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Advancements in Pneumonia X-Ray Image Detection: A Review

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Abstract

Pneumonia remains a primary cause of morbidness and mortality worldwide, necessitating the continuous advancement of diagnostic techniques for timely and accurate detection. Pneumonia is common, it is potentially a life-threatening infection for respiration, poses significant challenges to healthcare systems worldwide. Recently, the arrival of deep learning techniques has stirred up the field of medical imaging, offering promising avenues for enhanced pneumonia detection. In this paper, the advancements in pneumonia detection facilitated by deep learning techniques and their applications are discussed, and exploration is done that how deep learning techniques are changing the game. Beginning with an insightful introduction we dive into different deep learning methods, showing how they work and where they shine. This paper encompasses a thorough examination of diverse deep learning methods employed in pneumonia detection. This paper analyzes the performance of different techniques across different datasets, providing a comparative assessment of available research. By unpacking the latest advancements in a clear and friendly way, this review is valuable for anyone interested in using deep learning technology to detect and identify pneumonia effectively.

Keywords: X-Ray image, deep learning methods, pneumonia detection, CNN, radiologists

INTRODUCTION

Pneumonia, characterized by acute infection in the lungs, can result from bacterial and viral agents, or fungal agents. This infection leads to inflammation of air sacs and can cause pleural effusion, where fluid accumulates in the lung. Particularly concerning is, its impact on children under five years, over 15% deaths within this demographic. Pneumonia is especially prevalent in underdeveloped and developing nations, where factors, such as overpopulation, pollution, and poor hygiene contribute to its severity. Additionally, limited medical resources further compound the challenges in managing this condition [1]. Pneumonia poses a significant threat to both children and elderly individuals with compromised immune systems, often resulting in fatal outcomes. India holds the unfortunate distinction of having the second-highest mortality rate among children. UNICEF reports an alarm that 800, 000 children lost their lives due to pneumonia. Under two years age, infants are particularly vulnerable, exhibiting a higher mortality rate compared to other age groups [2].

There are three primary categories of pneumonia: First is community-acquired, other is viral, and the last is bacterial. Community-acquired pneumonia is distinguished from hospital-acquired pneumonia, with approximately 1.5 million individuals hospitalized annually in the US due to community-acquired pneumonia. Viral

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pneumonia affects roughly 200 million people globally each year, with an equal infection rate between adults and children. Bacterial pneumonia is further categorized as typical or atypical. Typical bacteria can be identified through Gram staining and standard culture media, whereas atypical bacteria do not display these characteristics. Examples of pneumonia caused by typical bacteria include Staphylococcus aureus, Chlamydia psittaci, etc. Mycoplasma pneumoniae typically causes atypical bacterial pneumonia. Additionally, other types of pneumonia include fungal, aspiration, and hospital-acquired pneumonia [3]. In 2019, approximately 740, 180 children under the age of 5 passed away. Specifically, data from Indonesia in the same year indicated that roughly 314, 455 children under five lost their lives due to pneumonia, as reported by Health Ministry, Indonesia [4]. Chest X-rays are a common method for diagnosing pneumonia, where radiologists analyze the presence of white spots indicative of pneumonia fluid. However, interpreting X-ray results can be challenging due to the limited color scheme, making it difficult to distinguish pneumonia fluid from other anomalies. Errors in diagnosis can have severe consequences. With advancements in deep learning and computing power, new techniques and algorithms now rival human accuracy. Neural networks, inspired by the human brain, excel in classifying and segmenting images [2]. A computerized device assists radiologists in identifying pneumonia by examining chest X-ray images [4]. CNNs are deep learning models that have become extremely effective tools for medical image processing, including the diagnosis of pneumonia. CNNs are a subset of deep learning models created effectively for processing images. CNNs and other deep learning models can automatically extract pertinent features from unprocessed image data. Deep learning models can be used to either totally or partially automate pneumonia identification, which will relieve radiologists and other healthcare workers of some of their workload. Some of the problems in Pneumonia X-ray classification and detection include lack high-annotated datasets and patient medical history for pneumonia detection. The major objective of review paper is to analyze and compare different methods for autonomously detecting pneumonia within X-rays. The paper aims to provide an extensive review of the topic, aiding other researchers in analyzing various methodologies (Figure 1).

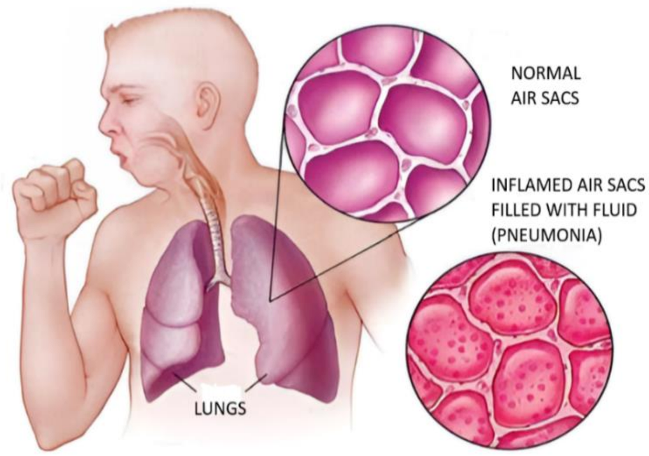

Figure 1. Pneumonia in lungs [2].

LITERATURE REVIEW

Abhishek et al. [5] introduced a method for identifying pneumonia automatically in X-rays, using image processing techniques. To identify pneumonia clouds, the researchers applied Otsu thresholding, a technique that separates healthy lung areas from those affected by pneumonia. The study's significance lies in providing a good, automated method for image processing, for Pneumonia. Enes et al. [6] used two well-known networks – Xception and Vgg-16 for classifying pneumonia in chest X-ray images. Diagnosing X-rays is a common method, but it is a challenging task even for expert radiologists. In this study, the researchers trained both networks- Xception and Vgg-16 with same parameters to ensure a fair comparison. The study demonstrated that Xception is more effective for identifying Pneumonia, while Vgg-16 performs better in identifying cases without pneumonia. Harsh et al. [7] explores the application of deep CNNs, offering potential improvements over traditional expert-based methods. The investigation into dataset size variations sheds light on the influence of data quantity on CNN performance. Overall, the findings contribute to an efficient pneumonia detection system.

Rong et al. [8] provided a Deep CNN model for pneumonia diagnosis for X-ray images. It was trained and then, tested on an X-ray database. Robert et al. [9] designed a deep learning pipeline with segmentation and an ensemble classifier. While many researchers focused on creating classifiers, only a small portion integrated a segmentation module, essential for practical clinical models. Recognizing the visual similarities between covid-19, pneumonia, and other lung related diseases. Varshni et al. [10] explained, pneumonia, a potentially fatal infectious illness affecting the lungs, poses a significant mortality risk in India. Utilizing chest X-rays for diagnosis necessitates skilled radiologists, resulting in treatment delays, notably in remote areas. Deep learning models hold promise in medical image analysis for identifying diseases. Employing pretrained CNN models aid in pneumonia detection, showing encouraging classification results. The objective of the study is to enhance medical capabilities in regions lacking radiologists, facilitating early pneumonia detection to avert adverse outcomes, particularly in remote locales. The model architecture proposed entails three stages: preprocessing, feature extraction, and classification. The DenseNet-169, trained on ImageNet dataset, utilized extraction features, with original 3-channel images resized to 224x224 pixels for computational efficiency. Study utilizes the ChestX-ray14 dataset [10]. In this research, the model's extensive convolutional layers necessitate substantial computational power.

Kubra et al. [11] concentrated on classifying between normal and abnormal chest X-rays by SqueezeNet. Transfer learning was utilized, adjusting a preexisting network for classification purposes, underlining the impact of deep learning in medical diagnostics for disease identification. Various preprocessing techniques, including image cropping, histogram equalization, and CLAHE, were used. A total of 660 images from the ChestX-Ray14 dataset were employed for classification. The convolutional neural network architecture of SqueezeNet was deployed for image classification, with the study emphasizing the identification of normal and abnormal X-ray images by pattern recognition and deep learning approaches. The study contains of 660 X-rays sourced from ChestX-Ray14 [11]. This research centered on a particular dataset (ChestX-Ray14), potentially restricting the applicability of its results. Additionally, it lacked a comprehensive comparative analysis with other deep learning techniques, which could have provided further understanding regarding the efficiency of the approach. Sirwa et al. investigated the usage of AI in the examination of X-rays in pediatric patients, highlighting a significant gap. The investigation found a shortage of extensive Xx-ray datasets specific to pediatric cases and strong focus on detecting pneumonia in AI research. While different studies claim high diagnostic precision, most lack validation on separate datasets, which provides a challenge to progress in AI for pediatric radiology [12]. Goram et al. proposed DL framework to categorize different chest infections, such as covid19, through X-rays. VGG19 and CNN combination is employed to extract patterns and classify the infections, surpassing previous studies with impressive performance metrics. Looking ahead further investigation could delve into incorporating CT scans and pinpointing specific interested areas for more advanced classification of severity levels [13]. Garima et al. [14] focuses, particularly CNNs, categorizing pneumonia chest X-rays. Model seeks to classify pneumonia instances within these images, tackling issues encountered in medical diagnosis. The study explores the utilization of the CNN algorithm alongside data augmentation methods to elevate classification accuracies and enhance model efficacy. Notably, the model is constructed from the ground up, foregoing reliance on preexisting frameworks, thus demonstrating progress in medical image classification. The study uses 5836 images of chest X-ray dataset [14]. CNN structures employed in this study might require substantial computational resources, resulting in overhead and possible constraints on scalability.

Khalid El Asnaoui [15] research revolves around the development and application of both individual and ensemble deep learning models, classifying pneumonia diseases utilizing chest X-ray images. This approach encompasses several crucial stages. Firstly, the dataset preprocessing stage involves amalgamating two publicly present datasets, namely chest X-ray dataset and CT, alongside the covid X-rays. This integration forms a unified dataset comprising four distinct classes: First is bacteria, second – COVID-19, third – normal, and last is viral. Subsequently, models undergo fine-tuning on the combined dataset to facilitate multiclass classification. During the training and classification phase, the preprocessed dataset undergoes augmentation, splitting, and subsequent passage through the refined models to extract features. After extraction of features, flattening is done and then, data is directed toward fully connected layers to execute classification tasks. Ensemble models are constructed by independent training single models and averaging their outputs, thereby diminishing variance and enhancing generalization. The study utilized a dataset formed by merging two publicly accessible image collections. First, X-ray and CT dataset: Comprising 5856 images. Second, Covid x-ray Dataset: Containing 231 X-rays specifically related to Covid-19 [15]. The study focused on using deep models, classifying pneumonia diseases from X-rays. While results may indicate promising accuracy rates within the dataset's scope, validating the real-world applicability and clinical usefulness of these models in diagnosing pneumonia across various patient demographics and healthcare settings would require further validation and testing (Figure 2).

METHODOLOGY

Basic procedure in order to classify X-rays for pneumonia is shown using the following diagram:

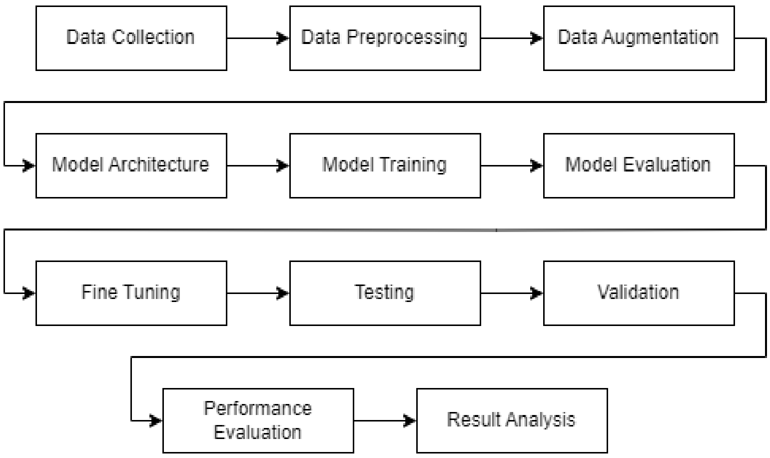

Figure 2. Basic methodology diagram.

Gather X-ray images of patients with and without pneumonia from different medical DB's. Before transferring or inputting the images in the model, standardization of their sizes should be done, like brightness, contrast level adjustment and noise reduction, to ensure consistency and enhancement in the quality of the data. For expanding the datasets and improving the model's capacity and ability to generalize the data, data augmentation techniques are used, such as rotation, flipping, scaling, etc. This will artificially create variations of the original images available in the dataset. After the model architecture is decided to continue further research, the model is trained. During training, the model's parameters are optimized and monitored on validation set. After which, the model's performance is evaluated and compared with existing approaches.

EXPLORING THE DIFFERENT DL METHODS

Convolutional Neural Network [14]

CNNs are fundamentally designed to process image-based information, enabling them to effectively handle various data types across diverse datasets. A key feature of CNN architecture lies in the organization of neurons into three dimensions, including height, width, and depth. These networks comprise three essential layers which are combined to form model. The convolutional layer calculates the outputs of numerous neurons connected to local regions by performing scalar product operations. Subsequently, the Rectified Linear Unit (ReLU) is applied to the resulting output. Following this, pooling layer reduces spatial dimensionality of input, often halving image dimensions within the process of activation. Finally, fully connected layers generate scores based on the activations, facilitating image classification into labels. These scores are then passed toward output layer, where every neuron represents a specific classification label [14]. Figure 3 shows the architecture of CNN.

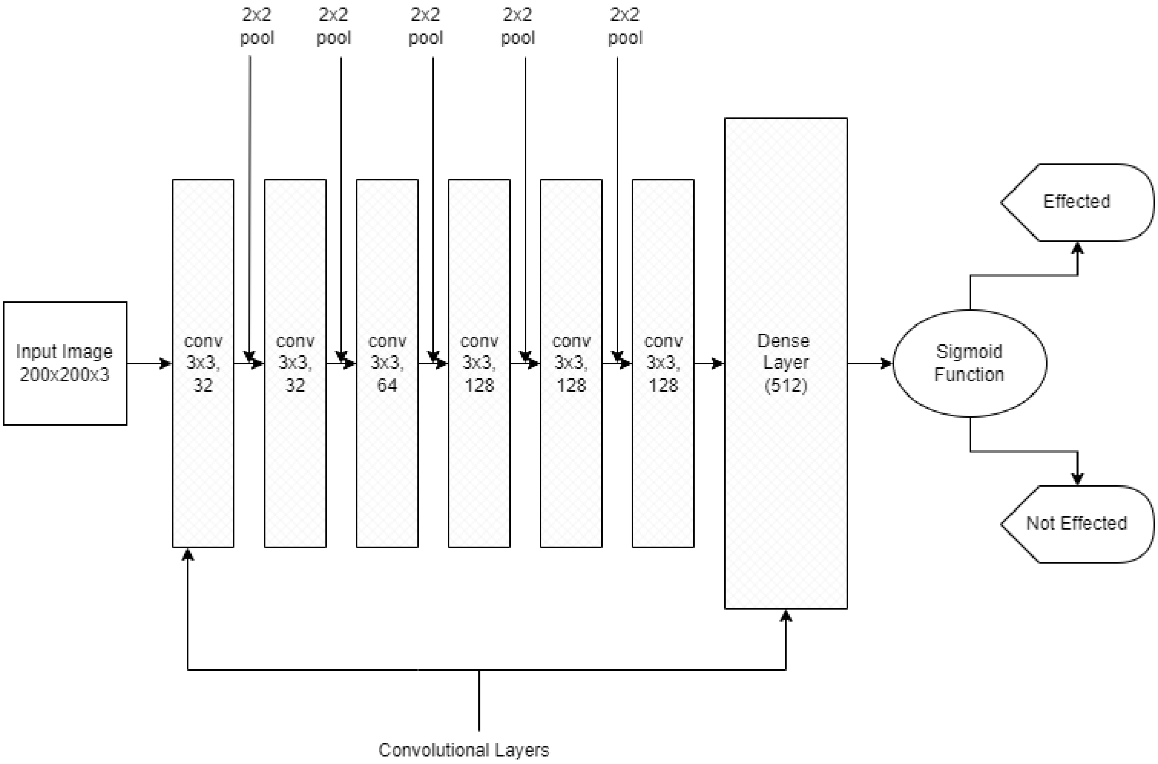

Figure 3. An overview of architecture of CNN [14].

SqueezeNet [11]

In various domains utilizing deep learning techniques, there is a need to establish patterns that define the data under examination. These patterns are used to enhance performance that refines the attributes of elements within the dataset. However, analyzing chest X-ray data poses challenges due to the dynamic nature of lung images, prominent rib cage edges, discernible heart shapes, and varying bone density around the clavicle. Moreover, lung infections often manifest as indistinct white spots with lower contrast, complicating pattern recognition. Preprocessing techniques, like-image cropping, histogram equalization, and adjustment of image color and size structures, can mitigate these challenges. SqueezeNet is chosen for its high accuracy achieved through parameter reduction, featuring a compressed design architecture with significantly fewer parameters compared to AlexNet. Its unique design employs 1 x 1 filters, down sampling late in the network, and utilizes fire modules for efficient feature extraction. These modules comprise “squeeze” layers with 1 x 1 convolutions, reducing the parameter numbering. The SqueezeNet model, tailored for this study, facilitates efficient processing and adaptation to embedded systems due to its parameter efficiency [11]. SqueezeNet architecture is given in Figures 4 and 5 Shows SqueezeNet Fire Module.

ResNet50 [15]

ResNet50, a convolutional neural network subclass developed by He et al. [16], is a prominent deep residual network utilized for image classification. This emerged as victory of the ILSVRC 2015 competition. Key advancement lies in its innovative architecture, which introduces residual layers within the network-in-network framework. Comprising five stages, ResNet50 incorporates convolution and identity blocks, with each block containing three convolution layers. With a total of 50 residual networks, ResNet50 is designed to process images sized at 224 × 224 pixels [15].

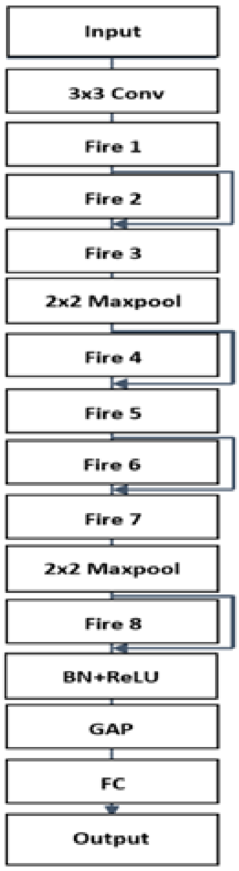

Figure 4. Squeezenet architecture [11].

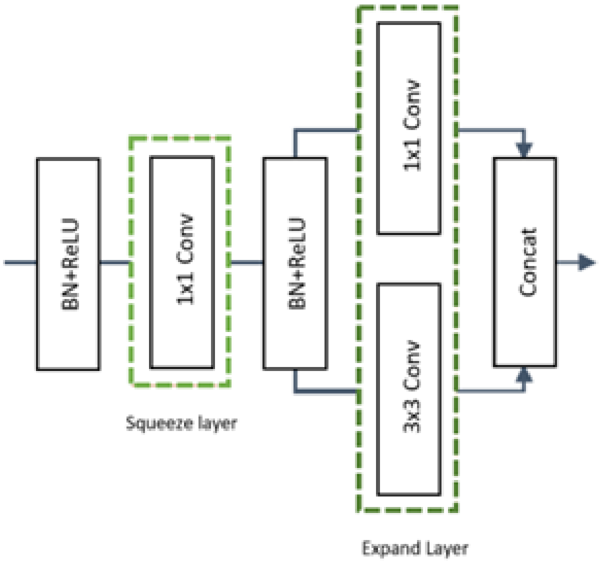

Figure 5. Fire module of Squeezenet [11].

MobileNet_v2 [15]

It an enhanced version of MobileNet_V1, which is a convolutional neural network detailed in [17]. Comprising 54 layers, it operates on input images sized at 224 × 224. Its primary feature lies in its utilization of depth wise separable convolutions. This approach involves separate kernels, resulting in reduced usage and parameter count during training, thereby yielding a compact and efficient model. The network architecture includes 2 blocks for down-sampling (Table 1) [15].

Table 1. Models' comparison and application.

Model	Number of Parameters	Model Size (MB)	Application
AlexNet	61, 100, 840	233.0	Finds normal or abnormal x-rays, aiding in early diagnosis.
SqueezeNet	1, 235, 116	4.8	Can efficiently process X-ray images, detecting signs of pneumonia, making itself valuable for quick and accurate diagnosis in healthcare settings [11].
InceptionResNet_v2	55, 873, 736	215.7	Excels in identifying subtle features indicative of pneumonia, providing detailed as well as accurate analysis for healthcare professionals [15].
ResNet50	25, 636, 712	98.0	Deep architecture allows for precise pneumonia abnormality detection within chest x-ray images, facilitating early intervention and treatment of the condition [15].
MobileNet_v2	3, 538, 984	13.5	Compact design and efficient processing make it suitable for real-time pneumonia detection applications, enabling rapid screening and diagnosis in clinical settings.

It is to be noted that the dimensions listed above might differ slightly based on how they are implemented and any compression methods utilized. These figures are estimates and could fluctuate with varying versions or implementations of the models. It is important to recognize the performance of models in pneumonia detection can vary due to factors, like the quality of the dataset, adjustments made to the model, and the environment in which they are deployed. Furthermore, it is essential to note that additional validation and regulatory clearance may be necessary before these models can be utilized in clinical settings.

LISTING DATASETS AND COMPARING RESEARCH

Some of the datasets containing X-rays are as follows [2]:

RSNA Dataset [18]

The RSNA dataset, published by RSNA, is publicly accessible for use by the scientific community [2]. It comprises 26, 684 samples created by the NIH, which contains 112, 000 samples. While, this dataset is derived from the NIH, significant distinctions exist between the two. Specifically curated for pneumonia cases, the RSNA dataset offers vital and precise information essential for the disease's classification and detection [18].

Pneumonia dataset Kaggle [2]

The Pneumonia DataSet on Kaggle is comprised of 5863 X-ray images. Within this, there are 1590 images classified-normal and 4273 images depicting-pneumonia cases. Commonly employed for disease detection [2].

NIH Dataset [2]

The data set held by the NIH clinical center was made publicly available to facilitate autonomous detection. It stands as largest collection of Chest X-rays, totaling 112, 120 images captured. This comprehensive dataset encompasses 14 different types of diseases and includes metadata in CSV format detailing patient information, such as age and gender (Table 2) [2].

However, different researchers used different data sets and models in their study:

Table 2. Comparing research approaches of different studies.

Author	Research Method Approach & Dataset	Advantages	Disadvantages
Gaobo et al. [19]	Introduces a method using a combination of residual structures and dilated convolutions providing accuracy of 90.5% [19]. Collection:5856 chest images [19].	Dilated convolutions and residual structures enhance classification accuracy. Uses transfer learning and have high recall rate.	Variations in image quality due to different equipment and operators can present difficulties in generalizing the model's performance across various clinical environments.
Rachna et al. [20]	The research paper employs two fundamental CNN models, labeled as Model 1 and Model 2. The highest accuracy of 92.31% achieved [20]. ImageNet dataset, comprising approximately 15 million images categorized into 22, 000 distinct classes [20].	The research paper introduces neural networks optimized for real-time applications, achieving exceptional recall and F1 scores, essential for reducing false negatives in medical imaging.	The study consolidates bacterial and viral pneumonia categories into a single group for simplicity, possibly sacrificing the ability to differentiate between various types of pneumonia.
Okeke et al. [21]	CNN is used, which provides 94% overall accuracy [21]. The dataset contains 5, 856 images, which were split into training and validation sets comprises 3, 722 and 2, 134 images [21].	Offers benefits in terms of efficiency, accuracy, customization, reliability, and performance. It efficiently minimizes computational costs while maintaining high validation accuracy.	CNN models can often be intricate, featuring multiple layers and parameters, thereby posing challenges in comprehending and adjusting the model's architecture.
Nada et al. [22]	DenseNet201, ResNet18, SqueezeNet, AlexNet, ResNet152V2, MobileNetV2, CNN, and LSTM-CNN models are utilized providing highest accuracy of 99.22% [22]. RSNA dataset consisting of 26, 684 chest X-ray images [22].	This significant level of accuracy showcases efficiency, precisely identifying and categorizing pneumonia images.	Sophisticated structures, such as ResNet152V2 can demand substantial computational resources and time for training, potentially hindering scalability and practical adoption in environments with limited resources.
Gaurav et al. [23]	The study employed four models for pneumonia: a CNN, along with VGG16, VGG19, and InceptionV3. The accuracy of	The models exhibited exceptional accuracy rates, demonstrating their	A potential drawback might arise from the necessity of abundant data to train

	the research is 97% [23]. The research dataset comprised 2992 pneumonia and 2972 normal chest X-rays for training [23], 854 pneumonia and 849 normal images for testing [23], and 427 pneumonia and 424 normal images for validation [23].	effectiveness in detecting pneumonia.	sophisticated models, such as VGG16, VGG19, and InceptionV3, which could demand considerable computational resources and time.
Rong et al. [8]	Deep Convolutional Neural Network is proposed providing 96.09% accuracy [8]. The dataset included 5856 images categorized as either pneumonia or normal, sourced datasets accessible on UCI Kaggle databases [8].	The proposed model attained high accuracy, surpassing other advanced methodologies [8].	Requirement for ample labeled data to effectively train deep learning models, which could be difficult to acquire in certain circumstances.
Harsh et al. [7]	Deep CNN architecture for performing classification is used which gives 90.68% accuracy [7]. The dataset utilized from-Kaggle, comprising 5863 chest X-rays [7].	The study introduced several customized CNN architectures specifically designed for pneumonia detection	The study did not specify the exact highest accuracy attained, potentially affecting the evaluation of the model's performance
Alhassan et al. [24]	Includes pretrained CNN models, such as DenseNet169, MobileNetV2, and Vision Transformer that are ensembled and provided 93.91% accuracy [24]. Chest X-ray dataset is used [24].	The ensemble approach enhanced classification accuracy by acquiring more intricate feature representations [24].	Ensemble techniques might demand greater computational resources and longer training duration in contrast to individual networks.

CONCLUSIONS

This review paper gives a detailed analysis of different deep learning research approaches applied to pneumonia detection. Through a detailed analysis of methodologies, such as convolutional neural networks, and their hybrids, significant progress in the field has been highlighted. From image classification to clinical diagnosis, deep learning models have shown remarkable capabilities in accurately identifying pneumonia patterns from medical imaging data and clinical records. However, several challenges including dataset bias, interpretability, and generalizability persist. Additionally, the integration of multimodal data sources and the exploration of novel architectures hold promises for further enhancing the performance and applicability of pneumonia detection models. As the field continues to evolve, alliance between researchers and technologists will become essential, unlocking full capability of deep learning to advance pneumonia diagnosis and enhance patient outcomes. Furthermore, researchers can focus on optimizing existing approaches and extending their applicability to broader medical imaging domains, such as CT and MRI scans. Additionally, researchers can plan to explore alternative CNN architectures and their ensembles, to enhance pneumonia detection for chest X-rays.

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