How to Cite:
Chellam, H. G. (2022). An efficient residual learning deep convolutional neural network for de-noising medical images. *International Journal of Health Sciences*, *6*(S3), 2503–2513. https://doi.org/10.53730/ijhs.v6nS3.6073

An efficient residual learning deep convolutional neural network for de-noising medical images

Heren Chellam G.
Assistant Professor in Department of Computer Science, Rani Anna Government College for Women, Gandhi Nagar, Tirunelveli-627 008, Tamil Nadu, India

***Abstract*---**Image denoising is a pre-processing technique that is done in every image processing applications. It plays a significant role in the performance of any methods. The objective of this paper is to remove Gaussian noises at different noise levels in medical images. This paper proposed an efficient Deep Convolution Neural Network model for denoising medical images to remove Gaussian noise using Residual Learning. Convolutional Neural Networks are a class of deep neural networks that can be trained on large databases and have excellent performance on image denoising. Residual learning and batch normalisation are various techniques used to enhance the training process and denoising performance. The proposed RL-DCNN method is tested with 20 layers and evaluated using the performance metrics Peak Signal to Noise Ratio, Mean Square Error and Structural Similarity. It is compared with Denoising Convolutional Neural Network and Shrinkage Convolutional Neural Network models and proved to be better than the other methods.

***Keywords*---**image denoising, gaussian noise, residual learning, convolutional neural network, peak signal to noise ratio.

Introduction

Image denoising plays an important role in daily life applications such as satellite TV, medical applications, remote sensing, geological application, astronomical applications etc. Noise in the images can be classified as: Gaussian Noise, Impulse (Salt & Pepper) Noise, Periodic Noise, Poisson Noise, Gamma Noise, Rayleigh Noise, White Noise and Uniform Noise. These noises are modelled based on correlation, probability distribution, nature, quantization and photon noise based on source. If the image I is corrupted with noise ξ, then the noisy image y is represented as:

Corresponding author*: Chellam, H. G.*
Manuscript submitted: 18 Dec 2021, Manuscript revised: 27 March 2022, Accepted for publication: 09 April 2022

$$y = x + \xi \qquad \ldots\ (1)$$

The variety of image de-noising methods have been developed such as filter-based methods, wavelet-based methods, diffusion-based methods, total variation based methods, Block-Matching and three-dimensional filtering (BM3D), sparse representation-based methods, Markov random field models, neural network-based methods etc. Most of these denoising models attempt to approximate the clean image x from the noisy image y. The residual denoising model approximates the noise ξ instead of the image x. The approximated image x̂ can be given as:

$$\hat{x} = y - \xi \qquad \ldots\ (2)$$

This paper proposed to find an efficient DCNN model for removing gaussian noise using residual learning approach. Florian Luiser et al. has designed a Poisson-Gaussian Unbiased Risk Estimate with Linear Expansion of Thresholds (PURELET) using variety of wavelet transform classes and thresholding algorithms for denoising images. This method has removed mixed Poisson-Gaussian noise. Goyal B. et al., 2018, has removed noise from medical images. Dang et al., has implemented an effective denoising method for Poisson noise corrupted images. Denoising medical images has been found to be one of the important image processing tasks. This will improve the quality of diagnosis and early detection of disease is also possible. Using the features and their adjacent coefficients in the same scale, a dependency of the coefficients on the heavy-tailed nature and the intra scale statistical dependency are being calculated (Malini.S, Moni.R.S 2016). The connection between the continuous directional wavelet and the discrete filter bank are established (Ryan Moore et.al., 2014). The remaining of the paper is organized as follows: Section 2 gives the work related to denoising based on CNN. Section 3 explains the proposed methodology for denoising. Section 4 demonstrates the experimental results of the proposed RL-DCNN method followed by conclusion in Section 5.

Related works

This section discussed few CNN models for de-noising. In sparse representation, sparse dictionaries are created by converting the image matrices into vectors. Thus 2D structural information is lost in this method. But the CNN models are capable of maintaining 2D structural information both in the training and testing phases. This is done by using convolution operation which considers the neighbouring pixels by using 2D masks (Cruz, C et al., 2018). The patch-based methods such as Non Local Means (NLM) and B3MDrequire high computation time and the performances of these methods is better if the images have a low number of self-similarity patches (Zhang, K. Zuo, et.al., 2018). Prior-driven Deep Neural Network (PDNN) (Dong, W et al., 2018) model maps low-quality images to desirable high-quality images with deep learning. Minarik, D et.al., 2020, has been investigated whether noise can be removed in whole-body bone scans using CNNs. The trained sets of noisy and noiseless images obtained by Monte Carlo simulation are used in their method. Denoising autoencoders has been constructed using convolutional layers with small sample size by Gondara, L. 2016. Heterogeneous images can be combined to boost sample size which subsequently increases denoising performance. Simple networks can reconstruct the corrupted images with less performance.

Kaur, P. et.al., 2018, has a review on six application of radiology: Medical Ultrasound (US) for fetus development, US Computer Aided Diagnosis (CAD) and detection for breast, skin lesions, brain tumor MRI diagnosis, X-Ray for chest analysis, Breast cancer using MRI imaging are focused. Thakur, R.S. et.al., 2019, showed that CNN based image denoising models is better than state-of-art non-CNN methods like BM3D filtering, contemporary wavelet and Markov random field approaches. Several CNNs that are used for image restoration like residual learning based models (DnCNN-S, DnCNN-B, IDCNN), non-locality reinforced (NN3D), fast and flexible network (FFDNet), deep shrinkage CNN (SCNN), a model for mixed noise reduction, denoising prior driven network (PDNN) are reviewed. DnCNN-S and PDNN remove Gaussian noise of fixed level, whereas DnCNN-B, IDCNN, NN3D and SCNN are used for blind Gaussian denoising. FFDNet is used for spatially variant Gaussian noise.

An image denoising technique has been introduced based on a Convolutional Denoising AutoEncoder (CDAE) (Lee, D et.al.,2018). A method called integrated diffusion is implemented for combining multimodal datasets to create a joint data diffusion operator(Kuchroo, M et.al., 2021). Karkare, R. et.al., 2021 has been shown that how deep autoencoders can be generalized to the case of inpainting and denoising, even when no clean training data is available. If noise is added both in input and in the stochastic hidden layer, it will improve the performance (ImIm, D et.al., 2017). A modified variational lower bound is introduced as an improved objective function in this setup. When input is corrupted, then the standard VAE lower bound involves marginalizing the encoder conditional distribution over the input noise, which makes the training criterion intractable. Instead, a modified training criterion is developed which corresponds to a tractable bound when input is corrupted. A Denoising Sparse Convolutional AutoEncoder (DSCAE) has been developed to defense against the adversarial perturbations (Ye, H. et.al., 2020). This is a pre-processing module works before the classification model, which can remove substantial amounts of the adversarial noise.

Methodology

Convolutional neural network based denoising models

Image denoisingusing CNN is done by removing noise from the noisy image using feed-forward CNN. Zhang, K., et al., 2017 , used residual learning and Batch Normalisation (BN) to improve the denoising performance. Residual learning is used to solve the performance degradation problem. In residual learning, the output is noise instead of a denoised image. The training efficiency of mini-batch stochastic gradient method is largely reduced by an internal covariate shift, i.e. changes in the distributions of internal non-linearity in inputs during training. BN is used to improve the training efficiency, which alleviates the internal covariate shift by incorporating a normalisation step and a scale and shift step before the nonlinearity in each layer.

The different algorithms used for training the CNN are first-order hybrid training methods, conjugate gradient methods, quasiNewton methods, Levenberg–Marquardt method and its variants and least squares method by Tivive, F. et.al.,

2005. The training algorithm uses an objective function approach and learning function approach. In the objective function approach, the minimisation of the reconstruction function is the solution of a problem. In the learning function approach, the solution of a regularised minimisation problem is a parametric function that is used to solve the denoising problem. The loss function or cost function is minimised to find the optimal parameters of the neural network. In supervised learning, this parameter is taken as the MSE.

$$E(k) = \frac{1}{P \times M} \sum_{j=1}^{p} \sum_{i=i}^{M} \left(z_i^j - t_i^j\right)^2 , \qquad k = 1, 2, \ldots S_k \qquad \ldots (3)$$

where M is the number of output neurons, P is the number of training patterns, S_k is the number of training iterations, z_i^j and t_i^j are the actual and desired responses of the ith output neuron due to the jth input pattern, respectively. The stochastic gradient descent method is used for optimising this MSE. The gradient descent method iteratively updates the weight w replacing w(t) by w(t+1) using the following update equation:

$$w(t+1) = w(t) - \eta \frac{\partial E(k)}{\partial w(t)} \qquad \ldots (4)$$

where η is the learning parameter. The general learning equation of CNN to solve the inverse problem in imaging given in [15] as

$$R_{\text{learn}} = \underset{R_\Theta}{\operatorname{argmin}} \sum_{j=1}^{F} C\left(x_j R_\Theta\left(y_j\right)\right) + g(\Theta) \qquad \ldots (5)$$

where a training data set of ground–truth images and their corresponding measurements $(x_j, y_j)_{j=1}^{p}$ are known. The cost function is denoted by C, R_θ is the function designed to extract denoised image $x_j$the regularisation function is denoted by g which promotes a solution that matches the prior knowledge of input image x_j. θ is the set of all possible parameters in CNN. This section gives the detailed description of DnCNN and SCNN which gives the background for our proposed methodology.

Denoising convolutional neural network

The Denoising Convolutional Neural Network(DnCNN) model is used for blind Gaussian denoising that is it can remove Gaussian noise of unknown noise level by Zhang, K., et al., 2017. The DnCNN model has Convolution (Conv.), Rectified Layer Unit (ReLU) and BN. The layer details are given below:

- Conv + ReLU: for the first layer, 64 filters of size $3 \times 3 \times c$ are used to generate 64 feature maps, and rectified linear units (ReLU, max(0,·)) are then utilised for non-linearity. Here c represents the number of image channels.
- Conv + BN + ReLU: for layers 2 (D − 1), 64 filters of size $3 \times 3 \times 64$ are used, and batch normalisation [20] is added between convolution and ReLU.

- Conv: for the last layer, c filters of size 3 × 3 × 64 are used to reconstruct the output. The training algorithm used in this deep CNN is Stochastic Gradient Descent and Adam's algorithm (Kingma, D.P et.al., 2015).

The averaged MSE between the desired residual images and the estimated ones from noisy input is taken as the loss function to learn the trainable parameters Θ.

Deep shrinkage convolutional neural network

Isogawa, K. et.al 2018, used Deep Shrinkage CNN to reduce noise, for all levels of noise. If the noise level of the training data set is different from that of testing data set, then most of the CNNs which do not have adjustable parameters fail to restore images effectively. In deep SCNN, the soft shrinkage activation function is used by Minarik, D. et.al., 2020. Soft shrinkage activation function has a threshold which is adjustable to the noise level and is given by:

$$F_{sh}(x,\tau) = \begin{cases} x-\tau & (x>\tau) \\ x+\tau & (x<\tau) \end{cases} \quad \text{... (6)}$$

where x is the pixel intensity of the given co-ordinate in the image and τ is the threshold.

Zhang, K., et al., 2017, mentioned SCNN architecture is the same as that of DnCNN. It had D number of layers and l is the identifier of layers. The first layer is the feature extraction layer, which consists of Nc convolution filters of size w × w and activation function (l = 0). The next layers from l = 1 to d − 2 is the feature conversion layer which has Nc convolution filters of size w × w × Nc, followed by a BN (Ioffe, S. et.al., 2015) and activation layer. The last layer d − 1 is the residual image generation layer, which consists of a convolution layer whose filter size is w × w × Nc. The loss function C(Θ) of SCNN is given by:

$$C(\Theta) = \frac{1}{2N}\sum_{i=1}^{N}\left\| R\left(y_i;\Theta\right) - \left(y_i - x_i\right)\right\|^2 \quad \text{... (7)}$$

Here $\{(y_i, x_i)\}_{i=1}^{N}$ represents the N noisy-clean training image pair, R represents the residual noise function and θ denotes the learnable parameters.

Proposed RL-DCNN method

The architecture of an efficient Deep Convolution Neural Network model for denoising medical images to remove Gaussian noise using Residual Learning (RL-DCNN)is shown in Fig. 1. The image is added with noise ξ. The proposed denoising RL-DCNN model consists of 20 layers. The input layer has Conv. and ReLU. The hidden layers contain Conv., BNand ReLU. The output layer consists of Conv. and ReLU. There are 18 hidden layers. The existing DnCNN model consists of 13 hidden layers. The addition of 5 more hidden layers in RL-DCNN model still approximates the noise ξ. Also,

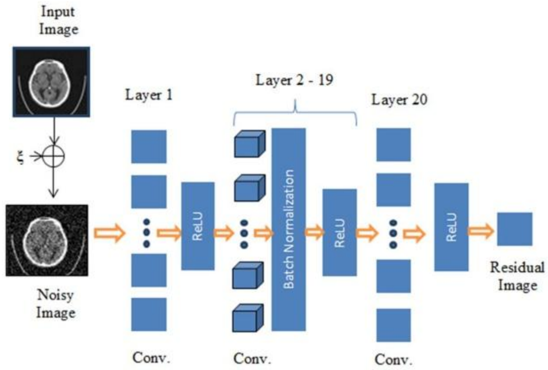


Fig 1. Proposed RL-DCNN Denoising Model Architecture

In Layer 1, 32 filters of size 3 x 3 x 1 are used to generate 32 feature maps, where 3 x 3 is the convolution width and height and 1 is the image channel size. This layer is followed by Relu activation function. Each 2-19 layers has 32 filters of size 3 x 3 x 32. This will generate 32 feature maps again. The model is then designed using Batch Normalization and Relu activation layer. The final layer 20 has 1 filter of size 3 x 3 x 32, which produces the residual image. The residual image is subtracted from the noisy image to produce the reconstructed image.Table 1 gives the detailed description of the proposed CNN denoising model.

Table 1
Layers of the Proposed RL-DCNN Denoising Model

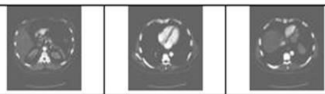
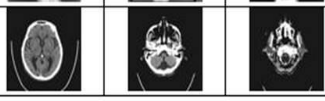
Layer	# Filter	Filter Size	Feature Map Size
Input Layer (Conv. + ReLU)	32	3 x 3 x 1	3 x 3 x 1 x 32
Hidden Layers (Conv. + BN + ReLU)	32	3 x 3 x 32	3 x 3 x 32 x 32
Output Layer (Conv. + ReLU)	1	3 x 3 x 32	3 x 3 x 32 x 1

Conv.– Convolution Layer, BN – Batch Normalization, ReLU – Rectified Linear Unit

Experimental analysis

This section explores the details of the dataset used in this work. It also displays some sample images, output images and the experimental results. The performance metrics used in the RL-DCNN method is also explained. The proposed RL-DCNN method is tested on publicly available Medical MNIST dataset. It consists of 58954 medical images of 6 classes: AbdomenCT, BreastMRI, CXR, ChestCT, Hand, HeadCT. All the classes have 10000 images except BreastMRI which consists of 8954 images. The size of the each image is 64 x 64.Some of the sample images from each class of medical MNIST are shown in Table 2. The dataset is randomly splited into 80% training and 20% testing.

Table 2
Details of the Dataset

Class	No. of Images	Samples
AbdomenCT	10000	
BreastMRI	8954	
CXR	10000	
ChestCT	10000	
Hand	10000	
HeadCT	10000	

The performance metrics are used to measure the quality between the noisy and denoised images. In this work Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) metrics are used. PSNR is one of the metrics used to find the maximum possible power of a signal to the corrupted power. It is usually defined using the Mean Square Error (MSE)

$$MSE = \frac{1}{MN}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad \ldots (8)$$

where I is the monochrome image and K is the noisy image.

$$PSNR = 20.log_{10}(MAX_I) - 10.log_{10}(MSE) \quad \ldots(9)$$

WhereMAX_I is the maximum value of the pixel in the image.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad \ldots(10)$$

Where μ_x is the average value of x, μ_y is the average value of y, σ_x^2 is the variance of x and σ_y^2 is the variance of y, σ_{xy} is the covariance of x and y, and x and y are two windows of the same size.

The proposed RL-DCNN model uses Stochastic Gradient Descent and Adam algorithm for optimization. The batch size is set to 10. The model is trained for 30 epochs. The learning rate is 10-2. We also used data augmentation such as clipping and rotation for training the proposed model. All experiments are carried out in the MATLAB (R2019a) environment running on a computer with Intel Core i7 with 2.80GHz CPU and NVIDIA GeForce GTX 1050. All the images in the dataset are added with Gaussian noise for two noise levels 15 and 25. The output of the proposed RL-DCNN method is shown in Table 3. The noisy images with noise level 15 and 25 are also shown. Single image from each class is displayed.

Table 3
Input, Noisy and Output Images

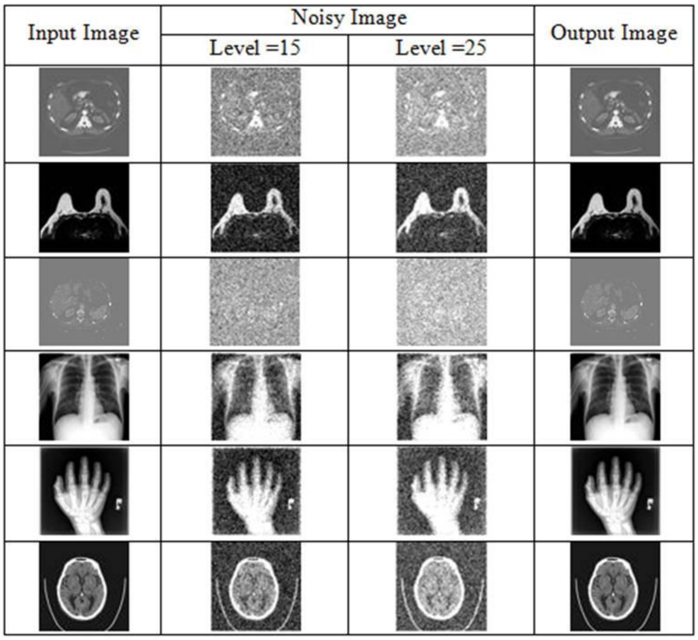


Table 4 gives the average PSNR and SSIM of the proposed RL-DCNN method for two noise levels 15 and 25. It also compares the proposed RL-DCNN method with conventional CNN denoising models like DnCNN[18] and SCNN[22] discussed in Section 3.

Table 4
Comparison of RL-DCNN Denoising Model with DnCNN[18] and SCNN[22]

Noise Level	Metrics	Existing Models		Proposed Model
		DnCNN	SCNN	RL-DCNN
15	PSNR	39.42	39.45	39.54
15	SSIM	0.94	0.94	0.95
25	PSNR	36.57	36.7	36.9
25	SSIM	0.9	0.9	0.92

From Table 3, it is observed that the proposed RL-DCNN method achieves little higher PSNR of 39.54dB and 36.9dB for noise levels 15 and 25. These values are greater than the PSNR obtained by DnCNN and SCNN denoising models. Fig.2 compares the PSNR value of the DnCNN, SCNN and proposed RL-DCNN models for Noise Levels 15 and 25. Fig. 3 compares the SSIM value of the DnCNN, SCNN and proposed RL-DCNN models for Noise Levels 15 and 25.

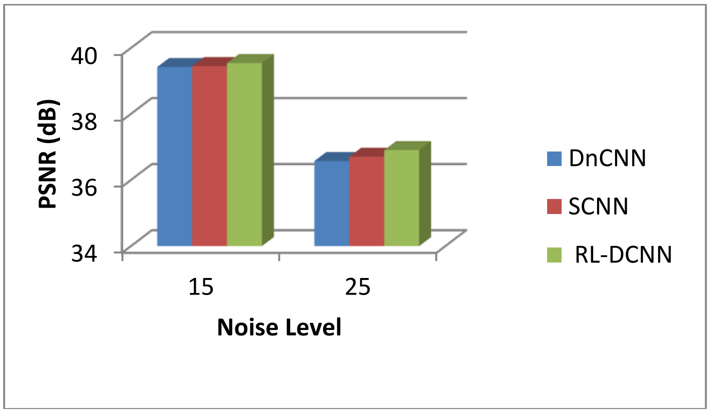


Fig 2. PSNR obtained by the Proposed RL-DCNN, DnCNN and SCNN

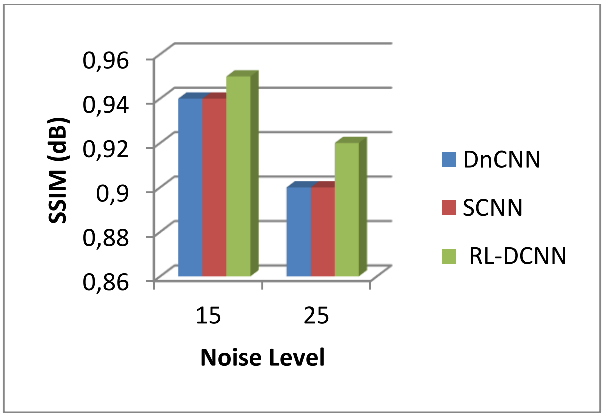


Fig 3. SSIM obtained by the Proposed RL-DCNN, DnCNN and SCNN

Conclusion

Medical image denoising is pre-processing step in all image processing applications. This step will increase the performance of the processing. This paper proposes an efficient deep CNN model for denoising using residual learning. The performance of the proposed RL-DCNN method is tested on medical MNIST dataset. The proposed method proved its efficacy by achieving PSNR of 39.54dB and 36.9dB and SSIM of 0.95 dB and 0.92 dB for noise levels 15 and 25 respectively. It is compared with DnCNN, and SCNN models and shows better results than those models. The proposed RL-DCNN method can be tested with other datasets as well. It can also be tested for various types of noises other than Gaussian noise.

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