely ResNet50 and InceptionV3, trained on a dataset of 1,109 X-ray images for multi-class classification (COVID-19, pneumonia, and normal). Interpretation of the experimental results shows that the InceptionV3 model achieved superior performance with 98.20% accuracy and 100% sensitivity, slightly outperforming ResNet50, which recorded 97.29% accuracy with high specificity of 99.41%. This study confirms that the proposed system has great potential as an efficient initial screening tool (assistive intelligence), but the relatively small size of the public dataset is a major limitation that requires further validation using a larger database to ensure the robustness and generalization of the model in real clinical scenarios. Definition of pneumonia classification in Chest X-Ray from various sources can be seen in Table 1.

Table 1. Definition of Pneumonia Classification in Chest X-Ray

No	Defintion Pneumonia Classification in Chest X-Ray	Referensi
1	This classification uses a neutrosophic set approach (True, False, Indeterminacy) to reduce image ambiguity and, through a deep learning model, extract lung opacity features to distinguish between infection types (normal, viral, bacterial, COVID-19).	[14]
2	This system applies a transfer learning approach to the trained VGG-19 architecture to classify chest X-ray images into COVID-19, Pneumonia, and Healthy categories, and utilizes a MongoDB database for efficient storage.	[15]
3	This method uses the ResNet-50-based CIDICXR-Net50 model with transfer learning techniques for ternary classification (COVID-19, viral pneumonia, normal) on a large dataset, while also exploring the risk relationship between COVID-19 and diabetes.	[16]
4	This classification compares CNN models trained from scratch with transfer learning models (VGG16, InceptionResNet) to detect lung disease and uses Grad-CAM to verify the learned pathological visual features.	[8]
5	This automated framework uses a trained DenseNet network with a feature concatenation approach from various dense blocks to extract multiscale information for accurate pneumonia detection and diagnosis.	[17]
6	This model modifies the ResNet50 architecture with the Squeeze-and-Excitation attention mechanism, Ranger optimizer, and adaptive Mish activation for multi-class classification, and uses Explainable AI to visualize saliency maps in abnormal areas.	[10]
7	This approach proposes a lightweight artificial neural network (LW-CBRGP-Net) that combines CBR blocks and global average pooling to perform multi-class and binary classification of X-ray images at low computational cost.	[18]
8	This study applies the pre-trained DenseNet-121 deep learning model with transfer learning and data augmentation techniques to diagnose COVID-19, viral pneumonia, and normal conditions in a limited image dataset.	[19]
9	This study compares the performance of four established CNN models (AlexNet, GoogleNet, ResNet-18, SqueezeNet) for automatically classifying chest X-ray images into COVID-19, bacterial pneumonia, viral pneumonia, and normal categories.	[20]
10	This smart healthcare system combines feature vectors from the VGG-19 and Inception-V3 architectures and applies multi-logistic regression feature selection for the automatic screening of infectious diseases such as pneumonia and COVID-19 in X-rays.	[21]

3. MATERIALS AND METHOD

A SLR that integrates a bibliometric approach aims to analyze the literature quantitatively, focusing on identifying trends, patterns, and key research entities in medical informatics. This approach adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, ensuring a comprehensive and replicable literature review. The inclusion criteria used in the literature screening process included: (1) articles indexed in the Scopus database as of December 23, 2025, (2) publications written in English, and (3) articles that specifically discussed the classification of pneumonia in chest X-ray images -ray images using Transfer Learning techniques, with a focus on model architectures such as ResNet, VGG, or DenseNet.

The bibliometric analysis was carried out using VOSviewer software to visualize bibliographic data, enabling analysis of citation networks, author collaborations, and frequently co-occurring keywords. This approach aims to reveal the intellectual structure and dynamics of Deep Learning applications in radiology. The combination of bibliometric analysis and SLR provides an important contribution by helping researchers synthesize empirical findings on model performance and map the rapidly developing research landscape in this field.

The integration of these two approaches enriches our understanding of the evolution of the algorithms used, the historical path of technology implementation, and the future direction of CAD. The initial stage of this scientific examination involved the rigorous selection of keywords using a top-down approach, starting with a broader search and then narrowing to more focused studies.

In response to the limitations of previous studies, which were too general in nature, this study specifically included keywords such as “Pneumonia,” “Chest X-Ray,” “Classification,” and the model architectures “ResNet,” “VGG,” and “DenseNet” as the main focus in the search for article titles, abstracts, and keywords. The Scopus database was chosen as the primary data source due to its broad coverage of engineering and computer science literature, enabling identification of current research trends and valid comparisons of model accuracy. SLR information flow using Prisma can be seen in Figure 1.

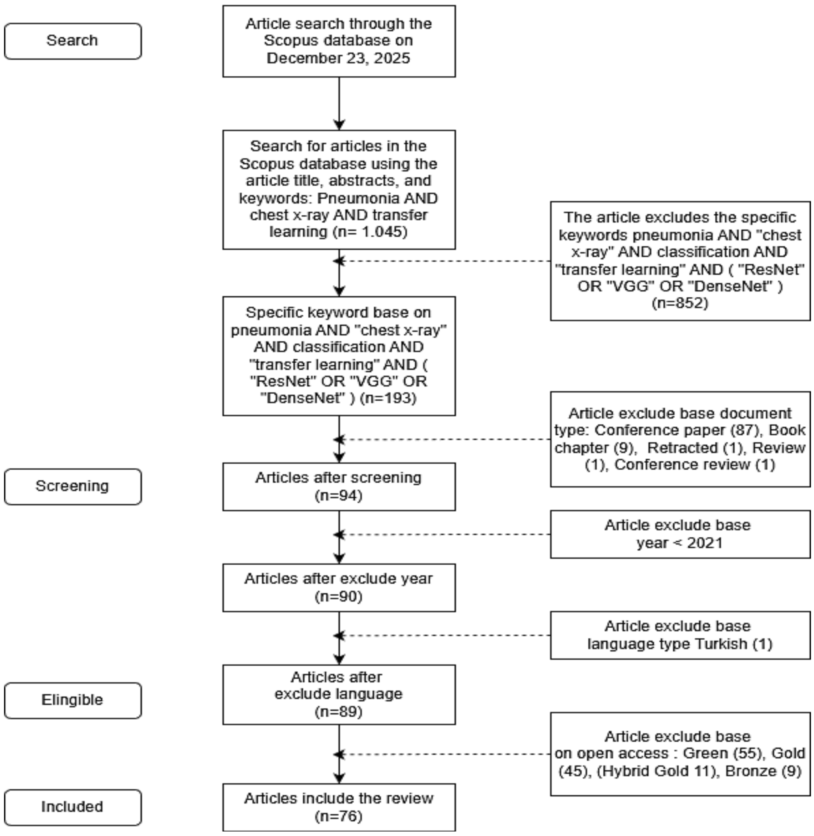

Figure 1. Systematic Literature Review Information Flow using Prisma

Referring to the PRISMA flow chart, a systematic literature search was initiated on December 23, 2025, through the Scopus indexed database. In the initial identification stage, the use of the fundamental keyword sequence “Pneumonia AND chest x-ray AND transfer learning” successfully identified 1,045 articles. The rationale behind this broad initial search was to capture a comprehensive, overarching pool of literature at the intersection of the target disease, imaging modality, and the primary artificial intelligence technique before applying strict filtering. Next, the search strategy was refined to improve the precision of the results by adding specific classification syntax and model architectures, namely “classification” AND (“ResNet” OR ‘VGG’ OR “DenseNet”). This keyword specification process significantly reduced the volume of data and eliminated irrelevant articles, leaving 193 articles that specifically focused on comparing these Deep Learning models.

The advanced screening stage was carried out by applying strict, systematic exclusion criteria to the article metadata. First, screening based on document type was performed by eliminating conference papers (87), book chapters (9), retracted articles (1), and review articles (2) to ensure that the references used were strictly original journal articles, leaving 94 articles. Second, temporal limitations were applied by excluding publications prior to 2021 to ensure the novelty of the technology, leaving 90 articles. Third, linguistic selection was performed by excluding Turkish-language literature, leaving 89 English-language articles. Finally, filtering based on document access categories was applied, resulting in a final corpus of 76 articles that met all the eligibility criteria. Ultimately, this multi-tiered, criteria-driven exclusion strategy demonstrates a highly rigorous, transparent, and reproducible methodological framework, ensuring that the final 76 selected articles represent the most valid and precisely relevant literature available. Furthermore, these documents were systematically analyzed to answer the following research questions: *RQ1: Does the application of Transfer Learning techniques in Chest X-Ray-based pneumonia classification still hold relevance and urgency of significance for future scientific research? RQ2: What is the current landscape of scientific publications related to the application of Transfer Learning for pneumonia classification in Chest X-Ray images in indexed literature? RQ3: What are the theoretical and practical implications from the perspective of future research development of Chest X-Ray-based pneumonia classification and Transfer Learning?*

4. RESULTS AND DISCUSSION

The results of this study present comprehensive findings from 76 articles that have undergone a rigorous selection process and been identified in the Scopus database, with a specific focus on the classification of pneumonia using chest X-ray images through a transfer learning approach (specifically the ResNet, VGG, and DenseNet architectures). This study aims to explore the effectiveness and development of Deep Learning algorithm implementation in improving the accuracy of automatic radiological diagnosis. The analysis presented includes quantitative mapping of the temporal distribution of publications over the last five years, as well as the identification of reputable journals that are the main platforms for disseminating research on this topic. Bibliometric findings reveal fluctuating publication trends, with a significant surge in research activity during the pandemic period followed by a stabilization phase, indicating that CNN-based CAD technology has reached a certain level of maturity within the scientific community.

In addition, this study also examines the intellectual contributions of various prolific authors, institutional affiliations, and the geographical mapping of countries that dominate this research landscape. The collaboration patterns revealed show the dominance of academic institutions and medical research centers with a strong focus on health informatics. The results of this analysis not only provide an overview of the global research landscape, but also emphasize the importance of interdisciplinary synergy in accelerating the innovation of accurate and efficient early detection systems for lung disease.

RQ1: Does the application of Transfer Learning techniques in pneumonia classification based on Chest X-Ray still hold relevance and urgency for future scientific research?

Based on quantitative data extracted from the Scopus database in Figure 2, the dynamics of publications on pneumonia classification using Chest X-Ray images and Transfer Learning show a fluctuating trend that reflects the scientific community's response to global health emergencies. In 2021, there was a high volume of publications (22 documents), driven by the urgent need for rapid detection of COVID-19 and other lung diseases. Studies in this early period, such as those conducted by [2], focused on developing powerful deep transfer learning networks for the automatic classification of tuberculosis and pneumonia from X-rays. In addition, [22] also conducted a comparative study of various artificial neural networks to ensure detection accuracy during the pandemic crisis.

Although there was a slight decline in 2022, the trend rebounded in 2023 (21 documents), signaling a phase of evaluation and model quality improvement. In this phase, the focus of the research began to shift to interpretability and data preprocessing. This can be seen in the research [6] which began analyzing Transfer Learning in the Vision Transformers architecture, as well as [1] which developed the PACE 2.0 processing pipeline to improve X-ray image contrast for better diagnostics. Research by [7] also reinforces the use of Deep CNNs for more precise disease-detection automation.

Entering the 2024 and 2025 period, the trend in publication quantity shows a pattern of stabilization, with around 10 publications in 2024 and 7 indexed articles in early 2025. This decline in quantity does not indicate a loss of relevance, but rather a shift in focus towards model specialization and the integration of XAI. A recent study by [10] introduces the SEA-ResNet50 model equipped with XAI, addressing the “black box” challenge of AI so that clinical decisions can be explained. Additionally) emphasize multiclass algorithms capable of distinguishing between healthy lungs, COVID-19, and regular pneumonia.

By 2025, the relevance of this topic is further solidified with more specific approaches to certain demographics and architectures. [9] developed a predictive model using DenseNet-169 specifically for pediatric pneumonia (children), while [23] optimized the VGG-19 network specifically for multiclass lung disorders. Thus, despite post-pandemic normalization in quantity, the exploration of image processing for pneumonia diagnosis remains crucial and is evolving toward more transparent, specific, and reliable models for future clinical decision-making.

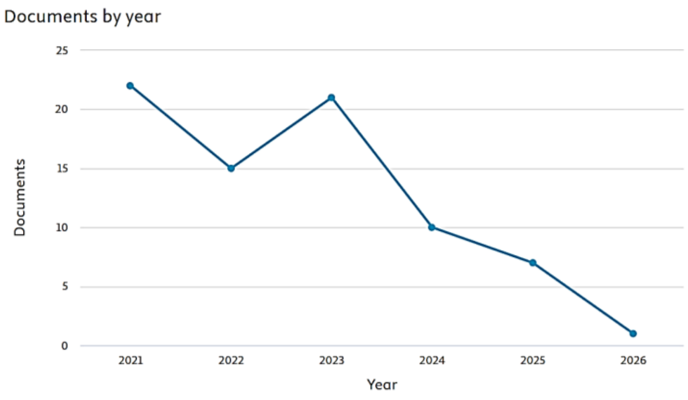

Figure 2. Document by Year

Since 2021, literature on Chest X-Ray-based pneumonia classification using Transfer Learning methods has shown a strong foundation, initially dominated by the urgency of responding to the pandemic. However, with the maturation of technology and increasing demands for diagnostic accuracy, publication trends from 2023 to 2025 show a crucial shift in focus from quantity to quality and model specificity, such as the integration of Explainable AI. This dynamic opens strategic opportunities for future researchers to fill existing research gaps, particularly in balancing the computational complexity of Deep Learning models with practical implementation needs in the field. This research is a vital foundation for advancing insights into the integration of artificial intelligence in radiology, which can improve the efficiency of early detection of lung disease and support more precise clinical decision-making. Going forward, further development in this domain is expected to facilitate the transition of CAD systems from experimental environments to sustainable and reliable adoption in various healthcare facilities.

RQ 2: What is the current landscape of scientific publications related to the application of Transfer Learning for pneumonia classification in Chest X-Ray images in indexed literature?

Analysis of the distribution of research on pneumonia classification in chest X-ray images using transfer learning techniques, published in the Scopus database, shows a high concentration in several countries with significant contributions. India dominates the publications with the highest number of documents, followed by Saudi Arabia, the United States, and South Korea, each of which has made substantial contributions to this research. In addition, countries such as Pakistan, Turkey, and China also show a significant number of publications, indicating a high level of interest in the application of Deep Learning in radiology in these regions. Australia, Canada, and Italy, despite having fewer contributions, still reflect the importance of Transfer Learning technology development in CAD in developed countries. This distribution shows the important role of countries with advanced healthcare systems in driving innovation and research in the field of medical image processing, as shown in Figure 3.

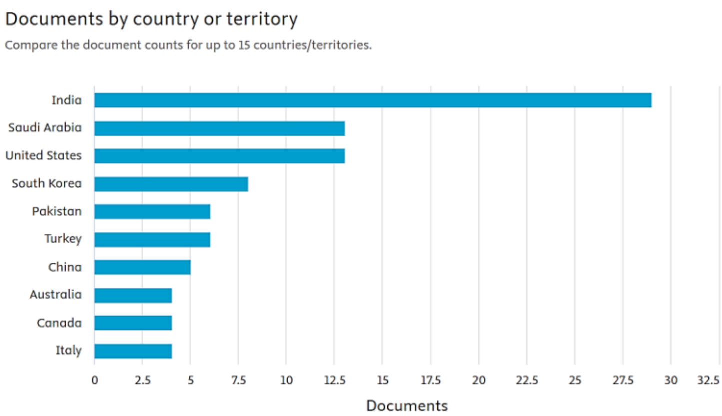

Figure 3. Number of articles by country or teority

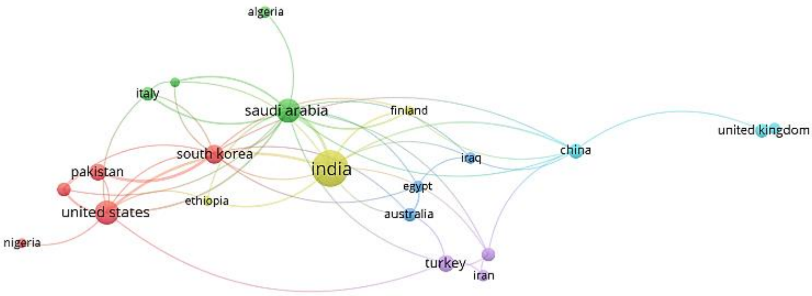

Figure 4. Country Visualization

Based on Figure 4, bibliometric analysis illustrates the landscape of international collaboration in publications related to Transfer Learning-based pneumonia classification. Node size represents publication volume, while line thickness reflects the intensity of co-authorship collaboration between countries.

The analysis shows that India occupies a central position as a major contributor in this research domain, reflecting the high productivity of academic institutions in that country in developing lung disease detection algorithms. India also functions as a global network hub, with extensive collaboration with various other country clusters. Meanwhile, the United States and South Korea show very close research synergy, with the participation of other countries such as Pakistan and Nigeria strengthening the collaboration network. This reflects a strong transfer of technological knowledge between developed and developing countries.

On the other hand, Saudi Arabia has emerged as a key player, forming a unique axis of collaboration with countries across continents, such as Italy and Finland, as well as neighboring countries such as Algeria. This phenomenon signals increased investment and research focus in the field of digital health in the Middle East. Meanwhile, China plays a strategic role in bridging collaboration with the United Kingdom and Australia. Overall, this network map confirms that the development of Transfer Learning for medical imaging is a decentralized global effort, where innovation is not only dominated by Western countries but also significantly driven by cross-country collaboration in Asia, the Middle East, and the Americas to address global health challenges.

Second, based on Figure 5, the allocation of research related to the application of Transfer Learning for pneumonia classification in Chest X-Ray images based on institutional affiliation shows a highly competitive and decentralized distribution. No single institution dominates absolutely, but rather there are clusters of leading institutions with equivalent productivity. Five academic institutions were identified as major contributors with the highest number of publications, each contributing 3 articles. These institutions include Sungkyunkwan University (South Korea), Vellore Institute of Technology and Kalinga Institute of Industrial Technology (India), King Saud University (Saudi Arabia), and Benha University (Egypt). The dominance of these institutions indicates that the center of innovation for the development of Deep Learning algorithms for radiology is currently strongly concentrated in Asia and the Middle East.

In addition to this core group, a number of other institutions also made significant contributions, each producing two articles. This group includes the College of Sciences, Taibah University, Akdeniz University (Turkey), SRM Institute of Science and Technology (India), and Université du Québec à Chicoutimi (Canada). This data illustrates that the research landscape for this topic is heavily driven by technology and science-based universities. The presence of technology institutes such as VIT, KIIT, and SRM in the top ranks confirms the crucial role of computer science and engineering faculties in developing model architectures such as ResNet and VGG, which are then applied to global medical diagnostic needs.

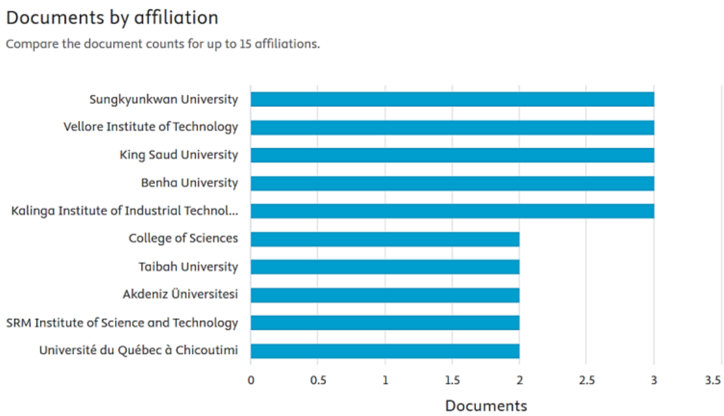

Figure 5. Affiliation visualization

Based on an analysis of the distribution of research related to pneumonia classification using Transfer Learning, the global publication landscape is dominated by countries in Asia and the Middle East, particularly India, Saudi Arabia, and South Korea. Leading academic institutions such as Sungkyunkwan University and Vellore Institute of Technology have made significant contributions, surpassing the traditional dominance of Western universities. These findings reflect a strategic shift in the center of digital health technology innovation and the strength of inclusive international collaboration in advancing research on precise and efficient lung diagnostic systems.

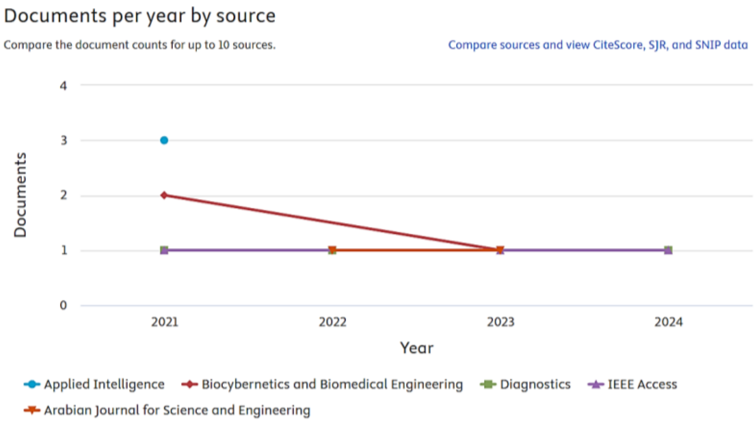

Figure 6. Number of articles by source

Figure 6 shows that the allocation of research related to Transfer Learning-based pneumonia classification based on publication sources shows a dynamic distribution across various reputable journals. The Applied Intelligence journal recorded the most notable contribution in the early phase (2021) with the highest number of publications, reflecting the rapid response of the artificial intelligence community to global health issues at that time. On the other hand, the IEEE Access journal shows the most consistent and stable contribution pattern, with publications maintained from 2021 to 2024, indicating that this topic has continued relevance in the discourse of computer engineering. The Biocybernetics and Biomedical Engineering journal also made a significant contribution at the beginning of the period, although it showed a gradual downward trend over time. Additionally, the presence of the Diagnostics and Arabian Journal for Science and Engineering journals in subsequent years demonstrates diversification in publication outlets. Overall, this trend indicates that the topic of Deep Learning integration in radiology has been widely accepted, both in journals focused on intelligent algorithms and applied biomedical engineering.

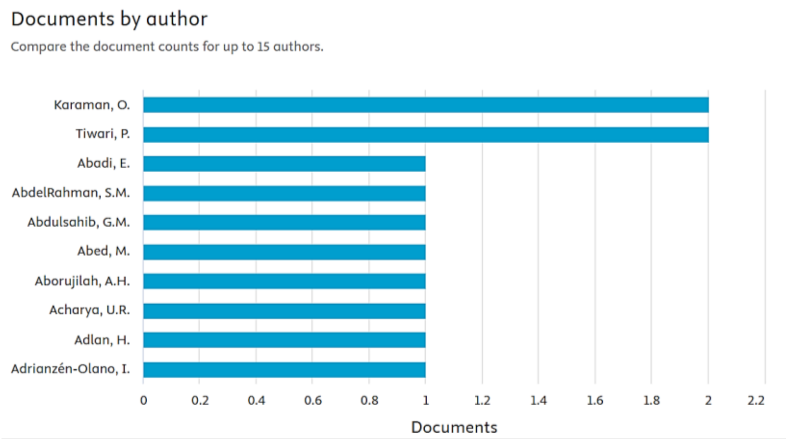

Figure 7. Count of publication by author

Based on Figure 7, the distribution of author productivity in this study shows an even pattern of participation without any single dominance. [24] and [3] were identified as the most active contributors, each having published two articles related to pneumonia classification using Transfer Learning. Meanwhile, other authors such as [25], [26] and a number of other researchers have each contributed 1 article. This egalitarian distribution pattern indicates that this topic is not monopolized by a particular research group, but is developed collaboratively by a broad community of experts in various global institutions.

RQ:3 What are the theoretical and practical implications of the perspective of developing pneumonia classification research based on Chest X-Ray and Transfer Learning in the future?

A systematic analysis of 76 articles explicitly extracted from the Scopus database, focusing on the application of Transfer Learning techniques (particularly ResNet, VGG, and DenseNet architectures) for pneumonia classification in Chest X-Ray images, reveals the evolutionary landscape of this topic from both theoretical and practical perspectives. A bibliometric analysis using VOSviewer reveals emerging research trends: although classic CNN architectures remain the standard, there is a shift towards research focused on model interpretability (Explainable AI) and specialization within specific demographics. These findings underscore the need for further research on the transparency of "black-box" algorithms and the development of more sophisticated data augmentation techniques to address class imbalance in medical datasets. From a practical perspective, these research results provide insight into the maturity of CAD technology, which is now ready to transition from the experimental stage to clinical implementation. This analysis also highlights the main challenges faced by practitioners, namely the need to develop systems that are not only statistically accurate but also reliable and seamlessly integrated into radiology workflows. This study emphasizes the importance of interdisciplinary collaboration between computer engineers and clinicians to ensure rigorous external validation. Overall, these findings provide a strong foundation for further research in the development of efficient, accurate, and explainable intelligent diagnosis systems, with the goal of supporting more precise clinical decision-making in the future.

Based on Figure 8, the frequency of keyword appearances is: Deep learning (58), Transfer learning (54), Covid-19 (44), Convolutional neural network (29), Thorax radiography (22), Pneumonia (23), Diagnosis (22), Chest x-ray images (18), Disease classification (11), Virus pneumonia (11), Medical imaging (12), Classification (15), Chest x-ray (15), Learning models (8), Learning system (15), x-ray analysis (4), x-ray (6), Diagnostic imaging (8), Coronaviruses (8), Coronavirus (5), Image classification (10), computer-assisted diagnosis (5), major clinical study (6), computer vision (4).

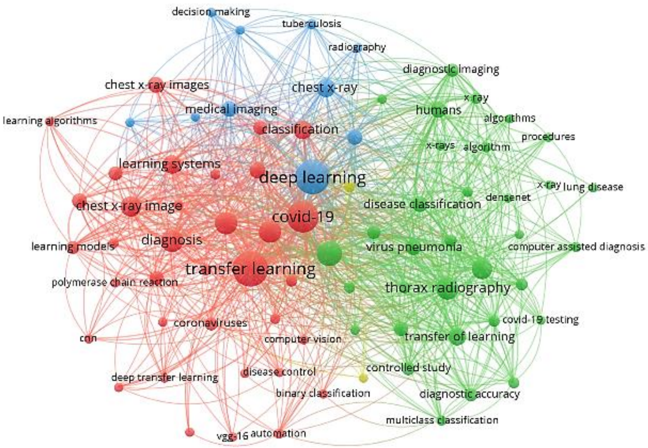

Figure 8. Co-occurence framework and representation of key items

Table 2. Keywords by author

Rank	Keyword	Total link strength
1	Deep learning	561
2	Transfer learning	532
3	Covid-19	488
4	Convolutional Neural Network	376
5	Thorax radiography	366
6	Coronavirus disease 2019	283
7	Pneumonia	270
8	Diagnosis	267
9	Transfer of learning	235
10	Chest x-ray image	209
11	Disease classification	194
12	Virus pneumonia	184

Based on the bibliometric analysis of the author's keywords presented in Table 2, methodological dominance is clearly evident in the term "Deep learning," which ranks first with a total link strength of 561, followed by "Transfer learning" in second place with a strength of 532, indicating that the development of intelligent diagnostic systems currently relies heavily on the adaptation of pre-trained deep learning models for computational efficiency. Contextually, the table shows that the global pandemic, as the main catalyst for this research, is reflected in the high position of the keyword “Covid-19” (Rank 3, 488) and its variation “Coronavirus disease 2019” (Rank 6, 283), which encourages the application of the “Convolutional Neural Network” architecture (Rank 4, 376) as the de facto standard in visual feature extraction. In terms of data modality, the use of the terms “Thorax radiography” (Rank 5, 366) and “Chest x-ray image” (Rank 10, 209) indicates consistent selection of chest radiography images as the primary diagnostic input. The clinical focus of research is increasingly directed at the detection of lung disease, as reflected in the keywords “Pneumonia” (Rank 7, 270) and its specific variant “Virus pneumonia” (Rank 12, 184), while the practical purpose of integrating all these technologies is represented by the keywords “Diagnosis” (Rank 8, 267) and “Disease classification” (Rank 11, 194), which confirms the research orientation to support precise clinical decision-making through accurate disease classification.

Research such as that conducted by [27] in Pneumonia Classification from X-ray Images with Inception-V3 and Convolutional Neural Network and [4] In Transfer -Learning-Based Approach for the Diagnosis of Lung Diseases from Chest X-ray Images, standard Deep Learning architectures have been applied to significantly improve the accuracy of lung disease diagnosis. In addition, studies by [5] in Diagnosis of Pediatric Pneumonia with an Ensemble of Deep CNN in Chest X -Ray Images and [28] on Enhancing Pediatric Pneumonia Detection and Classification Using Customized CNNs specifically highlights the effectiveness of ensemble methods and CNN customization in handling cases of pneumonia in children (pediatric) that have their own clinical feature challenges. The development towards more advanced hybrid technology is demonstrated by [29] in From Binary to Multi-Class Classification: A Two-Step Hybrid CNN-ViT Model for Chest Disease Classification Based on X-Ray Images, which integrates the power of Vision Transformer (ViT) for more precise multi-class classification. In line with this, research by [30] In the development of a pneumonia disease detection model based on a deep learning algorithm, further strengthens the evidence that the use of adaptive deep learning algorithms has great potential to accelerate the innovation of accurate and efficient CAD systems in healthcare services.

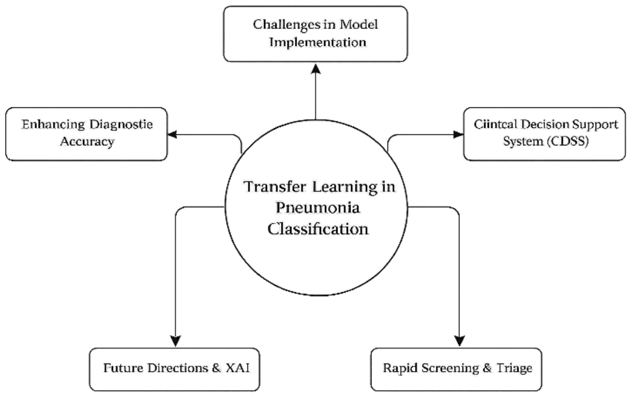

Figure 9. Atribut

Figure 9 illustrates the main attribute framework for the application of Transfer Learning in pneumonia classification based on Chest X-Ray, summarizing the key findings from the analyzed literature. The first and most fundamental attribute is “Improved Diagnostic Accuracy,” where the use of trained architectures such as ResNet, VGG, and DenseNet has been shown to significantly improve detection precision compared to conventional methods, especially in distinguishing between viral pneumonia (including COVID-19) and bacterial pneumonia [9], [23], [31]. The second attribute highlights “Early Screening Efficiency,” where these algorithms enable fast, real-time image processing for patient triage needs in emergency rooms [32], [33]. However, this diagram also maps “Model Implementation Challenges” as a critical attribute, which includes the issue of data imbalance that requires special handling techniques such as SMOTE [34], as well as the “black-box” nature of Deep Learning that hinders the transparency of medical decisions. This leads to the attribute “Future Development Potential,” which emphasizes the urgency of integrating XAI so that diagnosis results can be visually validated by medical personnel through heatmaps [10], [35]. Overall, all of these attributes contribute to the ultimate goal of a “Clinical Decision Support System,” in which AI serves as a reliable “second opinion” tool to minimize diagnostic errors and improve the sustainability of healthcare services [17], [36].

3.1. Improved Diagnostic Accuracy

The application of Transfer Learning techniques to Chest X-Ray image classification significantly improves diagnostic accuracy compared to conventional machine learning methods. In modern radiology practice, pre-trained Deep Learning architectures, such as ResNet, VGG, and DenseNet, can extract complex visual features to distinguish various types of lung pathologies with high precision. This is supported by the findings of [31], which show that Transfer Learning models have superiority in distinguishing between bacterial pneumonia, viral pneumonia, and COVID-19 infection, which often have overlapping clinical manifestations on X-ray images. [23] added that specialized models, such as VGG-19, can identify more subtle disease patterns that may be missed by manual observation.

In addition to general classification capabilities, this technology is also crucial for handling specific cases that require a high degree of accuracy, such as in pediatric patients. [9] emphasize that applying the DenseNet-169 model yields better predictive performance in diagnosing pediatric pneumonia, where smaller anatomical structures often complicate diagnosis. With this increased accuracy, the risk of misdiagnosis can be minimized, ensuring that patients receive targeted treatment from the initial stage of examination.

3.2. Early Screening Efficiency

One of the most tangible contributions of Deep Learning integration in medical workflows is its ability to automatically perform efficient initial screening. With algorithms capable of processing images in real time, this system can sort critical cases in emergency rooms (ERs) with high patient volumes, thereby speeding up triage. [33] state that CNN-based detection methods can operate in real-time to distinguish COVID-19-infected lungs from healthy ones, providing a layer of priority for patients who need immediate isolation or treatment. This efficiency not only affects speed but also optimizes limited medical resources.

With a reliable automated screening system, radiologists can focus more on analyzing complex cases that require in-depth expertise, while routine cases can be verified more quickly. [32] Highlight that Transfer Learning-based automated screening models offer a lightweight, fast solution that is invaluable for implementation in healthcare facilities with high workloads or in remote areas lacking specialist doctors.

3.3. Challenges in Implementing the Model

Despite offering numerous advantages, integrating Deep Learning models into clinical systems poses substantial technical challenges, particularly due to the characteristics of medical data. One of the main obstacles is data imbalance (class imbalance) in X-Ray datasets, where the number of positive case samples (e.g., COVID-19) is often much smaller than the number of normal cases or cases of common pneumonia. [34] emphasize that without proper handling, such as the use of SMOTE (Synthetic Minority Over-sampling Technique), models tend to be biased towards the majority class, thereby reducing the sensitivity of detection for rare but dangerous diseases.

In addition to data issues, the nature of Deep Learning algorithms, often referred to as “black boxes,” poses a challenge in clinical acceptance. Doctors and medical personnel often find it difficult to trust AI decisions when the system cannot explain its reasoning. This challenge is compounded by the need for high computational resources to run complex models, which may not be evenly available in all hospital infrastructures, requiring model optimization strategies to make them lighter yet still accurate.

3.4. Future Development Potential (XAI)

To address the challenge of model transparency, future technology development is strongly focused on integrating XAI. This technology enables AI systems not only to provide diagnostic labels but also to visualize the areas of infection that underlie these decisions through heatmaps. [10] suggest that models such as SEA-ResNet50 equipped with XAI modules can provide interpretable visualizations understandable to doctors, bridging the trust gap between humans and machines.

The application of XAI is expected to revolutionize the collaboration between radiologists and intelligent systems, making diagnoses more transparent and accountable. [35] add that the XAI approach using X-ray images is very effective for clinically validating model findings, ensuring that AI detects diseases based on correct pathological features, not because of artifacts or noise in the images. The future of EHR integration will depend heavily on these systems' ability to “communicate” visually with medical personnel.

3.5. Clinical Decision Support System

The ultimate aim of this research is to create a robust Clinical Decision Support System (CDSS). In this context, AI is not positioned to replace the role of doctors, but rather to serve as an objective “second opinion” to validate initial diagnoses. [17] assert that an AI-based framework for pneumonia detection is a crucial step toward sustainable healthcare, where technology helps reduce the cognitive load on doctors and improves the consistency of diagnoses.

By integrating image analysis results into electronic medical records, CDSS can provide comprehensive, data-driven recommendations. This has the potential to improve the overall quality of patient care by reducing medical errors and accelerating the initiation of treatment. Maquen-Niño et al. (2024) show that accurate classification models can serve as effective decision-support tools, helping create a more efficient, secure, and patient-safety-centered digital health ecosystem.

4. CONCLUSION

This study concludes that integrating Transfer Learning, particularly through the ResNet, VGG, and DenseNet architectures, has been empirically shown to significantly improve the diagnostic accuracy of pneumonia and the efficiency of initial triage compared to conventional methods. A bibliometric analysis of 76 selected articles from 2021 to 2025 reveals an evolution in research trends, initially driven by the urgency to publish during the COVID-19 pandemic, but now shifting towards a phase of technological maturity that focuses more on the quality of interpretation and on specialization in demographic models. Furthermore, the global innovation map shows strong decentralization, with research contributions from institutions in Asia and the Middle East, such as India and Saudi Arabia, signaling a strategic shift toward inclusive international collaboration in the development of digital health solutions.

Despite its great clinical potential, the full implementation of CAD in real-world settings still faces fundamental challenges, particularly data imbalance in medical images and the "black-box" nature of algorithms, which hinder medical personnel's trust. Therefore, the direction of future research is no longer merely to pursue improvements in statistical accuracy metrics, but to prioritize integrating XAI to ensure transparency in diagnostic decisions through the visualization of infected areas. This transformation is crucial to realizing a precise and reliable CDSS as a "second opinion" for radiologists, which ultimately aims to improve patient safety and the operational efficiency of healthcare services in a sustainable manner.

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