Lung Disease Classification and Detection based on Convolutional Neural Network: A review

Abstract

Pneumonia diseases are considered one of the most pandemic diseases by the WHO, claiming the lives of millions across the world. Therefore, the necessity of having mechanisms for early diagnosis and detection of these epidemic diseases to preserve people's lives. On the other hand, the increase in cases requires not relying on traditional means of detecting diseases due to these tests' limitations and high cost. Among the available methods for diagnosing Pneumonia diseases are X-rays and CT scans. For accurate and highly efficient diagnosis, computer-aided diagnosis (CAD) is required. Deep learning has been suggested as the best solution to enhance the prognosis for many lung diseases using CAD systems. The ability of machine learning algorithms was not sufficient to diagnose with high accuracy. The aspiration to deep learning to solve the problems of diagnosis more accurate, especially convolution neural networks, showed impressive results in the classification of images. The convolutions layer in the network with filters automatically discover the critical spatial and temporal features in an image. Hierarchical representations were used in human brains in designing the learning process of CNN. Several deep learning architectures have been used to detect pneumonia diseases, the most popular such as AlexNet, VGG-16, Inception-v1, Inception-v3, ResNet-50, Inception-ResNet-V2, and ResNet201. The strength of CNNs lies in the size of data to be trained. Previous algorithms have been used to pre-train on a vast dataset. An augmentation strategy has been used

in the model design to increase the dataset's size and quality artificially. The purpose of this review article is to present the different approaches and techniques used in the detection and diagnosis of epidemic diseases of Pneumonia. For concerted efforts to find out the best CNN model to detect and classify the disease.

Keywords: Pneumonia, Convolutional Neural Network (CNN), Transfer learning, Data Augmentation, COVID-19, Chest X-ray images.

1. Introduction

Lung diseases like Pneumonia and COVID-19 are recognized as one of the most pandemic diseases by the WHO [1]. Every year approximately 1.4 million children died due to pneumonia disease [2]. Coronavirus disease 2019 (COVID-19) is a type of viral Pneumonia caused by Coronavirus 2 (SARS-CoV-2) [3]. The risk of developing lung disease is increasing daily and is enormous in rapidly growing nations. Pneumonia is an infection that affects the lungs most often due to a virus or bacteria. It usually affects only one of the five lung lobes (3 lobes in the right lung and 2 in the left lung), hence the term lobar Pneumonia [4]. A COVID-19 infected person may experience hacking cough, fever, muscle pain, sore throat, headache, and mild to moderate respiratory illness. However, older adults and those having underlying medical conditions like diabetes, cardiovascular disease, cancer, and chronic respiratory disease are Most affected to develop severe illness [5].

The real-time polymerase chain reaction (RT-PCR) test of the phlegm is the gold standard for diagnosing common pneumonia diseases and Coronaviruses. However, these RT-PCR assays showed high levels of false-negative to substantiate positive COVID-19 cases [6]. Instead, radiological examinations using computed tomography (CT) scans and chest X-rays are now used to diagnose affected patients' health status, including pregnant women and children, regardless of the potential side effects from exposure to ionizing radiation [7]. CT imaging offers an effective method for screening, diagnosing, and evaluating patients' progress with COVID-19. However, clinical studies have shown that positive chest X-rays may eliminate the need for computed tomography and reduce the clinical burden on CT wards during the outbreak [8].

Chest X-ray plays an essential role as the first imaging technique in the diagnosis of Covid-19 disease. Figure 1 shows a negative example with a regular chest X-ray, a positive example with Pneumonia, and a positive example with COVID-19 [9].

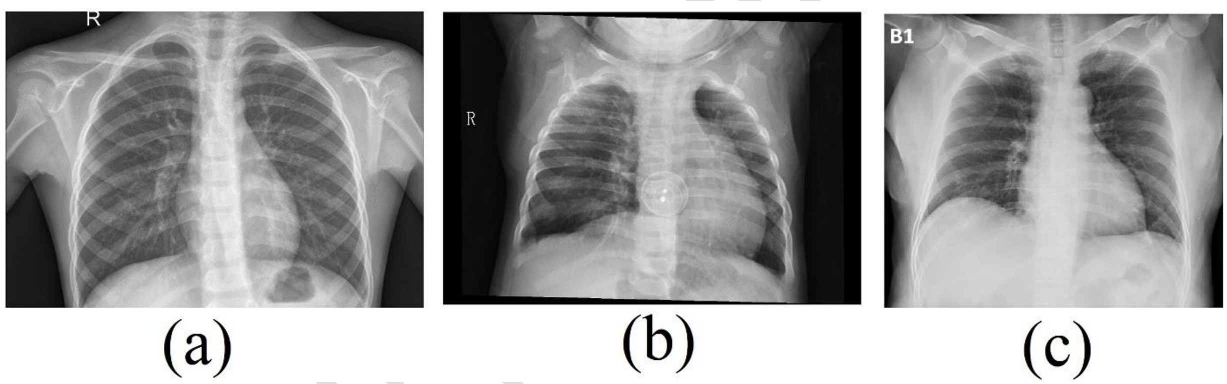

Fig. 1: Examples of chest X-ray images a) normal, b) pneumonia, and c) COVID-19

The Pneumonia X-ray images are not very straightforward and are frequently miscategorized into other illnesses or benign anomalies. Besides, specialists often ignore bacterial or viral Pneumonia photos, contributing to inaccurate medications for people and aggravating patients' conditions [2]. Therefore, there is a pressing need for computer-aided diagnosis (CAD) systems as a practical solution to overcome these limitations of chest X-rays, which can assist the radiologists are directly after acquisition to diagnose various forms of Pneumonia from chest X-ray images with low contrast [2][6].

Artificial intelligence (AI) has been proposed and applied as based solutions to advance many CAD systems' diagnostic performance for various biomedical applications such as brain tumor classification or segmentation, breast cancer detection, and detecting pulmonary diseases [10]. Recently, the machine learning (ML) techniques fail to diagnose such disease due to their restriction a thus induce us to usage advance and more accurate deep learning model, particularly convolution Neural Networks (CNNs), showed considerable promise in the categorization of photographs and were then taken to scale [11].

In this paper, we show different CAD systems that have been developed in recent years for their use in classification and detection. Our main goal is to exclude the critical points of various modern common CNN architectures in tabular format and make a comparative study of all CNNs on various criteria. We also show recently developed models used in lung disease detection and classification and point out some essential key points that aid researchers in lung nodule detection and classification tasks. The rest of the paper is organized as: Section 2 explain Convolutional Neural Networks (CNNs) Architecture and techniques used in related work, Section 3 focuses on related work. Finally, Section 4 depicts the conclusions.

2. Convolutional Neural Networks (CNNs) Architecture

CNN's became common because of its improved image recognition efficiency. Layers of convolutions in the network and filters automatically detect the important spatial and temporal features in an image. The layers have shared the intra-network weights for better performance and efficiency, reducing computation efforts [12]. The intermediate representations are used in CNN's learning process, the same as the hierarchical learning in biological brains. The success of CNN in most image processing applications due to this unique ability. The shape of input image is (number of images) * (image height) * (image width) * (image depth). The image becomes abstracted to a feature map after passing through the convolutional layer, with shape (number of images) * (feature map height) * (feature map weights) * (feature map channels) [1]. The CNN models are used to train and validate every input image of the dataset that cross layers with kernel-based filters, pools, fully connected layers and then use softmax to classify an object between probabilistic values between 0 and 1.

2.1 Layer Description

A Deep Learning method has been used to diagnose whether or not a chest X-ray image has Pneumonia or not. A Deep Learning method has been used to diagnose whether or not a chest X-ray image has Pneumonia or not. The Convolutional Neural Network is therefore made up of numerous two-dimensional layers.

(a) Convolutional Layer

The convolution layer is the central part of a revolutionary neural network that uses convolution rather than the general matrix. Its parameters include a range of learning filters known as kernels. The convolutional layer's primary function is to discover features common in the data set within the local areas of the input image and map their presence to a feature map. The convolution operation as shown in the equation below:

$$F(i,j) = (I * K)_{(i,j)} = \sum_m \sum_n I(i+m, j+n)K(m,n) \quad (1)$$

I is the input image, K is the kernel filter, and F represents the output feature.

In every convolutional layer, the output is fed to an activation function to introduce non-linearity. Many activation functions are available, but the recognized function for deep learning is the Corrected Linear Unit (ReLU). ReLU calculates activation by thresholding the input at zero. In other words, ReLU yields 0 if the input is less than 0, and the output is raw otherwise.

(b) Subsampling (Pooling) Layer

In CNN, the series of convolution layers is followed by a downsampling (pooling) layer to reduce the input feature and reduce the number of parameters in the network. A pooling layer takes each feature map output from the convolutional layer and downsamples it.

(c) Fully connection layer

The output from the feature extractor is converted into 1D feature vectors for classifiers. This process is known as flattening. The convolution operation output is flattened to generate a single long feature vector for the dense layer to be utilized in the final classification process [13]. Every neuron in the previous layer is connected to the next layer's neurons in a completely connected layer. Each value helps to predict how good the value of a given class matches. The last completely connected output layer will then be routed to the activation feature that generates the class scores. The two critical classifiers on CNN are Softmax and Support Vector Machines (SVM). Softmax function, which calculates the distribution of the probabilities of n output classes in equation 2:

$$Z^k = \frac{e^{x^k}}{\sum_{i=1}^{n} e^{x^n}} \qquad (2)$$

Where x is the input, and Z is the output vector. The summation of all Z equal to 1.

All of the above layers are used to create a complete CNN architecture, as seen in Figure 2. Over and above these, CNN can have optional layers such as the batch standardization layer to increase training time and the drop-out layer for treating overfitting issues.

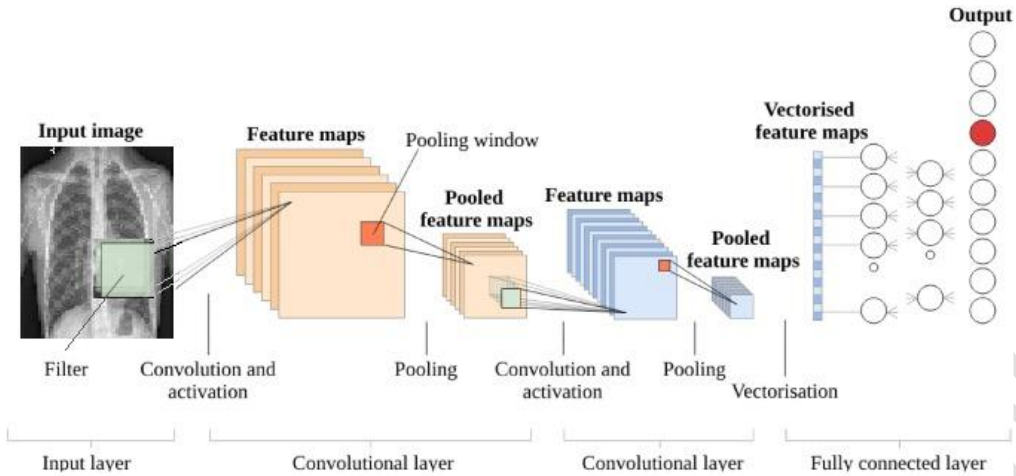

Fig. 2 Building blocks of CNN architecture

2.2 Deep Transfer Learning

Deep learning models require a large amount of data to perform feature extraction and classification accuracy. Concerning the analysis of medical data, especially if the disease is at an early stage, such as in Pneumonia, data limitation has been analyzed. CNN's typically outguess in a larger dataset than a smaller one [9]. In CNN implementations where the data collection is not significant, transfer learning may be helpful. The transfer learning principle is seen in figure 3, where models trained on large data sets such as ImageNet can be used for comparatively fewer dataset applications.

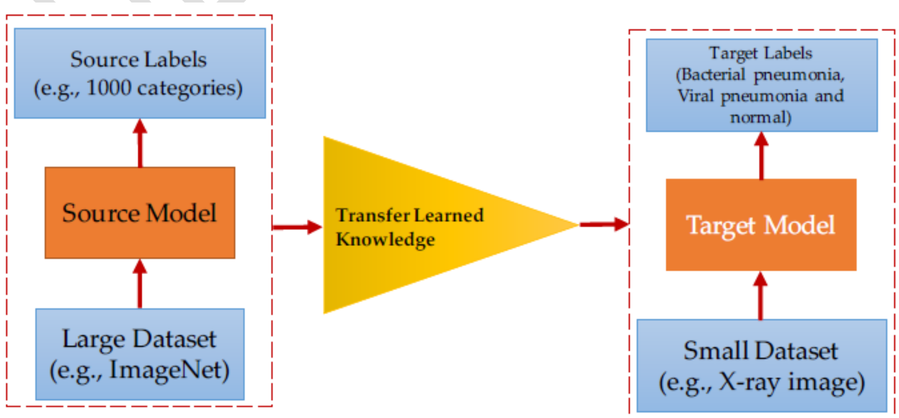

Fig. 3 diagram of Transfer Learning

Transfer learning has been successfully used for different fields in engineering applications. Therefore, removing the requirement for a long training period and having a large dataset should be available when developed from scratch in the deep learning algorithm [14]. Many popular CNNs deep learning pre-trained like AlexNet, VGG-16, Inception-v1, Inception-v3, ResNet-50, Inception-ResNet-V2 and ResNeXt-50 were used for pneumonia detection.

2.3 Data Augmentation

Data augmentation is a method widely used for deep learning that increases the number of samples available. Due to the lack of more usable samples, there has typically increased data using various pre-processing methods, leveraging Keras ImageDataGenerator during preparation. There are two ways to increase data; the first is known as offline augmentation. This approach is preferred with comparatively smaller datasets since the data collection would eventually be expanded by a factor proportional to the number of transformations you perform. The second choice is known as online augmentation or augmentation on the fly. This approach is favored with larger datasets as explosive growth in scale cannot be allowed. Instead, you will convert the mini-batches you would feed on your model. Some machine learning systems have improved online support, speeding up on the GPU [15]. These adjustments include random image rotation (maximum rotary angle 30 degrees), horizontal flips, shear, zooming, cropping, and minor random disruption to the noise. The increase in data increases generalization and improves the model's learning capacity. In addition, it is another successful way of preventing model overfitting by increasing the number of training data only in training. In contrast, color augmentation or color jittering often used to increase a data deals with improvements to the color characteristics of a pixel image [16].

- **Brightness** Increasing the brightness of the background is one way to improve it. The resulting picture is darker or lighter than the source.
- **Contrast** is defined as the degree to which the darkest and brightest areas of an image are differentiated. The picture contrast can also be modified.
- **Saturation** is the color differentiation of an image.
- **Hue** can be defined as the color shade in a picture.

2.4 Performance Metrics of Classification

Deep learning models' performance was evaluated to determine the results of diagnosed pneumonia diseases in X-ray images by using different classification metrics such as accuracy, precision, sensitivity, specificity, and f1-score [6].

- Accuracy: This metric is the most important for evaluating the deep learning classification.

$$Accuracy = \frac{Number\ of\ correct\ classified\ images}{Number\ of\ entire\ images} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (3)$$

- Precision: It is a metric of accuracy, calculated by dividing positive prediction identified as true positivity by the number of predictive positivity.

$$Precision = \frac{sum\ of\ all\ ture\ \ positive}{sum\ of\ all\ ture\ \ positive\ and\ false\ negative} = \frac{TP}{(TP+FP)} \quad (4)$$

- Sensitivity (Recall): Perfection is measured, calculated dividing positive prediction identified as true positivity by the number of actual positives.

$$Sensitivity\ (Recall) = \frac{TP}{(TP+FN)} \quad (5)$$

- Specificity: calculated by dividing true negatives by the total number of negatives in the data.

$$Sensitivity\ (Recall) = \frac{TN}{(TN+FP)} \quad (6)$$

- F1-score: a combination of recall and precision of the model gives a better measure of the incorrectly classified cases.

$$F1 - score = \frac{2\,(precision \times sensitivity\,)}{(precision + sensitivity\,)} \qquad (7)$$

TP is the proportion of true positive, FP is the proportion of negative or false positive, TN is the proportion of true Negative, FN is the proportion of positive or false negative. It was used to identify the number of pneumonia images identified as Pneumonia, the number of regular pictures identified as normal Pneumonia, the number of normal pictures wrongly identified, and the number of falsely identified pneumonia pictures as normal.

3. Literature Review

Stephen et al. [13] proposed a convolutional neural network model for training from scratch to classify and detect the presence of Pneumonia using chest X-ray image samples. Also, augmentation has been used to increase the size of the dataset and quality artificially. The proposed model consists of four convolution layer for feature extraction, composed conv 3 x 3,32; conv3 x 3,64; Conv 3 x 3,128; Conv 3 x 3,128. The validation accuracy has been obtained is 93.73%. Apostolopoulos et al. [17] evaluated the performance of five well-known pre-trained architectures (VGG19, MobileNet v2, Inception, Xception, and Inception ResNet v2) using two datasets. Firstly, a collection of 1427 X-ray images (Covid-19 disease 224 images, 700 images with bacterial Pneumonia, and 504 images of normal). Second dataset collection 1,442 X-ray images (224 images with Covid-19 disease, bacterial and viral Pneumonia 714 images, and 504 images of normal conditions). The better classification accuracy has been obtained for two classes 98.75% and three classes 93.48% using VGG16 architecture. Better classification accuracy has been obtained for two classes 96.78% and three classes 94.72% using MobileNet v2 architecture.

Four different pre-trained CNN architectures (AlexNet, ResNet18, DenseNet201, and SqueezeNet) using for transfer learning. A total dataset has been collected of chest x-ray images 5247 consisting of normal, bacterial, and viral chest x-rays. Three scenarios of classification pneumonia disease investigated: normal vs Pneumonia, bacterial vs viral Pneumonia, and normal vs bacterial Pneumonia vs viral Pneumonia. The better classification accuracy has been obtained for three scenarios are (normal vs Pneumonia 98%), (bacterial vs viral Pneumonia 95%), and (normal vs bacterial Pneumonia vs viral Pneumonia 93.3%) using ResNet201 architecture. Besides, Rahman et al. [2] used three augmentation strategies to generate new training sets (Rotation, Scaling, and Translation). Loey et al. [18] presented three in-depth transfer scenarios for pneumonia disease detection (normal, COVID-19, and bacterial and virus pneumonia) and utilized three deep transfer models: Alexnet and Googlenet, and Restnet18. Generative Adversarial Network (GAN) is an effective method for generating X-ray images that are used to overcome the small dataset in the training model. In the first scenario, the four dataset classes are based on Googlenet as the primary machine transfer model. The second scenario involved three classes, which have chosen Alexnet as the base model for Deep Transfer. While the third scenario consists of two classes (normal and COVID-19), Googlenet has chosen the base architecture. The accuracy has been obtained for four, three, and two scenarios were 80.6%, 85.2%, and 100%, respectively.

El Asnaoui et al. [19] comparing a dataset of three class of chest x-ray and CT images, which included normal, bacterial Pneumonia, and Covid19 using recent deep learning models (VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, Resnet50, and MobileNet_V2) for detection and classification of coronavirus pneumonia. Results found that inception_Resnet_V2 and Densnet201 provide better accuracy than other architecture used in work (Inception-ResNetV2 with 92.18% accuracy and 88.09% accuracy for Densnet201). Rahimzadeh et al. [20] presented training techniques that better help the learning network when the dataset is imbalanced. A neural network is produced through the Xception and ResNet50V2 networks' concatenation for the classification chest X-ray into three normal, COVID-19, and Pneumonia classes. The proposed architecture achieved better accuracy by using multiple features extracted by two robust networks. The overall average accuracy of the proposed model for detecting pneumonia cases 91.4%. Shibly et al. [21] introduced versions of CNN VGG16 and combine with Faster Regions with Convolutional Neural Networks (Faster R–CNN) framework to diagnose pneumonia diseases from chest X-Ray images. The model achieved more effectiveness using ten folds cross-validation method. The proposed model provides a classification accuracy of 97.36%.

Ahuja et al. [22] proposed the model used three phase detection to improve the accuracy. In the first phase using stationary wavelet as data augmentation techniques, decomposing image to three levels. To increase the dataset size, another operation such as random rotation, translation, and shear operations are applied. In the second phase, the pre-trained model was utilized to classify the CT scan image into binary classes. Therefore, those four different transfer learning models (ResNets-18, -50, -101, and Squeezenet) were used for the binary classification. In the last phase, abnormality localization in CT scan images is extracted from the network's deeper layer. The highest classification accuracy is achieved with the ResNet18 99.4%. Several new approaches have been proposed and investigated by Heidari et al. [11] to improve a deep transfer learning CNN model to diagnose and classify pneumonia cases using chest X-ray images. The results showed that the presented model generating better input image data by preprocessing operation includes removing unrelated regions (diaphragm regions), normalizing image contrast using a histogram equalization algorithm. In addition, using a bilateral low-pass filter to remove noise, then the original image and two filtered images are used to generate pseudo color images to feed into transfer learning CNN models to classify pneumonia disease. The transfer learning approach is applied VGG16 model which shown higher performance with the overall accuracy of 94.5 %.

The authors of [3]. Investigated the effectiveness of multiple pre-trained CNNs using a chest x-ray to diagnose COVID-19 disease automatically. The approach utilized a combination of features extracted from 5 pre-trained CNNs: Squeezenet, Darknet-53, MobilenetV2, Xception, and Shufflenet Correlation-based Feature Selection (CFS) technique and Bayesnet classifier for the prediction of disease case. The method was used two public datasets and achieved promising results on both datasets. In the first dataset, the method achieved an AUC of 0.963 and an accuracy of 91.16%, including 453 COVID-19 images and 497 non-COVID images. Simultaneously, the second dataset achieved an AUC of 0.911 and an accuracy of 97.44%, including 71 COVID-19 images and seven non-COVID images. Table 1 shows an overview of current methods based on different parameters used for lung disease diagnosis.

Table 1: Comparative study of related work

#	Authors	Type of image	Methodology	Number of classes	Evaluation (Accuracy %)
1	Stephen et al. [13]	X-ray image	Four convolution layer (conv 3x3,32; conv 3x3,64; conv 3x3,128; conv 3x3,128)	Binary Classes	93.73

2	Apostolopoulos et al [17]	X-ray image	Dataset 1 VGG16	Binary Classes	98.75
				Three classes	93.48
			Dataset 2 MobilNet v2	Binary Classes	96.78
				Three classes	94.72
#	Authors	Type of image	Methodology	Number of classes	Evaluation (Accuracy %)
3	Rahman et al [2]	X-ray image	Transfer learning (ResNet201	(normal vs pneumonia)	98
				(bacterial vs viral pneumonia)	95
				(normal vs bacterial pneumonia vs viral pneumonia)	93.3
4	Loey et al. [18]	X-ray image	Transfer learning GoogleNet and Generative Adversarial Network (GAN)	Four Classes	80.6
				Binary Classes	100
5	El Asnaoui et al. [19]	X-ray and CT scan image	Transfer learning Inception-ResNetV2	Three Classes	92.18
6	Rahimzadeh et al. [20]	X-ray image	concatenation of the Xception and ResNet50V2 networks	Three Classes	91.4
7	Shibly et al. [21]	X-ray image	VGG16 and (Faster R–CNN)	Binary Classes	97.36
8	Ahuja et al. [22]	CT scan image	Wavelet, transfer learning, and ResNet18	Binary Classes	99.4

9	Heidari et al. [11]	X-ray image	Histogram Equalization, Bilateral filter, and transfer learning VGG16	Three Classes	94.5
10	Abraham et al. [3]	X-ray image	Multi-CNN with Correlation-based Feature Selection (CFS) technique and Bayesnet classifier	Binary Classes	97.44

4. Conclusion

Medical statistics showed the rate of mortality depends on the early and accurate detection of pneumonia diseases. An appropriate treatment plan with timely intervention through a correct diagnosis of the disease can save many people's lives. Due to a large number of injured and the insufficient ability to diagnose critical cases, there is an urgent need for computer-aided-diagnosis (CAD). This paper summarizes the CAD systems recently used in deep learning to extract features and detect and classify chronic diseases. A comprehensive study of the latest models based-CNN is used to detect and classify chest CT and X-rays images. In the article, many models were presented that used distinct techniques in pre-processing the images that feed the convolutional neural networks to ensure better quality and accuracy in detection and classification processes. Moreover, previously mentioned, these algorithms require a large dataset to overcome the underfit and overfit problem. Augmentation is the most popular operation used to increase the dataset's size to ensure the performance of convolutional neural networks. Recent studies on the detection and classification of pneumonia diseases have shown that a CNN-based system is a best and more Purposeful approach to significantly improve early diagnosis and treatment of disease. However, work is still going on in a lot of research to improve the CNN model better and more accurately, and the current methods have some shortcomings that can be overcome through more studies. The detailed knowledge and advantages of these networks will significantly help detect pulmonary diseases that serve the radiologist to diagnose chronic pulmonary diseases and help in medical imaging.

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