Detection of Chronic Obstructive Pulmonary Disease using Convolutional Neural Networks: A Survey

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Abstract : This study proposes the use of computer-assisted analysis for better interpreting of images in the medical imaging field. On the image understanding front, recent advances in machine learning, especially deep learning, have made a big leap to help identify, classify, quantify patterns in medical images. Deep learning is rapidly proving to be the state-of-the-art foundation, achieving enhanced performances in various medical applications. We introduce the fundamentals of deep learning methods; review their successes to image registration and computer-aided disease diagnosis. In this Study, we surveyed the use of Computed Tomography (CT) scan and X-ray images as raw data input to a Convolutional Neural Network(CNN) and predict the presence of Chronic Obstructive Pulmonary Disease(COPD).

***Index Terms* – COPD, CNN**

I. INTRODUCTION

Chronic obstructive pulmonary disease (COPD) is a lung condition that causes breathlessness and makes it difficult to empty air out the lungs because of the airways becoming narrowed. More than 90% COPD deaths occur due to late diagnosis of the disease. The goal here is to find a system that can give a trustworthy result based on your lung scans and can be used by low and middle-income countries.

Neural network plays an important role in Health care. It really helps to predict the disease based on collected data. Diagnosis in the medical field is a complicated task that should be performed with accuracy and efficiency. A diagnosis performed by a physician for a single patient may differ significantly if the same is examined by the other physicians or by the same physicians at different times to that single patient. Which is why, automated medical analysis is used to help medical diagnostic problems and characterize its advantages and problems in the context of the medical background. Successful application examples show that human diagnostic capabilities are significantly worse than the neural diagnostic systems.

CNN are learning-based models that are trained using a large amount of data from individuals having known outcomes i.e. COPD .Once trained, the model will use the data from the end-user individuals to determine or predict the probability that outcome. It can help in quickly assessing the risk across large population without having extracting or reviewing of respective clinical features .

II. PROPOSED METHODOLOGY

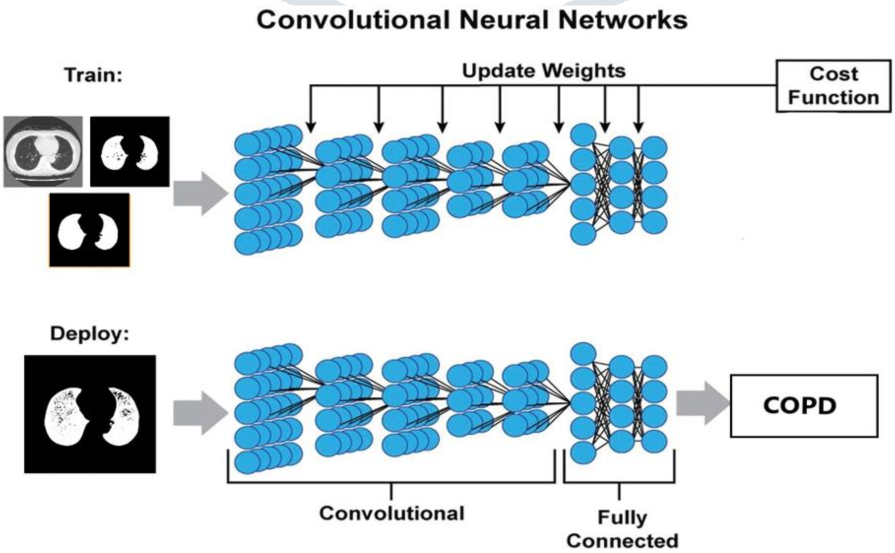

Figure 1: System Architecture

CNNs are very similar to ordinary Neural Networks, they are made up of neurons that have learnable weights and biases. Each neuron receives some weighted inputs, performs the dot product and follows it with some non-linearity. The whole network still expresses a single differentiable score function : from the raw image pixels on one end to class scores at the other.

The network converts the raw image pixels through a convolution layers, Rectified Linear Unit (RELU) layers and pooling layers; finally providing the input to the fully-connected layer which classifies the input into it's respective class based on the class score.

1.) CONVOLUTION LAYER

Convolution refers to the mathematical combination of two functions to produce a third function. Hence, it merges two sets of information. In our case, convolution is performed on the input data with the use of a kernel or filter to produce an activation or feature map. Convolution is achieved by sliding the filter over the input. At every location, a dot product of the input values and the filter is performed and the result is summed onto the feature map. The sliding of the filter is defined by the stride. Stride is the number of pixels the filter moves each time. With a larger stride, the filter has less overlap. By using multiple convolution layers with different filters, various feature maps can be produced and then combined to produce the final output of this layer.

2.) POOLING LAYER

Pooling Layer is commonly inserted in between successive convolution layers or between convolution and RELU layers. It reduces the number of parameters and computation in the network. It continuously reduces the dimensionality which results in shortened training times and controls overfitting. Max-pooling is frequently used; it simply takes the maximum value within a filter. This decreases the feature map size and keeps all the relevant information. It effectively summarizes the strongest activations over a neighborhood.

3.) RECTIFIED LINEAR UNIT LAYER (RELU)

RELU is an activation function responsible for transforming the summed weighted input from the node into activation of the node or output for that input. RELU sets the negative input values to zero. It makes the model easier to train and often achieves better performance than other activation functions.

4.) FULLY CONNECTED LAYER

The functional form of fully connected layer is identical to the convolutional layer. This layer serves as a classifier on top of the extracted features which were detected during convolutions and pooling operations. This layer only accepts one dimensional data, as a result flattening the input is necessary. Neurons in this layer have full connections to all the activations in the previous layer. This part is same as a regular neural network.

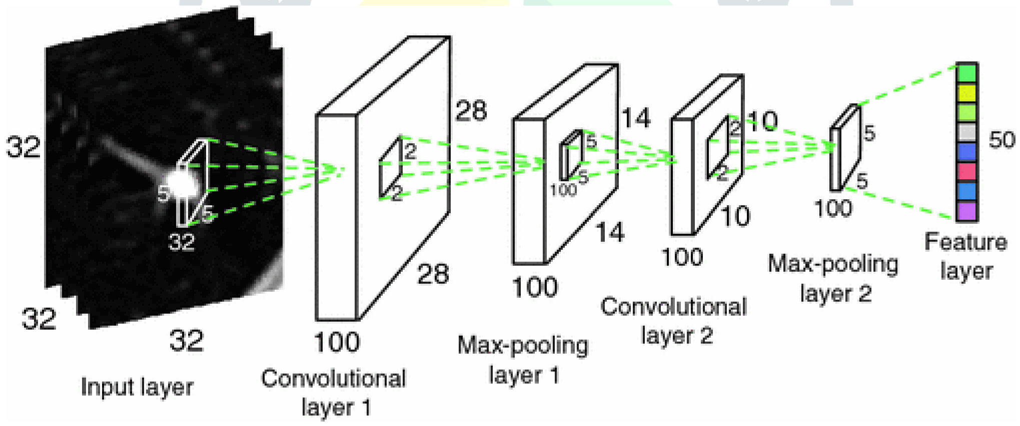

Figure 2: CNN

III. LITERATURE SURVEY

[1] Lung cancer is a leading cause of mortality and morbidity for patients suffering from Chronic Obstructive Pulmonary Disease (COPD). Both the presence of visually assessed emphysema on CT scans and abnormal pulmonary function tests are associated with the development of lung cancer. Based on recent results showing that convolutional neural networks (CNNs) applied to CT scans can predict spiromelectrically-defined COPD. .In their system the CNNs were training using image and clinical data from the Genetic Epi-demiology of COPD (COPDGene) study. CT scans from the baseline image collection and 5-year follow-up were available for training and validation. They developed a data reduction strategy that used a subset of image slices for training and processing. A set of 8 axial slices, each down-sampled from 512 x 512 to 256 x256 pixels, were randomly sampled from equally sized "zones" of the lung and combined into a single image montage. A limitation of this preliminary work is that CNN models were only trained to classify COPD and emphysema as binary categories even though more granular data was available.

Based on results showing that convolutional neural networks (CNNs) applied to CT scans can predict spirometrically-defined COPD ($FEV1FVC$<0.7), they hypothesized that CNN-based classification of COPD and emphysema is predictive of lung cancer development in the National Lung Cancer Screening (NLST) cohort. We trained spirometric COPD and visual emphysema CNN classifiers using data from the COPD Gene study. The classifiers were then used to generate COPD and emphysema scores (*CSCNN* and *ESCNN*, respectively) on 7347 CT scans from the NLST study. Cox proportional hazards regression was used to model the effects of *CSCNN*, *ESCNN*, age, body mass index, education, gender, smoking pack-years, and years since smoking cessation on lung cancer diagnosis. It was found that, individually, both *CSCNN* and *ESCNN* were statistically significant predictors ($p < 0.000$ and $p < 0.000$, respectively) of lung cancer diagnosis hazard.

[2] Their purpose was to determine if deep learning, specifically convolutional neural network (CNN) analysis, could detect and stage chronic obstructive pulmonary disease (COPD) and predict acute respiratory disease (ARD) events and mortality in smokers. Methods used were A CNN was trained using computed tomography scans from 7,983 COPD Gene participants and evaluated using 1,000 non-overlapping COPD Gene participants and 1,672 ECLIPSE participants. Logistic regression (C statistic and the Hosmer-Lemeshow test) was used to assess COPD diagnosis and ARD prediction. Cox regression (C index and the Greenwood-Nam-D'Agnostino test) was used to assess mortality.

[3] The FFNN and LSTM models are trained on data collected from remote monitoring of 94 patients through a real monitoring session and therefore represents realistic home monitoring situations. Most deep learning models require large datasets in order to predict with a high degree of accuracy. Their experiments show that with only 94 patients, the FFNN model is able to reproduce health condition provided by a medical doctor with an accuracy of 92.86% and the LSTM model able to predict COPD patients' health conditions one-day ahead with an accuracy of 84.12%. Based on their results, they believe that their work will help the medical doctors and nurses in identifying patients with acute exacerbation in advance which can lead to better patient care and decision making, and hence reduction of costs. In their study they explored whether deep learning models, and particularly Long- Short Term Memory (LSTM) can be used to predict exacerbation/condition of COPD patients even when the dataset is limited such as is typical in the case of home monitoring situations.

[4] They have proposed a two-step hybrid approach to make deep learned features accessible to a discrete optimization-based registration method. In a first step, in order to extract expressive binary local descriptors, we train a deep network architecture on a patch-based landmark retrieval problem as auxiliary task. As second step at runtime within a MRF-regularized dense displacement sampling, their binary nature enables highly efficient similarity computations, thus making them an ideal candidate to replace the so far used handcrafted local feature descriptors during the registration process. They evaluated their approach on finding correspondences between highly non-rigidly deformed lung CT scans from different breathing states. Although the CNN-based descriptors excel at an auxiliary learning task for finding key point, correspondences, self-similarity-based descriptors yield more accurate registration results. However, a combination of both approaches turns out to generate the most robust features for registration.
Thus they presented a three-dimensional framework for large lung motion estimation based on the combination of CNN-based and handcrafted descriptors efficiently employed in a discrete registration method. Achieving best results by combining learned and handcrafted features encourages further research in this direction.

[5] The Computer Aided Diagnosis System has been intended to diagnosis the COPD by using CT images. Computed Tomography (CT) images are generally chosen due to less distortion, less time consumption and low cost. The proposed work of computerized based diagnosis system for a Chronic Obstructive Pulmonary Disease (COPD) is to diagnosis the disease with accuracy using convolutional neural network (CNN). CNN classifier to classify the CT images and it will be evaluated using performance metrics. The Computer Aided Diagnosis System for COPD is composed of preprocessing, feature extraction, segmentation and classification. The preprocessing is to improve the quality of image like removing noise and isolating region of interest. The feature extraction is a method of capturing visual content of images for indexing and retrieval. The segmentation subdivides the CT image into different regions. The CNN classifier is to classify the segmented CT images for improving the accuracy of clustering under noise.

IV. CONCLUSION

Deep learning, including CNN, can provide a fast and flexible method for the integration of imaging into biomedical research. In addition, it may allow for the assessment of population-wide disease. Unlike current reductionist methods that require the use of a summary statistic of a feature of interest, deep learning uses all of the data available in the image to predict clinically relevant outcomes. Although current processing power limits the number of images that this technique can be applied to at the moment, this exciting new field may ultimately enhance the ability to identify disease subtypes because it is not hindered by the ability to *a priori* specify what imaging data should be used for investigation. Therefore it may provide a more standardized approach to image analysis and overall risk assessment across research and clinical care networks.

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