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CHEST X-RAY CLASSIFICATION BASED ON MACHINE LEARNING

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ABSTRACT

Chest X-ray images can be used to detect lung diseases such as COVID-19, viral pneumonia, and tuberculosis (TB). These diseases have similar patterns and diagnoses, making it difficult for clinicians and radiologists to differentiate between them. This paper uses convolutional neural networks (CNNs) to diagnose lung disease using chest X-ray images obtained from online sources.

We develop an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists. Our algorithm, CheXNet, is a 121-layer convolutional neural network trained on ChestX-ray14, currently the largest publicly available chest Xray dataset, containing over 100,000 frontalview X-ray images with 14 diseases. Four practicing academic radiologists annotate a test set, on which we compare the performance of CheXNet to that of radiologists. We find that CheXNet exceeds average radiologist performance on the F1 metric. We extend CheXNet to detect all 14 diseases in ChestX-ray14 and achieve state of the art results on all 14 diseases.

Pneumonia is the leading cause of death worldwide for children under 5 years of age. For pneumonia diagnosis, chest X-rays are examined by trained radiologists. However, this process is tedious and time-consuming. Biomedical image diagnosis techniques show great potential in medical image examination. A model for the identification of pneumonia, trained on chest X-ray images, has been proposed in this paper. The compound scaled ResNet50, which is the upscaled version of ResNet50, has been used in this paper.

1. INTRODUCTION

More than 1 million adults are hospitalized with pneumonia and around 50,000 die from the disease every year in the US alone (CDC, 2017). Chest X-rays are currently the best available method for diagnosing pneumonia (WHO, 2001), playing a crucial role in clinical care (Franquet, 2001) and epidemiological studies (Cherian et al., 2005). However, detecting pneumonia in chest X-rays is a challenging task that relies on the availability of expert radiologists. In this work, we present a model that can automatically detect pneumonia from chest X-rays at a level exceeding practicing radiologists.

Chest X-rays may be divided into three principal types, according to the position and orientation of the patient relative to the X-ray source and detector panel: posteroanterior, anteroposterior, lateral. The posteroanterior (PA) and anteroposterior (AP) views are both considered as frontal, with the X-ray source positioned to the rear or front of the patient respectively. The AP image is typically acquired from patients in the supine position, while the patient is usually standing erect for the PA image acquisition. The lateral image is usually acquired in combination with a PA image, and projects the X-ray from one side of the patient to the other, typically from right to left.

It is a very common disease all across the globe. Due to poverty, people refrain from having access to trained radiologists. As far as diseases like pneumonia are concerned, the level of accuracy in the diagnosis should be good enough to assure proper treatment of this fatal disease [4]. Hence, to reduce the mortality of pneumonia, there is a need for research in the field of computer-aided diagnosis. There are many tests for pneumonia diagnosis, such as the chest ultrasound, chest MRI, chest X-ray, computed tomography of the lungs and needle biopsy of the lung [5]. X-rays are the most widely available diagnostics imaging technique.

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2. Literature survey

Several biomedical image detection techniques have already been proposed by different authors. Authors in [8] discussed the identification of pneumonia. Razaak et al. addressed the challenges of methods for medical imaging [9]. Many authors proposed various methods for the detection of numerous diseases [10]. For example, Andre in his paper presented a deep CNN-based on Inception v3 architecture for skin cancer classification [11], Milletari also worked on a method for detecting the prostrate, using CNN, in MRI volumes [12], Grewal used deep learning for detecting the brain haemorrhage in computed tomography scans [13], Varun worked on a method for the detection of diabetic retinopathy [14]. Lakhani proposed an algorithm based on conventional neural networks (CNNs) for the automated classification of pulmonary tuberculosis [15]. Bar also published a paper in which he used deep neural networks (DNNs) for chest pathology detection [16]. CNN is a much better advancement over DNN as it can very easily operate on 2-D and 3-D images and also extract the features responsible to classify the disease. This is possible in CNN because the max-pooling layer is very efficient and they are also attached to some weights. CNNs also deal with the grave situation of diminishing gradient as they involve gradient-based learning, while it is being trained

Pranav, et. al.., [3], explains about detecting pneumonia on the Radiologist Level using CheXnet. The algorithm used here is ChexNet, that is a 121- layer CNN. ChexNet was used as feature extractor and classifier. Chest X-ray14 dataset was used which consisted of 112,120 images. The model outputs the probability of pneumonia along with heatmap, showing the areas that strongly indicates the presence of pneumonia. Comparison has been made with the radiologists and this model on F1 score metric and found to achieve 0.43, higher than the radiologists average which is 0.38. The accuracy achieved by the model is 76.80. Xianghong Gu, et. al.., [4], explains about the classification of bacterial and viral pneumonia. The algorithm used here is AlexNet and SVM classifier. AlexNet, which is pre-trained on PASCOL VOC dataset is used for segmenting the lung regions. Then, the target images were trained using the AlexNet DCNN model. SVM is used as a classifier. However, there was no comparison made with the other algorithms. The model was evaluated using the metrics accuracy, specificity, sensitivity and precision. The accuracy achieved by the model is 80.48.

Table 1. CNN architectures

	AlexNet	GoogLeNet	Resnet-18	ShuffleNet	SqueezeNet
Input size	224x224x3	224x224x3	224x224x3	224x224x3	227x227x3
Activation function	ReLU	ReLU	ReLU	ReLU	ReLU
Convolution kernel	3x3, 5x5, 11x11	1x1, 3x3, 5x5, 7x7,	1x1, 3x3, 7x7,	1x1, 3x3	1x1, 3x3
No of learnable layers	8	22	18	50	18

3. Methodology

In this study, a total of 1100 chest X-ray images were randomly selected from three different open sources: the GitHub repository shared by Joseph Cohen,22 Kaggle,23 Bachir,24 and Mooney.25 The chest X-ray images in the datasets were obtained from patients and had been interpreted and reported by expert radiologists. The labels generated were then validated in an independent test set, achieving a micro-F1 score of 0.93.26.

It has been documented that the images are suitable for training supervised models concerning radiographs.26,27 The datasets contain chest X-ray images of confirmed pnemonia cases, other pneumonia, and no-findings (normal). There are plenty of normal and other pneumonia X-ray images in these open sources. However, owing to the lack of pnemonia X-ray images, we limited the

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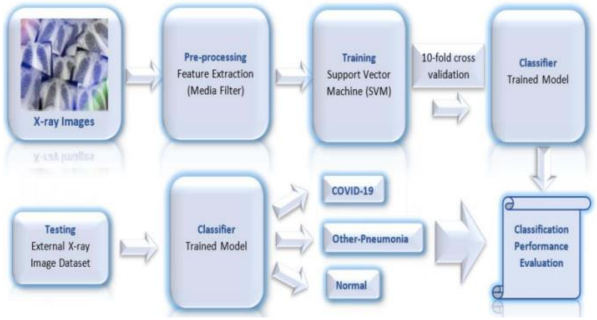
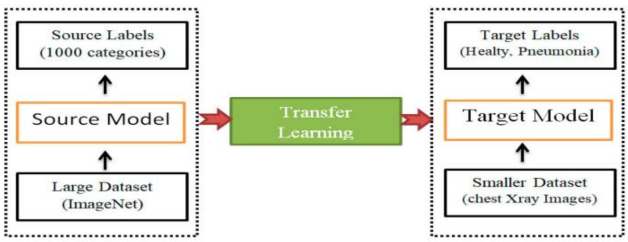
number of images for other pneumonia and no-findings to avoid problems with unbalanced data. Our experimental dataset contains 300 X-ray images of confirmed pnemonia patients, 400 images of other pneumonia patients, and 400 normal X-ray images.



Block diagram of the proposed model for distinguishing COVID-19 from other pneumonia and no-findings.

4. DATASET

Recognizing There were a total of 5836 images in the original dataset from the Guangzhou Women and Children's Medical Center [36]. It included the images of both healthy and pneumonia cases. There were 1583 healthy chest Xray images and 4273 pneumoni



images. The entire dataset was rearranged into training and test set with 700 images in the test set and 5136 images in the training set. Two sample images of the dataset have been shown in Figure 1.

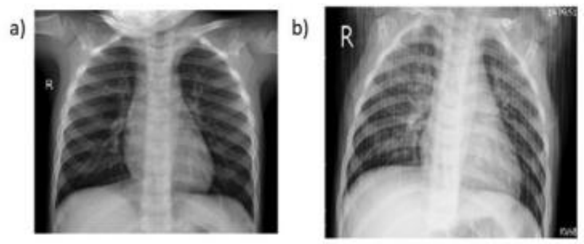
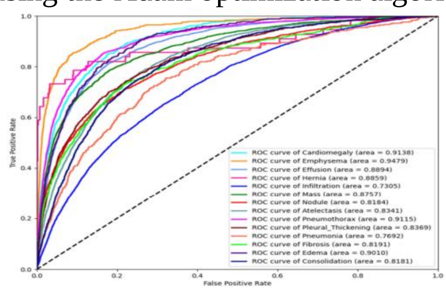


Fig :2 Chest X-ray of a healthy person (a) and a person suffering from pneumonia (b).

Before inputting the images into the network, we downscale the images to 224×224 and normalize based on the mean and standard deviation of images in the ImageNet training set. We also augment the training data with random horizontal flipping.

5. Results and Discussion

The details of the experiments, conducted to test the proposed architecture, are presented in this section. Keras open-source framework with TensorFlow as the backend has been used to implement the deep learning networks. Computation was done on a system having 16 GB RAM and NVIDIA Quadro 4000 graphic card with 2 GB GDDR5 GPU Memory and Intel i7, 7th generation processor .This experiment uses the pytorch framework to implement the AM_DenseNet network model and runs on a deep learning machine with a 32GB graphics card. The training parameters are as follows: the batch size is 8, the initial learning rate is 0.0001, the learning rate decays by 0.1 when the loss is stagnant, the epoch is 20, and the training stops when the training loss is no longer decreasing. The model is initialized with DenseNet-121 pre-trained on the ImageNet dataset and optimized using the Adam optimization algorithm.



CONCLUSION

In this paper, we proposed a multi-classification model AM_DenseNet combining attention mechanism for chest x-ray images and validated the model effectiveness using the large-scale public dataset Chest X-rays 14. Experimentally, the average AUC value of the AM_DenseNet model is 0.8537, which exceeds the performance of other experiments. In addition, an ablation experiment was performed to evaluate the value of the attention mechanism and the Focal Loss function in the model. Although the AM_DenseNet model cannot replace the radiologist's diagnosis for some reasons, it can provide a reference of great value to physicians. In future work, we will try to incorporate more information for computer-aided diagnosis to further improve the model results.

Pneumonia is a life-threatening infectious disease. For patients over 75 years, the mortality rate of pneumonia is 24.8% [38]. In this paper, an algorithm which can further support computer-aided diagnosis of pneumonia has been proposed. The deep residual network, proposed in the paper, has a more complex structure but fewer parameters and higher accuracy.

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Furthermore, this model was scaled up efficiently using the method of compound scaling. Data augmentation and transfer learning have also been used to tackle the obstacle of the insufficient training dataset. Different scores, such as recall, precision and accuracy, were computed to prove the robustness of the model. The proposed model attained an accuracy of 98.14%, a high AUC score of 99.71 and an F1 score of 98.3. The future works involve developing an algorithm which can localize the parts of the lung affected by pneumonia.

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