Pneumonia Detection Using Transfer Learning: A Systematic Literature Review

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***Abstract*—Deep learning models have significantly improved pneumonia detection using X-ray image analysis in the field of AI-driven healthcare, showing a major advancement in the effectiveness of medical decision systems. In this paper, we have conducted a systematic literature review of pneumonia detection techniques that applied transfer learning combined with other methods. The review protocol has been developed thoroughly and it identifies recent research related to pneumonia detection from the past five years. We have used very famous research repositories such as IEEE, Elsevier, Springer, and ACM digital library. After a thorough search process, 35 papers are finalized. The review summarizes those past papers that have implemented different methods of pneumonia detection and results are compared based on the best performing models. Also, these models have been categorized into three approaches to pneumonia detection: Deep Learning methods, Transfer Learning techniques, and hybrid methods. Then, there is a performance comparison of the best-performing models for pneumonia detection. This study concludes that while transfer learning holds substantial potential for improving pneumonia detection, further research is necessary to optimize these models for clinical application. This study concludes that while transfer learning holds substantial potential for improving pneumonia detection, further research is necessary to optimize these models for clinical application. This review is very helpful for the researchers in identifying the research gap for pneumonia detection techniques and how these gaps can be addressed shortly.**

***Keywords*—Pneumonia; machine learning; COVID-19: deep learning**

I. Introduction

Worldwide, pneumonia is thought to be the main reason behind the death of children. Pneumonia claims the lives of almost 1.4 million kids annually or 18% of all children who pass away before turning five, an estimated two billion people worldwide get pneumonia each year [1]. A virus or bacteria can be the carrier of lung illnesses like pneumonia. Many medicines that are antiviral and antibiotics are fortunately very effective for treating viral or bacterial infections. Conversely, if there is an early detection of viral or bacterial pneumonia and it can be treated promptly, then it can greatly reduce the risk of worsening patient condition and becoming fatal with time ultimately [2]. Until now, chest x-rays have been a very effective way to pneumonia diagnosis [3]. Pneumonia is not always evident on X-rays, and it is frequently mistaken for benign abnormalities or other illnesses. Furthermore, specialists may misclassify viral or bacterial-caused pneumonia images, which could be the reason that patients may get incorrect treatment leading to their deterioration [4-6]. Significant subjective discrepancies in radiologists' diagnoses of pneumonia have been documented. Additionally, low-resource countries (LRC) lack qualified radiologists, particularly in rustic areas. Subsequently, it is very much needed to have computer-aided diagnosis (CAD) systems that are designed to assist radiologists in the rapid identification of multiple pneumonia types using chest X-ray images.

Multiple studies in the past have used a wide variety of deep learning-based techniques in recent years for the classification of chest X-ray images. In the last five years, x-ray scans of lungs affected due to Covid-19 have attained a lot of attention. In [7], 97.11% accuracy was achieved in COVID-19 classification, Pneumonia infection, and Healthy states using the VGG19 architecture on a MongoDB dataset. On the Mendeley Data v2 dataset, a convolutional neural network (CNN) with 22 layers, was employed to extract features in [8] and Support Vector Machine, KNearest Neighbor (KNN), and Random Forest (RF) were used for the classification purpose. CNN model with an accuracy of 99.52%. In [9], the fusion approach without classifier layers was used in conjunction with the VGG16 and MobileNetV2 models for the classification of COVID-19, healthy person's chest X-rays, and pneumonia-affected images having an accuracy value of 96.48%. With an accuracy of 97.46%, a multiscale attention network technique was employed in [10] to classify COVID-19 and pneumonia variations. Another structure introduced to the DenseNet model called Feature channel attention block Squeeze and Excitation in [11], and the experiment produced an accuracy rate of 92.8%.

Many Machine learning classifiers like RF, SVM, and KNN were employed, and a variety of image processing techniques were examined [12]. Consequently, accuracy percentages ranging from 95% to 99% were achieved. The experiments in study [13] yielded an accuracy rate of 97% and automatically identified the best hyperparameters for using architectures VGG16 and ResNet50 architectures using the Genetic Fine Tuning approach. In study [14], deep learning models for transfer learning models including Xception, DenseNet169, and ResNet50 were employed, and the number of images was expanded with cGAN.

In study [15], the great combination of Xception and InceptionResnetV2 was utilized to detect COVID-19 with an accuracy rating of 0.9578. The amazing Transformer Encoder technique was integrated with the base of two ensemble learning models— VGG16, GoogleNet models, DenseNet201, and DenseNet201, InceptionResNetV2, and Xception model consequently, group B obtained a 96.44% accuracy, whereas group A reached a 97.22% accuracy. It was reportedly mentioned in study [16] that a unique voting method for the COVID-19 illness was created utilizing seven CNN models, which do classification of chest X-ray images as binary. This eventually led to achieving a diagnostic accuracy rate that is nearly 100%. Consequently, the suggested model had a 93.67% test accuracy. In study [17], data balancing was carried out using the smote algorithm. The multi-level based classification was used to classify tuberculosis, COVID-19, and pneumonia and achieved an accuracy value of 97.4% for pneumonia and tuberculosis, and 88% accuracy was obtained for bacterial, COVID-19, and viral classifications. A structure that combines the capsule network and transfer learning technique is suggested in study [18]. With the addition of capsule layers, the InceptionV3 model ultimately produced an accuracy of 94.84%.

A convolutional neural network technique with convolution and residual network assessments is shown in study [19]. The models that are pre-trained like ResNet50, Inceptionv3, and VGG19 architectures based on CNN yielded accuracy rates of 95.61%, 96.15%, and 95.16%, respectively. Convolutional neural networks and the VGG19 model were combined [20], and a 99.10% accuracy rate in the classification of various chest illnesses was attained. In study [21], the Deep Convolutional Generative Adversarial Network (DCGAN) and VGG19 network were used to classify, after the dataset of Chest X-ray8 had been pre-processed and techniques of data augmentation were performed. Consequently, a 99.34% accuracy percentage was achieved SVM, KNN, ensemble classifiers, deep learning classifiers, and deep learning models based on long short-term memory (LSTM) were employed [22]. ResNet50 and DenseNet121 models are merged with a layer created by the CNN block in study [23].

- The pre-trained models had accuracies of 95.61%, 96.15%, and 95.16%.
- The VGG19 model achieved a 99.10% accuracy in classifying chest illnesses.
- The combined accuracy of VGG19 and Deep Convolutional Generative Adversarial Network (DCGAN) is 99.34%.

Despite the various models used, accuracy rates proved to be consistently high with the different techniques applied throughout the research. We have formulated some research questions that will be answered in the review later on:

- RQ1: What are the major past research contributions towards pneumonia detection?
- RQ2: What are the main categories of past research based on technical patterns?
- RQ3: Which transfer learning models work best for medical image pneumonia detection in comparison to other traditional pneumonia detection approaches?
- RQ4: What are the limitations of best-performing transfer learning models?

II. Review Methodology

By Kitchenham's SLR standards, the systematic literature review approach was used for this investigation. It is a methodical approach to doing survey-based research that is based on earlier publications. First, a review methodology is created to ensure that the research is conducted methodically. The research topics are then thoroughly addressed, along with a tool analysis and a discussion of the relative merits of various instruments.

A. Review Protocol Development

The review procedure outlines the research parameters that are used to conduct SLR. It outlines the quality standards that were adhered to when gathering research. The inclusion/exclusion criteria, search procedure, quality assessment, and data extraction and synthesis are all included in the review protocol. Since there are many scientific databases, we have used some very famous databases like Elsevier, Springer, ACM digital library, and IEEE Xplore as we can see in Table I.

TABLE I. Search Keywords and Search Results From Different Databases

Sr.no	**Search keywords**	**No. of search results**			
		IEEE	**Elsevier**	**Springer**	**ACM**
1	Pneumonia Detection Transfer Learning	102	152	249	204
2	Pneumonia Detection	107	208	225	382
3	Pneumonia detection in chest X-ray	23	189	159	8
4	Transfer learning approach for pneumonia	253	174	139	3
5	Detection of pneumonia using transfer learning	396	73	122	204

B. Inclusion and Exclusion Criteria

1) Relevant papers from recent years: To ensure that the research is current and up to date, we have chosen articles that were released between 2020 and 2024. All works that were not published during these years have been eliminated.

2) Subject relevant: The articles that we have chosen are pertinent to the domain and research setting. Only studies that can respond to the study questions that have been developed are chosen.

3) Quality publishers: In our research, we have incorporated materials from one of the following well-known databases: ACM, IEEE, Elsevier, and Springer.

4) No repetition: The review does not contain any tools or procedures that are redundant or overlap. The papers are rejected if they share the same validation process or study environment.

5) Effectiveness of the proposed technique: Only those publications that contain useful and verified tools for a range of database management tasks are chosen.

C. Search Process

We have chosen to use four scientific research databases—IEEE, Springer, ACM, and Elsevier—to conduct the study process. First, a keyword that is acceptable, highly relevant, and able to yield the best and most relevant search results is chosen to identify search words. Since there were many unrelated research studies found using the OR keyword, we have limited our use of the "AND" operator to specifically relevant publications and from the most recent database spanning 2020 to 2024. In Fig. 1 and Fig. 2, our search procedure is displayed.

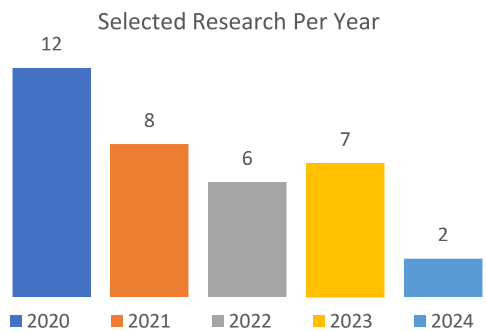

Fig. 1. Selected research per year.

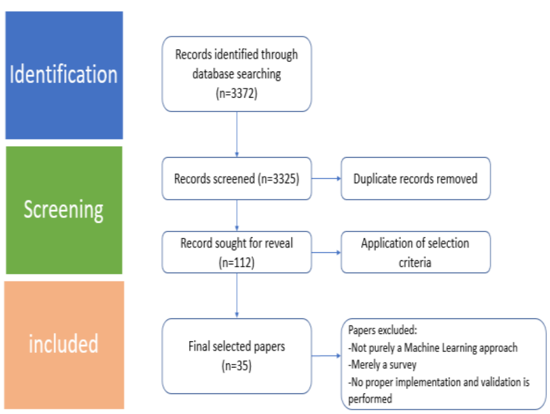

Fig. 2. Search process flow.

III. Review Analysis

Trained radiologists have traditionally been in charge of diagnosing and classifying pneumonia. Radiologists frequently make mistakes because, in certain situations, pneumonia may go undetected to the unaided eye. These situations are referred to as false negatives. In certain instances, radiologists may identify a patient with pneumonia even though they may not have the illness. For the categorization of chest x-ray images into multiple categories including viral pneumonia, bacterial pneumonia, etc., various key studies have been conducted. Here is a summary of some previous research that was chosen using our search procedure.

- RQ1: Pneumonia Detection Methods

Wirasto *et al.* [24] have presented a method for classifying CXR pictures using the InceptionV4 transfer learning type. The InceptionV4 model receives the pre-processed pictures. A 1x1 point-wise convolution is used; then there is a 3x3 depth-wise convolution and then performed a logistic regression.

To analyze COVID-19 cases utilizing chest x-ray pictures, Bahgat *et al.* in [25] have displayed an Optimized Exchange Learning-based Approach for Programmed Discovery of COVID-19 (OTLD-COVID-19). The Mantee-Ray Scrounging Optimization (MRFO) procedure is adjusted within the OTLD-COVID-19 approach to optimize the CNN architectures, organize hyperparameter values, and upgrade classification execution. The exploratory outcome demonstrated that the ideal engineering, DenseNet121, accomplishes the most excellent execution.

A profound convolutional neural network starring the ResNet-50 structure is schemed in this paper by Ansari N. *et al.* [26]. The ResNet architecture has bagged several contests of classification, including the ILSVRC 2015 classification duel, and outshined other traditional models. The model yielded from the Chest X-ray Images dataset, boasted an accuracy value of 94.06%, while the RSNA model hit an accuracy rate of 96.76%.

Using digital X-ray pictures, the authors of the research Rahman *et al.* [27] attempted to automatically identify cases of viral and bacterial pneumonia. For transfer learning, four pre-trained and varying deep convolutional neural networks (CNNs) were used. The authors of this paper have established three schemes of categorization: bacterial against viral pneumonia, normal against pneumonia, and normal against bacterial and viral pneumonia.

Authors determine whether a person has COVID-19, viral pneumonia, bacterial pneumonia, and healthy lungs in the paper by Pathari *et al.* [28] The cutting-edge CNN made a call out to Mobile Net. The top layer CNN known as Mobile Net was utilized to complete the specified assignment. Every model was modified for 2000 epochs. The ADAM enhancer is utilized to accelerate the setback work, with a value of 0.001 learning velocity, and 16 is set as gathering size.

A transfer-learning method using automated convolutional neural network employing four distinct pre-trained models was used in the paper by Salehi *et al.* [29]. The data set includes 5856 horizontal chest X-ray pictures (JPEG) divided into two categories: normal and pneumonia. There were 4273 photos in the "Pneumonia" category and 1583 photographs in the "Normal" category overall. For the identification of pneumonia from pediatric chest X-ray pictures, a CNN-based algorithm was employed.

The Xception model, as well as the VGG16 model, two very distinct transfer learning models, were combined to create this new and innovative model that is presented in the study carried out by Shafi *et al.* [30]. The pre-processing of images utilizing image augmentation and normalization was a key aspect of our research. To extract features, we made use of two very distinct transfer learning models, Xception, and VGG16. The training of the model was performed on both "NORMAL" and "PNEUMONIA" versions using 5216 pictures. The testing phase involved using 624 photos from the two classes, having the accuracy of the suggested model at 91.67% respectively.

The study by Güler O, Polat K. [31] utilized various models of deep learning such as ResNet50, DenseNet121, ResNet101DenseNet169, InceptionV3, MobileNetV2, VGG16, and Xception to classify chest X-ray pictures. These models were implemented in experiments involving 5856 labeled images from the dataset of chest X-ray images, and the comparison of results was performed. The Xception model, in particular, produced outstanding results with test accuracy at 95.73% and validation at 96.16%.

Authors Ali AM, Ghafoor K, Mulahuwaish A, Maghdid H. [32], used an artificial intelligence engine to categorize the COVID-19-confirmed patient's degree of patient's lung inflammation degree, which included moderate, progressive, or severe cases. To enhance the accuracy of the lung inflammation classification, they opted for a modified Convolution Neural Network (CNN) and k-nearest Neighbor models while contrasting the outcomes with other classification algorithms.

Study by Hashmi *et al.* [33], a very unique method based on a heavily weighted classifier is presented. It successfully optimally integrates the heavily biased predictions from some very advanced deep learning models. The recommended weighted classifier model ultimately attains a test accuracy of approximately 98.43% as well as an amazing AUC score of 99.76 when put into action on the data manually collected from the pneumonia dataset of the Guangzhou Women and Children's Medical Center.

In Manickam *et al.* [34] work specifically attempted to utilize the segmentation method of U-Net architecture to pretreat the chest X-ray images for the detection of pneumonia. Once pneumonia is identified, it is then classified as normal or, in some cases, abnormal (Bacteria, viral) using models that had been previously trained on the ImageNet dataset. Also, two optimizers the Stochastic Gradient Descent (SGD and Adam were intelligently employed to extract the effective features and enhance the accuracy of the pre-trained models.

Convolutional Neural Network models are effectively introduced by Jain *et al.* in a study [35] to classify varieties of pneumonia using X-ray images. These Convolutional Neural Networks were intensively trained with various parameters, hyperparameters, and different numbers of convolutional layers to correctly categorize X-ray images as pneumonia positive or negative. This special study references six different models. The validation accuracy of the initial two models becomes approximately 85.26% and superior 92.31%, respectively.

To efficiently extract diverse properties from chest X-rays, Authers propose a deep CNN-based architecture called CovXNet by Mahmud *et al.* [36], using depthwise convolution with different dilation rates. An integrated gradient-based discriminative attention mechanism is used to identify the anomalous regions of X-ray pictures that correlate with different types of pneumonia.

The deep learning model by author Salvia et al. [37] has been declared very helpful in diagnosis with chest X-rays (CXR) and CT scans. The authors examine the ranking of COVID-19 pattern detection on base and surface scales with two distinct grades using a credible dataset 18 consisting of 2908 frames over 450 inpatients. Twelve LUS examinations in various chest regions were performed on patients who were admitted to the ED, and each result was assessed using standardized severity measures.

The research conducted by Dey *et al.* [38] developed a Deep-Learning System that diagnoses lung pathology based on radiographs, namely chest X-ray pictures. For the first experimental testing of standard DLS models, a SoftMax classifier has been applied. The results showed that overall VGG19 has a better classification accuracy value of 86.97% compared to alternative methodologies.

The viability of a profound neural organize for the determination of lung contamination in chest X-ray dose-equivalent computed tomography (CT) was assessed by Schwyzer *et al.* in study [39]. The profound learning algorithm's regions beneath the bend for the standard measurements CT were 0.923, which was a significant increment over the zones beneath the bend for the lower measurements.

In research conducted by Muralidhar *et al.* [40], chest X-rays are handled employing four stages utilizing a progressed Profound Learning procedure. Picture upgrade, information enlargement, and nourishing come about to profound learning calculations (CNN, VGG16, InceptionResNetV2, Xception, Resnet50, and half-breed show) for the extraction of picture highlights for extra preparation constitute the primary three stages of the method.

Neural organize models were made in a diverse study conducted by Labhane *et al.* [41] to distinguish pneumonia from chest X-ray pictures. Utilizing exchange learning and convolutional neural systems (CNNs), four models—essential CNN, VGG16, VGG19, and InceptionV3—were built. After that, the models were prepared to employ a dataset of adolescent pneumonia cases, which included 2992 cases of pneumonia and 2972 cases of ordinary chest X-rays.

A paper by Paul *et al.* [42] employments a profound learning strategy, such as Convolutional Neural Organize (CNN) engineering, to characterize chest X-ray pictures and analyze pneumonia. We have utilized the 4110-image chest X-ray picture dataset from Kagle. By using MobileNetV2 as the essential show for the picture classification issues, they were able to utilize the exchange learning strategy with CNN in expansion to building an unused CNN demonstration at that time.

In a research led by Alharbi *et al.* [43], analysts utilized machine learning and picture division to precisely anticipate pneumonia cases based on X-ray pictures. A freely named database containing 4,000 X-rays of pneumonia patients and 4,000 X-rays of sound people is utilized. For exchange learning from their already computed weights, ImgNet and SqueezeNet are utilized. Employing a lion's share combination approach, the creators recommended an improved BoxENet show that joins exchange learning from both ImgNet and SqueezeNet.

Another work that has been proposed by Perumal *et al.* [44], presents a one-of-a-kind strategy that employments profound learning approaches to recognize COVID-19 disease.

Histogram equalization progressed picture quality without relinquishing data. The moved forward photographs are prepared to extricate Haralick surface highlights, which are at that point utilized as input for several pre-built CNN models. Max pooling layers are utilized to down-test the pictures for dimensionality decrease, while convolutional layers are utilized to extricate visual highlights in an assortment of pre-defined CNN models, such as Resnet50, VGG16, and InceptionV3.

For refined pneumonia picture classification, Chen W *et al.* in [45] presented a novel strategy that combines the most excellent highlights of EffcientNetB0 and DenseNet121 with a profound convolutional neural organize, supported by an assortment of attention methods.

Study by Rajasenbagam *et al.* [46], the Profound Convolutional Generative Ill-disposed Organize (DCGAN) and VGG19 organize were utilized for classification, after the Chest X-ray8 dataset had been pre-processed and information enlargement strategies performed. Subsequently, a 99.34 accuracy rate was accomplished.

A structure that combines the capsule organization and exchange learning method is proposed by Bodapati JD *et al.* in [47]. With the expansion of capsule layers, the InceptionV3 show eventually delivered a precision of 94.84%.

A modern demonstration, IVGG13, has been actualized by Jiang *et al.* [48] to address issues with restorative picture acknowledgment that happen when the VGG16 show is utilized. Compared to the VGG16 demonstrated design, the IVGG13 show brought down the arranged profundity advance and avoided over- and under-fitting.

A determined structure with an extended convolution was rejected by Liang *et al.* [49] for the picture categorization of adolescent pneumonia. A procedure known as exchange learning was utilized to initialize the show by weighting parameters obtained from expansive datasets inside the same field. They gave a profound learning method that combines extended convolution with determined consideration to classify and analyze pediatric pneumonia.

CNN models were displayed by Jain *et al.* [50] to recognize between bacterial and viral pneumonia utilizing x-ray pictures. Diverse convolutional neural systems have been developed to differentiate x-ray pictures into two fundamental categories: pneumonia and non-pneumonia, by changing different parameters, hyperparameters, and the number of convolutional layers. Six models were used by the scholars. There are two and three convolutional layers within the to begin with two models, individually.

Retraining the ImageNet Organize on the RSNA CXR dataset permitted Islam *et al.* [51] to perform modality-specific exchange learning, which permitted them to arrange to memorize CXR modality-specific highlights and recognize variations from the norm. Both typical CXRs and abnormal pictures with pneumonia-related opacities are included within the utilized collection. A randomized network look method is utilized to maximize the different CNN hyperparameters.

An exchange learning approach that can address the compact information awkwardness trouble in X-ray picture forecast was displayed by the creators of Alqudah *et al.* [52]. With an accuracy of 98.7%, this demonstrates progress in the exactness of recognizing between sound and non-healthy instances.

A procedure to cut the window of time for getting a COVID-19 demonstrative to 2.5 seconds was displayed by Brunese *et al.* [53]. Their approach is based on the VGG-16 show of exchange learning. They constructed two models to finish this. Finding out in case a chest X-ray is related to an understanding of who has generalized pneumonic illness was the point of the primary demonstration. They treat this as an input for the X-ray to a moment demonstrate in case the primary scenario is exact. The reason for the moment show is to recognize if the lung sickness is COVID-19.

To recognize pneumonia, the creators in Manickam *et al.* [54] utilized a profound learning and exchange learning technique that combines several optimization procedures on chest X-ray pictures. They utilized models that were at first prepared to utilize the assembled ImageNet information to classify the chest X-ray pictures into solid and pneumonia-infected states. A few methods were utilized to look at CNN models, counting DenseNet169 + SVM, VGG16, RetinaNet + Veil RCN, and Xception.

The Authers Chouhan *et al.* [55] used transfer learning to make a deep-learning model for pneumonia conclusions. After being prepared on ImageNet, several neural arrange models extract data from images and bolster them into a classifier to form expectations.

By utilizing exchange learning and consideration components, Cha SM *et al.* [56] made a noteworthy progression within the determination of pneumonia. The attention-based highlight choice used in this consideration, together with highlights from ResNet152, DenseNet121, and ResNet18, essentially progressed the execution of computer-aided diagnostic models with momentous accuracy and accuracy measurements.

Utilizing CNN and exchange learning, Rachna *et al.* [57] created a demonstration for the recognizable proof of pneumonia. Pre-trained models were utilized in this demonstration.

Trivedi *et al.* [58], scientists propose a profound learning-based design called "MobileNet" for the programmed recognizable pneumonia detection from chest X-ray pictures. The suggested model for the automatically recognizable proof of pneumonia was prepared in three hours and produced a training precision of 97.34%, approval exactness of 87.5%, and testing precision of 94.23%.

- RQ2: Classification of Past Techniques for Pneumonia Detection

Three distinct deep learning technique-related views may be used in the research being done on COVID-19 identification. These viewpoints are specific to hybrid architectures, transfer learning, and CNN. According to these viewpoints, the research projects for automation of the identification of COVID-19 are discussed in this part. The research efforts for the detection of pneumonia can be classified into three different types of techniques. These techniques are Deep Learning methods, Transfer Learning techniques, and hybrid methods as we can see in Table II.

TABLE II. PNEUMONIA DETECTION TECHNIQUES CLASSIFICATION

Study ref.	Approach	Proposed Method	Dataset Used
[24]	Transfer learning	InceptionV4 transfer learning	5,232 verified chest X-ray pictures
[25]	Transfer learning with DNN	Optimized Transfer Learning-based Approach (OTLD)	COVID-19, pneumonia bacterial, pneumonia viral, and normal
[26]	Transfer learning with DNN	A deep convolutional neural network that uses ResNet-50 architecture	RSNA dataset
[27]	Transfer learning with DNN	Pre-trained deep convolutional neural networks (CNNs) AlexNet, SqueezeNet, DenseNet201 and ResNet18	5247 chest X-ray images, including viral, bacterial, and normal chest X-rays
[28]	Transfer learning with DNN	CNN Mobile Net	6,000 x-ray images showing Covid-19 illness
[29]	Transfer learning with DNN	Pre-trained deep CNN DenseNet121, Xception, VGG19, and ResNet50	X-ray radiography records kept by the Guangzhou Females and Children's Medical Center for pediatric patients
[30]	Transfer learning with DNN	The Xception model and the VGG16 model	5216 photos from two classes: "PNEUMONIA" and "NORMAL" images
[31]	Transfer learning with DNN	Deep learning models VGG16, MobileNetV2 DenseNet121, InceptionV3, Xception, DenseNet169, ResNet50, VGG16 ResNet101.	5856 labeled images in the chest X-ray dataset
[32]	Hybrid	Modified Convolution Neural Network (CNN) k-nearest Neighbor	the CT scan pictures of the confirmed COVID-19 patients
[33]	Transfer learning with DNN	Deep learning models, including MobileNetV3, InceptionV3, mmmm, Xception, and ResNet18	Pneumonia dataset of the Guangzhou Women and Children's Medical Center
[34]	Transfer learning with DNN	ResNet50, InceptionV3, and InceptionResNetV2	ImageNet dataset
[35]	Transfer learning with DNN	VGG16, VGG19, ResNet50, and Inception-v3	x-ray pictures
[36]	DNN	CovXNet – a deep convolutional neural network (CNN)	COVID-19 chest X-ray pictures
[37]	DNN	Deep Learning	COVID-19 dataset consisting of 2908 frames from 450 hospitalized
[38]	Transfer learning with DNN	AlexNet, VGG16, VGG19, and ResNet50	Chest radiographs
[39]	DNN	Artificial intelligence-based X-ray dose-equivalent CT for the identification of pneumonia.	CT images
[40]	Transfer learning	Xception and ResNet50V2	Chest X-ray dataset
[41]	Transfer learning with DNN	CNN, VGG16, VGG19, and InceptionV3	Dataset of juvenile pneumonia cases
[42]	Transfer learning with DNN	CNN and MobileNetV2-based transfer learning	4110-image chest X-ray image dataset from Kagle
[43]	Transfer learning with DNN	InceptV6 , DSNet4 , DSNet6 Improved BoxENet	4,000 X-rays of pneumonia patients
[44]	Transfer learning with DNN	InceptionV3, Resnet50, and VGG16.	NIH Chest X-Ray-14 dataset
[45]	Transfer learning with DNN	EffcientNetB0 and DenseNet121 with a deep convolutional neural network	Chest X-ray pictures
[46]	Transfer learning with DNN	Deep Convolutional Generative Adversarial Network (DCGAN) and VGG19 network	Chest X-ray dataset
[47]	Transfer learning with DNN	Deep pre-trained CNN models, ResNet50 such as VGG16, Inception-v3, and VGG19	Chest X-ray dataset
[48]	Transfer learning with DNN	Modified VGG16, IVGG13	Pediatric pneumonia
[49]	Transfer learning	transfer learning method with deep residual network	Chest X-ray dataset
[50]	Transfer learning	Inception-v3, VGG16, VGG19, ResNet50	Chest X-ray dataset
[51]	Transfer learning with DNN	VGG19, DenseNet121, InceptionV3, and Inception-ResNetV2	CXRs and aberrant pictures with pneumonia-related opacities
[52]	Hybrid	CNN, support vector machine (SVM), and random forest (RF)	X-ray images
[53]	Transfer learning with DNN	VGG-16	Chest X-ray images
[54]	Transfer learning with DNN	DenseNet169, VGG16, RetinaNet, Xception, SVM and Mask RCN,	ImageNet data
[55]	Transfer learning	ImageNet	ImageNet data
[56]	Transfer learning with DNN	ResNet152, DenseNet121, and ResNet18	Pneumonia chest X-ray images
[57]	Transfer learning with DNN	VGG16, VGG19, ResNet50, and Inception-v3	Pneumonia chest X-ray images
[58]	DNN	MobileNet	Chest X-ray images

- RQ3: Best Performing Pneumonia Detection Transfer Learning Models**.**

This question highlights the best-performing past pneumonia detection methods based on the accuracy value. We have found from the review that there are mostly hybrid approaches of CNN and transfer learning that have been abundantly used in the past and outperforming models are VGG16, DenseNet121, and ImageNet. Given below in Table III are the outperforming models that are used along with other CNN-based transfer learning models under different circumstances and different datasets.

- RQ4: Limitations of the Best Performing Transfer Learning Models

The following are some of the drawbacks of the top-performing model of transfer learning for pneumonia detection:

1) Limited generalization: Due to domain shifts, transfer learning models may find difficulty in adapting well to a variety of patient populations or datasets from various sources, which can result in decreased performance on unseen data [59].

2) Data bias and imbalance: When data imbalances or uncommon pneumonia symptoms are present, pre-trained models may be biased toward the features of the source dataset, which could result in subpar performance or incorrect classification [60].

3) Interpretability challenges: Deep neural networks, which are transfer learning models, are sometimes considered "black-box" models, which makes it challenging to decipher the elements that contribute to predictions and comprehend the decision-making process—a critical skill in medical applications [61].

TABLE III. BEST-PERFORMING MODELS

Study ref.	Transfer Learning Models	Outperforming model	Accuracy
[24]	InceptionV4 transfer learning	InceptionV4	88%
[25]	Optimized Transfer Learning-based Approach (OTLD)	DenseNet121	98.47%
[26]	A deep convolutional neural network having ResNet-50 architecture	ResNet-50	96.76%
[27]	pre-trained deep convolutional neural networks (CNNs) AlexNet, SqueezeNet, DenseNet201 and ResNet18	DenseNet201	98%
[28]	CNN Mobile Net	Mobile Net	95.58 %
[29]	pre-trained deep CNN DenseNet121, Xception, VGG19, and ResNet50	DenseNet121	86.8%
[30]	The VGG16 model and the model Xception	Fusion of both Xception and VGG16	91.67%
[31]	Deep learning models VGG16, MobileNetV2 DenseNet121, InceptionV3, Xception, DenseNet169, ResNet50, VGG16 ResNet101.	Xception model	95.73%
[33]	deep learning models, including MobileNetV3, InceptionV3, DenseNet121, Xception, and ResNet18	Weighted Classifier	98.43%
[34]	ResNet50, InceptionV3, and InceptionResNetV2	ResNet50	93.06%
[35]	VGG16, VGG19, ResNet50, and Inception-v3	VGG19	88.46%
[38]	AlexNet, VGG16, VGG19, and ResNet50	VGG19	97.94%
[41]	CNN, VGG16, VGG19, and InceptionV3	VGG16	98%
[42]	CNN and MobileNetV2-based transfer learning	MobileNetV2	97%
[43]	InceptV6 , DSNet4 , DSNet6 Improved BoxENet	Improved BoxENet	98.6%
[44]	InceptionV3, Resnet50, and VGG16.	VGG-16	93%
[45]	EffcientNetB0 and DenseNet121 with a deep convolutional neural network	DenseNet121	95.19%
[46]	Deep Convolutional Generative Adversarial Network (DCGAN) and VGG19 network	DCGAN	99.34%
[47]	Deep pre-trained CNN models Inception-v3, VGG19, ResNet50 and VGG16.	InceptionV3	94.84%
[48]	Modified VGG16, IVGG13	IVGG13	89.1%
[50]	Inception-v3, VGG16, VGG19, ResNet50	VGG19	92.31%
[51]	VGG19, DenseNet121, InceptionV3, and Inception-ResNetV2	VGG19	99.9%
[53]	VGG-16	VGG-16	98%
[54]	DenseNet169, SVM, VGG16, RetinaNet, Mask RCN, and Xception	ResNet50	93.06%
[55]	ImageNet	ImageNet	99.62%
[56]	ResNet152, DenseNet121, and ResNet18	DenseNet121	95.35%
[57]	VGG16, VGG19, ResNet50, and Inception-v3	VGG19	88.46%

IV. Discussion

In many nations, particularly in developing nations, pneumonia is a frequent illness. This condition is known as obstructive pneumonia, and even medical radiologists may find it difficult to differentiate it from other lung conditions based on the similarity of the appearance of pulmonary radiographs. Recently, image processing and deep learning models have been created to swiftly and precisely identify pneumonia in different models an example shown in Fig. 3[62].

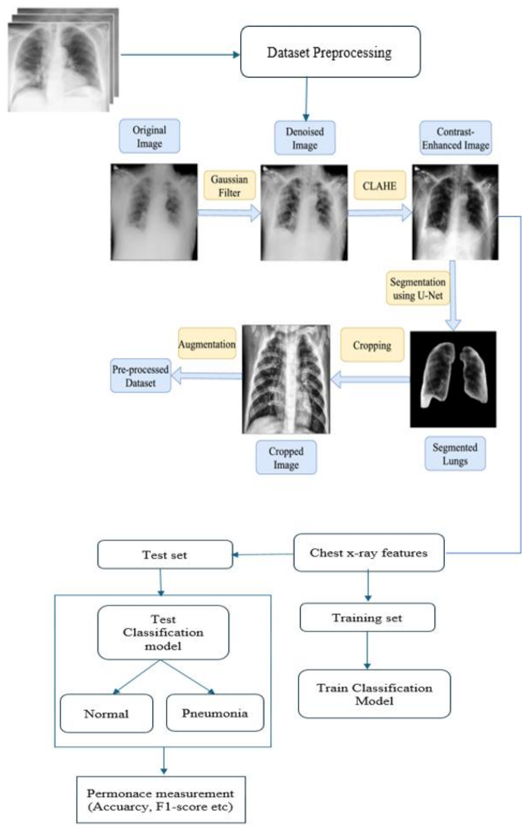

Fig. 3. System flowchart.

In this systematic survey, we have identified many machine learning methods applied for the detection of pneumonia and we have answered four different questions. Based on the first question, there are a total of 35 research that have been explained briefly about their contribution to pneumonia detection. In the next question, those techniques are classified into three categories: Deep Learning methods, Transfer Learning techniques, and hybrid methods. In the next questions, the survey is more refined to identify the best-performing method. This performance is measured based on the output accuracy of those models. However, according to the answer to question four that says what are the limitations of best-performing models and how they are affecting their performance, we are forced to put second thought when selecting any pneumonia detection model just based on its accuracy performance value. Models cannot be just chosen based on how accurate they are if they do not have a generic nature, that fits most of the datasets but they are trained just to classify any specific dataset. Such models do not apply to larger extents. Similarly, these models are pre-trained for a few features and there are new data samples with unknown features, these models are biased towards older features that have already been fed to them. This can greatly alter our assumed results. We have selected a few models based on the frequency of their best performance with a variety of datasets. DenseNet121 has outperformed multiple times and the highest accuracy achieved is 98% and the lowest is 86.8%. This applies to this model has an average good performance over the 5 research models in which it has outperformed. VGG19 model has outperformed 5 models and has achieved the highest accuracy of 99 % and lowest value of 88.46 %. Another model that has outperformed 4 times is VGG16. It has the highest accuracy value of 98% and the lowest 91% which shows it’s a very good model looking at its average accuracy that would be more than DenseNet121 and VGG19. Last but not least there is another worth noticing model ResNet-50 that has outperformed three times with an accuracy value ranging from 96% to 93% as we can observe in Table IV.

TABLE IV. Average Result of Best-Performing Models

Model	Number of research	Average performance
DenseNet121	5	94.76%
VGG19	5	93.41%
VGG16	4	95.16%
ResNet-50	3	94.29%

The above discussion proves that models cannot be merely selected based on any of their best performances but the average performance of their outperformance. Also, we have observed that out of those three categories of models, the best-performing models are from Transfer learning with the DNN category of model classification.

V. Conclusion and Future Work

This research aimed to identify various pneumonia detection methods using x-ray images. The review was conducted to identify best-performing methods from the past and to highlight the limitations of existing models. Many authors have used different techniques on different datasets of Chest x-rays and mostly these datasets belong to Corona patients. Some hybrid models have outperformed other models like VGG16, VGG19, and DenseNet121 multiple times. These models worked under different conditions and their parameter tuning also varies. That is the reason we unable to identify any single model to always outperform. However, the optimal performance is guaranteed from the models listed before. This is due to data bias imbalance as discussed in the limitations of these models. Most of the transfer learning models do not performed well due to ungeneralised of dataset and also the usage of trained models. Considering this limitation, medical applications are at greater risk if the models are particular on certain scenarios and the stochastic environments are left unnoticed. Thus, in future work, this research can be extended to address all the highlighted limitations and challenges of the transfer learning models for pneumonia detection and to present a more generic, and less data-specific model that can work in varying environments.

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