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# Deep Learning methodologies for diagnosis of respiratory disorders from chest X-ray images: A comparative study †

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**Abstract:** Chest radiography needs timely diseases diagnosis and reporting of potential findings in the images, as it is an important diagnostic imaging tests in medical practice. A crucial step in radiology workflow is fast, automated and reliable detection of diseases created on chest radiography. To overcome this issue, an artificial intelligence-based algorithm such as Deep learning (DL) are promising methods for automatic and fast diagnosis due to their excellent performance analysis of a wide range of medical images and visual information. This paper surveys the DL methods for lung disease detection from chest X ray images. The common five attributes surveyed in the articles are data augmentation, transfer learning, types of DL algorithms, types of lung diseases and features used for detection of abnormalities, data augmentation, transfer learning, and types of lung diseases. The presented methods may prove to be extremely useful for people to ideate their research contributions in this area.

**Keywords:** Chest X-ray; Computer Aided Diagnosis; Deep learning methodologies; Radiography; Respiratory Disorders.

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## 1. Introduction

On this planet Earth, the respiratory diseases are the main health threat to the mankind. Approximately, 450 million people i.e., almost 7% of the world's population are getting affected by pneumonia alone resulting in nearly 4 million deaths every year [1]. The diagnosis of these respiratory diseases is done through most common radiology methods such as chest X-ray (CXR) and chest radiography because they are easily accessible and low cost. Visual inspection of large quantity of chest radiographs is carried out slice by slice basis globally. This method involves more concentration, high degree precision and skill, and expensive, prone to operator bias, time consuming, and difficult to extract the valuable information present in such a large-scale data [2]. In many countries, the complexity of chest radiographs resulted in the shortage of expert radiologists because it is crucial task for them to discriminate the respiratory diseases. Hence, there is a necessity to develop an automated method for the computer-aided diagnosis of respiratory diseases based on chest radiography.

Deep learning (DL) methods have achieved a tremendous growth in the last decade in the area of various computer vision applications such as classification of medical and natural images [3]. This led to the development of deep convolutional neural networks (CNNs) for the diagnosis of respiratory diseases based on chest radiography.

The computer-based diagnosis of respiratory diseases consists of the detection of pathological abnormalities, followed by their classification. The challenging task is the automated abnormality detection on chest radiographs due to the diversity and complexity of respiratory diseases and their limited quality. On the chest radiographs, manual marking of abnormal regions needs even more labor and time than labelling it. Therefore, in many chest radiography data, the abnormalities are masked [4], which lead to the computer-aided diagnosis task to a weakly supervised problem by showing only the names of abnormalities in each radiograph without their locations.

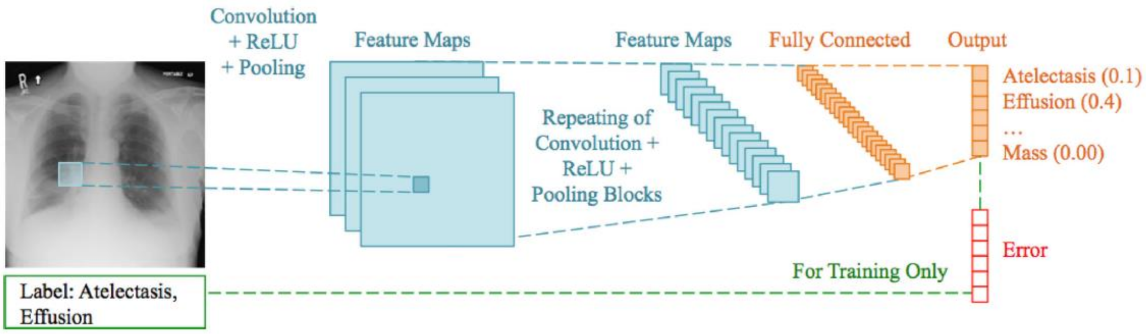


**Figure 1.** Deep CNN learning paradigm of a multi-labeled classification task using whole image.

To predict X-ray image diagnostic information, the machine learning based methods are proposed by many researchers [5]. The use of computer science-based methods to control huge volumes of medical records can decrease medical costs for health and medical science applications. In recent years, the use of DL algorithms on medical images for respiratory disease detection has grown to a great height. DL is derived from machine learning where its algorithms are inspired by the structure and function of the human brain. The identification, classification and quantification of patterns in medical images [6] are supported by DL methods. DL is gaining much importance by improving performance in many medical applications. Figure 1 describes a generalized manner in which Deep Neural Networks process data and classify images. In turn, these improvements support clinicians in classification and detection of certain medical conditions in a more efficient way [7].

The objective of this paper is to provide a comparison of the state-of-the-art DL based respiratory disease detection methods and also identifying the issues in this direction of research. Section 2 describes the taxonomy of various methods and respiratory issues that are considered for this study. Section 3 focusses on the issues that the authors observed during their research. The conclusion of the article is presented in Section 4.

## 2. Taxonomy of the state-of-the-art DL techniques for respiratory disorder from X-ray images

This section discusses the state-of-the-art DL techniques used for detection of lung diseases through CXR images. The main aim of this taxonomy is to provide a summarized and an articulated view of the main focus points and major concepts related to the existing work carried out in this area. A total of five attributes, which the authors found to be present commonly and imminent in the majority of the articles, are identified and discussed in detail. These attributes are the types of DL algorithms, features used for detection of abnormalities, data augmentation, transfer learning, and types of lung diseases.

### *2.1. Features extracted from images*

In the field of computer vision, a feature can be thought of as some form of numerical information that can be extracted from an image which could prove to be beneficial in solving a certain set of problems [8]. Features could be certain structures in the image such as edges, shapes and sizes of objects or even specific points in the image.

The process of feature transformation relates to the generation of new features of an image based on the information extracted from existing ones. The newly generated features might have a more powerful way to represent the regions of importance in the image when viewed from a different dimension or space as compared to the original. This improved representation of the image has proven to be extremely beneficial when they are subjected to various machine learning algorithms. Some of the most prevalent image features extracted includes Gabor, Local binary patterns (LBP), edge histogram descriptor (EHD), color and edge direction descriptor (CEDD), color layout descriptor (CLD) [9], autocorrelation, scale-invariant feature transform (SIFT), edge frequency and speeded up robust features (SURF). The concept of histograms was also used to generate features in the form of histogram of oriented gradients (HOG), pyramid HOG [39], intensity histograms (IH), gradient magnitude histograms (GM) and fuzzy color and texture histogram (FCTH). It has been observed form the recent literature that CNNs have the capability to automatically extract the relevant features without the need for explicit manual implementation of handpicked features from the images [10].

### *2.2. Data Augmentation*

Having a large training dataset image in DL helps in improving the training accuracy. When compared to a strong algorithm with modest data, a weak algorithm on a large data can be more accurate. Presence of imbalanced classes is another obstacle that is encountered. The resulting model would be biased when the number of samples belonging to a particular class is larger than the other class during binary classification training. For the optimal performance of DL algorithms, number of samples should be equal or balanced in each class. Image augmentation is a technique to increase the training dataset by creating variations of the original images, without obtaining new images. The variations are achieved by various processing methods such as flips, rotations, zooms, adding noise and translations [11]. Few examples of augmented images are shown in Figure 2.

Overfitting is also prevented during data augmentation, where the network tries to learn a very high variance function. Data augmentation addresses it by introducing the model with more diverse data which decreases variance and improves the generalization of the model. Some of the disadvantages of data augmentation are its inability to overcome all biases in a small dataset [12], transformation computing costs, additional training time and memory costs.

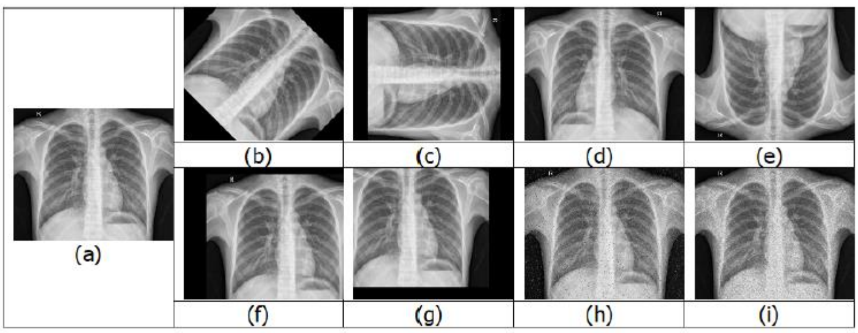


**Figure 2.** Examples of image augmentation: (a) original; (b) 45° rotation; (c) 90° rotation; (d) horizontal flip; (e) vertical flip; (f) positive x and y translation; (g) negative x and y translation; (h) salt and pepper noise; and (i) speckle noise.

### 2.3. *Types of DL Algorithm*

CNN is the common DL algorithm used to find patterns in images. CNNs consist of neurons with trainable weights and biases analogous to the neurons of the human brain. Several inputs are received by each neuron which computes its input weighted sum, which then is activated to produce an output. CNN has convolution layers as compared to other neural networks. Figure 3 shows a typical CNN architecture [13].

The two general stages during learning phase of CNN are feature extraction and classification. In the Feature extraction, a kernel or a filter is used to perform convolution on the input data which generates a feature map. The probability of the image belonging to a specific label/class is computed by the CNN in the classification stage. The main advantage of using CNN is that it automatically learns features for image classification and recognition without needing manual feature extraction. Transfer learning can be used to retrain CNN to be applied to a different domain [14], which is shown to produce better classification results.

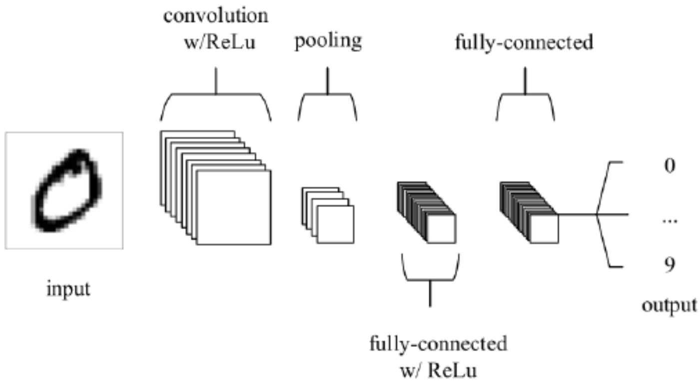


**Figure 3.** CNN structure.

Another DL algorithm which is a stack of restricted Boltzmann machines (RBM) is DBN [15]. Except for the first and final layers of DBN, each other layers has two functions, that is, they serve as input layer for succeeding layer nodes and as hidden layer for the preceding layer nodes. The design of first RBM is made as accurate as possible to train a DBN. The output from the first RBM is used to train the second RBM by treating the first RBM's hidden layer as the input layer. This process is iterated until all the network layer is trained. The model thus created during this initial training of the DBN can detect data patterns. DBN model finds applications in recognizing motion-capture data, objects in video sequences and images [16].

### 2.4. *Transfer Learning*

Transfer learning is an emerging and popular method in computer vision as it allows building of accurate models. A model trained in a particular domain can be retrained using Transfer learning to be used on a different domain. With/Without a pre-trained model, transfer learning could be performed.

A model that has been developed to solve an analogous task is called a pre-trained model, which can be used as a starting point to solve the current task. The weights and architecture obtained by the pre-trained models on the large datasets can be applied to the current task. Using such a pre-trained model, the main advantage is the reduction in the training cost for the new model [17], as it is sufficient to train and modify the weights related to last few layers.

When Transfer learning approach is followed, there is a necessity to consider two main criteria. The first one is selection of a pre-trained model by ensuring that the model has worked on a similar dataset as of the dataset into consideration. The second one is the weights of the CNN has to be trained and fine-tuned with lower learning rate, such that they are not distorted and are expected to be relatively good [18].

### *2.5. Type of Disease*

Application of DL techniques for detection of most common causes of critical illness related to lung [19] such as pneumonia, tuberculosis and COVID-19, an ongoing pandemic are discussed in the next few sections.

#### 2.5.1. Tuberculosis

The bacteria which cause Tuberculosis is Mycobacterium tuberculosis. WHO report says that tuberculosis ranks in the ten most common causes of death in the world. In 2017, tuberculosis caused a total death of around 1.6 million people out of 10 million people infected across the world. Therefore, in order to have an increase in the chances of recovery, there is a need for early detection of tuberculosis [20].

Computer-Aided Detection for Tuberculosis (CAD4TB) is a tool jointly developed by Delft Imaging Systems, University of Cape Town Lung Institute and Radboud University Nijmegen, for tuberculosis detection is used in two studies. The patient's CXR images are obtained and analyzed via CAD4TB cloud server/ computer, to display an abnormality score from 0 to 100 based on the heat map generated of the patient's lung. Murphy et al. [21] verified that CAD4TB v6 accurately performs in comparable to data read by radiology experts. Melendez et al. [22] combined clinical information and X-ray score by computer-aided detection for automated tuberculosis screening, which improved accuracies and specificities as compared when only either type of information is used alone.

Several works carried out in the literature, uses CNN to classify tuberculosis. Heo et al. proposed a technique to improve performance of the CNN by incorporating demographical information, namely gender, age, and weight. Results indicate that the proposed method has a superior sensitivity and higher area under the receiver operating characteristic curve (AUC) score than the CNN based on CXR images only. Pasa et al. proposed a simple CNN for tuberculosis detection with reduced computational requirements and memory without losing the performance in the classification that proved to be more efficient and accurate than previous models [23].

The use of transfer learning has also been researched by several authors. Hwang et.al claimed an accuracy of more than 90% along with an AUC of 0.96 through the use of transfer learning of ImageNet after they trained their network on more than 10000 chest X-rays. Lakhani and Sundaram [24] used pre-trained GoogLeNet and AlexNet for the classification of pulmonary tuberculosis. Their methodology displayed an AUC of 0.97 and 0.98 respectively. A combination of SVM for classification and pre-trained VGGNet, ResNet and GoogLeNet, for feature extraction, was used for the detection of X-ray image with tuberculosis by Lopes and Valiati. They obtained AUC in the vicinity of 0.9-0.912 [25].

Some authors have also used the NIH-14 dataset instead of ImageNet for pre-trained models. This dataset contains a wide variety of diseases and falls under the same modality as that of the dataset considered for tuberculosis. Models pre-trained on this dataset have shown to learn better features for classifying tuberculosis.

A variety of other methodologies such as k-Nearest Neighbors (kNN), sequential minimal optimization and simple linear regression have also been adopted for the classification of X-ray images related to tuberculosis [26]. Another technique that has been attempted along with the previously mentioned methodologies is the Multiple-Instance

Learning-based approach. This method presents the advantage of requiring a lower labelling detail during optimization. Additionally, the previously optimized systems can be retained easily due minimal supervision required by the method. Moreover, COGNEX developed an industry level DL based image analyzation software known as ViDi, which also displayed comparatively accurate detection of tuberculosis in chest X-ray images [27].

#### 2.5.1. Pneumonia

Pneumonia is a condition where alveoli of one or both the lungs getting filled by pus of fluid which leads to difficulty in breathing. Symptoms of this lung infection includes chest pain, severe shortness of breath, fever or fatigue and cough. It is still a recurrent cause for mortality and morbidity. A majority of the computer aided techniques used for detecting pneumonia are aligned towards the use of data augmentation and DL. Tobias et al. [28] used a direct and straightforward CNN technique to detect this condition. Stephen et al. used various data augmentation techniques such as shear, flip, rescaling, zooming, rotation and rescaling to train their CNN from scratch [29].

Authors have also used a pre-trained CNN architecture trained on augmented data for detection of pneumonia. Rajpurkar et al. [30] used randomized horizontal flipping as data augmentation while Ayan and Ünver [31] used flipping, rotation and zooming to augment their data. Chouhan et al. [32] on the other hand, also incorporated adding noise to the images along with the other methods to obtain an augmented version of the data to train their architecture on.

A Deep Siamese CNN architecture was also adopted for the purpose of classification of X-ray images with pneumonia. It utilizes a symmetric architecture which takes two images as inputs which consists of the X-ray being split into the left half and the right half. The architecture compares the amount of infection that has spread across both the regions in the image, which is claimed to make the classification system more robust. A study conducted [33]. [34] proposed that CNNs present a higher accuracy when compared with methods such as Random Forest, AdaBoost, Decision Tree, KNN and XGBoost.

#### 2.5.3. COVID-19

Coronavirus Disease 2019 or COVID-19 is a highly infectious disease that is caused by the very recently discovered coronavirus [35]. The most susceptible people are senior citizens and those who have a history of medical conditions such as chronic respiratory problems, cardiovascular disease, diabetes and cancer.

Approaches to detect this disease through X-ray image have also been attempted through CNNs trained on augmented datasets. [36] used an InseptionV3 architecture for this purpose and used it as a feature extractor. [37] also follow similar approaches. Methodologies to classify X-ray images into normal, COVID-19 and pneumonia with the help of transfer learning has been looked into. Other authors have also used transfer learning with CNN architectures trained on datasets augmented with techniques such as rotation, scaling, flipping, translation and shifting of image intensity for three class classification of X-ray images [38].

Along with classification of chest X-ray images for COVID-19, some authors also have modified CNN architectures to rather detect the disease. The authors in Sedik.et.al [39] used an amalgam of CNN and LSTM while Ahsan et al. [40] used an MLP-CNN model.

## 3. Issues observed in the present area of research

The main issues that were observed during this study were: (a) data imbalance (b) handling of images with large size and (c) limitation of datasets that can be used.

(a) Data imbalance: It is of paramount importance that there are similar number of images for each class. If this condition is not satisfied, then the trained model would tend to be more biased towards the class that has more amount of data. This can be disastrous in medical applications.

(b) Handling of images with large size: It is usually computationally expensive to work with high resolution data. For this purpose, researchers tend to reduce the size of the original images to counter this. Even with the use of powerful GPUs, training a DL architecture is quite time consuming.

(c) Limitation of datasets: To obtain extremely accurate results, it would be desirable to have thousands of images for each class that the images need to be classified into. But in real life situations, the number of images available for training is less than ideal.

## 4. Conclusions

The presented study is an attempt to summarize and provide, in an organized manner, the key focus and concepts used for the detection of lung diseases through DL methodologies. A taxonomy of the state-of-the-art methodologies for this purpose is presented. Along with these three issues that might hinder the progress of research in this area are also put forward, namely, data imbalance handling of images with large size and limitation of datasets. The authors strongly feel that in order for the research of this topic to progress in the right direction, such an investigative study would be helpful for other researchers who might be keen to contribute to this field.

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