Automatic Detection of Pneumonia on Compressed Sensing Images using Deep Learning

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***Abstract*—Pneumonia is one of the life threatening very common disease and needs proper diagnosis at an early stage for proper treatment of recovery. Chest X-ray is used as an imagining modality to identify the disease by a professional radiologist. This paper suggests a Compressed Sensing (CS) based deep learning framework for automatic detection of pneumonia on X-ray images to assist the medical practitioners. Extensive simulation results show that the proposed approach enables detection of pneumonia with 97.34% prediction accuracy and an improvement on reconstruction quality of the X-ray images in terms of PSNR by $1\pm0.76\ dB$ and SSIM by 0.2 ± 0.05 using the proposed method compared to the other state-of-the-art methods.**

***Index Terms*—Compressed sensing, Pneumonia detection, Deep Learning, CNN**

I. Introduction

Pneumonia is a very common infective disease caused by bacteria, viruses, or fungi [1]. In severe case, it leads to death specially in children younger than 5 years of age, older adults and people with other diseases or impaired immune systems. In every year, around 1 million people are detected with pneumonia and around $50,000$ die from the disease in the United States (U.S.) like country [2]. To diagnose pneumonia, chest X-ray is used by the medical practitioners as the best imaging modality. However, proper analysis of the X-ray images need a radiologist with rich domain expertise and experience. According to an estimate by the World Health Organization (WHO), two thirds of the people in the world don't have access to a radiologist for diagnosis of their disease yet. It would be very helpful if an automated computerized system is developed to analyze the X-ray images for assisting the medical advisor to diagnose appropriately. To offer proper medical services in remote villages, often imaging to be done at one end and the medical advisors are present at far end which needs transmission of images over wireless channels. To avail and adapt the limited bandwidth of wireless channel, far end image reconstruction (to be used for diagnosis) to be accomplished from sub-sample measurements [3]. This faster sensing i.e. sub-sample sensing is also used for reduction in radiation from X-ray imaging. Recently, Compressed Sensing (CS) is used in various medical imaging and a deep learning framework that enables detection of pneumonia more accurately.

Deep learning (DL) is a technique of extracting patterns from data through an artificial neural network (ANN) with a large number of interconnected units in order to perform real world complex tasks especially related to images [4]. Sometimes, the deep learning based systems perform better than human in term of accuracy in pattern recognition. The deep learning is chosen as a very natural application in the field of medical radiology as the diagnosis process as it relies on extracting useful information from images. The use of deep learning in CS paradigm ensures convergence bounds for the recovery of a signal in an underdetermined system [5]. An underdetermined system, instead of following the Nyquist sampling theorem, enables signal acquisition process by reducing the required sample size with significantly higher order [5]–[7]. Hence, the combining effect of DL with the CS leads to faster signal acquisition along with a guaranteed improvement in diagnosis accuracy.

The rest of the paper is organized as follows: a brief review on state-of-the-art methods and scope of the present work are reported in Section II. The proposed system model using DL framework for CS image reconstruction and pneumonia detection is described in Section III. Section IV presents the simulation results and performance evaluation. Finally, conclusions and scope of the future works are stated in Section V.

II. Literature Review and Scope of Present Work

This section presents a brief review on the related works and describes the scope and contributions of the present work.

A. Literature Review

Over the last decade, several machine learning based automated methods for identifying different types of pneumonia have been widely studied [8]–[11]. Fiszman et al [8] used a natural language processing (NLP) tool to identify acute bacterial pneumonia-related disease in chest X-ray. Performance of this type of resource intensive application is very much comparable to that of the human expert. Chapman et al [9] demonstrated three computerized methods using a rule base, a probabilistic Bayesian network, and a decision tree to diagnose the chest X-ray report associated with acute bacterial pneumonia. In [10], a study of feasibility of an NLP-based monitoring system is done to identify healthcare-associated pneumonia in neonates. However, practical clinical applications of these types of methods are limited due to the dependency on the information extracted from the narrative reports of the patients. Parveen et al [12] reports an unsupervised fuzzy c-means classification learning algorithm to detect pneumonia infected X-ray images. This approach improves classification accuracy as fuzzy c-means allocate weights to all the pixels of the input X-ray images. Rajpurkar et al [11] demonstrated ChexNet, a 121-layer deep convolutional neural network (CNN), that provides the probability of detecting or identifying pneumonia using a heatmap to localize the area of the infection. Kermany et al. [13] introduced a transfer learning based DL framework to diagnose pediatric pneumonia using chest X-ray images. However, none of the methods are exploited to classify X-ray images with pneumonia for the CS framework to meet the need of remote end analysis.

B. Scope and Contributions of Present Work

An accurate reconstruction followed by classification algorithm plays a very important role in developing an application specific medical imaging system to diagnose a disease reliably. An image classification system operated under CS framework needs to extract the most useful features from the observations for accurate classification and also to address an ill-posed inverse problem to reconstruct the X-ray image. Therefore, it is very much essential to develop a robust method which can be easily implemented in a low cost X-ray imaging system to detect pneumonia more accurately. To this aim, this paper suggests a DL based CS framework with the following contributions:

- A multi-layer convolutional neural network (CNN) is used to extract features from CS measurements for classifying the X-ray images of pneumonia patient.
- A sub-channel is used to provide the reconstructed X-ray image which helps to verify manually whether pneumonia is present or not.
- Extensive simulation results show that the proposed approach can classify the pneumonia infected X-ray images with 97.34% prediction accuracy.

III. Proposed System Model

This section presents the proposed system model using DL framework for CS image reconstruction and pneumonia detection. In CS, a sparse signal $x \in \Re^N$ is recovered from a measurement vector $y \in \Re^M$ (where $M << N$). Mathematically, the measurement vector can be represented using the following equation

$$y = \Phi x + \eta \tag{1}$$

where $\Phi \in \Re^{M \times N}$ is a linear operator called as sensing matrix and $\eta \in \Re^N$ is the noise on the sensing signal.

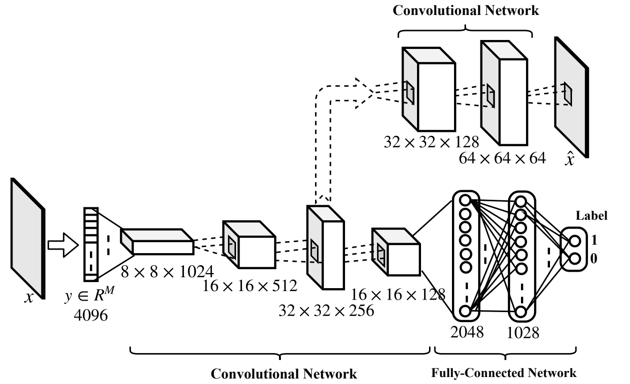

Fig. 1: Proposed CS based DL model for pneumonia detection and reconstruction of the X-ray images

A. CS Image Reconstruction Model

The image reconstruction is considered as an inverse problem which seeks an estimation $\hat{x}$ of the image by minimizing the following objective function

$$\hat{x} = \arg\min_{x \in S} \parallel \Phi x - y \parallel_2^2 + \lambda\varphi(x) \tag{2}$$

where S is a convex set, $\lambda > 0$ trade offs the weights between the terms in the objective function and φ is a regularization parameter.

The objective function in Equation 2 can be equivalently learned by a CNN through updating weights W using proximal (or projected) gradient descent [5].

$$\hat{x}^n = Q\Big(R\big(\hat{x}^{n-1}; \Phi, y, \varrho\big)\Big) \tag{3}$$

where, Q is defined as a quasi-projection operator onto the set of artifact-free images, n is the iteration number and α is the step size. The $C\big(\hat{x}^{(n)}\big)$ denotes the cost function which is defined as a reconstruction operator $R\Big(x; \Phi, y, \varrho\Big)$ to learn Equation 2 by the CNN. The ϱ is a set of parameters for the reconstruction method.

B. The classification Model

A simple multi-layer network, with 4 convolutional and 3 fully connected layers as hidden layers, is used to detect pneumonia for the CS framework as shown in Figure 1. To introduce non-linearity in the network, all the hidden layers use leaky Rectified linear unit (ReLU) activation function that has a non-zero gradient over its entire domain. The leaky ReLu (LReLU) activation function is defined as

$$f_{lR}(y) = \begin{cases} y & if\ y > 0 \\ 0.001y & otherwise \end{cases}$$

As shown in Figure 1, after reshaping the input measurement vector y, $2-d$ convolutional followed by up-sampling operations are performed to reconstruct the X-ray image. The last three layers are added as fully connected network for classifying the input with an appropriate label. The output layer uses a sigmoid function with 2 units (one for pneumonia and another one for normal) as defined follows:

$$f_S(y) = \frac{1}{1 + e^{-\Theta^T} y}$$

where, Θ denotes parameters of the model, defined as the weight matrices W and bias vectors b.

Now, the output of the final layer can be expressed mathematically as

$$f(y;\Theta) = f_S\Big(W^{h_F} f_{lR}\big(W^{h_F-1}y + b^{h_F-1}\big) + b^{h_F}\Big) \quad (4)$$

The output of the final layer can be defined as categorical probability distribution:

$$f(y)_c = \hat{p}(L_o = c|y)$$

where L_o denotes the output label and $c \in \{0, 1\}$ is one of the 2 output classes.

The parameters of the network is trained by minimizing the cross-entropy (negative log-likelihood) shown in Equation 5 between the models output and the target distribution using stochastic gradient descent (SGD) on mini-batches.

$$L\Big(f(y); L_o\Big) = -\sum_{c=0}^{1} \log f(y)_c = -\log f(y)_{L_o} \quad (5)$$

IV. Simulation Results and Discussion

This section illustrates performance of the proposed approach in term of prediction accuracy of the pneumonia. The performance of the reconstruction network is also evaluated on the reconstructed X-ray images in terms of quantitative analysis assessment measures like Peak-Signal-to-Noise-Ratio (PSNR) and mean Structural SIMilarity (SSIM). All the simulations presented here are carried out in Google's online cloud support tool for DL training known as Colaboratory (Colab) with 'runtime type' and 'hardware accelerator' chosen as 'Python3' and 'GPU', respectively. The KERAS 2.0.8 libraries and packages with TensorFlow 1.0 as backend are used to describe the network model in the Colab.

The data-set used for this work is obtained from Kaggle [14] which contains 5863 X-ray images (JPEG) of two categories (Pneumonia/Normal). This work uses 70% of the data-set for the training, 25% for the validation and 5% for the test purpose. All the simulations consider 25% most significant coefficients as measurements (M) captured from the discrete cosine transform (DCT) as sparsifying basis of the images.

In the proposed approach, the measurements are projected through the Inverse DCT (IDCT) operator and re-sized the images to 128 $\times$ 128 for feeding the network as shown in Figure 1. All the convolutional layers perform the convolution operations using kernels of size $5\times5\times T_S$ and stride of 1. Here, the T_s denotes the target size of the output activation maps. The subsequent layer performs pooling/upsampling using a kernel of size 2 $\times$ 2 with stride of 2. The hyper parameters used for the training of the network are mentioned with their respective values in Table I. This work uses batch normalization (BN) which ensures no activation passes too high or too low throughout the network and also adds regularization effect to reduce overfitting of the network on the training data [15].

TABLE I: Hyper Parameters used in the Training

Parameter Name	Value
Initial Learning Rate, α	0.0018
Momentum:γ, τ	0,0
Dropout Rate	0.4
Optimizer used	Gradient Descent
Layer activations	Leaky ReLu

Figure 2 shows the plot of the variation of the classification accuracy evaluated for both the training and the validation data-sets against each epoch. During the learning process, the training and the validation accuracy reach 98.82% and 99.80%, respectively after completion of 400 epochs. Variation of the MSE loss in every epoch is also studied as plotted in Figure 3 for both the training and the validation data-sets. The training and the validation loss go on reducing with the development of the learning process of the network as expected.

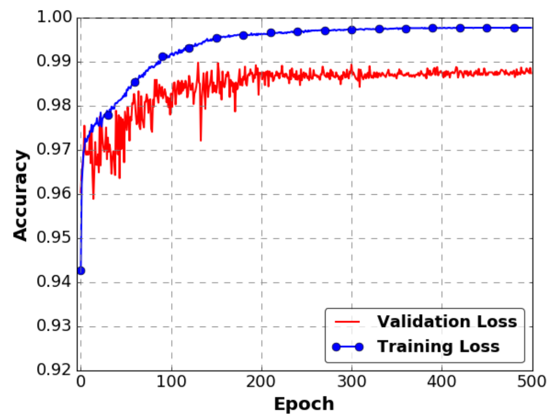

Fig. 2: Performance Evaluation of Reconstruction Network: Reconstruction Loss vs. Epoch.

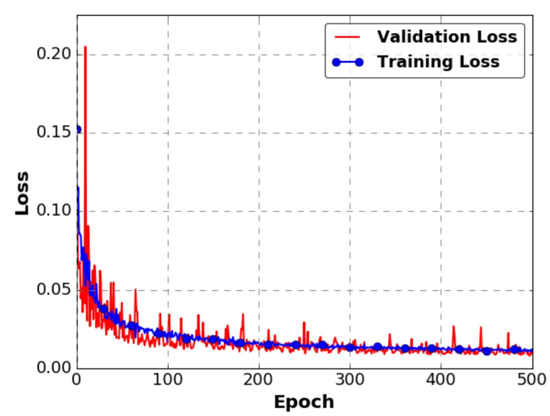

Fig. 3: Performance Evaluation of Reconstruction Network: Reconstruction Loss vs. Epoch.

Performance of the trained model is also assessed using the test data-set and compared with the existing methods like F-cMeans [12], DL [13] and ChexNet [11], in term of the prediction accuracy as reported in Table II. A study on the prediction accuracy is also performed with respect to the varying % of measurements input as shown in Figure 4. Figure 5 presents the reconstructed X-ray images using the DL-Guided CS [5], conventional CS [16] and the proposed method to compare their visual quality. The average values of the PSNR and SSIM of the reconstructed images using 25% measurements of the different test cases with respect to the full scale samples are reported in Table III.

TABLE II: Prediction Accuracy Comparison

Method Used	F-cMeans [12]	DL [13]	ChexNet [11]	PM
Prediction Accuracy (%)	85.87	91.16	95.28	97.34

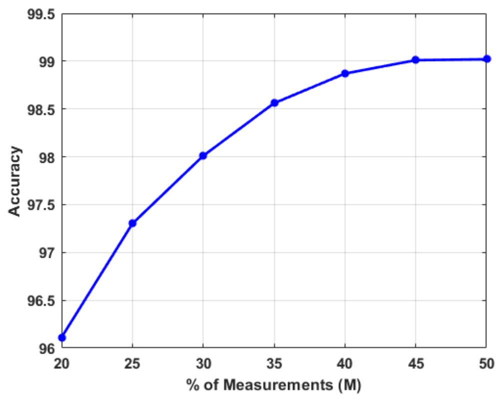

Fig. 4: Performance Evaluation: Accuracy vs. Measurement (%)

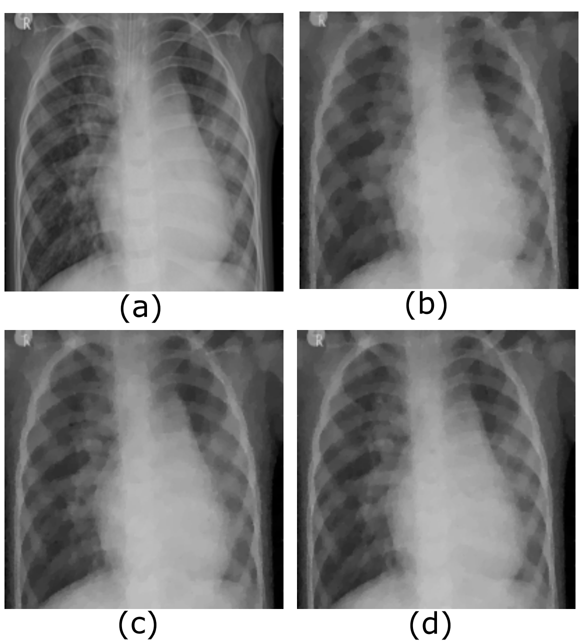

Fig. 5: Performance comparison: (a) Full scale X-ray image (b) Reconstructed X-ray image using DL-Guided CS [5] (c) Reconstructed X-ray image using conventional CS [16] (d) Reconstructed X-ray image using PM

V. Conclusions and Future works

This paper proposes an automatic computerized system for detecting pneumonia using a CS based DL model. The study shows that the use of DL in CS framework reduces the required observations for detecting pneumonia with desired accuracy compared to the conventional method. Simulation results show that the proposed CS based DL scheme offers very high prediction accuracy on X-ray images and its comparable reconstruction quality with respect to the full scale images in terms of PSNR with $28.53 \pm 2.07dB$ and SSIM with 0.92 ± 0.04.

The proposed method may be extended as a generalized automatic computerized system to assist medical professionals by localizing the region of interest (ROI) like brain tumor, cancerous cell, kidney and gallbladder stone etc.

TABLE III: Performance comparison of reconstructed X-ray images using different methods

Method Used	M (%)	PSNR (dB)	SSIM
DL-Guided CS [5]	25	26.22	0.78
Conventional CS [16]		28.77	0.88
PM		29.40	0.91

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