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Pneumonia Diagnosis using Convolutional Neural Network

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Abstract. This study presents the results of an automatic pneumonia diagnosis experimentation using a convolutional neural network. The experimentation involves combining two chest x-ray datasets from different sources to make the positive and negative labels balance. Result shows that balanced data yield promising accuracy as compared to the baseline model.

Keywords; cnn; convnetnt; ehealth; deep learning; biomedical

1. Introduction

Image processing is a subfield of machine learning, which converts an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. Image processing is a type of signal dispensation in which input is an image and output may be an image or characteristics associated with that image. Its applications have been widely used in computerized photography [1], space image processing [2], medical or biological image processing [3], automatic character recognition [4], fingerprint recognition [5], and a lot more.

Pneumonia is a bacterial, viral, or fungal infection of one or both sides of the lungs that causes the air sacs, or alveoli, of the lungs to fill up with fluid or pus [6]. Symptoms can be mild or severe and may include a cough with phlegm (a slimy substance), fever, chills, and trouble breathing. Imaging studies such as magnetic resonance imaging (MRI), computed tomography (CT), ultrasound, and nuclear

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medicine or X-ray exams play an increasingly important role in the diagnosis and treatment of disease.

After completing an imaging study, the radiologist will analyze the images and prepare a report summarizing the findings and impressions. The radiology report is primarily a written communication between the radiologist interpreting the imaging study and the physician who requested the examination. Typically, the radiology report is sent to the physician who originally requested the imaging study and who then conveys the results to the patient. In places where radiologists are limited, requests from a physician nearby for image results would take longer. Time is crucial for most people; hence patients are forced to wait for more than a day. Many patients can also directly access their radiology reports and, in some cases, their medical images using online patient portals and electronic health records. These records and reports often contain complex anatomical and medical terms which most people cannot understand without further knowledge.

Few researches were conducted about pneumonia diagnosis such as [7], which used an imbalance dataset with normal and pneumonia-diagnosed x-rays, and [8], used x-ray dataset with 14 labels and trained them together. This study however, creates a balanced data for training, testing and validation so that the algorithm will not favor the class with the largest proportion of observations that leads to misleading accuracies.

2. Methods

The data used to train the model are x-ray images [9], which contains 5, 863 x-ray images divided for training, testing, and validation sets. Each set contains normal and with pneumonia x-ray images. It is worth mentioning that the original dataset has an imbalance count of the label. The training set contains 1,340 negative x-ray images and 3,876 positive x-ray images. Test set contains 234 for negative and 390 for positive.

To make the data balance, the NIH Clinical Center CXR8 dataset was utilized. This is a dataset containing x-ray images with 14 labels, which include atelectasis, consolidation, infiltration, pneumothorax, edema, emphysema, fibrosis, effusion, pneumonia, pleural_thickening, cardiomegaly, nodule mass, hernia, and no finding (negative). The researchers extracted some images with pneumonia and negative labels and merged them to the previous dataset. The final dataset contains 8, 570 x-ray images with 1,285 counts for both labels in test set (30%) and 3, 000 (70%) for both labels in training set as can be seen in Figure 1.

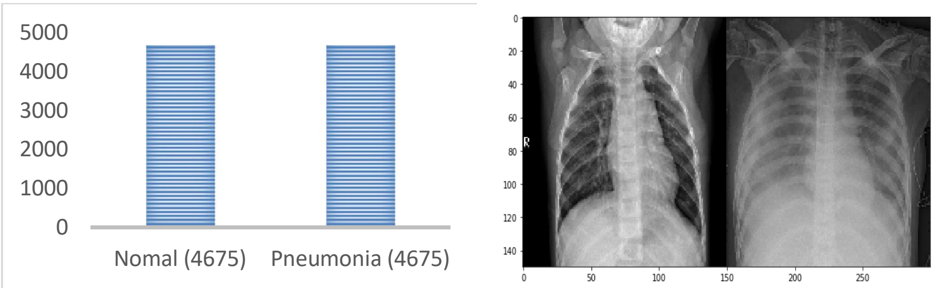

Fig 1. (Left side) Label distribution of the dataset.
(Right Side) Sample of the dataset with normal and with pneumonia labels respectively.

The training set was fed to a sequential convolutional neural network (CNN). A CNN is a deep learning model or a multilayered perceptron similar to Artificial Neural Network, which is most commonly applied to analyzing visual imagery [10]. Convolutional Neural Network were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. CNN's architecture (see Figure 2) is very similar to the regular Artificial Neural Network (ANN).

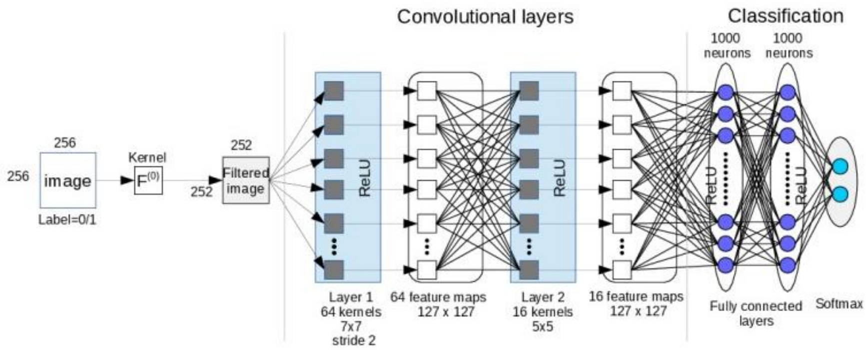

Fig 2. CNN architecture.

The CNN used comprised of five pairs of convolution layers, with each pair having one max pooling layer (see Figure 2). The network used Conv2D layers that performs the convolution operation by taking 4 arguments: the filter, shape of each filter, input shape and the type of image. This layer computes the output of the dot product between an area of the input image and a weight matrices called filter, the filter will slide throughout the whole image repeating the same dot product operation.

Next is MaxPooling2D layers that takes the maximum value pixel from the respective region of interest. The pooling operation reduced the spatial dimensions, but not depth, on a convolutional neural network by taking the highest number, also called the most responsive area in the image) of the input's area, basically an n x m matrix. Its core goal is to provide spatial variance, which means that the model will be capable of recognizing an object as an object even when its appearance varies in some way.

The non-linearity layer in the network used the Rectified Liner Unit (ReLU) activation function, which returns 0 for every negative value in the input image while returns the same value for every positive value in the input image. Then a Flatten layer was added to convert all the resultant 2 dimensional arrays into a single long continuous linear victor. Finally, a Dense function was used to perform the full connection of the neural network, where the number of nodes that should be present in the hidden layer is define. The final layer has one node for binary classification.

3. Results

After tuning the model, and feeding the training set, the model was evaluated using the test set. The test set was fed to the model and the model predicts the label of each image. The accuracy was computed based on the confusion matrix produced by the model. The model gives a soaring 93% accuracy on its training set, while the test set gives 85% accuracy. Since previous works has not included accuracy as its metrics, we compare the AUROC score to the best published results (see Table 1).

TABLE 1. THE AUROC COMPARISON SHOWS THAT OUR METHOD OUTPERFORMS THE BEST PUBLISHED RESULTS.

	AUC SCORE
Wang et al. (2017)	0.63
Yao et. Al (2017)	0.71
CheXnet	0.77
Quiroz et al. (ours)	0.81

4. Conclusion

Early diagnosis and treatment of pneumonia is critical to preventing complications including deaths [11]. Hence, we experimented the chest x-ray dataset and developed a model using convolutional neural network to detect pneumonia. The experiment shows that with the right amount of data, especially if it is balanced, a promising result could be yield. Further, this experimentation is not done yet, a lot can be done to improve the accuracy and other metrics for accurate and precise prediction of pneumonia. This can be done by tuning up the algorithm further and as well providing more data for training. With this endeavor, this work hopes to help the community in improving healthcare especially to far-flung areas where access to radiologist is limited.

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