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Diagnosis of Pneumonia from Chest X-Ray Images using Transfer Learning and Generative Adversarial Network

Shekofeh Yaraghi[1]; Farhad Khosravi[2]
[1]Department of Computer Engineering, Faculty of Engineering and Technology, Shahid Ashrafi Esfahani University, Isfahan, Iran
[2]Department of Electrical Engineering, Faculty of Engineering and Technology, Shahid Ashrafi Esfahani University, Isfahan, Iran

Abstract:- Pneumonia is a life threatening disease, which occurs in the lungs caused by either bacterial or viral infection. A person suffering from pneumonia has some symptoms including cough, fever and chills, dyspnea, and low energy and appetite. The symptoms will worsen and it can be life endangering if not acted upon in the right time. Pneumonia can be diagnosed using various methods and devices, such as blood tests, sputum culture , and various types of imaging, but the most common diagnostic method is chest X-ray imaging. According to the progress achieved in the diagnosis of pneumonia, there are some problems such as the low accuracy of the diagnosis. Hence the purpose of this article is to diagnose pneumonia from chest x-ray images using transfer learning and Generative Adversarial Network (GAN) with high accuracy in two groups of normal and Pneumonia and then diagnose the type of disease in three groups: normal, viral pneumonia and bacterial pneumonia. The dataset of the article contains 5856 chest X-ray images, including normal images, viral pneumonia and bacterial pneumonia. Adversarial generator network was used in order to increase the data volume and accuracy of diagnosis. Two different pre-trained deep Convolutional Neural Network (CNN) including DenseNet121 and MobileNet, were used for deep transfer learning. The result obtained in dividing into two classes, normal and pneumonia, using DenseNet121 and MobileNet, reached an accuracy of 0.99, which is improved compared to the previous method. Therefore, the results of proposed study can be useful in faster diagnosing pneumonia by the radiologist and can help in the fast screening of the pneumonia patients.

Keywords:- *Pneumonia, Chest X-ray Images, Generative Adversarial Network, Deep Transfer Learning.*

I. INTRODUCTION

Pneumonia is a lung disease that kills millions of people worldwide every year. Lung diseases are one of the most common medical problems in the world. This disease is a respiratory infection caused by bacteria, viruses and fungi in the respiratory alveoli (air sac). The symptoms of this disease can vary from mild to very severe and cause respiratory problems and even lead to death [1, 2]. The highest rate of pneumonia is in underdeveloped or developing countries that have a high level of pollution, overcrowding and unsanitary living conditions [3]. This disease can affect all age groups, but most cases of pneumonia are seen in children under five years old and the elderly. Patients often have symptoms include fever and chills, cough with sputum, breathing problems, chest pain, low energy and appetite [4]. There are several ways to diagnose pneumonia, including a medical examination, blood tests, sputum culture test, and chest X-rays. However, the diagnosis of lung diseases has often been a challenge due to limited medical facilities and expertise [5]. Considering the risk of widespread infection of people with pneumonia and the limited facilities for timely diagnosis and treatment of the disease, the use of Artificial Intelligence (AI) is of a great importance. The World Health Organization (WHO) estimates that more than four million premature deaths occur each year due to lung diseases such as pneumonia.

In underdeveloped and developing countries, the problem multiplies due to lack of medical facilities and resources. For these people, accurate and timely diagnosis is the most important issue. With timely diagnosis, the treatment process can be improved [6]. In this way, Deep Transfer Learning (DTL) [7, 8, 9] and Convolutional Neural Network (CNN) [10] are used to analyse chest X-ray images and diagnose pneumonia. By using a computer and artificial intelligence, it will be possible to diagnose the disease in the shortest amount of time even in areas with a lack of facilities and limited access to experts who can diagnose the disease from X-ray images. In this paper, a new architecture based on Convolutional Neural Network (CNN) and pre-trained transfer learning networks [11] is proposed, which automatically examines chest X-ray images and diagnoses pneumonia. This will lead to the reduction of costs and deaths rate all around the world, especially in deprived areas. The proposed study uses Generative Adversarial Network (GAN) to increase data volume and it also applies two different pre-trained networks including DenseNet121 and MobileNet in order to evaluates their performance. The most important feature of this paper is to present a transfer learning approach based on Convolutional Neural Network using different pre-trained models to diagnose pneumonia with high accuracy. In addition, the paper also provides methodological details that can be used by any research group to benefit from this work. Medical diagnoses are usually time-consuming and error-prone. The aim of this

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study is to use the power of machine learning to help diagnose pneumonia by analysing chest x-ray images.

II. RESEARCH BACKGROUND

In recent years, various methods have been used to diagnose pneumonia using chest x-ray images. According to Table 1, previous studies have tried to detect the presence or absence of pneumonia by using Artificial Intelligence techniques, including machine learning and deep learning, and especially Convolutional Neural Network.

- Uzair Shah et al. (2020) used a Convolution Neural Network based on the VGG16 architecture consisting of 16 fully connected convolution layers. The dataset used in this method includes 5856 chest X-ray images that were used for training, validation and testing of the model and achieved an accuracy of 96.6% [14].
- Pranav Rajpurkar et al. (2017) used the DenseNet-121 Convolutional Neural Network model to classify pneumonia. The dataset used in this model included 30805 images. The result of this method obtained only 76.8% f1 score for classification [15].
- Rohit Kundu et al. (2021) used the Deep Transfer Learning method to compensate for the lack of available data. GoogLeNet, ResNet-18, and DenseNet-121 are three Convolutional Neural Network models that have been used. In this method, two datasets named Kermany and RSNA were used and 98.81% accuracy was achieved [16].
- Dejun Zhang et al. (2021) used Convolutional Neural Network and VGG architecture with few layers and histogram enhancement technique for image pre-processing and achieved 96.06% accuracy. The used dataset was classified into two parts with pneumonia and normal using the above network [17].
- Kuang Ming Kuo et al. (2019) used 11 features to diagnose pneumonia in 185 schizophrenic patients. They applied these features to a large number of regression and classification models, such as decision trees, Support Vector Machines (SVM), and logistic regression, then they compared the results of the models. The accuracy of 94.5% is the highest accuracy obtained from decision tree classification. Other models obtained significantly less accuracy than the decision tree [18].
- Turker Tuncer et al. (2021) used a machine learning-based method in which they applied a new fuzzy tree classification to detect Covid-19 on images. They evaluated the method on a small dataset consisting of both Covid-19 and pneumonia samples and achieved an accuracy rate of 97.01% [19].
- Yue et al. (2021) used CT radiomic models based on logistic regression and random forest for the diagnosis of pneumonia in chest CT scan images of 52 patients with SARS-CoV-2 infection. The best AUC value they obtained was 97%. However, these methods are not generalizable because they were evaluated on small data sets [20]

III. REVIEW METHOD

In the data classification process, Convolutional Neural Networks (CNN) work better with large data sets. However, the available data sets are usually not large. The most common way for training deep learning algorithms to transform a smaller data set into a large data set is to use data augmentation techniques. The obtained results show that data augmentation can improve the classification accuracy of deep learning algorithms. So instead of trying to collect new data, new data can be generated with the help of available data. There are many methods for this, however, in this research, Generative Adversarial Network (GAN) is used to increase the data volume. [12]

In this article, chest x-ray images dataset was used for network training and testing. The number of images in different dataset categories is listed in Table 2.

In accordance with all ethical concerns, the dataset of chest X-ray images, whose information is freely accessible on https://kaggle.com/, was used in this study [13].

Two deep transfer learning algorithms based on convolutional neural network were employed in order to diagnose disease in two groups: normal and pneumonia. These two networks—MobileNet and DenseNet121—helped improve the method's accuracy and achieve better results.

As shown in Figure 1, in this method, the Generative Adversarial Network
(GAN) was applied to increase the data volume, and then the image features were extracted using two pre-trained deep transfer learning networks. Using pre-trained networks reduces the volume of calculations and saves time. Using transfer learning, the features were extracted from the images and the disease was categorised in two classes, normal and pneumonia.

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Table 1 Comparison of Different Methods used to Diagnose Pneumonia from Chest X-Ray Images

Row	Author	Class	Method	Database	Results
1	Uzair Shah et al [14].	Normal, Pneumonia	Convolution neural network based on VGG16 architecture	Paul Mooney	96.6 %ACC:
2	Pranav Rajpurkar et al [15].	Normal, Pneumonia	Convolution neural network based on DenseNet-121	Wang et al.	95 % F1:
3	Rohit Kundu et al [16].	Normal, Pneumonia	Deep transfer learning based on three models GoogLeNet, ResNet-18, DenseNet-1	Kermany ﻭRSNA	98.81 % ACC:
4	Dejun Zhang et al [17].	Normal, Pneumonia	Convolution neural network based on VGG architecture	Baltruschat et al.	96.06 %ACC:
5	Kuang Ming Kuo et al [18].	Normal, Pneumonia	Regression and classification models	Manually collected data	94.5% ACC:
6	Turker Tunser et al [19].	Normal, Pneumonia and Covid-19	Machine learning based on new fuz zy tree classification	Robnik-Šikonja M. et al.	97.01% ACC:
7	Yue et al [20].	Normal, Pneumonia and Covid-19	Logistic Regression (LR) and Random Forest (RF)	Manually collected data	97% AUC:

Table 2 The Number of Images in Three Classes of Dataset

Type	Number of training images	Number of test images
Normal	1341	234
Viral pneumonia	1345	148
Bacterial pneumonia	2530	242
Total images of pneumonia	3875	390

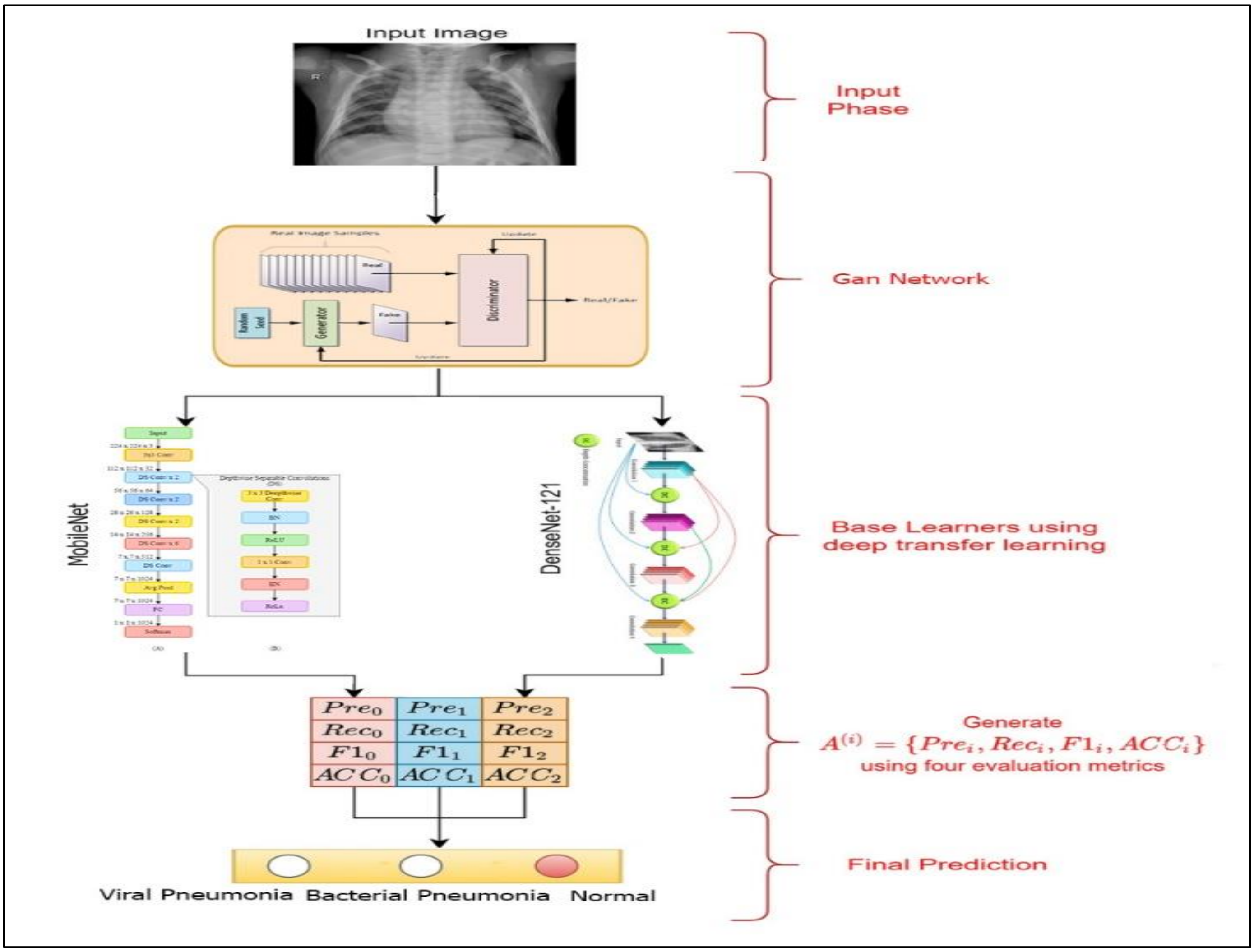

Fig 1 Diagram of the Proposed Solution in Two Classes of Normal and Pneumonia

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IV. EVALUATION AND RESULTS

To evaluate the proposed method on chest x-ray images data set four standard evaluation criteria were used including accuracy, precision, recall and f (F-score) similar to Uzair SHAH et al.'s method in 2020 [14], which is one of the basic studies in this research. In order to define these evaluation criteria, first the terms "True Positive" (TP), "False Positive" (FP), "True Negative" (TN) and "False Negative" (FN) have been defined:

- A true positive (TP) refers to a sample that belongs to the positive class and is correctly classified by a model.
- False positive (FP) refers to a sample that belongs to the negative class and is wrongly classified as belonging to the positive class.
- True negative (TN) refers to a sample that belongs to the negative class and is correctly classified by the model.
- False negative (FN) refers to a sample that belongs to the positive class and is wrongly classified as belonging to the negative class.

Now, the four evaluation criteria can be defined as:

$$Acc = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{1}$$

$$Pre = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

$$Rec = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

$$F1 = \frac{2}{\frac{1}{Precision}+\frac{1}{Recall}} \tag{4}$$

The results obtained from the classification of chest X-ray images using MobileNet and DenseNet121 networks in two classes of normal and pneumonia are shown in table 3. The hyper parameters used include batch-size=32 and epoch=25. In this section, the research results with and without using the Generative Adversarial Network (GAN) are compared.

Table 3 Results Obtained by Two Pre-Trained Networks MobileNet and DenseNet121 in Two Classes of Normal and Pneumonia with and without using Generative Adversarial Network (GAN).

Network		**Class**	**Precision**	**recall**	**F1-Score**
Densenet121	Using artificial data generation	Normal	0.99	0.97	0.98
		bacterial pneumonia	0.99	1.00	0.99
	without using artificial data generation	Normal	0.86	0.99	0.92
		bacterial pneumonia	1.00	0.94	0.97
MobileNe	Using artificial data generation	Normal	0.99	0.99	0.99
		bacterial pneumonia	1.00	0.99	1.00
	without using artificial data generation	Normal	0.92	0.99	0.96
		bacterial pneumonia	1.00	0.97	0.98

Generative Adversarial Network (GAN) was used to generate artificial data in this paper. In machine learning, artificial data generation is often used to compensate for the insufficient and limited number of training data. Artificial data generation increases the accuracy of training models. The results show that the use of Generative Adversarial Network (GAN) significantly increased the accuracy of both pre-trained networks.

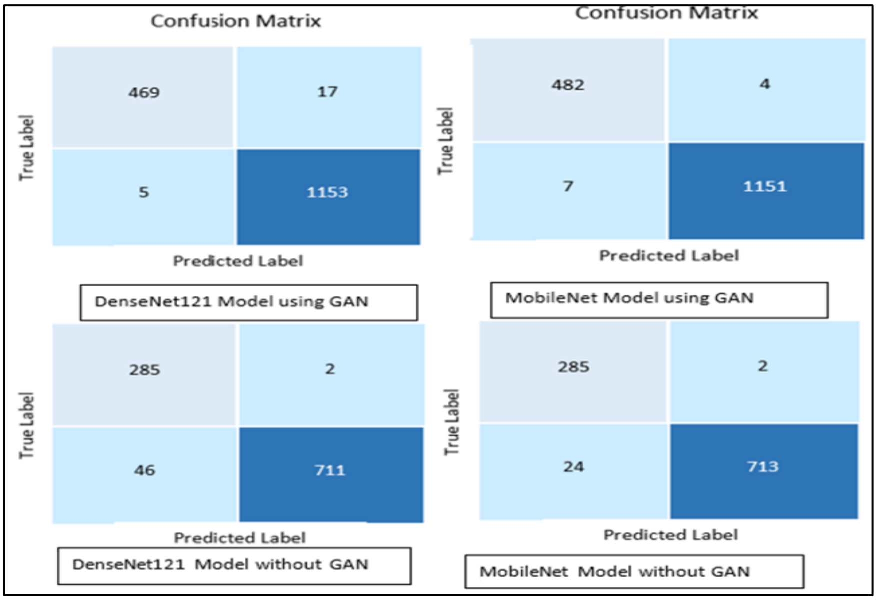

Fig 2 Comparison of Confusion Matrix for DenseNet121 and MobileNet Models with and without using Generative Adversarial Network (GAN) and in Normal and Pneumonia Classes.

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➢ *Comparing the Proposed Method with the Previous Method*

Due to the similarity of the dataset in this article with the dataset of Uzair SHAH et al.'s method [14], the proposed method is compared with the method of Uzair SHAH et al in this section. The goal of this method is to increase the accuracy of disease diagnosis in the two classes of normal and pneumonia. According to Table 4, an accuracy of 0.99 was achieved utilizing two networks, Densenet121 and MobileNet, which increased the accuracy compered to the Uzair SHAH et al.'s method.

Table 4 Comparison of the Results Obtained with the Method of Uzair SHAH et al

Research	**accuracy**	Class
Densenet121	0.99	Normal and pneumonia
MobileNet	0.99	Normal and pneumonia
Uzair SHAH et al.[14]	0.96	Normal and pneumonia

After evaluating the results in the two classes of normal and pneumonia, comparing it with the previous method of Uzair SHAH et al., and achieving better results, a step further was taken and the disease was diagnosed and evaluated in the three classes of normal, viral pneumonia, and bacterial pneumonia. In order to do so, two pre-trained networks DenseNet121 and MobileNet were employed. The hyper parameters used in these two networks include categorical_crossentropy, in which batch-size=32 and epoch=25 due to the multi-class method. For the three classes of normal, viral pneumonia, and bacterial pneumonia in this section, two methods with and without using Generative Adversarial Network (GAN) are shown in Table 5 in order to evaluate the results.

Table 5 Results Obtained by Two Pre-Trained Networks MobileNet and DenseNet121 in Three Classes of Normal, Viral Pneumonia and Bacterial Pneumonia with and without using Generative Adversarial Network (GAN)

Network		Class	Precision	Recall	F1-Score
Densenet121	Using artificial data generation	Normal	0.96	0.98	0.97
		Viral pneumonia	0.91	0.83	0.86
		Bacterial pneumonia	0.76	0.85	0.80
	Without using artificial data generation	Normal	0.97	0.96	0.96
		Viral pneumonia	0.76	0.79	0.77
		Bacterial pneumonia	0.62	0.60	0.61
MobileNet	Using artificial data generation	Normal	0.98	0.99	0.98
		Viral pneumonia	0.92	0.87	0.89
		Bacterial pneumonia	0.81	0.87	0.84
	Without using artificial data generation	Normal	0.98	0.97	0.98
		Viral pneumonia	0.75	0.92	0.83
		Bacterial pneumonia	0.79	0.52	0.62

Figure 3 shows a graphical representation of the classification performance of the DenseNet121 and MobileNet models with and without using artificial data generation. Confusion matrix indicates three classes of normal, viral pneumonia, and bacterial pneumonia, and in each class, the number of images that are correctly or incorrectly classified is displayed. In the figure 3, the accuracy of the model for classification of three classes of pneumonia is shown.

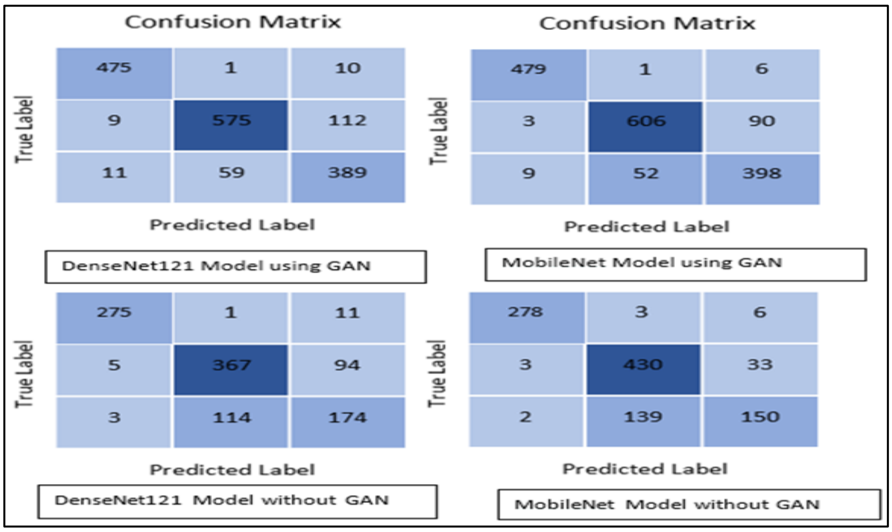

Fig 3 Comparison of Confusion Matrix for DenseNet121 and MobileNet Models with and without using Generative Adversarial Network (GAN) in Three Classes of Normal, Viral Pneumonia and Bacterial Pneumonia.

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V. DISCUSSION

As mentioned, millions of people die of pneumonia every year. A considerable number of people's lives can be saved by early diagnosis and effective treatment. Computer-aided diagnosis has the potential to save lives, especially in third-world countries where there are many patients due to the limitations of both life and medicine there.

For the automatic diagnosis of pneumonia, a deep trans fer learning method based on convolutional neural networks was presented in this research to different deep learning models based on convolutional neural system were trained and tested to classify patients using chest X-ray images. More accuracy was attained in the two-class method than in the previous method, and significant results were obtained when the data was divided into three classes. It was also found that both the DenseNet121 and MobileNet models were capable of performing effectively.

The findings of the study indicate that this network can considerably help radiologists in making faster and more accurate diagnosis of patients, as well as in providing faster treatment. By using this method and correctly diagnosing the disease many lives can be saved. The two networks employed in this method improved their performance by training themselves with more data, increasing accuracy, and boosting efficiency so that clinicians could use this system to produce more beneficial results.

VI. CONCLUSION AND FUTURE WORK

As mentioned, in recent years, many efforts have been made to diagnose pneumonia, but today the goal is to increase diagnosis speed and accuracy to the highest levels and these efforts have greatly helped patients and medical experts in accurately diagnosing the disease. Due to the fact that lung diseases make breathing difficult, it is it is crucial to focus on the rapid diagnosis and treatment of the disease using new approaches of data analysis in the field of artificial intelligence. It will be possible in the future to compare the accuracy of several pre-trained networks to the methods described in this article, as well as to see if any of them perform more effectively. In order to diagnose other lung and respiratory conditions, this model will be expanded. Additionally, it is intended to extend this model to diagnose other lung and respiratory diseases.

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