Vol 6 No 1 (2024) E-ISSN: 2682-860X

International Journal on Robotics, Automation and Sciences

Review on Detecting Pneumonia in Deep Learning

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Abstract - Deep learning is a machine learning technique that has been optimized for image classification and object detection. Deep learning has brought huge advancement to the medical field as it helps to diagnose various diseases through computed tomography (CT) scan or X-ray images. Pneumonia is a respiratory disease, and it is one of the killer diseases that causes numerous death all around the world. In 2019, the outbreak of COVID-19 has increased the number of pneumonia patients tremendously. With the increasing number of patients, the clinical and medical facilities have become insufficient. The lack of doctors and radiologists to diagnose pneumonia has caused a high number of patients to be misdiagnosed. Chest image is one of the most effective methods to diagnose this disease, however, examining the X-ray or CT images requires specialists such as radiologists. Meanwhile, examining chest CT or X-ray images might be subjective as the presence of pneumonia can be unclear in the images. The main objective of this paper is to provide a comprehensive review of recent advancement in the diagnosis of pneumonia with deep learning, including state-of-art methodology, datasets, discussion, challenges, and future improvements.

Keywords—Deep Learning, COVID-19, Convolutional Neural Network, Pneumonia Diagnosis, Chest X-Ray, Chest CT Scan.

I. Introduction

Pneumonia is one of the most common yet life-threatening diseases that causes numerous deaths around the globe. In 2019, this disease had taken lives of 2.5 million people and most of the patients were children under five years old [1]. Pneumonia is a respiratory disease that is caused by infection that inflames the air sacs of the lungs [2]. Patients usually will suffer from coughing, fever, difficulty in breathing, chills, and fatigue [3]. The global outbreak of COVID-19 in year 2020 had increased the number of pneumonia patients as COVID-19 has a high possibility to cause pneumonia disease. COVID-19 is a disease that caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) virus, and it brings severe damage to the respiratory system of the infected people [4]. According to the World Health Organization (WHO), the reported cumulative deaths caused by COVID-19 is around seven million while infected people is around seven hundred million in year 2023 [5]. The increasing of COVID-19 patients leads to the increasing of pneumonia patients. Researchers in [6] had conducted a result on 247 COVID-19 patients to study the relationship between COVID-19 and pneumonia, and the result showed that 21.4% of patients among the confirmed COVID-19 cases had been diagnosed with

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International Journal on Robotics, Automation and Sciences (2024) 6,1:70-77
https://doi.org/10.33093/ijoras.2024.6.1.10
Manuscript received: 22 Dec 2023 | Revised: 23 Jan 2024 | Accepted: 20 Feb 2024 | Published: : 30 Apr 2024

Published by MMU PRESS. URL: http://journals.mmupress.com/ijoras

pneumonia. COVID-19 is a respiratory illness that infects the lungs and airways of patients, and to fight the virus, the immune system is causing inflammation which has the potential to bring damage to your lungs and expose the air sacs of the lungs to fluid [7]. Another factor COVID-19 leads to pneumonia is the weakened immune system of the patients, allowing the bacteria to infect the lungs easily [8].

Up to this day, chest X-ray and CT scan images still play an important role when it comes pneumonia diagnosis [9]. Nonetheless, examining those images requires a high level of specialists such as radiologists to have a more reliable and accurate diagnosis. Still, involving specialists in the X-ray or CT scan image examination has the potential for subjective and variability in diagnosis, as most of the time they are using their bare eyes with the help of bright white light to interpret the images. The evolution of deep learning, a subset of artificial intelligence (AI) that feeds computers wealth of data and trains them to make optimal decisions based on the data has opened a boulevard for refining the pneumonia diagnosis process.

In recent decades, the prevalence of machine learning and deep learning has become higher in the medical field. For example, identify health trends, increase the accuracy of diagnoses, recommend suitable treatments, and more [10]. Deep learning model, a neural network which essentially consists of three or more layers that is attempting to stimulate the behavior of human brain by learning large amount of data and make a prediction according to the learning process [11] [59]. Convolutional neural networks (CNNs) from deep learning models have demonstrated extraordinary in automating the image analysis processes, such as identifying abnormalities in medical images. These models attracted the attention of researchers and scientists as they have a high potential to increase the diagnosis accuracy, reduce the human error and interpretation time, and provide validation to the decisions and reasonings of doctors significantly. Furthermore, investing in medical images diagnosis using deep learning will reduce the cost of hospital diagnostic imaging process as professional radiologists for X-ray and CT scan images are rare and expensive for some regions [12].

In recent years, many researchers have contributed to apply deep learning models to ease the process of diagnosing pneumonia and to increase the accuracy of diagnosis. According to a survey on the Internet, the deep learning model that gains the highest attention to diagnose pneumonia is convolutional neural networks (CNNs). Some popular pre-trained CNN models such as AlexNet [13], Xception [14], VGGNet [15], DenseNet [16], and ResNet [17] are being revised and improved for better accuracy in diagnosing pneumonia as well as other diseases through X-ray and CT scan images [18]. Thus, the primary goal of this study is to present and show the major and most current publications that developed or implemented the most effective and high accuracy deep learning models on pneumonia diagnosis.

C.P Lee and K.M. Lim [57], inspired by the accomplishments of deep learning, conducted a study to appraise the efficacy of four deep neural networks in detecting COVID-19 patients through the analysis of chest radiographs. Preliminary investigations encompassed the examination of deep neural networks, namely VGG16, MobileNet, ResNet50, and DenseNet201. Results indicate promising performance across all models, with DenseNet201 demonstrating superior efficacy compared to its counterparts. Nevertheless, the sensitivity rates of these models fell short of expectations. This shortfall can be attributed to various factors, including the scarcity of publicly available COVID-19 images, imbalanced sample sizes in both the COVID-19 and non-COVID-19 classes, potential overfitting or underfitting in the deep neural networks, and the suboptimal adaptability of pre-trained model feature extraction to the task of COVID-19 detection. To confront these factors, various improvements are suggested, including data augmentation, adjusted class weights, early stopping, and fine-tuning, with the aim of optimizing performance.

A. Musha et al. [58] have introduced COVID-CXDNetV2, an advanced computer-aided deep learning model for the real-time detection of both coronavirus disease 2019 (COVID-19) and pneumonia in X-ray images. The proposed model, which integrates YOLOv2 and a residual neural network (ResNet), is trained on a comprehensive X-ray images dataset comprising 3788 samples across three distinct classes: COVID-19, pneumonia, and normal. In the context of medical applications, the authors are optimistic about this method's viability for diagnosis, anticipating its noteworthy influence on real-life situations.

Deep learning has attracted huge research interest of researchers and scientists because of its efficiency, accuracy, and potential to make predictions on many data formats [20]. Undeniably, deep learning has assimilated into human daily life to solve a variety of problems. For instance, classification on images, object detection, self-driving vehicles and many more. This section discusses an overview of deep learning, especially convolutional neural networks (CNNs) that are widely used in detecting pneumonia disease [21].

Deep learning is one of the fields in machine learning and artificial intelligence, and the idea and structure of deep learning are inspired by the function and structure of the neural networks of human brain [22][23]. The significant difference between deep learning and other machine learning algorithms is that deep learning algorithms are neural networks that have multiple layers with interconnected nodes. These multiple layers learn automatically with fed data and extract useful information from data. Neural networks in deep learning are mathematical functions that stack on top of each other in layers form, passing processed data from first layer to the last layer, forming a depth, hence the name deep learning [24].

As the implementation of machine learning and deep learning in medical imaging continues to become more prioritized, the diagnosis process has become more accurate than human eyes [19], and it continues to evolve, offering a promising avenue to improve health of people and the health system all around the globe.

II. METHOD AND PREVIOUS WORK

This session introduces and discusses the recent research and publications about detecting pneumonia using deep learning. As part of this session, an overview of some of the most popular deep learning models such as CNNs that were implemented by researchers to detect pneumonia in real life. At the end of this session, a comparison table of the accuracy of each deep learning model will be shown and discussed to conclude the session.

A. *Convolutional Neural Network (CNN)*

Convolutional Neural Networks (CNN), a specific type of deep learning algorithm that is designed to process data that is in grid format, and commonly being implemented for more complex tasks such as image classification, text classification, and object detection [25]. CNNs are made up of at least three types of layers which are convolutional layer, pooling layer, and fully connected layer [26].

Convolutional layer is responsible for feature extraction. It identifies and separates the features in the images [27]. On the other hand, pooling layer performs down-sampling on the dimensions of the features map to reduce the computational complexity while preserving the important information of the data [27]. Finally, the fully connected layer assembles all the outputs from all layers and performs predictions for final output [27].

In CNNs, activation functions play an important role in deciding the activation of neurons by performing weighted sum and adding bias value to the next layer [28]. activation functions also introduced non-linearity to the neural networks to learn more complex relationship between features, resulting in better accuracy in prediction. some of the popular activation functions being widely used in CNNs are sigmoid, Rectified Linear Activation (ReLU), Tanh, and Softmax [29].

In order to reduce error and increase the accuracy of CNNs, backpropagation is being performed. this action is to adjust the weights of networks and to minimize the difference between predicted output and actual output. backpropagation is working backward, from output nodes to input nodes [30]. Figure 1 illustrates the standard structure of CNNs [31].

In research done by Gabruseva, Poplavskiy, and Kalinin in 2020, researchers implemented the deep learning by using RetinaNet as the base model on Pytorch with some of the modifications. For instance, researchers included images that consist of empty boxes to the model to calculate loss and extra output for small anchors so that CNN can handle smaller boxes.

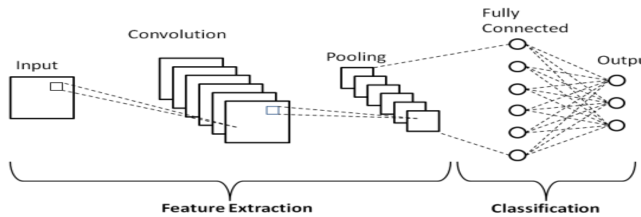

FIGURE 1. Standard Structure of CNNs [31].

The training set will be labelled by an expert while the testing set will be labelled by three other different radiologists. At the end, the real expected result can be obtained by performing intersection between their labels. In this paper, researchers obtained the accuracy of 0.24781 mAp with the model that makes use of SSD RetinaNet with SE-ResNext101 encoder [32].

P. Rajpurkar et al. have published research on detecting pneumonia using CheXNet in year 2017. CheXNet is a convolutional neural network that consists of 121 layers. In order to measure the accuract of the predicted output, four practicing radiologists from Stanford University were involved to label the 420 testing images, and the output will be compared with the output from CheXNet. Through this research, the model achieved the F1 score of 0.435 [33].

In the research performed by Varshni. D et al. in 2019, researchers proposed to implement DenseNet-169, a pre-trained densely connected convolutional neural network, to classify the normal and infected lung through chest X-ray images. Furthermore, a support vector machine (SVM) was used in the neural network as classifier to perform the classification on the input images. With this proposed deep learning model, 0.8002 AUC score has been achieved [34].

In recent years, object detection has been a headline in the world of machine learning as it has achieved a greater height in numerous fields, such as face recognition, medical images, and autonomous driving [35]. Jaiswal, A.K et al. has published a research paper about using Mask-RCNN to detect pneumonia. Mask-RCNN stands for Mask- Recurrent Convolutional Neural Network, is a region-based object detection deep learning that uses the CNNs to process and classify input images [36]. The proposed model also consists of ResNet101 as the foundation detector in Mask-RCNN, and ResNet50 as a comparison to compare with ResNet101. An accuracy of 0.2181 was obtained by the researchers with the ensemble model proposed [37].

A study was conducted by Pant. A et al. on deploying an ensemble deep learning model to detect pneumonia through chest X-ray images. The proposed model was ResNet-34 based U-Net and follows by EfficientNet-B4 based U-Net. Thanks to the encoder-decoder segmentation network in U-Net [38], it is very beneficial in biological categorization. By applying the ResNet-34 model with EfficientNet-B4 model, researchers managed to obtain high accuracy of 90% when classifying test dataset [39].

The research of applying Xception deep learning model to detect the presence of pneumonia has been conducted by Ayan. E and Unver. H. M in the year 2019. In this research, researchers found that VGG16, a 16 layers CNN model has higher accuracy than Xception model that has 71 layers of neural networks at the accuracy of 87% and 82% respectively [40].

A comparative study to examine the accuracy of the same ensemble CNN model on different datasets has been done by Kundu. R et al. The ensemble of three different CNN models involved in this research were ResNet-18, GoogLeNet, and DenseNet-121. They found that the model performed better on Kermany dataset with accuracy 98.81% than the RSNA dataset with accuracy of 86.85% [41].

AlexNet has always been a topic of conversation when it comes to CNNs, thanks to its ability to categorize more than 1000 different classes. Furthermore, AlexNet is the first CNN model to use GPU to boost its performance when performing classifications [42]. By applying AlexNet to detect pneumonia, the accuracy of 72% has been achieved when classifying the testing images in the research done by O'Quinn. W et al. [43]. CNN is a great deep learning model to perform classification, especially on images. However, accuracy of CNN will decrease after the number of hidden layers surpasses a certain amount, the model becomes too complicated. To overcome this problem, Urey. D. Y et al. (2019) have conducted research to include residual neural networks in the CNN network. Residual neural networks are used to skip connections and give the CNN model the ability to train deeper networks. Figure 2 shows the basic concept of residual neural networks [44]. In this research, researchers were able to obtain the accuracy of 78.73% when classifying the chest X-ray images using the proposed model [44].

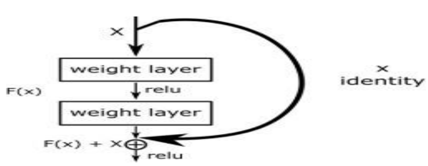

FIGURE 2. Residual Neural network [44].

B. Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) is one of the most popular deep learning models that uses time-series or sequential data to perform model training and predicting [45]. It has been widely used in temporal or ordinal problems, such as natural language processing (NLP) or speech recognition [46]. Unlike CNNs, RNN has "memory" as they use information or output from prior inputs to perform prediction on current output and pass to the next node [47]. All the weights in the network of RNN remains the same [48].

There are different types of RNN architecture available at the moment, such as one-to-one, one-to-many, many-to-one, and many-to-many. One-to-one shows that there is only one input and one output, while given the name one-to-many, it means that one input might produce numerous outputs. The many-to-one architecture receives many inputs but returns only one output. On the other hand, many-to-many returns numerous outputs given many inputs [49].

The most important part of RNN is the hidden layers located in the middle of the network. Each hidden layer has its own activation functions, biases, and weights to dictate whether the neurons should be turned off or on. Similar to CNN, the common activation functions being widely used in RNN are Sigmoid, Tanh, and ReLU [49]. Figure 3 illustrates the basic architecture of RNN [50].

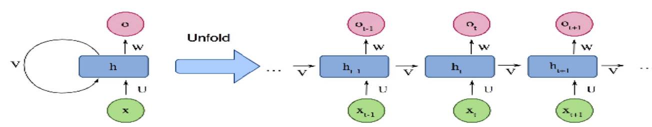

FIGURE 3. Basic Architecture of Recurrent Neural Network [50].

In the research done by Elshennawy. N. M and Ibrahim. D. M, a combination of long-short term memory networks (LSTM) with CNN was implemented to investigate the accuracy and efficiency when classifying real life chest X-ray images. Due to the characteristics of RNN, the input data was transformed into time series data before passing the data to LSTM. The proposed model starts with LSTM only then CNN as the final network to perform predictions on input data. By the end of the research, researchers have achieved 91.80% accuracy using LSTM-CNN model [51].

The study of implementing another type of RNN model, cascaded recurrent neural network (CRNN), to detect pneumonia was carried out by Shankar. K et al. The researchers proposed a model named BMO-CRNN, which is the combination of barnacle mating optimization (BMO) and CRNN. BMO acts as agent to determine the optimal hyperparameters for CRNN in terms of learning rate, activation function, and number of epochs. Through BMO algorithm, CRNN has the potential to achieve higher accuracy during the model training and testing on chest X-ray images. The result of this proposed model was promising with an accuracy of 97.31% [52].

III. Results and Discussions

An overview of the studies that were surveyed and discussed can be found in Table 1. In this section, more detailed information of how deep learning approaches change the game on detecting the existence of pneumonia.

TABLE 1. Approaches for detecting pneumonia using deep learning.

Ref.	Model	Dataset	Result	Measure
[32]	RetinaNet + SE-ResNext101	National Institutes of Health (NIH) Clinical Centre [53]	0.2478	mAp
[33]	CheXNet	NIH Clinical Centre [53]	0.435	F1-score
[34]	DenseNet-169 + SVM	NIH Clinical Centre [53]	0.8002	AUC
[37]	Mask-RCNN	NIH Clinical Centre [53]	21.80%	Accuracy
[39]	ResNet-34 + EfficientNet-B4	Kaggle	90%	Accuracy
[40]	VGG16	Kermany et al. [54]	87%	Accuracy
[40]	Xception	Kermany et al. [54]	82%	Accuracy
[41]	ResNet-18 + GoogLeNet + DenseNet-121	Kermany et al. [54]	98.81%	Accuracy
[43]	AlexNet	NIH Clinical Centre [53]	72%	Accuracy
[44]	CNN + ResidualNeural Network	NIH Clinical Centre [53]	78.73%	Accuracy
[51]	LSTM-CNN	NIH Clinical Centre [53]	91.80%	Accuracy
[52]	BMO-CRNN	GitHub [55]	97.31%	Accuracy

Convolutional neural networks are, in general, the most common approach when detecting pneumonia through chest X-ray image of the patients. The reason behind it is that CNNs has the ability to reduce the dimensions of input images without losing any information. This reduces the computational time during model training as well as reduces the cost of finance.

Recurrent neural networks are sometimes being used to perform image and video classification, but the frequency is not as much as CNNs. Unlike CNNs, RNNs are only able to interpret with time series and sequential data, this characteristic has limited RNNs to be as efficient as CNNs when dealing with image, video classification problems. However, RNNs are advantages if they are introduced in CNNs for the fact that RNNs has the capability to store the output from prior input.

It is worth noting that dataset from different sources might return vary accuracy even when using the same trained deep learning model.

TABLE 2. Advantages and disadvantages of the approaches for detecting pneumonia using deep learning.

`	Model	Advantage	Disadvantage
[32]	RetinaNet + SE-ResNext101	High accuracy and effective in detecting features in medical images.	Computationally expensive, requiring powerful hardware.
[33]	CheXNet	Specifically designed for chest X-ray image analysis. Pre-trained on a large dataset, which enhances generalization.	May not perform well on pneumonia cases with unusual patterns or in diverse populations.
[34]	DenseNet-169 + SVM	DenseNet architecture encourages feature reuse and reduces the risk of vanishing gradients. SVM classifier can effectively handle non-linear patterns in data.	May require substantial computational resources during training. The performance heavily relies on the quality and quantity of training data.
[37]	Mask-RCNN	Provides precise instance segmentation, enabling localization of pneumonia regions. Can detect multiple instances of pneumonia in a single image.	Computationally intensive, leading to slower inference times. Requires substantial annotated data for effective training.
[39]	ResNet-34 + EfficientNet-B4	EfficientNet's parameter efficiency and ResNet's depth contribute to robust feature extraction.	Requires careful hyperparameter tuning. May face challenges in deployment on resource-constrained devices due to computational demands.
[40]	VGG16	Simplicity in architecture facilitates ease of understanding and implementation. Effective feature extraction capability for various tasks, including pneumonia detection.	Prone to overfitting, especially with limited data. Computationally demanding compared to more modern architectures.
[40]	Xception	Depthwise separable convolutions enhance computational efficiency. Strong feature extraction capabilities.	Training may require more data compared to shallower architectures. Complex architecture may be harder to interpret.
[41]	ResNet-18 + GoogLeNet + DenseNet-121	Combination of residual connections (ResNet) and inception modules (GoogLeNet) can capture diverse features.	Increased complexity may lead to longer training times. Requires careful coordination of different components for optimal performance.
[43]	AlexNet	Pioneering deep learning architecture for image classification. Relatively lightweight compared to later models, making it suitable for resource-constrained environments.	Prone to overfitting, especially with limited data. Not as deep as more modern architectures, potentially limiting its feature representation capabilities.
[44]	CNN + Residual Neural Network	Incorporating residual connections (ResNet) enhances training stability and facilitates the learning of more complex features. Suitable for handling image data with hierarchical feature representations.	Increased model depth may lead to longer training times. - May require careful tuning of hyperparameters to avoid issues like vanishing or exploding gradients.
[51]	LSTM-CNN	Combining LSTM with CNN can capture temporal dependencies in sequential medical data. Effective for tasks where temporal context is crucial.	Training can be computationally expensive and time-consuming. Requires careful tuning of hyperparameters for optimal performance.
[52]	BMO-CRNN	Integrating attention mechanisms (BMO) with CRNN can enhance the model's focus on relevant features. Effective for capturing long-range dependencies in sequential	Training complex models with attention mechanisms may require significant computational resources. Interpretability of attention mechanisms can be challenging.

For instance, the ensemble model that consists of ResNet-18, GoogLeNet, and DenseNet-121 was to predict the classes of the test images, and the accuracy of the model is different when it was trained with different dataset. When the model was trained and tested with the dataset from Kermany et al., the accuracy was significantly higher than the accuracy when the model was trained with the dataset from RSNA. The reason why this problem happened was the dataset from RSNA might contain chest X-ray images that were not in good quality, such as blurry, loss of information, and bad resolution.

Furthermore, the accuracy of the models that introduced RNNs seems promising. Such as the ensemble model that consists of ResNet-18, GoogLeNet, and DenseNet-121able to produce the 98.81% of accuracy [54], where as the BMO-CRNN model was promising with an accuracy of 97.31% [52].

Other the contrary, most of the CNNs model, such as VGG16 with an accuracy of 87%, and Xception with an accuracy of 82% respectively where as the researchers have achieved 91.80% accuracy using a combination of long-short term memory networks (LSTM) with CNN (LSTM-CNN) model [51].

Table 2 illustrated the advantages and disadvantages of the approaches for detecting pneumonia using deep learning. It should be worth mentioning here that the effectiveness of these models can depend on factors such as the size and diversity of the dataset, computational resources, and specific requirements of the application.

IV. Conclusion

Deep learning is one of the best approaches for providing accurate diagnosis against the pneumonia disease. In this paper, a comprehensive review of the methodologies used in detecting pneumonia is discussed, supported by some of the important works published in recent years. An overview of deep learning was included to enable the viewers to have a basic picture about deep learning before going deeper into the state- of-art. Moreover, an in-depth overview of the deep learning models that were being used in most of the work, along with the details of how the models work was being emphasized. Throughout the research, it is obvious that deep learning models, especially convolutional neural networks (CNNs), have demonstrated exceptional efficiency and accuracy in pneumonia detection problem through chest X-ray and CT images. A great number of studies have continuously found good sensitivity, specificity, and accuracy rates, highlighting the potential of AI-driven solutions for diagnosing pneumonia. In addition to it, dataset that is used to train and test the deep learning model is also playing an important role. The quantity and quality of data do affect the accuracy of the final model. Larger and more diverse datasets with high resolution and image quality have contributed to improved model generalization and accuracy. With that being said, image preprocessing is essential for making sure to feed the model with high quality data without losing any significant information during the training phase. For example, histogram equalization, image sharpening, and random flipping are the common image preprocessing to be performed before model training [53]. At the moment, the research on applying recurrent neural networks (RNNs) to detect pneumonia is still limited. In section 3, it is noticeable that RNN models have great performance on detecting pneumonia when compared to CNNs, hence, more effort should be put into the field of using RNNs to detect pneumonia by the science community. Besides, exploration in cutting-edge transfer learning strategies using pre-trained models on big datasets like ImageNet could be a future direction for the scientists as fine-tuning those models can hasten model convergence and improve performance. In order to move pneumonia detection forward in leaps and bounds, global collaboration is much needed. International collaboration among researchers, physicians, and scientists should share datasets, standardize benchmarks, and establish best practices for detecting pneumonia using deep learning. This approach will expedite the development of robust and accurate deep learning models. To conclude, the successful implementation of deep learning model in pneumonia detection in worldwide healthcare system has brought huge impact on health of patients, making the treatment process better and faster. With the assistance of deep learning models such as CNNs and RNNs, the diagnosis process becomes more accurate as deep learning acts as a proof to validate the first diagnosis from physicians. Even though significant progress has been made, ongoing issues with data quality, interpretability, and clinical application highlight the need for research and innovation. Scientists are prepared to develop more accurate, accessible, and equitable solutions for pneumonia diagnosis by outlining these potential future approaches and collaborating to overcome these obstacles. The growing fusion of artificial intelligence and medical knowledge has the potential to significantly improve patient outcomes and patient care in the field of respiratory health.

Acknowledgement

We thank the anonymous reviewers for the careful review of our manuscript.

Funding Statement

There is no financial support from any agencies funding this research work.

Author contributions

Toh Jun Jie: Writing – Original Draft Preparation;

Md Shohel Sayeed: Writing – Review & Editing.

Conflict of Interests

No conflict of interests were disclosed.

Ethics Statements

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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