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Exploring Deep Learning Models for Pneumonia Classification in Chest Radiological Images: A Systematic Review

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ABSTRACT

Pneumonia continues to be a significant global health issue, with timely and precise diagnosis playing a vital role in patient care. Traditional diagnostic approaches relying on chest radiological images often encounter limitations such as inconsistent interpretations among observers and delays in analysis. To overcome these challenges, the use of deep learning models has emerged as a promising approach for achieving automated and accurate pneumonia detection. This systematic review seeks to deliver a comprehensive summary of recent progress in deep learning applications for pneumonia classification using chest imaging. The review adds value by examining the evolution of deep learning architectures, summarizing widely used datasets, highlighting current challenges, and suggesting directions for future research. A systematic search was carried out across several scientific databases, including ScienceDirect and IEEE Xplore, covering studies published between 2022 and 2024. The studies were chosen according to established inclusion and exclusion criteria, followed by content-based screening to maintain relevance. This review encompasses 36 studies featuring a range of deep learning models, such as CNN, transfer learning techniques (VGG16, ResNet, DenseNet, MobileNet, EfficientNet), hybrid models, ensemble methods, attention-based mechanisms, domain adaptation frameworks, and federated learning approaches. Diverse publicly available datasets, including ChestXRay2017, Guangzhou Medical Center, RSNA, and Covid-19 Radiography Dataset, were widely utilized. Preprocessing techniques such as resizing, normalization, data augmentation (including GAN-based), and segmentation were frequently applied to enhance model performance. Reported classification accuracies ranged from 78.9% to over 99%, with ensemble and hybrid models often achieving superior performance. Nevertheless, challenges such as class imbalance, domain generalization, computational complexity, and clinical interpretability persist. In conclusion, deep learning demonstrates significant potential in improving pneumonia diagnosis through chest radiological image analysis. However, addressing current limitations and enhancing clinical integration remain critical for future advancements in this field.

1. Introduction

Pneumonia continues to be a major contributor to illness and death globally. The WHO reports that it accounts for around 20% of all fatalities among children under the age of five, ranking it among the most prevalent infectious diseases worldwide [1]. It is estimated that pneumonia affects more than 450 million people annually, contributing to nearly 3 million deaths each year, with the majority of these deaths occurring in low-income countries. The burden of pneumonia is not only a major health challenge but also a significant economic concern, as it leads to high hospitalization costs and a strain on healthcare systems [2]. Prompt and precise diagnosis is essential for enhancing patient prognosis, as early treatment greatly lowers the likelihood of complications [3]. Conventionally, diagnosing pneumonia has depended on clinical evaluations, laboratory tests, and imaging methods like chest radiography. Nevertheless, the manual assessment of radiological images is often subjective and labor-intensive, potentially postponing timely therapeutic interventions [4].

Recent progress in AI and machine learning has opened new possibilities for automating pneumonia diagnosis through deep learning techniques. Among these, CNNs have shown impressive performance in identifying pneumonia from CXR scans, often surpassing traditional diagnostic methods [5]. These models enable clinicians to detect pneumonia more rapidly and accurately, thereby enhancing patient care and lessening the burden on healthcare providers. The swift advancement of deep learning approaches in medical image analysis has driven extensive research into their applications for pneumonia detection. With pneumonia cases continuing to increase globally, especially during respiratory disease outbreaks, these AI-powered models provide a scalable approach for quick and precise diagnosis. The growing availability of large, labeled imaging datasets has greatly improved the development and training of these models, establishing them as a valuable tool in clinical environments [6], [7].

This systematic review aims to explore the application of deep learning models in the classification of pneumonia from chest radiological images (CXR). By synthesizing findings from recent studies published between 2022-2024, this review provides a comprehensive understanding of the progress, performance, challenges, and future directions of deep learning approaches in this field. It delivers an in-depth evaluation of the methodologies utilized in pneumonia classification, covering various deep learning architectures. In addition, it summarizes and analyzes the data preprocessing techniques used across studies, as well as compiles and evaluates the most commonly utilized publicly available datasets for pneumonia classification. The review also identifies key challenges faced in implementing deep learning models, such as data imbalance, domain generalization, and interpretability issues. Finally, it explores future prospects to advance deep learning-based pneumonia classification, highlighting directions such as domain adaptation, explainable AI, federated learning, and clinical integration.

2. Methodology

A systematic literature review approach was utilized to effectively select pertinent studies for this review [8], [9]. First, a search protocol was designed incorporating specific keywords relevant to the topic. Then, inclusion and exclusion criteria were applied to screen studies by evaluating their titles, keywords, and abstracts. Most of the articles analyzed in this review were obtained from the ScienceDirect and IEEE Xplore databases.

2.1. Search Query

To begin, we selected search terms including “Pneumonia”, “Deep Learning”, “CNN”, “Image Classification”, “Chest X-Ray”, and “Radiological Imaging”. By limiting the publication dates to the past three years (2022-2024), we tested multiple combinations of these keywords and performed searches within the databases. Articles containing our selected search terms in their titles and keywords were subsequently retrieved for detailed analysis.

2.2. Inclusion and Exclusion Criteria

Once a wide range of papers containing the relevant search terms was collected, the inclusion and exclusion criteria were applied for thorough screening. Only studies proposing novel methods in pneumonia image classification and deep learning were included. To evaluate the worldwide progress in pneumonia radiological image classification, preference was given to studies from various countries; however, publications in languages other than English were not considered.

2.3. Content-Based Exclusion

Furthermore, it was essential to evaluate the papers based on their overall content, including the title, keywords, and abstract. Only studies that provided a strong theoretical basis along with detailed experimental methods were considered. Papers that were not closely related to the research focus were excluded. In the end, thirty-six papers were chosen as suitable for analyzing pneumonia classification from chest radiological images through deep learning methods. Prior works related to pneumonia classification using deep learning models (2022 – 2024) shown in Table 1.

Table 1. Prior works related to pneumonia classification using deep learning models (2022 – 2024)

Authors	Year	Methodology	Preprocessing	Dataset information
Sourab et al. [10]	2022	▪ Mendeley Dataset V2, ▪ Preprocessing and Augmentation, ▪ Proposed CNN Architecture, ▪ Feature Extraction, ▪ Classification (Random Forest, K-NN, SVM), ▪ Results analysis	Rotation of images, zooming, shifting in width, shifting in height, flipping horizontally, rescaling, and converting to grayscale	Mendeley Dataset V2: 5856 CXR images (Pneumonia and Normal)
Li et al. [11]	2022	▪ CXR images from public datasets, ▪ Preprocessing, ▪ Transfer learning models (17 pre-trained CNN), ▪ Classification tasks (pneumonia with healthy; viral with bacterial infections; COVID-19 with other viruses; COVID-19 with bacteria; COVID-19 with healthy individuals), ▪ Accuracy measurements	Splitting and Resizing Data	CXR Public datasets: 5510 normal, 2530 bacterial pneumonia, 2142 viral pneumonia
Szepesi et al. [12]	2022	▪ CXR dataset from Guangzhou Women and Children's Medical Center, ▪ Data preprocessing, ▪ Process of learning using proposed CNN, ▪ Evaluation criteria	A GAN was utilized to produce additional images for the underrepresented class	5856 CXR images (4273 pneumonia and 1583 normal)
Lotfy et al. [13]	2022	▪ CXR Dataset, ▪ Preprocessing, ▪ Splitting using 10-fold CV, ▪ Training (Generate Augmented Data) and Testing (Validation), ▪ Deep CNN for Classification, ▪ Detection and Labeling	Conversion to grayscale, image resizing, application of adaptive histogram equalization (AHE), and semantic image segmentation	▪ Dataset-1: 15664 images (pneumonia and normal) ▪ Dataset-2: 2295 images (normal, COVID-19 pneumonia, and bacterial pneumonia)
Singh et al. [14]	2022	▪ Dataset CXR from children at Guangzhou Women and Children's Medical Center, ▪ Data Augmentation, ▪ Implementation Environment and Tools Used (Google Colaboratory)	Grayscale transformations, horizontal and vertical flipping, random cropping, color distortions, translations, rotations, and various other augmentations	5856 CXR images (4273 pneumonia and 1583 normal)

Authors	Year	Methodology	Preprocessing	Dataset information
Absar et al. [15]	2022	▪ SqueezeNet, ▪ Data augmentation, ▪ SVM classification, ▪ Texture-feature extraction, ▪ Training and prediction functions, ▪ Accuracy evaluation	Vertical and horizontal reflections, rotation, and shear on training data	7180 CXR images (619 Covid-19, 1341 normal, and 5220 viral pneumonia)
Zhang et al. [16]	2022	▪ The structure of the proposed FG-CPD (automatic data augmentation, feature extraction, BAP fusion, and attention-guided data augmentation), ▪ Data preprocessing, ▪ Attention network, ▪ Attention regularization	Data Conversion, The Chest Detection and Positioning using YOLOv4, and Automatic Data Augmentation	▪ Chest X-Ray 2017: 5826 chest X-ray images (pneumonia and normal) ▪ CXR Dataset from Tongji Hospital: 7251 CXR images (4726 pneumonia and 2555 normal)
Gour et al. [17]	2022	▪ CXR images and CT-scan dataset, ▪ Preprocessing, ▪ Pre trained models (xception and VGG19), ▪ Stacked Convolutional Neural Network, ▪ Evaluation Metrics, ▪ Results analysis, ▪ Performance comparison	Resizing and Data splitting (training and testing)	▪ Covid-19 CXR Dataset: 546 covid, 1139 normal, 1355 pneumonia ▪ Covid-19 CT-scan Dataset: 2249 covid, 2396 healthy
Toro et al. [18]	2022	▪ Datasets (GWCMCx and Josep-NIH), ▪ Image preprocessing, ▪ Image characterization (fractal dimension image textural, radiomics image textural, and superpixels based histon image textural), ▪ Classification (KNN, SVM, RF), ▪ Validation	Normalization of intensity, exclusion of clearly non-lung regions through masking, and enhancement of image texture	▪ GWCMCx dataset: 4273 pneumonia, 1583 normal ▪ Josep-NIH dataset: 728 pneumonia, 728 normal
Musallam et al. [19]	2022	▪ CXR images dataset, ▪ Preprocessing, ▪ Proposed "DeepChest" model, ▪ Performance comparison for the DCNN models (VGG16, DenseNet-121, MobileNet, DeepChest)	Removing confounding variables, denoising X-ray images with the NLM algorithm, applying histogram equalization, and evaluating the proposed preprocessing method using BRISQUE	Chest X-ray images dataset: 1323 covid-19, 4240 pneumonia, 1949 normal
Sanchez et al. [20]	2022	▪ Datasets and Metrics, ▪ Proposed Similarity-Constrained Data Selection, ▪ Proposed GAN-Based Image-to-Image Translation, ▪ CNN-Based Classification, ▪ Quantitative Classification Results, ▪ Comparison Results	Similarity-Constrained Data Selection and GAN-Based Image-to-Image Translation	▪ CXR images dataset from Guangzhou Women and Children's Medical Center (China): 4266 pneumonia, 1583 normal ▪ CXR images dataset from Toulouse University Hospital (France): 275 normal, 298 pneumonia
Feng et al. [21]	2022	▪ CXR images dataset, ▪ Preprocessing, ▪ Framework of Deep Supervised Domain Adaptation (DSDA), ▪ Implementation framework, ▪ Results analysis and comparison with other methods	Resizing and Data splitting (training and testing)	▪ TTSH dataset: 3021 non-pneumonia, 1164 pneumonia ▪ The RSNA dataset: 20672 non-pneumonia, 6012 pneumonia ▪ Chest X-ray14 dataset: 1353 pneumonia, 110767 non-pneumonia

Authors	Year	Methodology	Preprocessing	Dataset information
Yaseliani et al. [22]	2022	▪ CXR images dataset, ▪ Data preprocessing, ▪ Proposed Hybrid CNN, ▪ Transfer Learning models, ▪ Machine Learning models, ▪ Results and analysis	Resizing, normalize pixel values, and rescaling	CXR images dataset: 1583 normal, 4273 pneumonia
Feng et al. [23]	2022	▪ Datasets (ChestXRay2017 and Covid-19 Radiography Dataset V4), ▪ Framework of PCXRNet (Condense Channel Attention Module and Multiconvolution Spatial Attention Block), ▪ Implementation framework, ▪ Comparisons with other Attention Methods	Data splitting (training and testing)	▪ ChestXRay2017 dataset: 3973 pneumonia, 1583 normal ▪ Covid-19 Radiography Dataset V4: 11956 Covid-19, 11263 non-Covid infections (Viral or Bacterial Pneumonia), 10701 Normal
Sharma et al. [24]	2023	▪ CXR images dataset, ▪ Preprocessing, ▪ Pre trained models (VGG16), ▪ Features extraction, ▪ Classification (NN, SVM, KNN, NB, and RF), ▪ Performance evaluation	Data splitting (training and testing), balancing, and normalizing the data	▪ Dataset-1: 5856 anteroposterior CXR images (pneumonia and normal) ▪ Dataset-2: 4273 pneumonia, 1583 normal, 576 covid-19
Alalwan et al. [25]	2023	▪ CXR images dataset, ▪ Preprocessing using Weinmed filter, ▪ Segmentation using Otsu Thresholding, ▪ Feature extraction using GLCM, ▪ ABO based feature selection process, ▪ Classification using CNN, ▪ Results analysis (affected regions and unaffected regions)	Wienmed filter	▪ Dataset-1: 5856 anteroposterior CXR images (pneumonia and normal) ▪ Dataset-2: 6939 posteroanterior CXR images (normal, pneumonia, covid-19)
Bhatt et al. [26]	2023	▪ CXR images dataset, ▪ Pre-processing, ▪ Convolutional Neural Network (CNN) model, ▪ Evaluation metrics, ▪ Results analysis	Grayscales conversion, resizing, normalize pixel values, rotation, zooming in, and flipping the image	5863 CXR images (pneumonia and normal)
Ukwuoma et al. [27]	2023	▪ Dataset of chest X-ray (CXR) images ▪ Data preprocessing ▪ Pre-trained models (including DenseNet201, VGG16, GoogleNet, Xception, InceptionResNetV2, and EfficientNetB7) ▪ Deep learning with multi-model ensemble approach ▪ Transformer encoder (fine-tuned vision transformer model) ▪ Classification of bacterial pneumonia, normal cases, and viral pneumonia	Resizing, rescaling, zooming, rotating, and horizontal flipping	▪ Mendeley dataset: 3834 normal, 4290 viral pneumonia ▪ Chest X-ray dataset: 5000 normal, 5000 viral pneumonia, 5000 bacteria pneumonia
Ravikumar et al. [28]	2023	▪ CXR images dataset, ▪ Data Preprocessing and Augmentation, ▪ Transfer Learning models (VGG16, MobileNetv2, DenseNet169), ▪ Ensemble model, ▪ Data Parallel Model, ▪ Result Analysis	Rescale, rotate, shifting, shearing, zooming, flipping, and SMOTE implementation for class imbalance problem	5863 CXR images (pneumonia and normal)
Mabrouk et al. [29]	2023	▪ CXR dataset and ImageNet, ▪ CNN models (densenet121, densenet169, inceptionv3,	Fixed filter and data splitting (training and testing)	Guangzhou Women and Children's Medical Center dataset:

Authors	Year	Methodology	Preprocessing	Dataset information
		mobilenetv2, resnet50, resnet152v2, vgg16, and xception), ▪ Select the best 2 models, ▪ Ensemble Deep Learning model (ensemble federated learning), ▪ Evaluation metrics and results analysis		1583 normal, 4273 pneumonia
Go et al. [30]	2023	▪ Chest Xray dataset from Guangzhou Women and Children's Medical Center, ▪ Preprocessing, ▪ Training the pre-trained models (DenseNet201, MobileNetV2, ResNet50, ResNet101, and Xception), ▪ Training the pre-trained models (DenseNet201, MobileNetV2, ResNet50, ResNet101, and Xception), ▪ Ensemble Model, ▪ Performance Evaluation	Random oversampling, image resizing, random rotations, zooming, and horizontal image translation	Chest Xray dataset: 1583 normal 4273 pneumonia
Kusk et al. [31]	2023	▪ CXR images dataset, ▪ Preprocessing, ▪ CNN training, ▪ Performance evaluation	Gaussian noise levels adding and data splitting (training and testing)	5856 CXR images (1583 normal, 4273 viral and bacterial pneumonia)
Kareem et al. [32]	2023	▪ Data collection (CXR images) and pre-processing, ▪ Exploratory Data Analysis (EDA), ▪ Classification (FL DenseNet, FL AlexNet, FL Inception, FL VGG19, FL ResNet50), ▪ Evaluation of model selection	Rotating, zooming, shifting, and resizing images	5856 CXR images (4273 pneumonia and 1583 normal)
Kabi et al. [33]	2023	▪ CXR images database, ▪ Preprocessing, ▪ Multiscale Eigenanalysis of Chest X-Ray Images, ▪ Classification using MEGB, ▪ Results analysis	Resizing CXR images	▪ Dataset-1: 700 tuberculosis, 3500 normal ▪ Dataset-2: 4338 normal, 1525 pneumonia
Hussain et al. [34]	2023	▪ CXR images dataset, ▪ Preprocessing, ▪ Model training (VGG16, Inceptionv3, ResNet101, Xception, DenseNet201, EfficientNet-B0, and MobileNetv2), ▪ Model Ensemble, ▪ Prediction and results analysis	Image resizing, data augmentation, and data splitting (training and testing)	CXR images dataset: 1259 covid-19, 1259 normal, 1259 pneumonia
Liu et al. [35]	2023	▪ Datasets, ▪ Attention-guided Partial Domain Adaptation (AGPDA) framework, ▪ Evaluation Metrics, ▪ Comparison with Peer Methods, ▪ Results analysis	Data splitting (training, validation, and testing)	▪ Covid-19 Radiography Database: 2955 pneumonia, 1660 normal, 1456 lung opacity ▪ Lung Disease Dataset: 5643 pneumonia, 2013 normal, 2034 tuberculosis
Zhang et al. [36]	2023	▪ CXR images dataset, ▪ Image Preprocessing, ▪ A CXR Based Multi-Task Deep Neural Network (CXR-Net), ▪ Performance of CXR-Net, ▪ Results analysis	Lung Segmentation and Image Enhancement	6499 CXR images (636 covid-19 and 5863 non-covid19 viral pneumonia)
Fu et al. [37]	2023	▪ Dataset CXR images, ▪ Preprocessing, ▪ The Structure of PKA2-Net,	Random rotations, shearing, zooming, and shifting	ChestXRay2017 dataset: 3973 pneumonia, 1583 normal

Authors	Year	Methodology	Preprocessing	Dataset information
Zaeri et al. [38]	2024	▪ Ablation Experiments for Active Attention Mechanism, ▪ The Effect of Baseline Model on Experimental Results, ▪ Comparison of PKA2-Net and Existing Pneumonia Diagnosis Models ▪ CXR dataset, ▪ Data splitting (training and testing), ▪ Local binary patterns calculation (LPB SQR, LPB CR, LPB AD, LPB RD), ▪ Data fusion, ▪ Similarity Measure, ▪ Decision Making, ▪ Results and analysis	Data splitting and radiographic imaging features extraction	▪ X-ray Guangzhou Medical Center dataset: 1575 normal, 3980 pneumonia ▪ IEEE8023-CXR dataset: 771 CXR images (viral, fungal, and bacterial pneumonia)
Haque et al. [39]	2024	▪ CXR dataset from Radiological Society of North America, ▪ Preprocessing, ▪ Interpretation using modified Class Activation Maps (mCAM), ▪ Classification (Capsule Networks Cluster), ▪ Model evaluation	Resizing, normalize pixel values, and data splitting (training, validation, testing)	Radiological Society of North America dataset: 20672 normal, 6012 pneumonia
Zhou et al. [40]	2024	▪ Proposed MSD-Net model (Multi-scale Residual Feature Extraction Module, Multi-scale Directional Feature Perception Module, and Axial Compression Former Module), ▪ Datasets and Data Pre-Processing, ▪ Experimental Environment, ▪ Evaluation Metrics, ▪ Ablation Experiment, ▪ Comparison Experiment	Data splitting (training and validation with ratio 9:1), image cropping, convert image to vector, and normalize pixel values	▪ Covid-19 Radiography Database: 1332 covid, 1335 lung opacity, 1362 normal lung, 1345 viral pneumonia ▪ Chest X-Ray pneumonia datasets: 5863 CXR images (pneumonia and normal)
Yang et al. [41]	2024	▪ Data Collection and Processing, ▪ Data Augmentation, ▪ Background Removal, ▪ Transfer Learning, ▪ Deep Learning Model Construction (ResNet50 and VGG16), ▪ Explainable Analysis by the Grad-CAM Method, ▪ Analysis and comparion of the Results	Data splitting (training and testing), background removal, and rescaling images	5840 CXR images (4265 pneumonia and 1575 normal)
Arulananth et al. [42]	2024	▪ Dataset handling, ▪ Preprocessing, ▪ Training of proposed DenseNet121 models, ▪ Performance Evaluation, ▪ Results analysis	Resizing, normalize pixel values, rotating, and data splitting (training, validation, testing)	5856 CXR images (1583 normal and 4273 pneumonia)
Guddati et al. [43]	2024	▪ Database of CXR images and preprocessing, ▪ FPGA Implementation of DCNN, ▪ Results analysis	Resizing and Data splitting (training and testing)	▪ Dataset-1: 3500 normal, 700 tuberculosis ▪ Dataset-2: 1525 pneumonia, 4338 normal
Ali et al. [44]	2024	▪ Dataset description and preprocessing, ▪ Deep Learning Models (InceptionResNetV2, Xception, VGG16, ResNet50, and EfficientNetV2L), ▪ Proposed novel EfficientNetV2L, ▪ Evaluation Performance,	Resizing, normalizing pixel values, applying contrast adjustments, rescale, rotation range, horizontal flip, vertical flip, height shift range and width shift range	5863 X-ray images (1583 normal and 4273 pneumonia)

Authors	Year	Methodology	Preprocessing	Dataset information
Shilpa et al. [45]	2024	▪ Results and analysis ▪ Data description, ▪ Data preprocessing, ▪ Deep Learning models for classification (ResNet50, EfficientNetB0, AlexNet, MobileNetV2, and Xception), ▪ K-fold cross validation, ▪ Performance models, ▪ Results and analysis	CLAHE, resizing, and augmentation	5233 anterior-posterior chest X-ray (1349 normal and 3884 pneumonia)

3. Results

3.1. Methodology in Pneumonia Classification

Recent studies related to the classification of pneumonia based on chest radiography images generally adopt a fairly consistent deep learning pipeline methodology approach. The first stage begins with the collection of datasets from various public sources such as the Guangzhou Women and Children's Medical Centre, the NIH ChestXray dataset, RSNA, and even multi-dataset combinations to expand data diversity [10], [11], [18], [39]. A large volume of data is essential given that the characteristics of pneumonia can vary significantly, both in terms of clinical symptoms and radiological appearance. After data collection, the preprocessing stage is crucial for preparing raw data into an optimal format for the model. This process includes image intensity normalisation, resizing, noise removal, and data augmentation to increase image pattern variation. Specialised methods such as Weinmed filtering, Otsu thresholding [25], background removal [41], and segmentation are used to enhance the visual clarity of the lung area. Data augmentation using rotation, flipping, zooming, and shifting techniques is also commonly used to address overfitting issues due to limited data variation [10], [14], [28].

The feature extraction stage primarily relies on the automatic capabilities of deep learning through convolutional CNN layers. Some studies enrich this process by combining deep features with texture-based handcrafted features, such as the use of GLCM [25], fractal dimension & radiomics [18], and local binary pattern [38]. This combinative strategy aims to capture the complex characteristics of pneumonia that are sometimes difficult to detect using standard CNN features alone. From a model architecture perspective, transfer learning has become the dominant strategy. Pre-trained models such as VGG16, ResNet50, DenseNet121, MobileNetV2, EfficientNet, and InceptionResNetV2 are widely used due to their ability to transfer learning from general datasets (ImageNet) to medical image domains [11], [17], [32], [44]. Additionally, some studies have developed new CNN models specifically tailored for pneumonia classification tasks, such as FG-CPD [16], DeepChest [19], PCXRNet [21], PKA2-Net [37], and MSD-Net [40]. To enhance prediction stability, some studies have implemented ensemble learning, which combines the strengths of multiple models into a unified classification system [29], [27], [39].

Final classification is performed either with an end-to-end CNN model or combined with classical machine learning models such as RF, SVM, KNN, and NB to enrich the decision-making process [10], [24]. The evaluation of model performance is conducted using a range of indicators, such as accuracy, precision, recall, specificity, F1-score, and ROC-AUC [26], [43], [34]. On the other hand, some studies have begun to incorporate XAI components such as Grad-CAM and mCAM, which allow for the visualization of radiological regions influencing the model's decision process, thereby improving the clinical comprehensibility of the model outcomes [41], [39]. In general, the most prominent methodological enhancements across all these studies are the use of transfer learning, integration of attention mechanisms, combination of handcrafted and deep features, and application of ensemble learning as a performance optimisation strategy. However, challenges remain, particularly regarding dataset quality variability, class imbalance, and limitations in external validation across broader populations [46].

3.2. Preprocessing Data

The preprocessing stage is a key step in the pipeline for developing a pneumonia classification model based on chest radiography images [47]. This process serves to prepare the image data so that it meets the optimal input standards for the deep learning architecture that will be used [48]. From the data collected, it appears that there are variations in the preprocessing strategies applied by each study, reflecting the researchers' efforts to improve image quality, improve data distribution, and adjust the data to the characteristics of the model used [49]. Generally, almost all studies perform image resizing to standardise the model's input dimensions, as pretrained CNNs have fixed input sizes (e.g., 224×224 or 299×299 pixels) [11], [17], [22], [45]. After resizing, pixel value normalisation is commonly performed, which involves transforming the pixel intensity range to a scale of 0-1 or -1 to 1 [22], [24], [39]. This step is crucial for accelerating model training convergence and preventing the dominance of high pixel values.

Some studies go further by performing noise removal and image quality enhancement. For example, Musallam et al. [19] use the Non-Local Mean (NLM) algorithm for denoising, while Lotfy et al. [13] apply adaptive histogram equalisation (AHE) to enhance lung area contrast. Alalwan et al. [25] even applied the Wienmed filter as a specific effort to address noise specific to CXR data. Some studies also applied image enhancement based on lung segmentation or lung area detection, such as Zhang et al. [16] using the YOLOv4 approach and another Zhang et al. [36] study using lung segmentation. To increase data variability and reduce the risk of overfitting, many studies perform data augmentation. The augmentation techniques used include random rotation, horizontal and vertical flipping, zooming in/out, shifting, shearing, and random cropping [10], [14], [28], [30], [37]. This augmentation is important given the significant variation in the position, size, and intensity of pneumonia infiltrates in clinical CXR images. Some studies have even applied augmentation methods based on GANs to generate new data for minority classes [12], [20], as an effort to address the issue of class imbalance. Additionally, some studies adopt statistical data balancing techniques such as random oversampling [30], SMOTE [28], and similarity-constrained data selection [20] to ensure the model is not biased toward the majority class. These balancing techniques are particularly important in the context of pneumonia, where the number of normal category data is often far greater than that of viral or bacterial pneumonia categories. From an in-depth analysis of all the preprocessing strategies used, it is evident that the combination of conventional approaches (resizing, normalisation, augmentation), advanced filtering (denoising, histogram equalisation), segmentation based on lung area detection, and balancing based on GAN and SMOTE, is key to improving the quality of input data. Optimal preprocessing plays a significant role in ensuring that deep learning models truly learn from relevant radiological features and are not influenced by noise, artefacts, or data imbalance [50].

3.3. Dataset

In developing a chest radiography-based pneumonia classification system, the availability of an adequate dataset is the main foundation for the success of the model [51]. Almost all of the studies reviewed utilised public CXR datasets that have been widely used in medical research. The most commonly used datasets are ChestXRay2017 from the NIH and the dataset from Guangzhou Women and Children's Medical Centre (GWCWC), each containing thousands of images labelled as pneumonia and normal [16], [29], [37]. Some studies expanded their data sources by adding COVID-19-specific datasets, in line with the emergence of the global pandemic. For example, the COVID-19 Radiography Dataset V4 was used by Feng et al. [23] and Liu et al. [35], which includes thousands of COVID-19 images, viral and bacterial pneumonia, as well as normal images. Additionally, the Radiological Society of North America (RSNA) dataset is widely used due to its large size, encompassing over 20,000 normal images and thousands of pneumonia images [21], [39]. The use of multiple dataset sources reflects researchers' efforts to address the limitations of single-source data and enhance image pattern diversity.

Data composition varies significantly across studies, both in terms of size and classification label types. Some datasets classify images into two main classes (normal vs. pneumonia), while others further subdivide pneumonia into viral pneumonia, bacterial pneumonia, and COVID-19 pneumonia

[11], [15], [40]. Some researchers even added other disease categories such as tuberculosis [33], [43] and lung opacity labels [35], [40]. This variation in labels reflects a shift in the pneumonia classification paradigm toward more complex, multi-category detection of lung diseases. In terms of quantity, the datasets used range from hundreds to tens of thousands of images. For example, the Mendeley Dataset V2 used by Sourab et al. [10] contains 5,856 images, while the RSNA dataset [21], [39] includes over 26,000 images. This variation in size has implications for model training strategies, where smaller datasets tend to rely on transfer learning to leverage pretrained weights from general datasets like ImageNet, while larger datasets allow for end-to-end training from scratch.

Some studies also adopt a multi-centre approach by combining datasets from multiple hospitals or institutions, such as the merger of data from Guangzhou Medical Centre (China) and Toulouse University Hospital (France) by Sanchez et al. [20]. This multi-centre approach contributes to increased diversity in population data variation, imaging settings, and radiographic equipment heterogeneity, thereby enhancing the model's generalisation capabilities. Overall, from an in-depth analysis of the dataset sources used, it can be concluded that the success of pneumonia classification models is highly influenced by the quality, diversity, and volume of the dataset. The more diverse the data sources used, the greater the likelihood that the model will learn biological and technical image variations [52], which ultimately improves generalisation performance when applied in real clinical settings [53]. The main challenges moving forward remain standardisation of labels, consistency in image acquisition protocols, and open access to large-scale multi-institutional data to expand the scope of machine learning in the field of medical radiology [54].

3.4. Deep Learning Models

In an effort to develop a chest radiography-based pneumonia classification system, the application of deep learning technology has become the dominant approach [55]. The ability of deep learning algorithms, particularly CNNs, to recognise complex visual patterns in medical images makes them highly effective in detecting radiological abnormalities such as infiltrates, consolidations, and pneumonia-specific lesions in chest X-ray images [56], [57]. Various studies have explored and adapted diverse deep learning model architectures, including the use of pretrained models, the development of custom architectures, and the integration with conventional machine learning algorithms [58]. In addition to model architecture selection, the type of dataset used also plays a crucial role in classification success [59]. Almost all studies utilise CXR datasets due to their widespread availability, relatively low examination costs, and relevance in daily clinical practice [60]. Some researchers have expanded the scope of the dataset by including variants of pneumonia caused by bacterial, viral, and COVID-19 infections, with some even adding data from CT-scan modalities to enrich the variety of input data [61]. As a performance indicator for the model, accuracy metrics are generally reported to be very high in most studies, indicating the significant potential of this deep learning approach in supporting automated pneumonia diagnosis [62]. However, differences in model architecture, preprocessing techniques, and dataset variations lead to performance variations across studies. Therefore, a systematic comparative evaluation of models, data types, and accuracy levels is crucial to understanding the strengths and limitations of each approach that has been developed. The following is a comparison table of deep learning models used in pneumonia classification.

In the development of a CXR image-based pneumonia classification system, the selection of deep learning model architecture is a central component that greatly determines the final performance of the model [63]. Based on a review of various studies, most research utilises Convolutional Neural Network (CNN) architecture as the primary foundation, whether through the development of new architectures, transfer learning, or integration with classical machine learning methods [10], [11], [16]. CNN models demonstrate superiority in extracting spatial features from image data, particularly for detecting patterns of infiltrates, consolidations, or characteristic texture changes associated with pneumonia on CXR. Various CNN variants were applied in these studies. Most research adopted pre-trained methods such as ResNet50, VGG16, DenseNet121, DenseNet201, Xception, MobileNetV2, InceptionResNetV2, and EfficientNetB0 [11], [24], [27], [44]. These pretrained models have the advantage of having pre-trained weights on general datasets (such as ImageNet), making it easier to adapt them to medical image domains through fine-tuning. In addition to standard architectures, some studies developed innovative models such as DeepChest [19], PCXRNet [23], PKA2-Net [37], MSD-Net [40], and explainable approaches like Capsule Networks Clusters [39]. Some studies also combine CNNs with classical algorithms such as RF, SVM, and KNN [10], [15], [18]. All reviewed studies utilise Chest X-Ray-based data as the primary data source, with minor additional variations in the form of CT-Scan data [17] in a small portion of the research. The homogeneity of this data type is reasonable, considering that CXR images are the most common and cost-effective radiological modality for diagnosing pneumonia globally. The compatibility of planar image data such as CXR with CNN architecture is also a reason for the dominance of convolutional models in this domain. In terms of performance, the majority of the developed models showed very high accuracy, ranging from 84% to 99%, with some studies achieving near-perfect accuracy. Comparison of deep learning models for pneumonia classification shown in Table 2.

Table 2. Comparison of deep learning models for pneumonia classification

Deep learning models	Dataset type	Accuracy	References
CNN-RF	Chest X-Ray	99.52%	[10]
Voting algorithm by 17 pre-trained CNN approach (AlexNet, GoogleNet, GoogleNet, ResNet18, SqueezeNet, MobileNetv2, Inceptionv3, DenseNet201, Xception, Vgg19, Places365GoogleNet, InceptionResNetv2, ResNet50, ResNet101, NASNetMobile, NASNetLarge, and ShuffleNet)	Chest X-Ray	99.62%	[11]
CNN (VGG16) + modified dropout	Chest X-Ray	97.40%	[12]
ResNet-50 + DenseNet	Chest X-Ray	99.60%	[13]
Resnet50	Chest X-Ray	95.47%	[14]
SqueezeNet + SVM	Chest X-Ray	98.83%	[15]
Fine-Grained CNN	Chest X-Ray	96.91%	[16]
Stacked ensemble convolutional neural network	Chest X-Ray and CT-Scan	97.27% (covid-19 CXR dataset) and 98.30% (covid-19 CT-scan)	[17]
KNN-RF	Chest X-Ray	91.30% (GWCMCx dataset) and 99% (Josep-NIH dataset)	[18]
DCNN "DeepChest"	Chest X-Ray	96.56%	[19]
GAN-CNN	Chest X-Ray	97.78%	[20]
Deep Supervised Domain Adaptation (DSDA)	Chest X-Ray	90.00%	[21]
Hybrid CNN based on VGG+ML	Chest X-Ray	98.55%	[22]
Attention-based Convolutional Neural Network (PCXRNet)	Chest X-Ray	94.61%	[23]
VGG16-NN	Chest X-Ray	92.15% (dataset 1) and 95.40% (dataset 2)	[24]
ABO-CNN	Chest X-Ray	96.95%	[25]
CNN	Chest X-Ray	84.12%	[26]
Ensemble convolutional networks + Transformer Encoder	Chest X-Ray	99.21% (mendeley dataset) and 98.19% (chest X-ray dataset)	[27]
MobileNetV2 + DenseNet169 + VGG16	Chest X-Ray	98.60%	[28]
Ensemble method-based Federated Learning (EFL)	Chest X-Ray	96.63%	[29]
Xception	Chest X-Ray	93.00%	[30]
CNN	Chest X-Ray	97.60%	[31]
Federated Learning DenseNet	Chest X-Ray	96.00%	[32]
Multiscale Eigendomain Gradient Boosting (MEGB)	Chest X-Ray	96.42%	[33]
Ensemble models (DenseNet201, EfficientNet-B0, and VGG16)	Chest X-Ray	97.00%	[34]
Attention-guided partial domain adaptation (AGPDA) network	Chest X-Ray	90.03%	[35]
CXR Based Multi-Task Deep Neural Network (CXR-Net)	Chest X-Ray	87.90%	[36]

Deep learning models	Dataset type	Accuracy	References
Prior Knowledge-Based Active Attention Network (PKA2-Net)	Chest X-Ray	97.63%	[37]
LBP (Local Binary Pattern) fusion	Chest X-Ray	82.70 % (Guangzhou Medical Center dataset) and 78.9% (IEEE8023-CXR dataset)	[38]
Capsule Network Clusters (CNsC)	Chest X-Ray	98.30%	[39]
MSD-Net	Chest X-Ray	97.76% (covid-19 radiography database) and 97.78% (CXR pneumonia dataset)	[40]
VGG16	Chest X-Ray	95.60%	[41]
Modified DenseNet-121	Chest X-Ray	97.03%	[42]
FPGA-DCNN	Chest X-Ray	95.63%	[43]
Novel EfficientNetV2L	Chest X-Ray	94.02%	[44]
EfficientNetB0	Chest X-Ray	99.78%	[45]

For example, Sourab et al. [10] achieved 99.52% accuracy using a CNN-RF approach, while Li et al. [11] reported 99.62% accuracy using voting from 17 pretrained CNN models. Ensemble and hybrid models generally produce more stable performance, such as the combination of MobileNetV2-DenseNet169-VGG16 [28] which recorded an accuracy of 98.60%, or the combination of Transformer Encoder with ensemble CNN [27] with an accuracy of 99.21%. However, some models with simpler architectures or limited datasets recorded lower accuracy, such as the basic CNN [26] with an accuracy of 84.12%, or LBP fusion [38] with an accuracy of 78–82%. Upon deeper analysis, the trend of increasing accuracy appears to be influenced by several key factors, such as the size and diversity of the dataset, the strength of the pretrained architecture used, the use of ensemble learning, reinforcement with attention mechanisms and domain adaptation, and the efficiency of the data preprocessing applied. However, it is important to note that the high accuracy figures require further scrutiny, as many studies only use internal validation. External evaluation across different populations and clinical settings is urgently needed to ensure the model's generalisation in the real world.

4. Discussion

4.1. Contribution to Literature

The studies conducted have made significant contributions to the scientific literature in the field of pneumonia classification using deep learning approaches, particularly through the use of CXR images. The first notable contribution is the enrichment of classification methodologies, where various studies have successfully developed and adapted deep learning models, both through the use of popular pretrained CNNs such as VGG16, ResNet, DenseNet, MobileNet, and EfficientNet, as well as through the development of innovative new models such as DeepChest, PCXRNet, PKA2-Net, MSD-Net, and Capsule Networks. These approaches have enriched the methodological landscape while demonstrating high effectiveness in detecting various manifestations of pneumonia in medical images.

Furthermore, these studies have also made important contributions to the development of more advanced and effective data preprocessing strategies. The combination of various preprocessing methods such as resizing, normalisation, image augmentation, noise removal through Non-Local Mean (NLM), adaptive histogram equalisation (AHE), and the application of lung segmentation has been proven to improve the accuracy and generalisation performance of the model. Special innovations such as GAN-based data augmentation and balancing methods like SMOTE also contribute to addressing classic challenges like data imbalance between pneumonia classes, which previously posed a significant obstacle in pneumonia classification literature.

From the perspective of dataset utilisation, these studies have made significant contributions by exploring and combining various multi-institutional and multi-label datasets such as ChestXRay2017 from the NIH, the Guangzhou Women and Children's Medical Centre dataset, the Radiological Society of North America (RSNA) dataset, and datasets specifically addressing COVID-19 pneumonia. The use of multi-institutional datasets not only expands the scope of disease representation but also enhances the validity and reliability of classification results, thereby strengthening the scientific evidence required for future clinical applications.

Another important contribution lies in improving model interpretability through explainable AI (XAI) approaches. Studies applying techniques like Grad-CAM and modified Class Activation Maps (mCAM) are beginning to show how deep learning model decisions can be visually interpreted, helping doctors and radiologists understand the clinical rationale behind model predictions. This step is crucial for reducing barriers to AI technology adoption in clinical contexts and building trust among medical practitioners in deep learning technology. Overall, the various studies reviewed provide extensive and in-depth contributions to addressing technical, clinical, and methodological challenges in the literature on CXR-based pneumonia classification. Moving forward, these findings serve as a crucial foundation for more comprehensive future research, particularly those focused on cross-population external validation and the integration of deep learning-based pneumonia classification systems into real-world clinical practice. Challenges and prospects of deep learning models in pneumonia classification shown in Table 3.

Table 3. Challenges and prospects of deep learning models in pneumonia classification

Deep Learning Models	Challenges	Prospects
CNN-RF	Additional computational time required for manual feature extraction.	Combining CNN and Random Forest effectively enhances pneumonia prediction accuracy.
Voting algorithm by 17 pre-trained CNN approach	High computational complexity due to the simultaneous use of multiple pretrained models.	Significant potential for achieving very high classification accuracy through collective strength of diverse CNNs.
CNN (VGG16) + modified dropout	Risk of overfitting if dropout is not optimally tuned.	Optimized dropout significantly improves model generalization, particularly with limited data.
ResNet-50 + DenseNet	Increased complexity potentially slows training.	Leveraging strengths of both models significantly enhances pneumonia classification performance.
Resnet50	Potentially suboptimal with small datasets and prone to overfitting.	Effective residual architecture prevents vanishing gradient problems, ideal for large datasets.
SqueezeNet + SVM	Requires additional feature extraction step, risking loss of relevant features.	Lightweight model, ideal for fast implementation with high computational efficiency and adequate accuracy.
Fine-Grained CNN	Sensitive to minor variations in data, needs detailed datasets.	Excellent in capturing fine-grained features, suitable for high-precision pneumonia diagnosis.
Stacked ensemble convolutional neural network	High implementation complexity, demands significant computational resources.	Ensemble approach enhances robustness and accuracy compared to single-model approaches.
KNN-RF	Dependent on manual feature extraction quality, feature selection strongly influences performance.	Highly flexible and easy to implement in simple clinical settings.
DCNN "DeepChest"	High model complexity requiring significant computational resources.	Potential for deep feature extraction tailored specifically to pneumonia diagnosis from CXR.
GAN-CNN	GAN training complex, prone to mode-collapse, synthetic data quality control is challenging.	Significant potential in generating additional effective data, helping overcome class imbalance.
Deep Supervised Domain Adaptation (DSDA)	Complex implementation and requires additional parameter tuning for domain adaptation.	High potential for cross-domain generalization, ideal for multi-institutional deployment.

Deep Learning Models	Challenges	Prospects
Hybrid Convolutional Neural Network (CNN) based on VGG+ML	Integration complexity requires intensive validation of CNN-ML combination results.	Best combination of CNN deep features and classical machine learning methods to improve performance.
Attention-based Convolutional Neural Network (PCXRNet)	Requires additional computational resources for complex attention mechanisms.	Strong potential for enhancing model focus on clinically important areas, improving interpretability.
VGG16-NN	Risk of overfitting with limited data, requires optimal regularization.	Simple model effective for rapid classification with relatively good results.
ABO-CNN	Complex ABO-based optimization process, scaling difficulties in larger applications.	Offers advanced optimization techniques improving pneumonia classification accuracy and efficiency.
Convolutional Neural Network (CNN)	Highly dependent on data quality, suboptimal performance with small and noisy datasets.	Classical, effective, flexible architecture suitable for various medical imaging applications.
Ensemble convolutional networks + Transformer Encoder	High complexity in training, demands considerable computational resources.	Transformer's global interpretation combined with CNN's local features yields excellent classification performance.
MobileNetV2 + DenseNet169 + VGG16	High complexity, integrating multiple models may extend training time.	Robust and highly effective combination for improving pneumonia classification accuracy.
Ensemble method-based Federated Learning (EFL)	Requires specific federated learning infrastructure, complex practical implementation.	Ideal for data privacy preservation among institutions, well-suited for multi-center research.
Xception	Risk of overfitting with small datasets, requires optimal regularization.	Highly effective in medical image classification with high accuracy and good parameter efficiency.
Convolutional Neural Network (CNN)	Performance heavily depends on data quality, suboptimal performance with limited, noisy datasets.	A proven effective and flexible architecture suitable for diverse medical imaging applications.
Federated Learning DenseNet	Complex data distribution management and inter-model communication.	Great potential for inter-institutional collaboration without direct sharing of sensitive patient data.
Multiscale Eigendomain Gradient Boosting (MEGB)	Difficult optimal feature and domain scale selection, complex training process.	Significant potential for accuracy enhancement through multi-scale approaches, ideal for heterogeneous datasets.
Ensemble models (DenseNet201, EfficientNet-B0, and VGG16)	Extended training time, demands significant computational resources.	High classification performance, greater robustness compared to single models.
Attention-guided partial domain adaptation (AGPDA) network	Complex training due to domain adaptation, requires careful parameter tuning.	Enhances generalization across diverse datasets, ideal for cross-domain deployment.
CXR Based Multi-Task Deep Neural Network (CXR-Net)	High complexity, risk of imbalanced multitask training.	Simultaneous training of multiple tasks improves overall training efficiency.
Prior Knowledge-Based Active Attention Network (PKA2-Net)	Complex attention mechanism implementation, extensive optimal parameter tuning required.	Enhances interpretability and classification accuracy with knowledge-based attention mechanisms.
LBP (Local Binary Pattern) fusion	Limited ability to accurately represent global features, lower performance on complex datasets.	Lightweight, fast computation ideal for scenarios with limited resources.
Capsule Network Clusters (CNsC)	Computationally demanding complex models, challenging to train compared to standard CNNs.	High potential for representing spatial relationships among features, ideal for precise medical applications.
MSD-Net	High training complexity, requires intricate additional parameter tuning.	Captures multi-scale features effectively, significantly improving pneumonia classification accuracy.
VGG16	High risk of overfitting, particularly with limited datasets, requires careful regularization.	Robust architecture, easy to implement, and consistently achieves good results in medical image classification.
Modified DenseNet-121	Complex model structure, requiring significant computational resources and careful parameter tuning.	Effectively captures complex features with improved connectivity patterns, resulting in enhanced pneumonia classification accuracy.
FPGA-DCNN	Complex hardware implementation with high initial development cost.	Ideal for high-efficiency, real-time clinical environment implementations.

Deep Learning Models	Challenges	Prospects
Novel EfficientNetV2L	Potential overfitting without optimal parameter tuning on smaller datasets.	Offers high performance and computational efficiency, suitable for large-scale clinical applications.
EfficientNetB0	Complex hyperparameter tuning, requires intensive training time.	High accuracy with optimal computational efficiency, well-suited for practical clinical implementations.

4.2. Challenges

The use of various deep learning models in chest radiography-based pneumonia classification faces a number of challenges that need to be considered. One of the main challenges is the high computational complexity, particularly in models such as the Voting Algorithm with 17 pretrained CNN models [11], Ensemble CNN with Transformer Encoder [27], and Stacked Ensemble CNN [17]. This complexity results in lengthy training processes and requires significant computational resources, which often pose constraints in real-world clinical settings with limited resources. Another significant challenge is the risk of overfitting, particularly in popular models such as VGG16 [41], ResNet50 [14], Xception [30], and EfficientNetV2L [44]. This risk increases especially when the available data is limited or the dataset quality is inadequate, causing the model to overlearn from the training data, resulting in suboptimal performance on new data.

Additionally, some studies indicate that the process of integrating or combining deep learning models with classical machine learning algorithms presents its own challenges. For example, CNN-RF [10], SqueezeNet + SVM [15], and Hybrid CNN with additional machine learning methods such as VGG+ML [22] face challenges in the complex process of manual feature extraction and the risk of losing important feature information. This can impact the final model performance and increase the complexity of development and validation. Furthermore, some studies using domain adaptation approaches or attention mechanism-based approaches such as Deep Supervised Domain Adaptation (DSDA) [21], Attention-guided Partial Domain Adaptation (AGPDA) [35], and Attention-based CNNs like PCXRNet [21] and Prior Knowledge-Based Active Attention Network (PKA2-Net) [37], face additional challenges in terms of parameter tuning complexity and additional computational requirements. This necessitates special efforts in the training process and parameter optimization to achieve optimal results on medical datasets that are inherently heterogeneous and complex.

Finally, a specific challenge that arises in clinical implementation is the issue of model interpretability, particularly in complex approaches such as Capsule Network Clusters [39] and Federated Learning DenseNet [32]. The complexity of the architecture and the non-transparent information processing make it difficult for doctors or medical practitioners to understand the basis for the decision-making of these models. Therefore, further development is needed regarding the interpretation mechanism of prediction results so that these models can be more widely accepted in the medical community. In general, these challenges need to be addressed effectively through careful methodological approaches, better data management, and improved model interpretability to fully leverage the potential of deep learning models in the context of clinical pneumonia diagnosis.

4.3. Prospects

Despite facing various technical and clinical challenges, the reviewed research results show very promising prospects for the development of a deep learning-based pneumonia classification system. One of the main prospects is the ability of ensemble models to consistently improve prediction accuracy and stability. Several studies, such as the voting algorithm with 17 pretrained CNNs [11], Stacked Ensemble CNN [17], and the combination of CNN with Transformer Encoder [27], demonstrate that ensemble approaches can leverage the strengths of various architectures to address the complex variability of clinical data. Additionally, the development of attention mechanism architectures such as Attention-based CNN (PCXRNet) [21], Attention-Guided Partial Domain Adaptation [35], and Prior Knowledge-Based Active Attention Network (PKA2-Net) [37], opens up significant opportunities to enhance both the accuracy and interpretability of prediction results. By focusing the model's attention on clinically relevant radiological areas, this method enables more precise predictions and provides visualizations that can be validated by clinicians, thereby increasing the likelihood of its application in real-world practice.

Another prospect lies in the development of generative data augmentation techniques such as GAN-CNN [20], [12], which hold great potential in addressing the issue of data imbalance (class imbalance) that has long been a challenge in medical data. GAN's ability to generate additional synthetic data opens the door to enriching data variability without the need for large-scale clinical data acquisition, which is often costly and difficult to obtain in practice. Furthermore, some studies have begun to explore federated learning models such as Ensemble Federated Learning [29] and Federated Learning DenseNet [32], which enable multi-institutional collaboration without the need to physically transfer patient data. This approach not only addresses data privacy challenges but also opens up prospects for developing global models with stronger generalization through learning from more diverse data populations. Equally important, the use of explainable AI (XAI) such as Grad-CAM [41] and Capsule Network Clusters [39] demonstrates the potential for integrating artificial intelligence with clinical needs that prioritize transparency in decision-making. This approach paves the way for broader adoption by the medical community, as prediction results that can be visualized and understood by doctors will strengthen trust in AI systems.

With these innovations, the development of deep learning-based pneumonia classification systems not only promises high prediction accuracy but also has the potential to produce adaptive, interpretable, safe, and collaborative systems in real clinical settings. The future of this research is wide open, particularly with advancements in multi-modal data integration (e.g., CXR, CT-scan, clinical data), integration with hospital systems, and large-scale external validation, which will solidify AI's position as a reliable clinical decision-support tool.

5. Conclusion

This paper offers an extensive review of pneumonia classification using chest radiographic images leveraging deep learning methods, encompassing 36 studies released between 2022–2024. The review outlines a broad spectrum of deep learning models applied, the variety of datasets used, key obstacles faced by researchers, and possible future directions highlighted in the literature. We believe this review can act as a valuable resource for future investigators striving to create robust, precise, and clinically relevant diagnostic systems for detecting pneumonia from CXR images. The ultimate goal of research in this field is to assist clinicians in providing rapid, reliable, and interpretable pneumonia diagnoses, thereby enabling timely treatment and improved patient outcomes, particularly for conditions such as viral pneumonia, bacterial pneumonia, and COVID-19-related pneumonia. However, deep learning-based image classification remains a highly complex domain involving numerous processes, multiple hyperparameters, and a variety of sophisticated model architectures. Despite the impressive progress demonstrated in many studies, current models still face considerable limitations such as data imbalance, limited generalization across multi-center datasets, high computational cost, and challenges in model interpretability for clinical deployment.

In conclusion, rather than exclusively pursuing complex model architectures that aim to simultaneously solve multiple challenges, we encourage future researchers to adopt a more pragmatic approach by addressing specific limitations or focusing on optimizing one particular aspect at a time, such as improving generalization across institutions, developing more efficient data augmentation strategies, or enhancing explainability through advanced attention mechanisms and explainable AI techniques. As demonstrated in this review, the field of pneumonia classification using CXR images remains rich with opportunities for further research. Continued advancements in this area will require collaborative efforts across multidisciplinary teams, combining expertise from medical imaging, artificial intelligence, clinical medicine, and healthcare systems to realize the full potential of AI-assisted diagnostic systems in real-world clinical practice.

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