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A Review of CXR-Based Lung Disease Classification Using Convolutional Neural Network

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ABSTRACT-

Lung diseases are some of the most severe and prevailing health problems in people's life. A large percentage of the human population around the world is diagnosed annually with lung disease affecting adults, teens, children, smokers, and even non-smokers making it be considered as the leading cause of death and disability worldwide. Early and correct diagnosis of chest diseases is mandatory and needed for timely and successful treatment to prevent further complications and to increase likelihood of survival. This study demonstrates the feasibility of classifying lung diseases in chest X-rays using convolutional neural network approach. It covers only six types of lung disease namely atelectasis, effusion, infiltration, mass, nodule and pneumothorax. Thus, the developed applications can only diagnose chest x-ray image belonging to any of these diseases. With 8,125 sample images, the trained neural network model managed to achieve 82.53% accuracy and a Cohen's kappa value of 0.788 in classifying lung diseases. The prototype was designed which could meet the necessary desires of computer-based and mobile-based applications. Further, this work can help as a supplemental tools for the radiologists and doctors in their decision making and in diagnosing lung diseases.

Keywords: chest diseases, CNN, deep learning, x-rays.

1. Introduction

Chest radiography also known as chest X-ray (CXR) is commonly used in diagnosing pulmonary disorders through the formation and presence of cavities, consolidations, nodules, infiltrates, pleural abnormalities, and blunted costophrenic angles [1]. Traditionally, when performing the chest X-ray test, an X-ray film is used to capture images of the chest and the internal organs. However, with the advent of technology, digital radiology has been introduced and considered as a more efficient and cost effective method of producing diagnostic images [2] [3].

Interpretation of chest X-ray requires a careful screening through the trained eye of a radiologist. Full knowledge of the standard structure of the chest and the basic anatomy of chest diseases, keen observation and deep analysis on specific patterns in the radiograph, and a systematic system of scrutiny are essential [4] [5]. Skilled radiologists have a high degree of accuracy in diagnosis. However, there are remaining problems in the detection of some diseases due to complicated image patterns and similarity of appearances of some lung diseases making it very challenging to achieve accurate classification. Perceptional diagnosis is indeed critical or challenging factor for any radiologist. If radiologist commits any mistake in identifying any abnormalities present in the patients it may lead to change in the treatment protocol or primary plays critical role in the lives of the patient [6]. These are not only a tremendous amount of work but also suffer from two main issues: excessive processing time and subjectiveness rising across different experts.

Speedy recognition and diagnosis of pulmonary disorders will expedite effective treatment of the patient, prevent further complications and ensures better chance of surviving the disease. Thus, recent advances in computer vision particularly application of machine learning techniques have been applied in the medical field like medical image processing, computer-aided diagnosis, and extraction of information from the images and representation of this information effectively and efficiently [7] [8].

Authors in [9] embraced the advancement of artificial intelligence for radiology applications. In the study [10], deep learning approach was applied in classifying lung nodules and detecting its malignancy level based on Computer Tomography (CT) images. Another study [11], implemented convolutional neural network in diagnosing Tuberculosis through chest X-ray images and achieved an accuracy rate of 85.68%. Also in the studies [12], [13] and [14] they used the deep convolutional neural network in diagnosing chest diseases.

Though various researches were carried out on this domain, this study intends to explore more on the applicability and efficiency of convolutional neural network for image classification in machine vision as well as to deploy the trained model in a computer-based and a mobile-based applications that will facilitate the radiologists and medical professionals in diagnosing lung diseases in chest X-ray images.

2. Methodology

2.1. Dataset Preparation

The dataset of [15] containing frontal-view chest X-ray images were downloaded, in which images were labeled with common lung disease categories, namely Atelectasis, Consolidation, Infiltration, Pneumothorax, Edema, Emphysema, Fibrosis, Effusion, Pneumonia, Pleural Thickening, Cardiomegaly, Nodule, Mass and Hernia.

Individual image was then manually mapped into the reference file containing the metadata of the image and grouped according to its disease type. For this study, only single labeled images and with view position "PA" were considered.

Likewise, disease types with insufficient number of images were not included. Afterward, the entire dataset used in this study was divided into three subgroups, wherein 80% of which is for the training phase, 10% for the validation phase, and 10% for the testing phase.

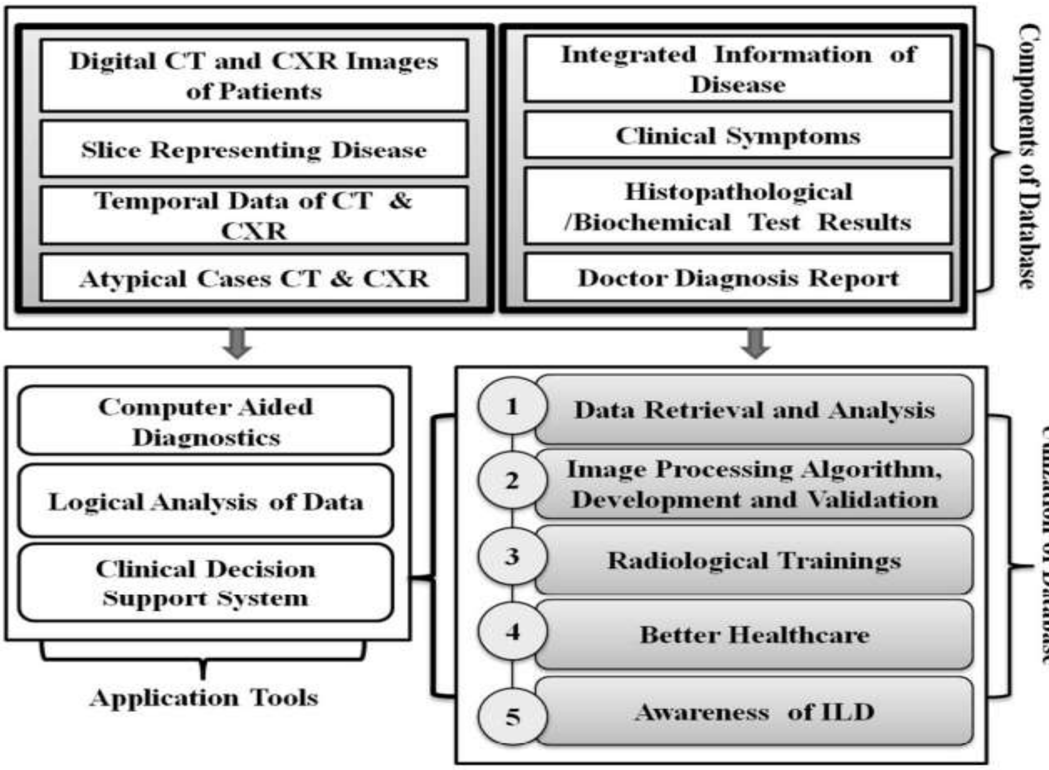

Figure 1: Representation of HRCT and CXR of IPF patient

2.2. Conceptual Framework Design

Figure 1 represents the conceptual framework for this study wherein the dataset was divided into two main subgroups, for the training phase and for the testing phase. During the training phase, the data were further split into the training set for building the CNN model and the validation set for model validation. Afterward, through the images in the testing set, the performance of the trained model was measured by computing basic evaluation metrics. Finally, computational efforts were made to develop the most suitable prototype for the automated recognition of pulmory disorders of chest X-ray image. This prototype may be further utilized in the leading applications related to computer-based and mobile-based real time approach.

2.3. Convolutional Neural Network Model Design

The architecture for this study is shown in Figure 2, which consists of chest X-ray image. This image is further processed for the correct identification of infected positions related to lungs. Consequently, it further classifies for the accurate detection of lung infection. The sequential flow of this work involves series of convolution and pooling layers. These layers were helpful in the extraction of low level to high-level features. These layers are further connected to fully connected layers which are extensively used for mapping the information of extracted features into the final output (classification).

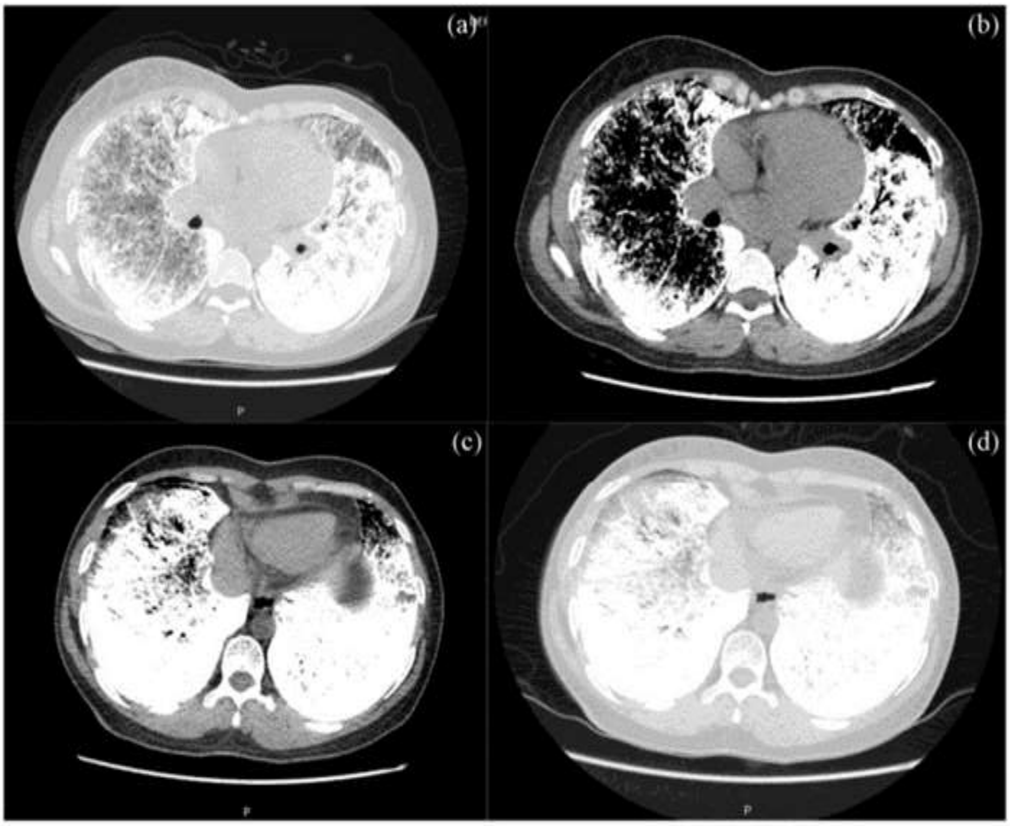

Figure 2: Architecture of Proposed study using patient Images

A sequential neural network with input parameters (64, 64, 1) was designed. The parameters 64x64 addresses the dimension of the input image and 1 represents the grayscale nature of the image. The neural network considered in this work consists of linear stack composed of 4 sets of convolutional (Conv2D) – pooling (MaxPooling2D) layers. The Convolutional 2D layers will have 32, 64, 64, and 128 output channels respectively, with a kernel size of 3x3. The activation function is the Rectified Linear Unit (ReLU), is employed for each of the MaxPooling and convolutional layer. This activation function reduces the number of parameters in the model by sliding a 2x2 pooling filter.The flatten layer is the interface layer connected between the convolutional and the dense layers. The first two dense layers consists of 128 nodes, each activated by a ReLU function. The added Batchnormalization is for normalizing the matrix and for learning suitable parameters in the network. Also, the Dropout method was introduced to help reduce overfitting by randomly disabling neurons during the learning phase. The final dense layer comprised of six nodes or number of classes activated by softmax activation function. Thus the output of the model is interpreted as highest probabilities based on the number of clasess.

The Convolutional Neural Network was trained using the default learning rate of the keras which is 0.01.

3. Implementation

Necessary installations were made to support the generation of a CNN model suitable for the classification of lung diseases and the development of the graphical user interface of the applications for which the trained model is going to be deployed for actual implementation.

The technology tools that were used in implementing this study include Python version 3.6 through the Anaconda distribution, Tensorflow, Keras, Pandas, Numpy, Jupyter, Qt designer, PyQt5 and Android Studio.

4. Results and Discussion

Figure 3 and Figure 4 demonstrates the benefit of utilizing the convolutional neural network in the automated recognition of pulmonary infections from the X ray image. This study inculcating the CNN also illustrates that how the information is transformed from one layer to other. These layers uses the activation function such as RelU function and extracts the detailed information of the image. However, when the layers get more in-depth, the feature maps show less information on image visual contents and more information on image class. Furthermore, filters that are left blank indicates that they are not activated at all.

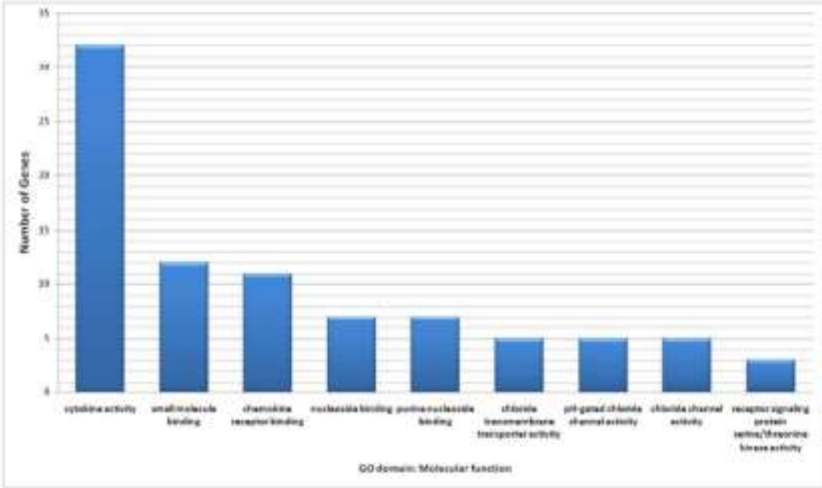

Figure 3: Simulation Results based on the gene behaviours

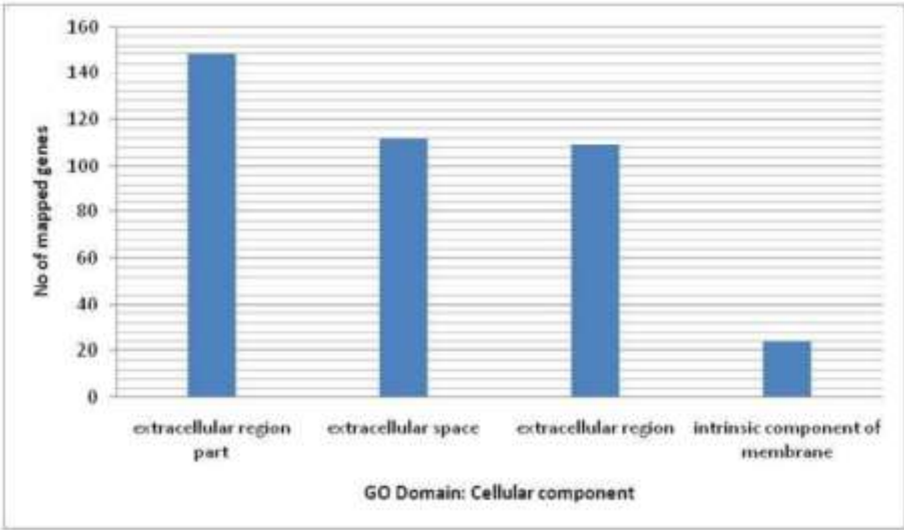

Figure 4: Simulation Results based on the mapped genes

As observed, infiltrations were sometimes misdiagnosed as atelectasis. This result is supported in a study [16] which states that there might exists a numerous reasons for the cause of “alveolar consolidation” pattern (ACP). This pattern exhibits enamorous challenges for the clinicians to differentiate between “infiltrative” or “atelectatic” etiologies.

It is observed that Atelectasis has the highest recall of 88.74% and low precision of 77.46%, which signifies the most of the predicted results are positive in nature. However, only a few of them are correct. On the other hand, the Mass has the highest precision of 90.80% and lowest recall of 76.70% demonstrating that the model is proposing with few results and most of its predicted labels are correct when compared to the training labels.

Additionally, the Mass class has signified with highest specificity percentage of 98.87% which is said to be accurate towards recognizition of the chest X-ray images.

In general the model is 82.53% accurate on its prediction with the different lung diseases. Also, the performance of the classifier was further evaluated by computing Cohen kappa value. The statistics of kappa approach was strongly initiated by the medical field, where it could be successfully applied and is also considered as an effective measure for the interpretation of classification models [18]. Kappa prediction value vary in a range from 0-1.00, indicating better reliability for larger or higher values. The interpretation scheme for kappa is reflected in Table V [19].

As a result, the classifier attained a Cohen’s kappa value of 0.788, indicating a substantial level of agreement. The empirical results demonstrate good reliability of the generated model’s predictions relative to the actual data.

The trained model was deployed in two versions of chest x-ray classifier for its actual implementation. Both application forms displayed the prediction outcomes of the model on every class and emphasized that the class which obtained the highest probability value, is the final classification of model on the uploaded or selected image.

6. Conclusion and Recommendation

This study was able to demonstrate the performance of the lung disease classification model successfully embedded into a computer-based and android-based applications. With the application of convolutional neural network, the generated model obtained an overall accuracy rate of 82.53% and a Cohen's kappa value of 0.788 which indicate that the model has a good reliability for the prediction of the chest X-ray images in the testing dataset.

However, there is a need to further improve the performance of the model that is essential for the radiologists and other medical personnel in their diagnosis and decision making. Also, further study can be made to include chest X-ray images with multiple findings and with other CXR projections

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