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ARTIFICIAL INTELLIGENCE BASED PNEUMONIA DETECTION USING IMAGING MODALITIES: A REVIEW

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Abstract

Pneumonia remains to be one of the leading causes of morbidity and mortality across the world. Timely and correct diagnosis is important for clinical treatment and to minimize the mortality. Medical imaging modalities play an important role in the detection of pneumonia, its severity and monitoring of treatment. This is a general review of the imaging technologies applied in detecting pneumonia covering the evolution of the early conventional methods and the modern advanced technologies into emerging technologies. The conventional modalities are explained in relation to the diagnostic performance, clinical utility, and limitations, including radiation exposure and access issues, i.e. chest X-ray (CXR), computed tomography (CT), the methods of ultrasound and their increasing place as bedside, radiation-free methods. The recent advances in the field of artificial intelligence (AI) and machine learning is to detect and classify pneumonia in different imaging modalities are reviewed in a systematic manner. This review will mainly concentrate on the use of artificial intelligence (AI) in the pneumonia detection using imaging. The

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application of machine learning (ML) and deep learning (DL) methods to chest X-ray and computer tomography images to obtain automatic classification of diseases and the evaluation of their performance is thoroughly reviewed. Moreover, the novel findings of AI-based pneumonia detection in thermal imaging are discussed, which is one of the radiation-free, non-contact, and fast screening modality. This review compares model, data sets, and reported performance metrics of imaging modalities and determines the challenges concerning data quality, generalizability, and clinical validation. Lastly, research directions in the future are described, which include the necessity to further examine the thermal imaging modality and multimodal AI systems to create safe, accessible, and clinically portable pneumonia diagnostic systems.

1. Introduction and Background

Pneumonia is among the most common causes of morbidity and mortality in the world with susceptible groups of children below the age of five years, the elderly, and immunocompromised people being the most affected in developed countries [1], [2]. It is the inflammatory process of the lung parenchyma that is caused by bacterial, viral, fungal, or other pathogenic infections and that impairs the process of gas exchange and can cause severe respiratory failure, in case of failure to diagnose and treat it [3]. According to the World Health Organization (WHO), more than 800,000 children younger than 5 are killed by pneumonia in a single year [4]. Early and correct diagnosis of pneumonia is important to minimize clinical complications and enhance patient outcomes. The available method for diagnosis is imaging techniques since they are non-invasive methods of visualization of lung anatomy and pathology [5].

Some of the typical techniques applied in the diagnosis of pneumonia include the chest X-rays (CXRs), chest computed tomography (CT) scans, magnetic resonance imaging (MRI) of the chest, and the chest ultrasound scans, etc. [6]. The chest X-ray has served as the primary tool of pneumonia diagnostics because of its access and low cost, as well as, speed of acquisition. CXR can be used to see the presence of lung consolidations, interstitial infiltrates, and other radiographic findings of pneumonia [7]. Although being widely used, radiographs tend to have poor sensitivity and inter-observer reliability, particularly in early disease appearance as well as in patients with coexisting lung conditions [8]. Most clinical guidelines around the world still use CXRs as the gold standard of diagnosis of pneumonia [9]. In addition, CXRs are highly cost effective [10], readily available and contain very low radiation doses as opposed to CT scans [11] .

Computed tomography (CT) scanning provided clinicians with more high-resolution and cross-sectional images that significantly enhance the identification of parenchymal abnormalities, ground-glass opacities, and complications (abscess formation or pleural disease). Nevertheless, CT is more expensive, exposes excessive radiation and is not readily available in resource

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Rehman et al - 2026

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constrained environments, which has led to a consistent interest in alternative imaging modalities [12].

Simultaneously, the lung ultrasound (LUS) technique is radiation-free, bedside, and has a rapidly growing clinical use. LUS has shown competitive or better diagnostic performance compared to CXR in a number of clinical settings especially in pediatric populations and critical care populations where frequent imaging is required through the analysis of B lines, consolidations and pleural abnormalities [13]. Its usefulness has been highlighted by the systematic reviews which have reported high pooled sensitivities and specificities and the creation of standard protocols (e.g., BLUE) to simplify the process of lung assessment [14].

Besides the traditional radiography, studies have also investigated new imaging modalities and analysis methods with the view of enhancing early diagnosis, availability, and non-invasiveness. Thermal imaging (infrared thermography) is one of the technique, which takes advantage of changes in heat distribution that can be detected on the chest surface which are associated with inflammation. Thermal imaging is noninvasive, radiation free and low cost technique. Initial clinical studies show that it can perform well in diagnostic tests and has the potential to offer real-time and portable diagnostic tests, particularly in low resource settings [15].

Another significant change in pneumonia detection research in the last ten years is the use of artificial intelligence (AI) and machine learning (ML) algorithms with imaging data to automate and add to diagnostic interpretation. Since the early machine learning classifiers through deep learning networks, including convolutional neural networks (CNNs), researchers have paid much attention to enhancing the accuracy, generalizability, and clinical applicability. Such AI systems have been used on CXR images, where they have demonstrated performance comparable or better than that of expert radiologists and most recently to tasks like distinguishing between bacterial and viral pneumonia and to augment radiological tasks. The literature on the COVID-19 pandemic and in its outcome demonstrates how big data and transfer learning methods helped in speeding up improvement in pneumonia and pulmonary infection detection through CXR images [16]. Table 1 shows the comparison of conventional imaging modalities.

Table 1. Comparison of Conventional Imaging Modalities

Imaging Modality	Radiation	Cost	Diagnostic Accuracy	Limitations
Chest X-ray	Yes (Low)	Low	Moderate	Overlapping structures, observer variability

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Rehman et al - 2026

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CT	Yes (High)	High	High	Radiation exposure, cost
Lung Ultrasound	No	Low	Moderate–High	Operator dependent
Thermal Imaging	No	Very low	Emerging	Limited datasets, indirect indicators

The history of technology development of imaging analytics is a growing area in which the old-historic radiologic practice is combined with the innovations of computational imaging. Although CXR and CT are still the core clinical modalities, such adjunctive methods as LUS and AI-based interpretation are defining the future of pneumonia diagnosis. The use of exploratory technologies like thermal imaging explains current moves to make the diagnostic toolkit broader than the more traditional radiography. The papers reviewed in this paper were published within the past decade, in the field of pneumonia detection by use of imaging modalities, like CXR images, CT images, and Thermal Imaging. The search of the articles was conducted in the following electronic research databases, which are IEEE Xplore, Springer Link, PubMed and Science Direct. The paper has presented a detailed review and critical assessments of the literature searched.

2. Artificial Intelligence in Pneumonia Detection

Artificial intelligence techniques have been playing a major role in medical image analysis in the diagnosis of diseases such as brain tumors, breast cancer, pneumonia etc. [17]. Several scientists came up with different methods of diagnosing the pneumonia disorders using the ML and DL methods. A lot of research has been conducted in the field by different researchers and this has come up with a number of different models with different levels of success in prediction [18]. Here we have represented the work done in the area of medical image detection. We have analyzed the discovery on the advantages and weaknesses. With regard to medical image detection, various datasets have been used in the piling up of useless model.

2.1 Pneumonia Detection using Chest X-ray Images

The use of both DL and ML has been found to be successful in lung disease detection using X-ray images. It is already being applied in the medical practice to aid disease diagnosis. Moreover, another category of DL-based systems is also developed to diagnose pneumonia in the covid-19 patients automatically by using radiology images [18].

The study shows that convolutional neural network (CNN) based on feature extraction was used to construct a pneumonia diagnosis system. CNN (InceptionV3) was applied to extract features of the chest X-ray images. Three classification algorithm models, which used the extracted feature to predict the cases of pneumonia, were trained on a Kaggle dataset. Three of them include K-Nearest Neighbor, Neural Network, Support Vector Machines. It has been determined that the Neural Network model obtained the best results. Support vector machines (84.1%) and K-Nearest Neighbor Algorithm (83.3%) are the next best with highest sensitivity and sensitivity respectively. Among all the models of classification, Support vector machine machines model achieved highest Area Under the Curve (AUC) of 93.1 % [19].

Three popular models of the convolutional neural networks, i.e. Faster RCNN ResNet-101, Mask RCNN ResNet-101, and Mask RCNN ResNet-50 as the detection of pneumonia. The training stage involves the use of data augmentation, transfer learning and fine-tuning. Through experimental results it has been found out that various networks exhibit different characteristics on the same dataset [20].

The four various models are designed by varying the deep learning method; two of the pre-trained models, ResNet152V2 and MobileNetV2, a Convolutional Neural Network (CNN), and a Long Short-Term Memory (LSTM). These findings show that deep learning model achieves 99.22 %, 99.43 %, 99.44 %, 99.44 %, and 99.77 %higher accuracy, precision, F1-score, recall, and AUC than the previous ones. As the results vividly show, the ResNet152V2 model is more effective compared to other recently offered works. Furthermore, the rest of the suggested models MobileNetV2, CNN, and LSTM-CNN recorded over 91 % in accuracy, recall, F1-score, and precision, as well as, an AUC [21].

The application of transfer learning through four pretrained CNN networks, including AlexNet, ResNet18, DenseNet201 and SqueezeNet to classify chest X-ray images. A total of 5,247 CXR images (normal, bacterial pneumonia, and viral pneumonia) was preprocessed and trained. The models were assessed in three classification tasks, normal vs. pneumonia, bacterial vs. viral pneumonia, and multi-classification of normal, bacterial and viral pneumonia. The result of the proposed method was classification accuracies of 98%, 95%, and 93.3% in that order, which show the applicability of pretrained CNNs in detecting pneumonia in CXRs [22].

The creation of a computer aided diagnosis system to automatically detect pneumonia in a chest X-ray image. To deal with the limited amount of data available, deep transfer learning was used and developed an ensemble of three convolutional neural network models GoogLeNet, ResNet-18, and DenseNet-121. A weighted average ensemble method was embraced with the weights that the base learners received being calculated in a new method. The weight vector is a fused product of the scores of four standard evaluation measures, precision, recall, f1-score and the area under the curve, which in literature studies was often established solely by experiment, a technique that

Vol. 5 No. 1 (2026)

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https://pakjmcr.com/index.php/1/about

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is likely to be erroneous. The models had the accuracy rates of 98.81 % and 86.85 %, and the sensitivity rates of 98.80% and 87.02% for two data sets [23].

A deep learning based model that utilizes pretrained AlexNet to classify X-ray (CXR) images as COVID-19, bacterial pneumonia, non-COVID-19 viral pneumonia or normal using publicly available data. The model was tested on binary, three-class and four-class classification problems. It performed well in a binary classification task, with a range of accuracy between 91.43 % and 99.62 % including accuracy of 99.16 % on the COVID-19 vs. normal and 99.62 % on COVID-19 vs. non-COVID-19 viral pneumonia. With three-class classification (COVID-19, bacterial pneumonia, normal) the model has the highest accuracy 94.00% and four-class classification (COVID-19, bacterial pneumonia, normal) has the highest accuracy 93.42 % with a high sensitivity and specificity. The findings indicate that pretrained AlexNet is effective in detecting multi-class pneumonia and COVID-19 by using CXR images [24].

The deep learning model first creates the useful features of the X- ray images by preprocessing it, then divides the images into normal and pneumonia infected individuals based on X-ray images by utilizing the threshold segmentation technique, then identifies the individuals based on the X-ray images using the YOLOv3 detector and discriminates them as normal and with pneumonia with the help of support vector machine (SVM) and softmax. Training and testing of the proposed model was done with a database of chest X-ray images. The findings demonstrate that the overall accuracy, precision, recall and F1-score are all 99%. The results indicate that deep features gave valid and reliable pneumonia detection characteristics [25].The summary of the pneumonia detection using chest X-ray images is given in Table 2.

Table 2. Detection of Pneumonia using Chest X-ray Images

Authors	Year	Model	Classification	Dataset	Performance
Sara Lee Kit Yee et al. [19]	2020	CNN (Inception V3), KNN, SVM	Pneumonia, Normal	Chest X-ray	AUC 93.1%
Zong ye yang et al. [20]	2020	RCNN ResNet-101, Mask RCNN ResNet-101, and Mask RCNN ResNet-50	Pneumonia, Normal	Chest X-ray	Precision 96%

Vol. 5 No. 1 (2026)

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https://pakjmcr.com/index.php/1/about

Online ISSN 3007-2387 Print ISSN 3007-2379

Rehman et al - 2026

DOI: http://doi.org/10.5281/zenodo.20176045

Nada M. Elshennawy et al. [21]	2020	ResNet152V2, MobileNetV2, CNN, LSTM	Pneumonia, Normal	Chest X-ray	Accuracy 99.2%
Tawsifur Rahman et al. [22]	2020	AlexNet, ResNet18, DenseNet201 and SqueezeNet	Normal, Bacterial Pneumonia and Viral Pneumonia	Chest X-ray	Accuracy 98%
Rohit kundu et al. [23]	2021	GoogLeNet, ResNet-18 and DenseNet-121	Pneumonia, Normal	Two data set of Chest X-ray	Accuracy 98.81% and 86.85 %
Abdullahi Umar Ibrahim et al. [24]	2021	Pretrained AlexNet	COVID-19, Bacterial Pneumonia and Normal	Chest X-ray	Accuracy 93.42%
Nigus Wereta Asnake et al. [25]	2024	YOLOv3, SVM, Softmax	Pneumonia, Normal	Chest X-ray	Accuracy 99%

2.2 Pneumonia Detection using CT Images

The use of CT scans in COVID-19 diagnosis has increased most of the CT scan image databases. Since X-rays have low resolution and less image information, the difference between the presence and absence of abnormal lungs CXR cannot be easily determined by either an expert radiologist or an efficient machine learning model [26].

The research presented an AI based model, named as the fast-track COVID 19 classification network (FCONet), to evaluate the COVID-19 pneumonia in the chest CT images and differentiate it with non COVID 19 pneumonia and non-pneumonia. FCONet is a simple 2D deep learning model that has been created based on transfer learning with four pretrained backbone models: VGG16, ResNet-50, Inception-v3 and Xception. CTs were separated into training and test sets in an 80:20 proportion and performance of models assessed on an inner testing set as well as external testing set of low-quality CTs obtained through published studies. The ResNet 50 version of FCONet had the highest accuracy, sensitivity, and specificity of 99.87 %, 99.58 %, and 100 % on

Vol. 5 No. 1 (2026)

Pakistan Journal of Medical & Cardiological Review

https://pakjmcr.com/index.php/1/about

Online ISSN Print ISSN

3007-2387 3007-2379

Rehman et al - 2026

DOI: http://doi.org/10.5281/zenodo.20176045

the internal test set, respectively. It was also found to be more robust on the external low-quality dataset with the highest accuracy 96.97% making it the best facing Xception, Inception v3, and VGG16. On the whole, FCONet especially when using a ResNet-50 backbone was a rapid, precise, and solid method of detecting COVID-19 pneumonia by CT scanning [27].

A DL system to detect pneumonia disease in an effective and efficient manner. Deep Convolutional Neural Network (DCNN) transfer learning include AlexNet, SqueezeNet, VGG16, VGG19 and Inception-V3, which are used to extract beneficial features using the data of the chest X-ray images. This proposed system uses a number of machine learning (ML) classifiers. Training and testing of the proposed system were done using the chest X-ray and CT images dataset [28] .

Machine learning workflow, which combines deep learning algorithms to extract features and standard classifiers, which are capable of identifying and diagnosing COVID-19 using chest CT scans. The maximum mean accuracy achieved was 99.9 % with the modified ML process with 2000 features extracted with GoogleNet and ResNet18 and with support vector machine (SVM) classifier. The findings realized on the modified ML process were increased after comparison with other similar methodologies in the available literature on the similar datasets and higher datasets of similar size; therefore, the study can be regarded as being of an added value to the present literature [29].

A deep learning algorithm called HarDNet /Pneumonia-Plus, which was created on the basis of chest CT images to effectively identify the type of pneumonia (bacterial, fungal and viral pneumonia). This model was trained and tested on CT data on 2,763 patients whose diagnoses with the pathogen were confirmed and on an additional cohort of 173 patients (prospectively). The performance of Pneumonia-Plus was good with AUC of 0.934, 0.816, and 0.715, respectively, in bacterial, viral, and fungal pneumonia. The sensitivity of a classification of viral pneumonia was high (0.847), specificity (0.919), and accuracy (0.873). In comparison with radiologists results, the performance of the algorithm was similar to that of radiologists. On the whole, Pneumonia-Plus showed the performance of the attending-radiologist level and could prevent misdiagnosis and unnecessary use of antibiotics and promote timely clinical decision-making to achieve better patient outcomes [30]. The summary of pneumonia detection using CT images is given in Table 3.

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Table 3. Detection of Pneumonia using CT Images

Authors	Year	Model	Classification	Dataset	Performance
Hoon Ko et.al [27]	2020	FCONet (VGG16, ResNet-50, Inception-v3 and Xception)	Covid-19, Pneumonia and Normal	Chest CT	Accuracy 99.87 %
Yar Muhammad et al. [28]	2021	AlexNet, SqueezeNet, VGG16, VGG19 and Inception-V3	Pneumonia and Normal	Chest X-ray and CT	Accuracy 97.19 %
Ghazanfar Latif et al. [29]	2022	GoogleNet, ResNet18 and Support Vector Machine	Covid-19, Pneumonia and Normal	Chest CT	Accuracy 99.9 %
Fang Wang et al. [30]	2023	HarDNet/ Pneumonia-Plus	Pneumonia (Bacterial, Fungal, Viral)	Chest CT	AUC of 0.934, 0.816 and 0.715, respectively

2.3 Pneumonia Detection using Thermal Images

Thermal imaging has become a data-oriented technique of detecting pneumonia with the development of artificial intelligence and computer vision. IR thermal images record spatial changes in temperature which represent the inflammatory processes in pulmonary perfusion and metabolism in pneumonia. Even though such patterns are not always visible and can be hardly evaluated visually, AI processes allow automated feature detection and strong pattern retrieval. More specifically, deep learning models have the ability to acquire non-linear representations (directly with thermal data), which can be used to perform precise classification and severity estimation. Due to the non-contact and radiation-free nature, and fast acquisition, AI-assisted

Vol. 5 No. 1 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN 3007-2387
Print ISSN 3007-2379
Rehman et al - 2026
DOI: http://doi.org/10.5281/zenodo.20176045

thermal imaging has a promising future in terms of accessible pneumonia screening and subsequent monitoring [31].

The study investigated the use of thermal imaging (TI) in detecting focal pneumonia versus the gold standard, the chest X-ray in 47 patients with ages between 10 months and 82 years. TI and CXR were carried out within 4 hours and blindly evaluated. TI had high sensitivity 80.0%, and large negative predictive value 93.8% and moderate specificity 57.7%. The results indicate that chest TI has the capability to detect pneumonia in similar body parts as CXR, and hence it can be used as a point-of-care screening device, which requires additional validation [32].

A new point-of-care, non-contact, thermal imaging system to detect COVID-19, which has developed image processing algorithms. The thermal imaging of the back of the people with and without COVID-19 was taken with a handheld thermal camera, which is connected to smart phones. The novel image processing techniques were used to extract multiple texture and shape characteristics of the thermal images automatically to achieve an area under the curve value of 0.85 when detecting COVID-19 with a maximum sensitivity of 92 percent. They show that a hand-held thermal imaging device can be applicable to detect COVID-19 since the scores of a hand-held thermal imaging were negatively correlated with clinical variables of COVID-19 disease progression. Non-invasive thermal imaging COVID-19 screening may be feasible to occur in out-of-hospital settings, especially in high-income-neighborhoods with limited imaging services.[33].

The application of inexpensive, portable thermal imaging combined with image processing and machine learning to non-invasively detect pneumonia. The back skin surface of 69 subjects consisting of healthy, fever patients but not with pneumonia, general pneumonia patients, and COVID-19 patients provided thermal and RGB images. By using automated method of feature extraction using temperature distribution, location, and shape features, it was possible to discriminate successfully between positive and negative cases of pneumonia. The accuracy of the proposed method was 93%. Also, thermal monitoring of two pneumonia patients every day successfully predicted the clinical outcome that was in line with the lab results. The findings indicate the technical possibility of intelligent thermal imaging in the screening and treatment evaluation of pneumonia, and it can be applied in the resource-constrained environment to control epidemics [34].

A smartphone-based application based on thermal images of a human back was created to detect COVID-19. The sensitivity and specificity with image analysis with a deep learning algorithm was 88.7% and 92.3%, respectively. The results positively endorse the future application of the noninvasive thermal imaging in the first-line screening of COVID-19 and related pneumonia [35].

A screening device based on artificial intelligence to detect human breathing patterns that are identified due to a deep learning model. The machine is constructed based on Convolutional Neural Network to derive features and Long Short-Term Memory (LSTM) network to categorize time-

Pakistan Journal of Medical & Cardiological Review
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Online ISSN Print ISSN
Rehman et al - 2026
3007-2387 3007-2379
DOI: http://doi.org/10.5281/zenodo.20176045

series patterns. The Softmax classifier is very precise in the classification of respiratory patterns. It is trained on a dedicated dataset of six breathing signal patterns, and therefore is an effective model to the real-time surveillance of the public health. The result of the experiment proves that the proposed CNN-LSTM model has an accuracy of 91 %, a precision of 90 %, a recall rate of 93 %, and an F1-score of 91 % [36]. The summary of pneumonia detection using Thermal images is given in Table 4.

Table 4. Detection of Pneumonia using Thermal Images

Authors	Year	Model	Classification	Dataset	Performance
Linda T Wang et al. [32]	2018	Fisher's exact test	Pneumonia and Normal	Posterior thoracic upper lung region	Accuracy 80 %
Rafael et al [33].	2021	Higuchi's algorithm	Covid-19 and Normal	Posterior thoracic upper lung region	Accuracy 92 %
Yingjie Qu et al. [34]	2022	SVM KNN Decision tree Gaussian NB LDA QDA	Covid-19, Pneumonia, Fever and Normal	Posterior thoracic upper lung region	Accuracy 93 %
Oshrit Hoffer et al. [35]	2024	SVM, ResNet50	Covid-19 and Non Covid-19	Posterior thoracic upper lung region	Accuracy 90.09 %
Abisha D. [36]	2025	Softmax	Respiratory Patterns	Thermal videos sequencing	Accuracy 91 %

Vol. 5 No. 1 (2026)

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Online ISSN Print ISSN

3007-2387 3007-2379

Rehman et al - 2026

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3. Conclusion

Pneumonia diagnosis and management rely heavily on imaging modalities, where chest X-ray and computer tomography are currently the most widely used imaging modalities in the clinical practice because of their accessibility and diagnostic ability. Imaging modalities such as ultrasound and thermal imaging have become useful complements in the conditions where radiation exposure, portability, and bedside examination are crucial factors. Although traditional imaging is generally required to deliver anatomical and physiological data, its application is usually delayed by variability in observation, radiation issues, and rising diagnostic burdens.

In this review, pneumonia detection using artificial intelligence, especially machine learning and deep learning methods, has greatly improved with the use of imaging data. Models based on AI approaches to chest X-ray and CT images have demonstrated high accuracy in the classification of disease, the severity of the disease, and decision-making, and the performance of these models is often comparable to a human specialist. Developing work on AI with thermal imaging also suggests that any inflammatory alterations in pneumonia can be identified with the help of indirect temperature distribution patterns that cannot be easily identified by simply looking at them.

Nevertheless, AI-based pneumonia detection is associated with such challenges as the lack of data diversity in the datasets, the absence of standard imaging procedures, and the absence of prospective clinical validation. The following research directions will be needed in the future: large-sized, well-annotated datasets, explainable, robust AI models, and multimodal methods which would include anatomical, physiological, and thermal data. Specifically, thermal imaging is a radiation-free and non-contact modality with significant available potential, particularly in terms of large scale screening and real-time monitoring, and in resource-constrained environments. Future advances in AI-based thermal analysis should be of great importance in designing safer, more convenient, and accessible solutions in the detection of pneumonia.

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Pakistan Journal of Medical & Cardiological Review
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