De-blurring X-ray Radiographs using Deep Learning Approach

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***Abstract*— X-ray is the most common imaging test used by physicians for a long time. X rays are a form of electromagnetic radiation that can penetrate or pass through the human body and produce shadow-like images of internal body structure. Nearly about 100 million X-ray tests are done annually in India. Out of which a number of tests need to be redone attributed to improper or blurred imaging. Such retakes increase the cost as well as the amount of radiation entering patient's body.**

A Deep Learning based Image Deblurring System for X-rays can be an effective solution for this problem. We used a few deep learning techniques to deblur X Ray images such as SRCNN, UNET, DAE and compared the results to select the one with better results and also with the traditional deblurring techniques. Comparison metrics used are PSNR, SSIM and Validation loss. We found that Deep Learning gives better resolution compared to those with traditional methods. At last, we deployed our trained model in a Web App where blurred digital X-ray images can be deblurred.

Keywords—Deep Learning, SRCNN, DAE (Deep Auto Encoder), UNET, Image deblurring, X-ray.

I. Introduction

Medical images are of high importance as they are used for diagnosis of various severe diseases. Among all the medical imaging techniques, X-rays are the most common one. X-rays are backbone for any major diagnosis that may range from treating broken bone to complex surgeries to understand in depth problem with the part undergoing surgeries. Annually on an average 100 million X-rays are conducted in India only. But out of these almost 20% X-ray images need to be taken again due to deterioration of images due to varied reasons.

Improper setup of imaging machinery, environmental disturbance, Body movements of patients or other factors introduce blur into the X-ray image. The blurry images cannot detect the sharp edges and are insufficient for diagnosis. Due to such blurry images X-ray retakes has become a common practice. However, the amount of radiation entering a patient's body increases with each extra retake for a single purpose. If a patient gets exposed to high amounts of radiation it may lead to severe diseases such as Cancer.

In this Paper we have discussed the comparison of the results given by various deep leaning algorithms to deblur X-ray images. We trained the models such as Deep Autoencoder, Super Resolution Convolution Neural Network, UNET architecture and evaluated them using some Evaluation metrics. Besides the Neural Networks we also tried to deblur X-ray images with standard Computer Vision algorithms such as LRA (Lucy Richardson algorithm), Weiner Filter and Low Rank Prior algorithm [10]. We selected the one which provided better results to integrate it within the Web app created for X-ray image deblurring.

II. Related Work

Previously image deblurring problem has been addressed using non-linear methods such as Lucy Richardson algorithm, Wiener filter, and B-direct inverse filtering. [9] uses LRA for x-ray digital images. The algorithm works by assuming that the blurred image can be modelled as a convolution of the original image with a blurring kernel, and that the noise in the blurred image is additive and Gaussian. The goal is then to estimate the original image by reversing the convolution process. The Lucy-Richardson algorithm iteratively estimates the original image by alternating between deconvolving the blurred image with the estimated image and deconvolving the result with the blurring kernel. The algorithm continues to iterate until convergence is achieved, meaning that the difference between the estimated and blurred images is below a certain threshold.

[8] proposed Enhanced Deformable Convolutional, Networks (EDVR) for Multi-frame deblurring and is useful for images taken from smart phones. [13] uses blind deblurring Expectation Maximization (EM) deblurring algorithm for Gaussian blur which Reduces CT scan image blurring by about 24%. In another paper [3] they used Two network models based on the U-Net architecture to deblur the low-resolution PCB images but found that predicted images may suffer from unexpected artifacts when the edge-knife images, which have a much simpler structure. In one of the works [4] Ten models were trained for different levels of angular super-resolution (ASR), denoted as ASRN, where for every Nþ2 frames, the first and the last frames were submitted as inputs to super-resolve the intermediate N frames. They found that ASR technique is capable of super-resolving rotational angiographic frames at intermediate

projection angles. Apart from these [2] largely Deep Convolutional Neural Networks have been used when it comes to Image deblurring with Deep Learning. However, we found that the area of applications of Deep Learning algorithms to remove blur from medical images is not explored much compared to general image deblurring. This is due to the fact that medical images such as X-ray are very crucial in the medical diagnosis hence, they have to be crystal clear sharp for their effective use. This criticality leads to the retakes of X-rays to understand the anomalies clearly that may not be possible with blurred images. However, we tried to recover the sharpness of edges in X-ray images using various Deep Learning algorithms which have been previously applied for other image deblurring tasks in order to check their usability, effectiveness, and accuracy in generating sharp images for blurred X-rays radiographs.

III. DATASET

The data required to train the model for image deblurring is the blurred X-ray images. Since we are focusing on medical X-ray images, we required X-ray samples of a particular. We choose to use Chest X-ray radiographs. The particular dataset used consists of the images of chest X-rays diagnosed as Pneumonia stored in .jpeg format. All these images are sharp and perfect for making diagnosis. But we need the pairs of Sharp and corresponding blurred image to effectively train the model. We couldn't find such dataset for Medical X-ray images.

To get the pairs of Blurred and corresponding sharp X-ray image, we considered to introduce the blur in the sharp image to create blurred samples of available sharp images. We particularly added Gaussian Blur to the images with Kernal size that gave satisfactory blur which may represent the real-world blur introduced due to a number of external factors.

In Gaussian blur, an image is convolved with a kernel that has a Gaussian distribution. This kernel is a two-dimensional array of values that determines how much each pixel in the image is affected by its neighboring pixels. The values in the kernel are weighted according to the Gaussian distribution, with the highest weight given to the central pixel and the weights decreasing as the distance from the central pixel increases.

Since the dimensions of images are of varying types, we needed to have images with uniform dimensions we defined a transform to be applied before the data goes in training process. The dimensions defined were 224 x 224 pixels. We came to the figure from the literature survey conducted [1] which gives good results when trained using deep learning for image processing tasks.

IV. METHODOLOGY

In the data preprocessing stage, we created blurred images from the sharp one. Hence, we had pairs of sharp X-ray images which is gong to act as ground truth and corresponding blurred images which we wish to deblur. Sharp images act as Label for Blur image Train test split was defined in 4:1 ratio.

A. SRCNN

The architecture of the network consists of three convolutional layers with ReLU (Rectified Linear Unit) activation functions and different kernel sizes and number of output channels. The input to the network is a 3-channel image (e.g., an RGB image), and the output is a 3-channel deblurred image [27].

The specific details of the architecture are as follows:

The first convolutional layer has 64 output channels, a kernel size of 9x9, and a padding of 2 pixels. This layer applies 64 different filters to the input image, each with a receptive field of 9x9 pixels, to extract various features and patterns from the image. The second convolutional layer has 32 output channels, a kernel size of 1x1, and a padding of 2 pixels. This layer applies 32 filters to the output of the first layer, which helps to reduce the number of channels and capture more abstract features. The third convolutional layer has 3 output channels, a kernel size of 5x5, and a padding of 2 pixels. This layer applies 3 filters to the output of the second layer, which produces the final deblurred image with 3 channels (e.g., RGB). The forward method of the network applies each of these layers in sequence to the input image x, using the ReLU (Rectified Linear Unit) activation function to introduce nonlinearity between layers. The ReLU activation function returns the input if it is positive, and zero if it is negative. The mathematical expression for ReLU is:

$$f(x) = \max(0, x)$$

Finally, the output of the third layer is returned as the deblurred image.

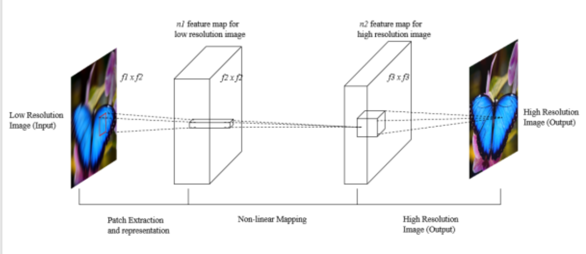

Fig. 1. SRCNN Architecture[27]

Algorithm:

1. Define the network architecture0
2. Define the input and output of the network
3. Implement the forward method of the network
4. Train the network
5. Evaluate the performance of the network

B. DAE

The encoder architecture consists of a series of convolutional layers with increasing number of filters and decreasing size of feature maps, followed by two fully connected layers that produce the mean and variance of the Gaussian distribution from which the latent vector is sampled. The encoder is trained to minimize the KL-divergence between the latent distribution and a standard Gaussian distribution, while also minimizing the reconstruction loss between the original and reconstructed images.

The decoder architecture is designed to be symmetric to the encoder architecture, with a series of transposed convolutional layers that gradually increase the size of the feature maps until the final reconstructed image is produced. The decoder is trained to minimize the reconstruction loss between the original and reconstructed images.

C. UNET

It consists of an encoder network and a decoder network. The encoder network is composed of several convolutional layers with a decreasing resolution that gradually extracts features from the input image. The decoder network is composed of several up sampling layers that gradually restore the original resolution and reconstruct the segmented image.

The architecture has a total of 23 layers, including five max-pooling layers and four up sampling layers. It also includes skip connections that concatenate the feature maps from the encoder with the corresponding feature maps in the decoder. These skip connections help to preserve high-resolution features and avoid information loss during the up sampling process. The model has three output channels corresponding to the three classes in the segmented image (background, object, and boundary). The activation function used in the output layer is sigmoid. The input image size is 224x224x3, and the output size is also 224x224x3.

D. Integrating with Web Application

In the second phase the selected Deep Learning model was integrated in the web app to carry out image deblurring application in user friendly way. The Web app takes the user input of Blurred X-ray image and provide the corresponding sharp image for better visualization and in turn for better diagnosis which would not be possible with blur radiographs.

V. RESULTS

We trained and tested 3 Deep Learning models to get the Sharp image from the Blur image that will be close to the Ground Truth. We compared the results obtained. The evaluation metrics used for the comparison are:

- PSNR: PSNR measures the difference between two images in terms of their pixel values. It calculates the ratio between the maximum possible value of the image's pixel (for example, 255 for an 8-bit grayscale image) and the mean squared error between the two images. Higher PSNR values indicate a smaller difference between the two images. A PSNR value of 35 dB for a deblurred image is a relatively high value, indicating that the deblurred image is similar to the original image.

- SSIM: SSIM compares the structural similarity between two images, taking into account luminance, contrast, and structural information. It measures the similarity between two images by comparing the local patterns of pixels between them. SSIM values range from -1 to 1, with 1 indicating a perfect match and -1 indicating no similarity at all.

- Both PSNR and SSIM are widely used in image and video processing, and they have their own advantages and disadvantages depending on the application. PSNR is simpler to calculate and is often used as a benchmark for image compression algorithms. SSIM, on the other hand, is more complex and takes into account human visual perception.

- Validation Loss: Validation loss metrics is also considered in conjugation with PSNR and SSIM. It measures the difference between the predicted output and the true output on a validation dataset, which is a subset of the data used during training. The lower the validation loss, the better the model's generalization performance.

TABLE I. Comparison of different models trained

Trained Deep Learning Model	**Evaluation Metrics**		
	PSNR	***SSIM***	***Validation Loss***
SRCNN	37.75516	0.98565	0.00009
DAE	33.25303	0.988993	0.00047
UNET	16.396184	0.4653409	0.0041

The table above compares the results of models with the evaluation metrics stated above. We can observe from the above comparison that SRCNN proved to be most suitable model for X-ray Image Deblurring task with Higher PSNR (37.75516), lower SSIM (0.98565) and much lower validation loss (0.00009) as compared to others.

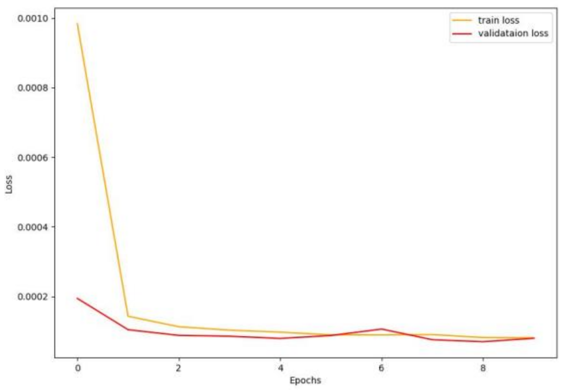

Fig. 2. SRCNN loss vs epochs graph

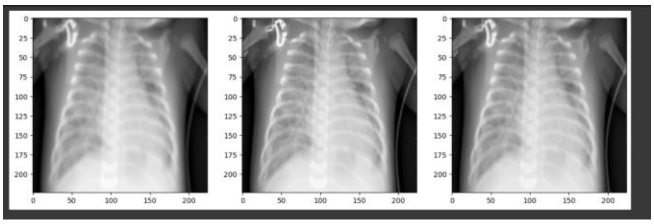

Fig. 3. Results of SRCNN 1.Blurred Image 2.Ground Truth 3.Deblurred Image

VI. CONCLUSION

In this paper we have thoroughly studied different methods of deblurring techniques including standard Computer Vision algorithms such as LRA, Weiner Filter and Low Rank Prior. We mainly focused on applicability, usability and effectiveness of Deep Learning algorithms to deblur the Medical X-ray images specifically for Chest X-ray. We compared the results of SRCNN, DAE and UNET for PSNR, SSIM and Validation loss. We found that SRCNN gives the most promising results in our case with average PSNR 37.75516 and SSIM 0.98565. We used this trained model to predict the Deblurred images of real world Blurred X-ray images and got satisfactory results.

Although the results were satisfactory with test and validation data, they are not perfect when compared with high resolution X-ray images. Also, the models were trained for only Gaussian Blur type. Hence, we need to train the models for much bigger dataset of varying blur type which will demand high end GPU and computing resources.

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