A Novel Approach for Detecting Pneumonia in Machine Learning

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Abstract-- Machine Learning (ML) provides methods, techniques, and tools that can help solving diagnostic and prognostic problems in a variety of medical domains. ML is being used for the analysis of the importance of clinical parameters and their combinations for prognosis, e.g. prediction of disease progression, extraction of medical knowledge for outcome research, therapy planning and support, and for the overall patient management. ML is also being used for data analysis, such as detection of regularities in the data by appropriately dealing with imperfect data, interpretation of continuous data used in the Intensive Care Unit, and intelligent alarming resulting in effective and efficient monitoring. Chest X-rays are used to diagnose multiple diseases. From pneumonia to lung nodules multiple diseases can be diagnosed using just this one modality using Deep Learning. Chest X-ray 14 dataset as recently released by NIH which has over 90000 X- ray plates tagged with 14 diseases or being normal. In this work we are working on detecting pneumonia diseases using machine learning approach.

Keywords-- *Machine Learning, Deep Learning, pneumonia, chest X-ray, NIH.*

I. INTRODUCTION

Pneumonia accounts for a significant proportion of patient morbidity and mortality. Early diagnosis and treatment of pneumonia is critical to preventing complications including death. With approximately 2 billion procedures per year, chest X-rays are the most common imaging examination tool used in practice, critical for screening, diagnosis, and management of a variety of diseases including pneumonia. However, two thirds of the global population lacks access to radiology diagnostics, according to an estimate by the World Health Organization. There is a shortage of experts who can interpret X-rays, even when imaging equipment is available, leading to increased mortality from treatable diseases.

Medical X-rays are images which are usually used to diagnose some delicate human body parts such as bones, chest, teeth, skull, and so on [1]. Medical specialists have used this method for some periods to discover and visualize fractures or aberrations in body organs. This is due to the fact that X-rays are very actual diagnostic tools in revealing the pathological modifications, [2] in addition to its noninvasive features and economic reflections. Chest diseases can be shown in CXR images in the form of cavitations, infiltrates, blunted cost phrenic angles, and small broadly distributed nodules [3-4] .

Categorizing the chest X-ray abnormalities is measured as a tedious task for radiologists; hence, numerous algorithms were proposed by researchers to precisely perform this task [5–7]. Over the past decades, computer-aided diagnosis (CAD) systems have been developed to extract suitable information from X-rays to support doctors in having a quantitative insight about an X-ray.

The histogram equalization in image segmentation was applied for image preprocessing, and feed forward neural network is used for classification purpose. The above research works have been efficiently used in classifying medical diseases; however, their performance was not as efficient as the deep networks in terms of accuracy, computation time, and minimum square error achieved. Deep learning-based systems have been applied to increase the accuracy of image classification [10, 11]. Most commonly used deep learning architecture is the convolutional neural network (CNN). CNN has been applied to various medical images classification due to its power of extracting different level features from images [11–15].

II. REVIEW

A Machine learning-based method. The category can also be referred to as pixel-based methods. For chest radiographs, each pixel is assigned to a corresponding anatomical structure, such as lung, heart, mediastinum, diaphragm and so on. The classifier can use various features, such as the gray value of the pixel, spatial location information, and texture statistical information. There features are inputted into some classifier, e.g., a k-nearest neighbor (KNN) classifier, support vector machine (SVM), Markov random field (MRF) model, or neural network (NN), to train the classifier. The method can be subdivided into shallow machine learning-based methods and deep learning-based methods. In shallow machine learning-based methods, the feature extraction process is intuitive, and the main challenge is to determine the appropriate categories of the features and extract them in a robust way. Mcnittgray et al. first proposed a method of lung field segmentation using features. Additionally, this method goes beyond the advanced methods in the clavicle and heart segmentation tasks. Dai et al. proposed a structure correcting adversarial network (SCAN) framework that uses a confrontational process to develop an accurate semantic segmentation model for segmenting lung fields and the heart in chest X-ray images. This method improves the FCN and achieves segmentation performance comparable to human experts. Suzuki et al. developed a method to suppress the contrast between ribs and clavicles in a chest X-ray with a multiresolution, large-scale training

artificial neural network (MTANN). Subtracting a bone image from the corresponding chest radiograph produces a "soft tissue image", where the rib and clavicle are substantially suppressed. Nguyen et al. used independent component analysis (ICA) to separate the ribs and other parts of lung images. The results showed that 90% of the ribs could be completely and partially inhibited, and 85% of the cases increased the nodule visibility. The results showed that this method can produce high-quality and high-resolution images of bone and soft tissue. Gordienko et al. detected lung cancer using a deep learning method, which demonstrated the efficiency of the bone suppression technique. The study found that the pretreatment dataset without bones showed better accuracy and loss results.

III.   METHODOLOGY

Artificial neural networks (ANNs) are computational models inspired by the human brain. They are comprised of a large number of connected nodes, each of which performs a simple mathematical operation. Each node's output is determined by this operation, as well as a set of parameters that are specific to that node. By connecting these nodes together and carefully setting their parameters, very complex functions can be learned and calculated.

We will use ChestX-ray14 dataset which contains 112,120 frontal-view X-ray images of 30,805 unique patients. we randomly split the dataset into training validation and test. There is no patient overlap between the sets. 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 Image Net training set. We also augment the training data with random horizontal flipping.

IV.   PROBLEM STATEMENT

The pneumonia detection task is a binary classification problem, where the input is a frontal-view chest X-ray image X and the output is a binary label $y \in \{0,1\}$ indicating the absence or presence of pneumonia respectively. For a single example in the training set, we optimize the weighted binary cross entropy loss

L (X,y) = − w + · y log p (Y = 1 | X) − w − · (1 − y) log p (Y = 0 | X),

where,

p(Y=i|X) is the probability that the network assigns to the label i, w+=|N|/(|P|+|N|), and w−=|P|/(|P|+|N|) with|P| and |N| the number of positive cases and negative cases of pneumonia in the training set respectively.

A. The Logistic Function

Most often, we would want to predict our outcomes as YES/NO (1/0).

For example:

Is your favorite football team going to win the match today? — yes/no (0/1) Does a student pass in exam? — yes/no (0/1)

The logistic function is given by:

where,

1. L – Curve's maximum value
2. k – Steepness of the curve
3. x0 – x value of Sigmoid's midpoint

A standard logistic function is called sigmoid function (k=1, x0=0, L=1)

The sigmoid curve

The sigmoid function gives an 'S' shaped curve.

$$S(x) = \frac{1}{1+e^{-x}}$$

This curve has a finite limit of:

'0' as x approaches $-\infty$, '1' as x approaches $+\infty$

The output of sigmoid function when x=0 is 0.5 Thus, if the output is more tan 0.5 , we can classify the outcome as 1 (or YES) and if it is less than 0.5 , we can classify it as 0(or NO) . Thus the output of the sigmoid function cannot be just used to classify YES/NO, it can also be used to determine the probability of YES/NO.

B. Convolution Neural Network

In mathematics (and, in particular, functional analysis) convolution is a mathematical operation on two functions (f and g) to produce a third function that expresses how the shape of one is modified by the other. This operation is used in several areas such as probability, statistics, computer vision, natural language processing, image and signal processing, engineering, and differential equations.

This operation is mathematically represented as the convolution of f and g is written f∗g, using an asterisk or star. It is defined as the integral of the product of the two functions after one is reversed and shifted. As such, it is a particular kind of integral transform:

$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau)g(t-\tau)\,d\tau$$
$$= \int_{-\infty}^{\infty} f(t-\tau)g(\tau)\,d\tau.$$

While the symbol t is used above, it need not represent the time domain. But in that context, the convolution formula can be described as a weighted average of the function f(τ) at the moment t where the weighting is given by g(−τ) simply shifted by amount t. As t changes, the weighting function emphasizes different parts of the input function.

CONCLUSION

An important challenge in data mining and machine learning areas is to build accurate and computationally efficient classifiers for Medical applications. In this propose work. we will work on Pneumonia disease using machine learning and we will used ChestX-ray14 dataset. We will tried to compare efficiency and effectiveness of those algorithms in terms of accuracy, precision, sensitivity and specificity to find the best classification algorithm as per result will get after implementation.

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