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Investigation of Different Pre-processing Quality Enhancement Techniques on X-ray Images

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Abstract: To maximize the accuracy of classification for medical images especially in chest- X ray, we need to improve quality of CXR images or high resolute images will be needed. Pneumonia is a lung infection caused by organism like bacteria or virus. Mostly Chest X-Ray (CXR) is used to detect the infection, but due to limitation of existing equipment, bandwidth, storage space we obtain low quality images. Spatial resolution of medical images is reduced due to image acquisition time, low radiation dose. Quality in medical images plays a major role for clinical diagnosis of disease in deep learning. There is no doubt that noise, low resolution and annotations in chest images are major constraint to the performance of deep learning. Researchers used famous image enhancement algorithms: Histogram equalization (HE), Contrast-limited Adaptive Histogram Equalization (CLAHE), De-noising, Discrete Wavelet Transform (DWT), Gamma Correction (GC), but it is still a challenging task to improve features in images. Computer vision and Super resolution are growing fields of deep learning. Super resolution is also feasible for mono chromatic medical images, which improve the region of interest. Multiple low-resolution images mix with high resolution and then reconstruct a target input image to high quality image by using Super Convolution Neural Network (SRCNN). The objective evaluation based on pixel difference-based PSNR and Human visual system SSIM metric are used for quality measurement. In this study we achieve effective value of PSNR (40 to 43 dB) by considering 30 images of different category (normal, viral or bacterial pneumonia) and SSIM value varies from 97% to 98%. The experiment shows that image quality of CXR is increased by SRCNN, and then high qualitative images will be used for further classification, so that significant parameter of accuracy will be finding in diagnosis of disease in deep learning.

Keywords: Chest X-ray (CXR) Contrast-limited Adaptive Histogram Equalization (CLAHE), Deep Learning, Convolution Neural Network (CNN)

I. INTRODUCTION

Pneumonia is a lung infection caused by organism like bacteria or virus. Due to hardware, bandwidth, storage space limitation, we obtain low quality images. Actual dimension of normal X-ray image is difficult to process, so images reduced to optimal size while conserve information in it. Due to noise and compression techniques transmitted images degrade their quality and resolution to minimize memory space. Due to equipment, patient posture, involuntary movements and density of tissue also affect the quality. Hard structure of tissue absorbs more rays and appear whiter, soft tissue absorb less rays and appear darker. Major factors that affect the X-ray image quality are:

- *Contrast:* Contrasts of X-ray images are directly depend on density and tissue thickness. And contrast is generated by different attenuation of X-ray by different tissues. X-ray attenuation is least in air and highest in bones and soft tissue. Contrast can be adjust or modify by using post processing techniques where pixel value is modified to expected range of contrast.
- *Noise:* Noise is structured or random variation with in an image that does not correspond to X-ray attenuation variation of the object.
- *Signal to noise Ratio (SNR):* Higher the signal and lower the noise, produce better image quality. And image with higher SNR allow the recognition of smaller and lower contrast structure.
- *Blurring*: X-ray images may be blurred due to less radiation dose, due to breathing problem or heartbeat problem patient posture is not appropriate.
- *Artifacts:* Error or Distortion in an image and some unrelated is known as artifacts. Means poor image quality due to factor like unequal magnification

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(a) Low quality CXR image

Fig 1: (b) High quality CXR images

A. Need for pre-processing technique

In figure 1, the dataset which is use in this study has combination of low and high quality images, publically available dataset. The objective of pre-processing is an improvement on undesired distortion or make internal structure more visible so that relevant features highlighted for further processing. In medical health system, image enhancement plays an important role because de-blurring, filtering and sharpening image features like edge contrast or boundaries to make accuracy in correct diagnosis and consumption of time reduces significantly. Performance like classification accuracy of deep learning model depends on the nature and quality of dataset used during training. Access to big dataset of medical images considered good factor, as well as small, multi feature, proper labeling and well annotation are also desirable. In medical image analysis, other factor like color, contrast, shape position, size, edges, resolution and appearance also affect the quality. But researchers used augmentation (scaling, rotation, cropping) techniques to increase size of dataset, but still problem of over fitting and not obtained desired result. So now researchers used different techniques to increase the region of interest. Good quality of medical images is highly challenging task in deep learning. In this study we discussed some popular image enhancement techniques used by different researchers. We applied super resolution convolution neural network to increase quality of chest X-ray and compare with PSNR value with other and find effective value.

II. DIFFERENT TECHNIQUES FOR IMAGE ENHANCEMENT

Famous and widely used Image Enhancement Methods: 1) Histogram Equalization 2) Filters 3) Discrete Wavelet Transform 4) Gamma Correction

A. Histogram Equalization

This is very popular and common technique used for image enhancement, based on pixel brightness transformation. Histogram is representation of frequency distribution and based on spatial domain processing. Contrast is defined as difference in intensity between two objects in an image. Equalization means distributed each grey level with equal probability. To make image more clearly, it re-distribute grey level with histogram transformation function. This function represent intensity of image in range [0, L-1] with $h(r_k) = n_k$ where n_k represent the pixel having intensity k^{th} intensity value (r_k) then histograms are normalized by total pixel in M by N image with

$$p\ (r_k) = n_k / M*N$$

Then chance of occurrence of k^{th} intensity level in an image. Global histogram Equalization is simple and fast technique but enhancement power is low. Whole input image is used to compute the histogram transformation function. Overall contrast is improved. Local histogram Equalization enhance overall contrast but drawback is that it can change mean brightness of an image significantly as a consequence of histogram flattening and this is not a desired property in some cases.

Contrast Limited Adaptive Histogram Equalization (CLAHE) is updated version of local and global histogram equalization technique and it provides solution of lost information due to over brightness. Adaptive histogram equalization divides the image into small block (tiles), instead of whole image, and then each block is histogram equalized. It consist two phases, in first phase log normalization function is used on input image to adjust the intensity level, then in 2^{nd} phase enhance the small details, local contrast and texture. Some researchers also focused on improved version of histogram equalization like Bi-Histogram Equalization (BHE)

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which was invented to overcome the brightness preservation problem. In this method input histogram divided in two parts, in the first part equalized independently and in the second part criteria used to choose the threshold for separation denoted by $X_{t..}$ Dynamic Histogram Equalization (DHE) employed a partition operation on the input histogram to chop it into sub-histogram so that no dominating component. Multi-Histogram Equalization (MHE) enhances brightness and contrast with a natural look. Gray Scale and RGB Histogram Equalization (GRHE) are also advance histogram equalization techniques.

Related Work: Sarkar et al. [1], proposed a novel method using CLAHE to aid the detection of pneumonia clouds in X-ray images, with deep residual learning with obtained Classification accuracy 98.288% and AUROC score is 0.99726. Hussein et al. [2], proposed hybrid architecture of CLAHE and deep convolution network for lung disease, and result increased to 91% after hybrid method, but still need improvement. Sharma et al.[3] analyzed different advanced pre-processing image enhancement techniques (TVF, GC, CLAHE, Gaussian) based on deep learning architecture that was applied on 4 public CXR datasets with 10 popular CN network model. Result belongs to CLAHE having accuracy level 92.80, Sensitivity=92.80, Precision= 92.92, F1 score = 92.76. And concluded that mixed pre-processing method are better than single method. Nefoussi et al. [4] proposed various values of clip limit like 1.5, 2.0, 4.0, and 150.0 tested on balanced and imbalanced datasets of CXR images and obtained Imbalanced dataset accuracy (0.97) higher than balanced dataset (0.95). Recall 0.90 is the best value in histogram equalization. But result still needs improvement.

B. Filters

X-ray images are used to observe internal organs of the human body. Main drawback of X-ray images are poor contrast, low resolution and various types of noises like Gaussian, speckle noise and passion noise. Main cause of low quality and noises in X-ray images are intensity of X-ray beam, structure of tissue, hardware and other factors. In x-ray images very important factor is that how much time the patient is exposed to the x-rays and how much dose of x-ray is given to patient. If dose of X-ray is high then noise level of the image will be very low, but meantime it is dangerous for patient. Sometime noise automatic produce inside image due to architecture of machine, which is used to capture image. Noise represents unwanted information which destroys the quality of image. This is the factor which tends to produce variation in displayed image. Noise removal has to be performed by using suitable filters, this process is called de-noising. The intensity of pixel and image's quality enhanced after de-noising and quality of an image is improved now. A good image de-noising model is that, which completely remove noise and preserve edge in an image. Models are of two types, linear models which are good in speed but not able to preserve edges and sometime add blurring to the image. Non-linear models which can handle edges in better way but take more processing time for e.g. Total variation (TV) filter, Which remove noise and preserve edge in an image. Models are of two types, linear models which are good in speed but not able to preserve edges and sometime add blurring to the image. Non-linear models which can handle edges in better way but take more processing time for e.g. Total variation (TV) filter.

Poisson Noise: This type of noise is an electronic noise which is a form of ambiguity related with the quantity of the light. This occurs in an image when the limited number of particles that carry energy, such as electrons which are small enough to give rise to measurable variations. Also known as photon noise or shot noise. It is an undesirable signal which gets added in desired signal at the time of acquisition. Consider a light combination of photons coming out of a source and striking a point which creates a evident spot, the physical process which governs the light emission are such that those photons which are emitted from the light source hits the point many times but to create visible spot billions of photons are needed. However, if the source is not able to emit required number of photons which hits the point every second then this noise is caused.

Gaussian Noise: Gaussian distribution which is also known as electronic noise as it arises due to electronic source. Normal distribution whose Probability Density Function is equal to statistical noise known as Gaussian Noise. This noise is removed from the digital images by smoothening of the image pixels which helps in reducing the intensity of the noise present in the image which is caused due to acquisition but the result may be sometime undesirable and also which can result in blurring edges of the high-quality images.

Blurred noise: Blurred Noise is caused due to the light intensity and external factors. Capturing images under low light conditions create blurred or noise in an image. Often these kinds of images containing hazy and blurred pixels are referred to as Blurred. Noise which is present in the image hazy and blurred pixels are referred to as Blurred Noise which is present in the image.

Speckle noise: Speckle noise is a granular noise that inherently exists in and degrades the quality of the active radar and Synthetic Aperture Radar (SAR) images. Speckle noise in conventional radar results from random fluctuations in the return signal from an object that is no bigger than a single image-processing element. It increases the mean grey level of a local area. Speckle noise in SAR is generally more serious and causing difficulties for image interpretation.

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Filtering approach means replacing each pixel's intensity value with a new value. The images which are often corrupted by random variations in intensity and illumination should be passed to the filters [5]. Filters transform the pixel's intensity values to reveal certain image characteristics like enhancement and smoothing. Filters remove some frequencies and also reduce background noise [3]. Following filtering methods are considered to remove noise present in X-ray images.

Median filter: It is commonly used filter to remove noise from an image or signal which is widely used for a specific reason. It is non linear filtering method so preserves edges while removing noise. Mainly median filter is used in signal processing and time series processing. It is very popular technique for removal of impulse noise because it works through the signal cell by cell and replace value of each cell with median intensity level with mathematical accuracy.

Wiener filter: The goal of the Wiener filter is to filter out noise that corrupt a signal. It is based on statistical approach to remove noise from each pixel of an image. The Wiener filter is linear filter based on frequency domain. One is assumed to have knowledge of the spectral properties of the original signal and the noise. One seeks the LTI filter whose output would come as close to the original signal as possible present in the image. It removes the blurring and noise present in the image and it also depends on minimum mean square error. Although it gives good result but computational time is slower due to transformation in frequency domain.

Gaussian filter: Gaussian filter is used to remove speckle noise, caused due to internal and external factors. In this technique, average value of the surrounding pixel or neighboring pixel replaces the noisy pixel present in the image based on Gaussian distribution.

Bilateral filter: Bilateral filter is non-linear method to smooth image while preserving edges to increase quality of image. It is easy to calculate and each pixel is replaced by weighted average of its neighbors. It preserves size and contrast feature in an image.

Related work: Farhan. [6] Proposed novel framework HDLA (Hybrid deep learning Algorithm) for classification of chest X-ray. Author improved quality of chest X-ray using different filtering techniques with minimum data loss. Wiener filter show better outcome as compared to others based on quality metric PSNR, SSIM, and RMSE. Proposed model improves the overall accuracy by 3.1 % and reduce computational complexity by 16.9 %. Gielczyk et al. [7] author tested different pre-processing techniques and their effects on the final classification. Bilateral and Gaussian blur methods are used to reduce noise and unwanted details that are confusing for neural network, but main feature is to preserve edges. Mix pre-processing and adaptive masking with Gaussian blurs and histogram equalization perform better result than other techniques. ACC= 98.31, Precision = 97.47, Recall = 97.46, F1 score= 97.47. Heidari et al. [8] author applied two images pre-processing step to remove majority of diaphragm and process the CXR image using HE algorithm. Then a bilateral low pass filter. Then proceed images are used to form pseudo color image and fed into CNN. CNN based CAD (Computer aided design) achieve overall accuracy of 94.5 % with 95% confidence interval in classifying three classes and achieved Sensitivity= 98.4% , specificity = 98.0. Kirti et al. [9] focused on reduction of Poisson noise which is present in X-ray images. In this modified Harris corner point detector which is used to predict noisy pixel and find response matrix for noisy image. Also identify region of interest and non interest, then apply median filter in spatial domain. Simple noise prediction mechanism and give good visual quality and less execution time, but still need accuracy improvement.

C. Discrete Wavelet Transform

Traditional method like histogram, CLAHE improves the brightness and contrast of the image, but ability to enhance image's details is low. Now aim of researchers is to how effectively reduce the noise amplification and over contrast problem faced by different enhancing algorithms. With increasing demand of de-noised images, it is still a challenge for researchers to develop an efficient algorithm. Noise in X-ray images is from multisource and mainly from photon production. Wavelets transform are a mathematical tools which are used to extract the information from image. Wavelets are localized in both time and frequency, so now it is widely used in image retrieval, medical imaging, and image compression. For de-noising medical images, orthogonal wavelets played a dominant role. Wavelets represent an image as a sum of wavelet function with different location and scale. An image decomposed into high frequency wavelets which represent detailed part called wavelet function, and with low frequency represent smooth part called scaling function. When an image is decomposed using wavelet transform, it produce four sub images, horizontal details, vertical details, approximation details and diagonal details in which small coefficient raise due to noise and large coefficient generated due to signal feature.

Related Work: Wen et al. [10] author proposed an image enhancement algorithm which is based on wavelet domain homomorphic filtering and CLAHE. Firstly, an image is decomposed by wavelet transformation; then decomposed into low frequency and high frequency coefficient of 1st layer of wavelet domain. Low frequency coefficients are processed by a homomorphic filter, and then linear amplified. High frequency coefficient is processed by the wavelet threshold shrinkage and then the wavelet reconstruction is performed. The proposed method effectively enhances the texture, increasing the

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brightness and contrast, suppress the noise and obtained MSE= 4.85E+3, PSNR= 25.96, Entropy= 7.88. Liu et al. [11] proposed an algorithm which is based on Shannon-cosine wavelets; a multi-scale interpolation wavelet operator is constructed to divide the image into sub-images from high frequency to low frequency. And perform different multi-scale wavelet transform on the detailed image of each channel. Through visual comparison, it is shown that algorithm achieves better result than traditional algorithms. PSNR =36.9548 is great advantage of this study.

Georgieva et al. [12] analyzed image enhancement which is based on CLAHE following by morphological processing and noise reduction, based on wavelet packet decomposition and adaptive threshold of wavelet coefficient in high frequency sub-bands of the shrinkage decomposition. Visual quality improved, PSNR=29.815, enhanced X-ray images can be used for better visualization in 3D reconstitution. Deeba et al. [13] proposed a wavelet-based mini-grid network medical image super resolution (WMSR). Author used SWT instead of DWT. It is possible to retain additional information and high resolution of an image. For training, wavelet sub-based image combined into predefined full-scale factor. Different scale factors are used in this study, the mapping between the wavelets sub-band image and its approximation is then determined. SSIM index is used to compare four medical images, in case of chest X-ray SSIM= 30.01, with scale factor 2.

D. Gamma Correction (GC)

Gamma correction performs a non-linear operation on source image pixels. Gamma correction alternates the pixel value to improve the image using the projection relationship between the value of the pixel and the value of the gamma according to the internal map. Gamma correction is a technique used to compensate for the non-linear display characteristics of a device. Gamma correction is achieved by mapping the input values through a correction function. Decreasing Gamma makes dark areas lighter and light areas darker. Increasing Gamma makes dark areas darker and light areas lighter. It's more in to contrast than anything. Brightness decreases the range of lightness without changing the starting dark point. Gamma is defined by $V_{out} = V_{in}^{gamma}$ where V_{out}t is the output luminance value and V_{in} is the input/actual luminance value.

Related work: Rahman et.al. [14] Introduced five different image enhancing techniques, Histogram Equalization (HE), CLAHE, Image complement, Gamma Correction (GC), Balance Contrast enhancement Technique (BCET) ON Covid-19 CXR images dataset. A novel U-Net model was proposed and compared with standard U-Net model for lung segmentation. Gamma correction based enhancement technique perform better than other technique, accuracy=95.11%, precision=94.55%, sensitivity=94.56%, F1-score =94.53, specificity = 95.59%. Omarova et al. [15] Presented adaptive method on 1000 images from kaggle database. To obtain better result, before apply gamma correction, equalized the histogram of X-ray images. Proposed method provides noticeable effect on contrast in X-ray images. Objective metric NIQE and BRISQUE which do not required reference image to measure quality of images. NIQE score correlate better with visual assessment of image. Author recommendation is that choosing the proper parameter of gamma correction and histogram equalization makes contrast well without the intensification of noise in the image.

Conclusion: In this paper we studied different pre-processing image enhancement techniques. Mostly studies focused on brightness, contrast, saturation and sharpness (related to edges). Researchers focused on different techniques such as pixel-difference, edge detection, correlation for image enhancement, CLAHE algorithm improves contrast and preserve brightness and widely used by researchers for medical images. Gamma correction algorithms show very poor result in case of CXR imaging system. De-noising techniques with combination of various type of filter is very common choice and better result for increasing region of interest. But most of studies suggest that combination of two or more techniques gives better result as compare to single technique. CLAHE method with combination of other method is widely used by researchers to improve medical images, and suggest better method to all above. Sharma et.al.[3] also proposed a study In which various techniques (HE, CLAHE, Gamma, TVF, AMF) are compared with different neural network, and gave advice that single method is not enough to get good result, so author focus on an advance pre-processing technique. M. Sharma et al. [20] Proposed a study in which CLAHE method is used and compare with combination like morphological operation, median filter, and discrete cosine transform (DCT), discrete wavelet transform (DWT) and find that CLAHE + DWT is better than other and obtained 29.62 value of PSNR. Evaluation parameter Peak Signal to Noise Ratio (PSNR) is use to describe the quality assessment. In this study we also compare our proposed technique with CLAHE with PSNR as a metric assessment.

III. SUPER RESOLUTION CONVOLUTION NEURAL NETWORK (SRCNN)

As we know that computer vision and super resolution is growing field of deep learning. SRCNN, which is emerging deep-learning based super resolution method, has been proposed in computer vision. Dong et al. [16] developed a super resolution convolution neural network (SRCNN) in which SR achieved with higher accuracy than previous method. At present three types of super resolution methods are widely used.

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Based on interpolation: this method uses nearest neighbour, bicubic and bilinear. In this process, using known discrete sample points to estimate unknown intermediate values.

Reconstruction: this method uses high-frequency information from multi-frame low resolution images and combined them to generate high resolution. It is difficult to generate accuracy in this method.

Learning: deep learning widely used in computer vision. SRCNN uses three-layer structure in which feature of images are extracted and reconstructed.

- *Features of SRCNN*

SRCNN (Three -layer fully convolution NN): we can give any input size and run on it. SRCNN has training and testing phase, some dataset is used for training.

1) We train the filters, not for accuracy: in this method, our focus on filter learning by SRCNN, which enable to upscale an image.
2) Not to optimize a loss function: After a SRCNN has learned a set of filters, it can be applied as feed forward pass to obtain the super resolution image.
3) Totally end-to-end: input an image to network and obtain the higher resolution output

- *Working of SRCNN*

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With low resolution image, firstly upscale it to the desired size using bi-cubic interpolation (convolution operation), consider it Y. then to achieve F(Y) from Y which is same as input image but high-resolution image. It consists three main operations.

(i) Patch extraction and Representation: In this operation, extract patches from low resolution image and represent each patch is a high dimensional vector, which is considered set of feature maps. In First layer operation is expressed as

$$F_1(Y) = \max(0, W_1 * Y + B_1)$$

Where W_1, B_1 shows filters and biases and * shows convolution operation. W_1 corresponds to n_1 filters with $c \times f_1 \times f_1$, where f_1 is spatial size of a filter. Output is composed n_1 feature maps.

(ii)Non-linear mapping: In first layer, extract n_1 dimensional features for each patch. In second layer map each of n_1 dimensional into n_2 dimensional. Operation in second layer is

$$F_2(Y) = \max(0, W_2 * F_1(Y) + B_2)$$

Where W_2 contains n_2 filters size $n_1 \times f_2 \times f_2$ and B_2 is n_2 dimensional. Output is representation of a high-resolution patch, which is used for reconstruction.

(iii)Reconstruction: The predicated overlapping high-resolution patches are averaged to produce final image. Operation in third layer is

$$F(Y) = W_3 * F_2(Y) + B_3$$

Where w_3 corresponds to c filters of size $n_2 * f_3 * f_3$, B_3 is dimensional vector

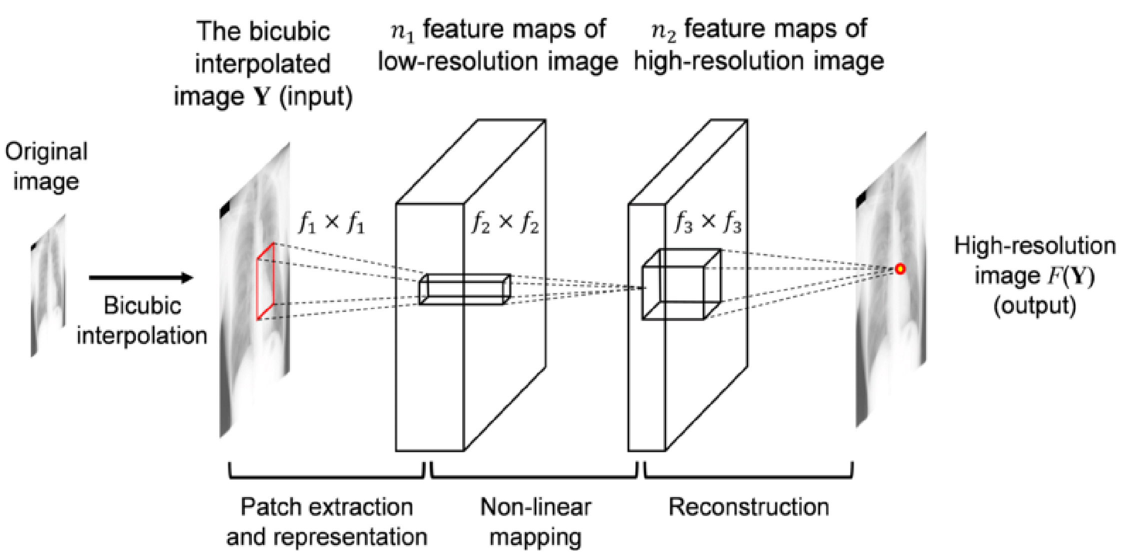

Figure 2: Super Resolution Convolution neural network

In order to translate low resolution inputs to higher resolution outputs, our SRCNN aims to train a collection of filters. The model creates two sets of images patches rather than actual full resolution images.

(i)A low-resolution patch that will be the input to the network
(ii) A high-resolution patch that will be the target for the network to predict/reconstruct.

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Dataset Description: A Kaggle repository Kermany et. al[17] is used in this study, It was collected and labeled pediatric CXRs from the Guangzhou Women and Children Medical Centre(Ghuangzhou, China) which contain 5,856 CXR images from pediatric patient aged 1-5 years, 4273 pneumonia images(2,780 bacterial and 1,493 viral) and 1583 normal images. These images are distributed in 8 bit grayscale images scaled in various resolutions such as 1040 ×664, 1224 ×1000 and 1848 × 1632 pixels.

Table 1 showing the description of images in term of training and testing with normal and pneumonia images along with size of image and storage parameters.

Table 1. DESCRIPTION OF IMAGES

Partition	Class	No. of Images	Size of images (Range)	Storage
Training	Normal	1341	(992 × 816) to(2916 × 2583)	(135.7 KB) to (2.3 MB)
	Pneumonia	3875	(400 × 138) to (2160 × 2304)	(5.3 KB) to (508.7 KB)
Testing	Normal	234	(984 × 496) to (2720 × 2458)	(45.1 KB) to(668.5 KB)
	Pneumonia	390	(744 × 424) to (2000 × 1456)	(21.6 KB) to(240.3 KB)

(a)Need to build a dataset of low- and high-resolution input patches

(b)Train a network to map the low-resolution patches to their high-resolution counterparts.

(c)Create a script that utilize loops over the input patches of low-resolution images, passes them through the network and then creates the output high resolution image from the predicted patches.

The successful training on high quality images is the main characteristic of deep learning system but publicly available dataset has limitation of quality due to many factors. As we see in above table Kermany dataset consist large variation in image dimension, it directly affects the quality of images. So SRCNN is a strategy that builds high-resolution images from low resolution for enhancing ROI. In this experiment we select 30 images (low resolution to high resolution) of normal and pneumonic images. Main goal is to analyze how this technique improves the quality (resolution) of X-ray images

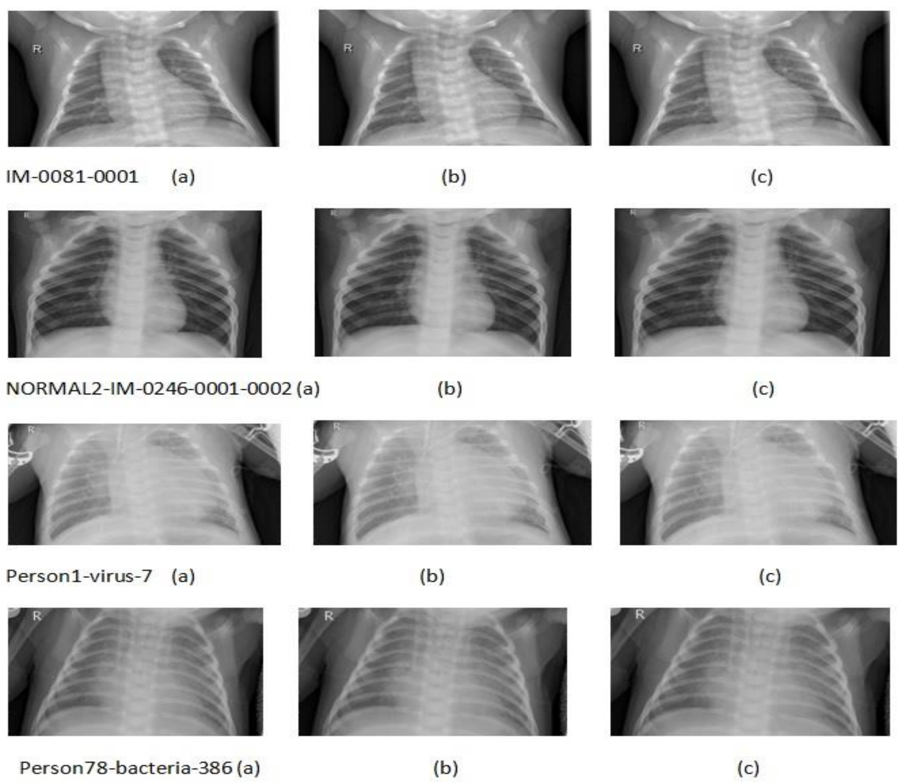


Figure 3: SRCNN three-layer structure (a) original image (input) (b) intermediate image (baseline) (c) high resolute image (output)

IV. IAMGE QUALITY ASSESMENT

Image quality assessment is considered as characteristic of an image. Subjective and objective, two methods are used for evaluation. Subjective method is costly, time consuming, expensive and need number of observations. Objective method use algorithms to assess quality of image, Quality assessment divided into mainly in two types 1) full Reference (FR), where a perfect reference (ground truth) image is available for comparison with test image. 2) No Reference (NR), where no information regarding reference image is available for assessment. PSNR and SSIM are widely used metric for quality assessment. PSNR are based on pixel difference measurement; SSIM and UIQI are based on human visual based measurement.

MSE (Mean Squared Error): This is most common and widely used FR-IQA method, which is calculated by squared intensity difference of distorted and reference image pixels and then averaging them. Values come near to zero, are better output.

$$MSE = \frac{\sum (y_i - \hat{y}_i)^2}{n}$$

PSNR (Peak Signal-to-Noise Ratio): This is used to calculate the ratio between maximum possible signal power and the power of distorting noise which affects the quality. Their unit is decibel (dB), PSNR value varies from 30 to 50 dB for 8 bit representation and 60 to 80 Db for 16 bit data.

$$PSNR = 10 \text{ Log}_{10} (\text{peakval}^2) / MSE$$

Where peakval is the maximal in the image.

In 8-bit unsigned integer data type peakval is 255. Higher PSNR means less distortion.

Universal Image Quality Index: Wang [18] proposed this measure and divide the comparison of original and distorted image into three parts:

Luminance $l(x,y) = (2\ \mu_x\mu_y)/(\ \mu^2_x+\mu^2_y\ )$

Contrast $c(x,y) = (\ 2\ \sigma_x\sigma_y\ )/(\ \sigma^2_x+\sigma^2_y)$

Structural $s(x,y) = (2\sigma_x\sigma_y\ )/(\ \sigma_x+\sigma_y)$

Where μ_x μ_y represents mean value of original and distorted image, and σ_x σ_y represent standard deviation of original and distorted images, σ_x σ_y is covariance of both images.

$$UIQI(x, y) = l(x, y).c(x, y).s(x, y) = (4\mu x\mu y\mu xy) / ((\mu 2x+\mu 2y)(\sigma 2x+\sigma 2y)$$

SSIM (Structural Similarities Image Metric): SSIM is also type of FR introduced by Wang et al. [19], improved version of UIQI, where it measures similarities between perfect reference image and a test image based on luminance, contrast, and structure. The term structural information about strongly inter-dependent pixel or spatially closed pixel. Those strongly inter-dependent pixels give more information about visual object in image domain. Luminance masking is a term where distortion part of an image is less visible in the edges of an image. Contrast is term where distortions are less visible in the texture of an image. Range of SSIM varies -1 to 1, for perfect image it will be 1.

$$SSIM (x, y) = ((2\ \mu x\ \mu y + C1)\ (2\ \sigma x\ \sigma y + C2))/\ ((2\ \mu 2x\mu 2y + C1)\ (\ 2\ \sigma 2x\sigma 2y + C2))$$

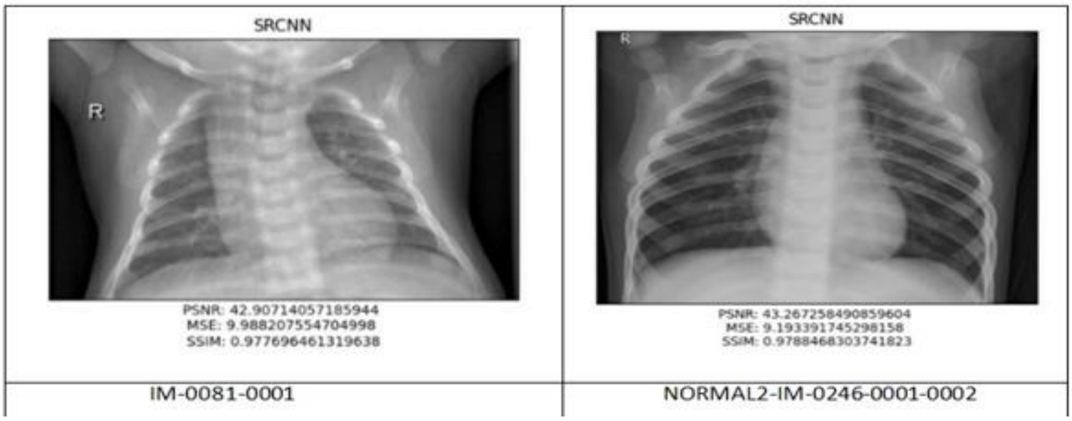
Where μx, μy, σx, σy are local means, standard deviations and cross-covariance for image.

IV. RESULT AND DISCUSSION

In this paper we discussed many methods to increase parameter as brightness, contrast, sharpness and clarity. But medical images usually require a high-level detail. In above methods, CLAHE method is considering better for X-ray images to increase clarity of images. So we also focus on resolution of an image. To achieve high ultra quality of low resolution images, neural network like SRCNN is used to reconstruct low quality images. By using SRCNN, we obtained high quality images, Table 2 has shown the result of CLAHE method and .

Table 2: Comparison of different CLAHE methods

Sr.No	Author Name	PSNR	Method
1.	Wen et.al. [10]	25.96	CLAHE with wavelet domain homomorphic
2.	Georgieva et.al. [12]	29.815	CLAHE with noise reduction based on decomposition
3.	Liu et.al. [11]	36.95	CLAHE with noise reduction
4.	Megha et.al. [20]	29.62	CLAHE with DWT



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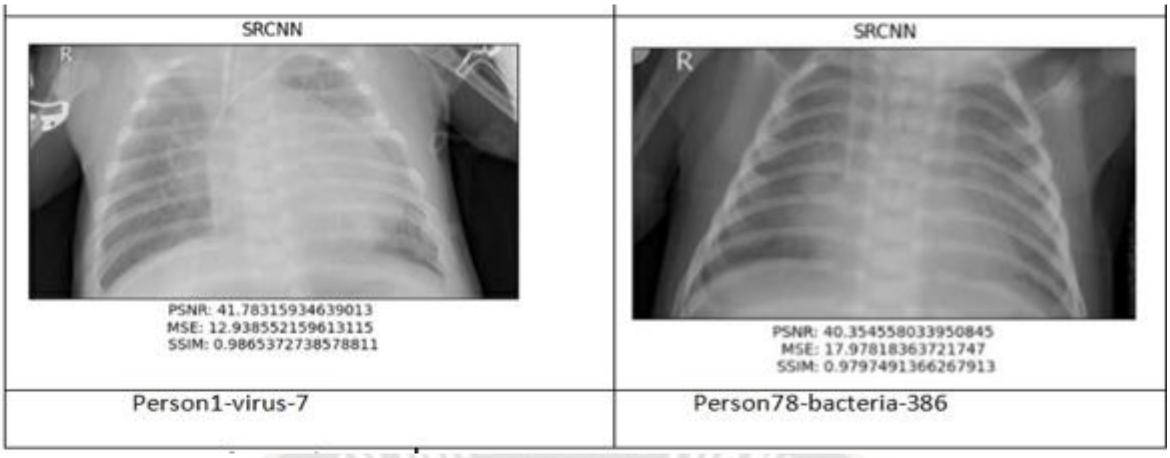

Figure 4: After applying SRCNN

After analyzing the value in table 2 and with visual observation shown in figure 4, it is clearly seen the differences of performance of super resolution. To verify the effectiveness of the proposed method, PSNR and SSIM metrics are used for quality assessment. Higher the PSNR and SSIM value, better super resolution results. SSIM uses the contrast, luminance and structure to compare the image. We achieved PSNR (41.78-43.26) and SSIM (0.9776-0.9865) for X-ray image in this study. As of the result testing, SRCNN gives better efficiency compared to others, and this is prime objective of creating superior quality of clinical images. In future these reconstruct high resolute images are used for classification of pneumonia disease in deep learning. This study gives a satisfactory help in future work for classification of

pneumonia and normal case. By using SRCNN, we can enhance quality of CXR images to find pneumonia disease in deep learning.

V. CONCLUSION

In this study, a different approach is proposed in which SRCNN is applying on X-ray images to increase the quality by increasing resolution. This experiment can be able to improve PSNR (40 to 43 DB) and SSIM (97 to 98 %), so proposed work will help in future to increase accuracy for prediction pneumonia in X-ray images using deep learning. The experiment shows that image quality of CXR is increased by SRCNN, and then high qualitative images will be used for further classification, significant parameter of accuracy will be finding in diagnosis of disease in deep learning.

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