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DENOISING MEDICAL IMAGES USING HDNCNN-IL

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Abstract
In Medical imaging, several noises are being found which may disrupt the process of diagnosis, hence the noise has to be filtered and a noise free image has to be reconstructed in image processing such as medical image segmentation, tumour detection, image recognition etc. In this paper a Convolutional Neural Networkmodel in deep learning is used for denoising the image. Weiner filtering, Average filtering, median filtering etc. are some of the traditional image denoising methodologies. The major drawback of this traditional method is, it cannot change the parameters that it uses, hence adaptive methods cannot be used here. In this paper a Convolution Neural Network that uses feed-forward for Denoising (DnCNN) is used which gives good results because of its deep architecture, regularization method and learning algorithm. The proposed approach handle Gaussian Noise, Salt & Pepper noise, Speckle noise and Poison noise for an unknown level than the Denoising Convolution Neural Network, U-Net Denoising Convolution Neural Network and Dilated U-Net Denoising Convolution Neural Network model.
Keywords : Image Denoising;Poisson noise; Speckle noise;Gaussian noise; Convolutional Neural Network; CNN; DnCNN; UDnCNN;DUDnCN; PSNR; SSIM.

INTRODUCTION

A digital image is made up of pixels, whose values range from 0 - 255, called as the intensity of the pixel element. A color image consists of three planes, the red plane, the Green plane and the Blue plane. When an image is transmitted from one place to another, image acquisition and compression there is always a chance of a disturbance being introduced due to noise. The denoising process is disturbing the quality of the original image which may lead to poor decisions either by humans or machines. Therefore, the goal of noise removal or reduction in the medical image should take high consideration about accuracy asmuch as possible.Medical images usually introduce White Gaussian Noise, that may disturb the identification or segmentation of crucial parts.

Medical images are mostly corrupted with different types of noises such as Gaussian noise , Speckle noise, Poisson noise and Salt & Pepper noise. There are many ways the noise can be added to an image, the most crucial way is through the acquisition of the image, compression and transmission. Image de-noising is a pre-processing task in image processing. The main goal of image de-noising is not only to suppress noise signals but also to preserve the useful information of the images such as edges, fine structures, texture details etc. (Choubey et. al., 2011).

Most of the traditional denoising methods have produced reasonably good results, still suffers with these drawbacks include poor test phase optimization, manual parameter settings, and specific denoising models. To conquer these downsides, a few discriminative learning strategies have been as of late evolved to learn image earlier models with regards to diminished deduction strategy. Roth, S. and Schmidt, U. (2014) states that the computational efficiency has been achieved by construction through the use of a convolution and DFT as the core components, high rebuilding quality is accomplished through loss based preparing of every model boundary and its parameters of the utilization of the cascade architecture. Unlike heavily engineered solutions, their learning approach can be adapted easily to different trade-offs between efficiency and image quality.

Though Machine learning has seen some dramatic developments, which are driven by breakthroughs in artificial neural networks, often termed deep learning, a set of techniques and algorithms that enable computers to discover complicated patterns in large datasets. The sudden progress and wide scope of deep learning, it is now one of the hottest areas of study world-wide. Over the past decade, various models have been exploited for image denoising. In the early developments of CNN, the vanishing gradient, activation function sigmoid (Daunizeau J., et al., 2008) and Tanh(Jarrett K, 2009), and unsupported hardware platform made CNN difficult. However, the development of AlexNet(Hinton GE., et al., 2012) in 2012 has changed the difficulty in CNN usage.

Bengio Y et.al.(1998), states that in medical imaging the interest in deep learning is mostly triggered by CNNs a powerful way to learn useful representations of images and other structured data. NattanunThatphithakkul . et al.,(2020) addresses a new image denoising method for removing Poisson noise based on the Deep Convolutional Neural and Multi-directional Long-Short Term Memory Networks to denoise images corrupted Poisson noise. Chen, Y et al., (2017) used the denoising CNN (DnCNN) for image denoising, super-resolution, and JPEG image blocking. The network consists of convolutions, back-normalization (Hou X et al., 2018) rectifed linear unit (ReLU) (Hinton GE and Nair V., 2012) and residual learning (An. J, et al., 2021)

We propose to broaden DnCNN for dealing with medical image denoising errands, includingdenoising medical images affected by different types of noises. Broad examinations shows that, our DnCNN prepared with anunknown noise levels can yield preferable denoising results over DnCNN, UDnCNN, DUDnCNN. In addition, we show the viability of preparing just a solitary DnCNN model for denoising medical images with different types of noises such as Gaussian, Speckle, Poisson and Salt & Pepper noises. The contributions of the work are summarized as follows:

We observe that ReLU and batch normalization can incredibly help the CNN learning as they would not just accelerate the preparation be able to yet additionally support the denoising execution. The ReLU activation is the default and most popular activation, when developing multilayer perceptron and convolutional neural networks.

The proposed method is also promising medical image denoising with medical images having different type of noises like gaussian noise, speckle noise, poisson noise and salt & pepper noise for unknown noise levels.

The potential challenges and future scopes are discussed.

The rest of the paper is coordinated as follows. Segment II gives a concise overview of related work in CNN.Section III first presents the DnCNN model, UDnCNN model and DUDnCNN model to medical image denoising. In Section IV, the proposed method is discussed. The broad tests that led to assess DnCNNs, UDnCNNs and DUDnCNNs and the proposed method are discussed in Section V. At long last, a few concluding remarks and future developments are given in Section VI.

RELATED WORK

From last decades, deep learning techniques have received much attention in the area of image denoising. There have been several models to handle the denoising problem by deep neural networks. However, there are significant differences in the various types of deep learning methods dealing with image denoising. In particular, discriminative learning based on deep learning can successfully address the issue of Gaussian noise. Deep learning based optimizationmodels are effective in estimating the realnoise. However, there has thus far been little related research to summarize the different deeplearning techniques for denoising images. After the invention of AlexNet in 2012, the interest in CNN has grown exponentially ever since. There have been various attempts to handle the denoising problem by deep neural networks.

CNNs for image denoising is proposed to use and claimed that have similar or even better representation power than the MRF model(Jain and Seung 2009). A method with multi-layer perceptron (MLP)is proposedfor image denoising (Burger et al., 2012). A significant work done by (Elhoseny and Shankar, 2019) shows that for medical imaging tasks, denoising has the potential to improve medical image classification performance. They propose a system that preprocesses images with a bilateral filter with parameters optimized for best image denoising performance.

The Deep Convolutional Denoising of Low-Light Images,DenoiseNet method that deploys the deep CNNs to eliminate Poisson noise (Bronstein et al., 2017). The DenoiseNet can outperform than the existing denoising algorithms in both objective and subjective qualities under weak Poisson noise environments. Unfortunately, there are still some obvious artefacts scattered throughout the reconstructed images in situations with high Poisson noise levels.

The Residual Learning of Deep Convolutional Neural Network for Image Denoising (DCNN) technique is proposed and that utilizes the deep Convolutional Neural Networks (CNNs) to eliminate the AWGN(Chen et al., 2017). The DCNN can perform better than the previous denoising techniques in both qualitative and quantitative results. A novel method to eliminate Poisson noise by putting together the deep convolutional and multi-directional LSTM networks was proposed (NattanunThatphithakkul et al., 2020). Poisson noise is challenging to remove since the noise level isrelied on its corresponding pixel intensity. The deep convolutional networks extract the noise bases with different variances. The noise variance decreases and becomes more sparse as the layer depth increases. Then, the multi-directionalLSTM networks remove the remaining noise. The denoising results under the Poisson noise environment from the DCNN give near optimal qualities under different hyper parameter settings such as a number of CNN layers. We empirically find that, the convolution neural network model can result in fast and stable training and better denoising performance.

MATERIALS AND METHODS

It is generally known that deep convoluted neural networks(DCNN) can learn to extract non linear features far better than human handcrafted features. The DnCNN is used in the image denoising problem to learn about and extract noises from corrupted images. Then in order to create the denoised images, noise is subtracted from the corrupted images. Notice that each layer of the DCNN extracts noise features from the input by convolving the trained weights with the features extracted from the previous layer. The output feature at layer i can be written as follows

$$F_{k,i}(x_p,y_p)=\sum_{m=1}^{M_{i-1}} || W_{m,i-1} \text{ o } Z_{m,i-1}(x_p,y_p)||_{\mathrm{F}} \quad (1)$$

Where $F_{k,i}(x_p,y_p)$be the feature value k at position (xp , yp) be the feature value k at position (xp,yp) of the ith layer of the DCNN. ‖F is the Frobenius norm and o is the Hadamard operation. Mi−1 is a number of feature map m at the (i−1)th layer. Wm,i−1, is the trainable weight matrix of feature map m at the (i−1)th layer. Zm,i−1(xp,yp) is an N×N-patch of feature map m in the (i−1)th layer with the centre at position (xp,yp). The noise component is then obtained by weighted averaging the output features at layer i. In the DCNN, the number of layers and the number of neurons per layer directly relate to the complexity of the neural network. The larger the number of parameters, the longer the training periods.

Denoising Convolution Neural Network (DnCNN)

We start from a DnCNN model for medical image denoising, which has been pre-trained on 200 gray scale images of size 256 x 256 and Gaussian noise level of □ = 1. In this work, this unique DnCNN is custom fitted in view of reproduced MRI images. MRI images are thought to be upset by added substance low-portion noise, indicated by y = x + n, where y is the noisy image, x is the part of full- portion image, and n is the noise. DnCNN benefitsfrom residual learning and batch normalisation, with learning speed up and execution upgradein taking care of general image denoising issue. Rather than straight forwardly looking for a reversal model H(y) □ x, DnCNN learns a residual mapping R(y) □nˆand produces the denoised image via xˆ = y – R(y). this plan actually addresses the evaporating inclination issue in extremely profound organisations, yielding more effective preparation and more precise results (Hinton et at., 2012). Figure 1 shows the structure of DnCNN.

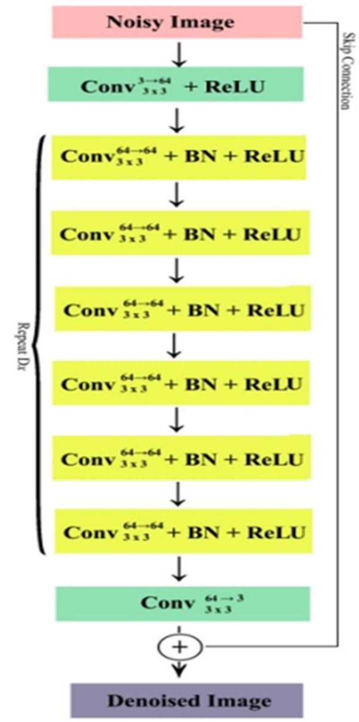

Fig.1 Framework of DnCNN

The input patch size in training is 40×40 in this study (Ruan et al.,2019). The DnCNN has 17 layers, which is empirical choice following the work in (Chen et al., 2017). For the first 16 layers, 64 convolutional filters are used to the size of 3×3, and rectified linear unit (ReLU) is used for nonlinearity. Batch normalization (BN) is performed between the convolution unit and the ReLU in all the middle layers to reduce the internal covariate shift, which brings benefit to training speedup and performance improvement (Chen et al., 2017) as shown in Fig. 1.

U-Net Denoising Convolution Neural Network (UDnCNN)

For the denoiser, comparatively as (Fangzhou Liao et al., 2018), utilize a UDnCNN based on denoising convolution neural network. The construction of the UDnCNN denoiser has an encoding part offering skip associations with an unravelling part (Bassit, A and Rezgui, 2021). Theskip associations permit the exchange of fine-grained data that could be lost in a normal auto-encoder. Convolution filters alongside rectified linear units (ReLU) (Ioffe and Szegedy, 2015) and batch normalization (Hinton et al., 2012) is performed between the convolution filters and rectified linear units as shown in Figure 2.

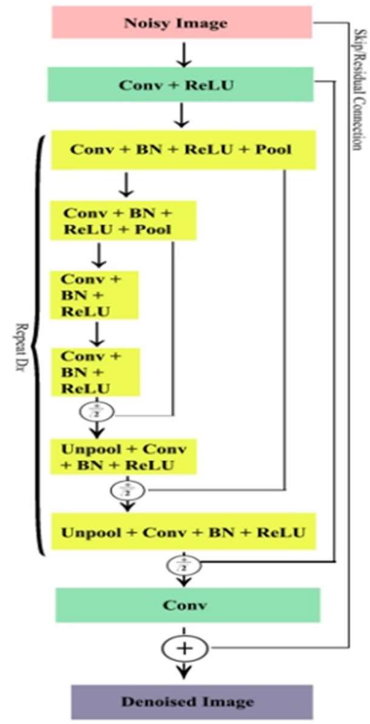

Fig.2 Framework of UDnCNN

The UDnCNN delivers more speculation, which can dispose of eliminating low-frequency swell noise with high accuracy. The after effects of both model data tests and genuine information handling show that the new UDnCNN is fit for effective learning and high-accuracy noise removal and can keep away from the overfitting issue is exceptionally normal in conventional neural network techniques. This new UDnCNN can likewise be summed up somewhat and can really preserve low-frequency effective information. Contrasted and the traditional high-pass filtering methods generally utilized in the process, the new UDnCNN can wipe out low-frequency and grow noise with higher accuracy while really low-frequency successful data, which is of extraordinary importance for result handling, for example effective information saving imaging and full wave form reversal. Residual operation applied to each layer following the maximum pooling (Jung et al., 2020) or addition based resize up-testing increases denoising strategy. This activity is added to compare to the size of the contributionprior toacquiring the last element. Truth be told, pooling activities will more often than lose data, so analysts and designers don't really want to utilize them. In any case, we added this interaction to manage noises of different dispersions at different scales.

Dilated U-Net Denoising Convolution Neural Network (DUDnCNN)

Dilated Convolution is a technique that expands the kernel (input) by inserting holes between its consecutive elements. In simpler terms, it is the same as convolution but it involves pixel skipping, so as to cover a larger area of the input. An additional parameter l (dilation factor) tells how much the input is expanded. In other words, based on the value of this parameter, (l-1) pixels are skipped in the kernel.

Every convolution set after k pooling and 1 unpooling in the network, ought to be supplanted by a dilated filter with 2(k−1) – 1 holes. This can be accomplished with a enlargement discretionary contention of nn.Conv2d. ensure set up the contention cushioning in like manner to keep up with tensors with the similar spatial aspect during the forward spread. We utilize the expression “dilated filter” rather than “convolution with a dilated filter” to explain that no “dilated filter” is developed or addressed.Figure 3 indicates the various dilated filters that are being used in the denoising strategy

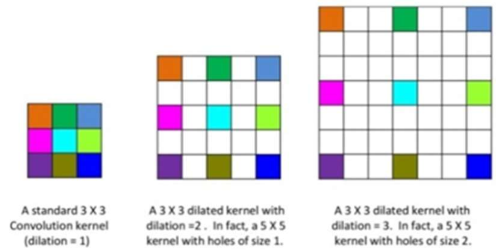

Fig.3 Dilation Filters of DUDnCNN

If we denote r as the dilation factor, the one dimensional mathematics of the dilated convolution are as follows:

$$z[i] = \sum_{l=1}^{L} x(i + dl)\, w[l] \quad \_\_\_\_\_\_ (2)$$

Where x[i] and z[i] denote the input signal and output signal, respectively; l denotes the size of the convolution kernel; d denotes the dilation rate. One dimensional dilated convolution is achieved by inserting ‘0’ between the pixels of the convolution kernel. For a 1∗k convolution kernel, the dilation factor d is k_d, and the size of k_dcan be defined as

$$k_d = k + (k - 1)(d - 1) \quad \_\_\_\_\_\_ (3)$$

Batch normalization (BN) is proposed to improve the performance of CNN. The BNlayer canimprove the data distribution during training and speed up the training of the model. Also, the BN layer has the characteristics of improving network generalization ability, to avoid the problem of overfitting and gradient disappearing during training. Define the input dataset of a hidden layer of the network as {μ_1,…,μ_m }, m is the number of samples in the batch. First, it should compute the mean value E(μ) and variance D(μ) by

$$E(\mu) = \frac{1}{m}\sum_{h=1}^{m} \mu_h \quad \_\_\_\_\_ (4)$$

$$D(\mu) = \frac{1}{m}\sum_{h=1}^{m} [\mu_h - E(\mu)]^2 \quad \_\_\_\_\_ (5)$$

Then, each dimension is normalized to μ_h, whose distribution has the expected value of 0 and the variance of 1:

$$\widehat{\mu_h} = \frac{\mu_h - E(\mu)}{\sqrt{D(\mu) + \varepsilon}} \quad \_\_\_\_\_\_\_ (6)$$

Where ε is a positive number close to zero. Finally, a pair of parameters α and β are introduced to reconstruct and transform the data; the output data y of the BN layer is as follows:

$$y_h = \alpha\widehat{\mu_h} + \beta \quad \_\_\_\_\_ (7)$$

Parameters α and β are learned along with the original model parameters.

In general, CNN finally derives robust features with the invariant character for translation, rotation and scale from the raw data. It is as a result of the convolution operations of multiple

convolution kernel network structure, which extracts the features contained in the data, and the features are abstracted as the number of network layers increases.
The DUDnCNN has implemented with 20 layers. The convolution administrator itself is altered to involve the filter boundaries in an alternate manner. The dilated convolution operator can apply similar channel at various reaches utilizing different enlargement factors. Our definition mirrors the legitimate execution of the dilated convolution operator, which doesn't include development of widened channels. Our design is aroused by the way that widened convolutions support dramatically extending responsive fields without losing goal or inclusion (YoshuaBengio and Yann LeCunn 2016)

ProposedHybrid model of DnCNN and U-net DnCNN with Increased Layers (HDnCNN-IL)METHOD

In this section, we present the proposed denoising CNN model, i.e., the proposed method is the Hybrid method of DnCNN and U-net DnCNN with Increased Layers(HDnCNN-IL) and is extend for different types of noises in medical image denoising tasks. Training a deep CNN modelfor a specific task generally involves two steps:

- Architecture design of the Network and
- Model Learning from training data.

For the architectural design of the proposed denoising network, we adopt the VGG network to make it suitable for image denoising, and set the depth of the network based on the effective batch learning formulation for model learning and combine it with batch normalisation for quick training and enhanced denoising performance. We use the residual learning formulation for model learning and combine it with batch normalisation for quick training and enhanced denoising performance. 'DilatedConv + BN + ReLu' is the fundamental block of our model. The initial and the final convolutional layer still use regular convolution with dilation factor of 1, hence they are denoted by 'Conv'. 'DilatedConv' refers to the dilated convolution with factor of 2. To maintain the output size, zero-padding is set to 2. Also we use the convolutional filter size as 3. Our proposed model has adopted with 24 convolution layers
The size of convolutional filters to be 3×3 but remove all pooling layers. Therefore, the receptive field of DnCNN with depth of d should be (2d+1)(2d+1). In order to exploit the context information in a larger region, the receptive field size might be increased. Setting the right depth for DnCNN is a critical part of architectural design for a better trade-off between performance and efficiency. As has been observed, the effective path size of denoising neural networks. In the case of high noise levels, usually requires larger effective patch size to capture more context information for restoration. Thus, by fixing the depth of noise levels in different amounts, we analyse the effective patch size of several leading denoising methods to guide the depth design of DnCNN, UDnCNN, DUDnCNN.

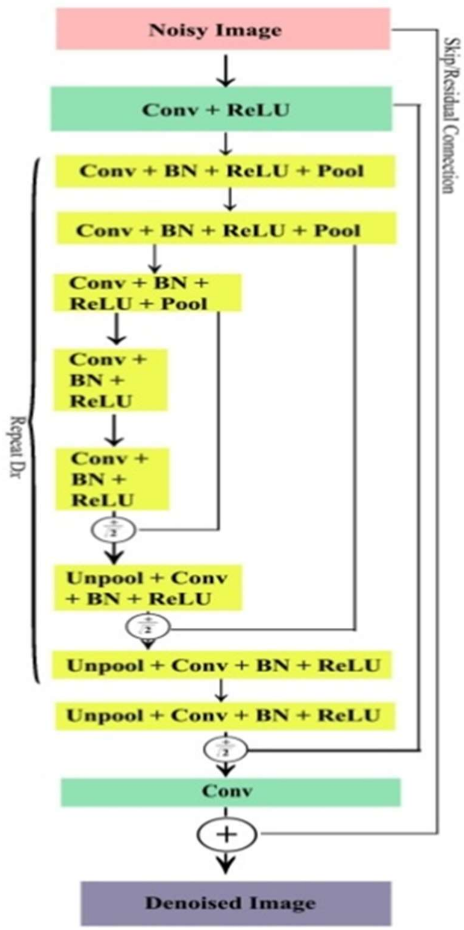

Fig.4 Framework of proposed HDnCNN-IL

For the denoiser, we utilize a UDnCNN based Denoising Convolution Neural Network with 3×3 dilated filter with dilation = 2. In fact, a 5 × 5 kernel with holes of size 1 is used. The DnCNN has 19 layers, which is an optimal choice for the work. Theconstruction of the UDnCNN denoiser has an encoding partoffering skip associations with an unravelling part with extra layers being added than the UDnCNN. The skip associations permit the exchange of fine-grained data that could be lost in a normal auto-encoder and give good results. Figure 5.5 indicates the framework of the proposed method.

Given the HDnCNN-IL with profundity, there are three kinds of layers, displayed in Fig. 5.4 with four various tones.

Conv + ReLU: for the main layer, 64 channels of size 3 × 3 × c are utilized to produce 64 element maps, and redressed straight units (ReLU, max(0 ; .)) are then used for nonlinearity. Here c addresses the quantity of the picture channels, i.e., c = 1 for grayimages and c = 3 for color images.

Conv + BN + ReLU: for layers in middle of 2∼ (D − 1), 64 channels of size 3 × 3 × 64 are utilized, and Batch Normalization is added among convolution and ReLU.

Conv + BN + ReLU+Pool/Unpool first three and last three of of 2∼ (D − 1) layers.

Conv: for the last layer, c no of filters of size 3×3×64 are utilized to regenerate the result.

To summarize, our DnCNN model has two fundamental elements: the lingering learning plan is embraced to learn R(y), and group standardization is consolidated to accelerate preparing as well as lift the denoising execution. By integrating convolution with ReLU, HDnCNN-IL canbit by bit isolate image structure from the high noise level through the hidden layers. Such acomponent is like the iterative noise removal technique took on it strategies like the othermethods DnCNN, UDnCNN and DUDnCNN, yet our proposedHDnCNN-IL is prepared in a start to finish design.

.EXPERIMENTAL RESULTS DISCUSSION

5.1 Hardware and Software used :

One reason for the success of the deep learning is the modern powerful GPU. The GPU uses the NVCUDA, OpenCL and cuDNN platforms to strengthen its parallel computing ability, which exceeds the speed of the CPU by 10 to 30 times. The GPU consists of an NVIDIA consumer line of graphics cards (for eg. GTX 680, Tesla K80, Quadro GP100).

The implementation of the proposed HDnCNN-IL was done using Python. Some of the important software packages included are Tensorflow, Keras and PyTorch which offers a relatively high-order machine learning library and Python interface and is used in object detection, image classification, denoising and image resolution.

5.2 Training and Testing Data:

For medical image denoising with either known or obscure noise level, we utilize 200 medical images of size 256 × 256 for training. The dataset we have used for this experiment is obtained from the kaggle.

For medical image denoising with either known or obscure noise level, we utilize 200 medical images of size 256 × 256 for training. We found that utilizing a bigger training dataset can bring little improvement. To prepare DnCNN for medical image denoising with realized noise level, we experiment the proposed model with two different noise variances. The two different noise variance for different noise types we considered are given in table 1.

Noise	Noise Level I	Noise Level II
Gaussian(0.05)	σ = 1	σ = 2
Speckle	σ = 1	σ = 2
Salt & Pepper	Amount = 0.1	Amount = 0.5
Poisson	Amount = 0.	

Table 1 – Noise Levels used for different noise types

Then the same 200 images are experimented with DnCNN, UDnCNN, DUDnCNN and the proposed HDnCNN-IL models. Various experiments have been conducted to train and validate the proposed model for denoising medical images. The training set is 80% of the total samples and the testingset has 20% of the total samples. The model was trained and validated by by running 40 rounds and 70 rounds of 5-fold cross-validation with different noises that affect medical images commonly. Various types of noises that include poisson noise, speckle noise, salt & pepper noiseand gaussian noise were added to the images in the dataset we considered. The noisy image is then denoised using our proposed method with 40 epochs and 70 epochs.

The performance metrics Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) were taken into account to measure the quality between noisy and denoised images. A comparative study for all the images were done based on the above metrics, the mean square error is the average of the square of the difference between the original and denoised image, MSE is calculated using the equation (2)

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

Where I is the monochrome image and K is the denoised image.

The Peak Signal to Noise ratio(PSNR) is obtained using MSE. PSNR is used to calculate the ratio between the maximum possible signal power and the power of the distorting noise which affects the quality of its representation and the ratio is computed in decibel form. It is an engineering term that measures the ratio between maximum original signal and MSE.

$$PSNR = 20.log_{10}(MAX_I) - 10.log_{10}(MSE) \qquad (3)$$

where 〖MAX〗 _I is the maximum value of the pixel in the image.

Structural Similarity Index Measure (SSIM), measure perceptual difference (such as contrast, luminance and structure) of two similar images. Higher SSIM value means better image quality.

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$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (4)$$

Where μx is the average value x, μy is the average value of y, σx is the variance of x and σy is the variance of y, σxy is the covariance ofx and y, and x and y are two windiws if the same size.

Thereafter, for each class, the accuracy, specificity, sensitivity, precision and F1 scores were calculated. The average value of the metrics over all rounds was then computed and their expected values presented within a 96.6% confidence interval. A description of the metrics is below: sensitivity is also called as true positive rate(TPR).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (5)$$

$$Precision = \frac{TP}{TP \quad FP} \qquad (6)$$

$$Specificity = \frac{TN}{TN+FP} \qquad (7)$$

$$Sensitivity\ or\ TPR = \frac{TP}{TP \quad FN} \qquad (8)$$

$$F1\ Score = \frac{Precision*Recall}{Precision+Recall} \qquad (9)$$

$$True\ Negative\ Rate(TNR) = \frac{FP}{TN \quad FP} \qquad (10)$$

$$Geometric\ Mean = \sqrt{(TPR \times TNR)} \qquad (11)$$

$$Area\ Under\ Curve\ (AUC) = \frac{TPR+TNR}{2} (12)$$

Where

True Positive (TP) represents the model correctly classifying an image from a particular class as that class.

True Negative (TN) represents the model correctly classifying an image not belonging to a particular class as not being from that class.

False Positive (FP) represents the model incorrectly classifying an image not belonging to a particular class as belonging to that class

False Negative (FN) represents the case when a model incorrectly classifies a model belonging to a particular class as not belonging to that class.

The confusion matrix for the four models is given in table 2 and shown graphically in Fig.5. From the graph it is seen that the proposedmethod increases the TP and TN cases than the otherthree models we considered DnCNN, UDnCNN, DUDnCNN.

DnCNN			
N = 200		Predicted	
		NO	YES
Actual	NO	TN = 70	FP = 8
	YES	FN = 12	TP = 110

(a) Confusion Matrix of DnCNN

UDnCNN			
N = 200		Predicted	
		NO	YES
Actual	NO	TN = 72	FP = 7
	YES	FN = 9	TP = 112

(b) Confusion Matrix of UDnCNN

DUDnCNN			
N = 200		Predicted	
		NO	YES
Actual	NO	TN = 73	FP = 6
	YES	FN = 8	TP = 113

(c) Confusion Matrix of DUDnCNN

HDnCNN-IL			
N = 200		Predicted	
		NO	YES
Actual	NO	TN = 75	FP = 4
	YES	FN = 6	TP = 115

(d) Confusion Matrix of proposed HDnCNN-IL

HDnCNN-IL

Table 2–Confusion Matrix of the different CNN Network

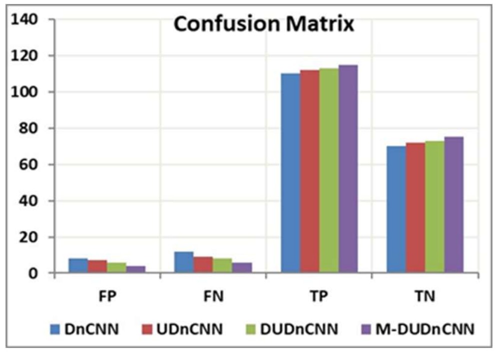


Fig. 5 Confusion Matrix of the different CNN Models

The Performance measures of Accuracy, Precision, Sensitivity, Specificity (TPR), F1 Score, TNR, Geometric Mean (GM), Area under the Curve (AUC) for the four models DnCNN, UDnCNN, DUDnCNN and the proposed HDnCNN-IL is tabulated below in Table 3, for the value of Sigma = 1 and iscalculated using equations (5) to equations(12).

Table 3 – The Performance metrics of the four models

	DnCNN	UDnCNN	DUDnCNN	Modified DUDnCNN
Accuracy	90.0	92.0	93.0	95.0
Precision	93.2	94.1	95	96.6
Specificity	89.7	91.1	92.4	94.9
Sensitivity	90.2	92.6	93.4	95.0
TNR	10.3	8.86	7.59	5.06
F1 Score	45.8	46.7	47.1	47.9
GM	30.4	28.6	26.6	21.9
AUC	50.2	50.7	50.5	50.1

Fig.6 The Performance metrics of DnCNN, UDnCNN, DUDnCNN and the proposed HDnCNN-IL model

The graph shown in Fig.6 gives the graphical representation of the Performance metrics given in table 3. From the graph it is seen that the proposed method increases the TP and TN cases outperforms than the other three considered models DnCNN, UDnCNN, DUDnCNN. It is found that the HDnCNN-IL, the proposed method outperformed than the other three CNN models considered.

Fig. 7 shows the Sample Images that have not been classified well by the proposed model in our dataset is listed below.

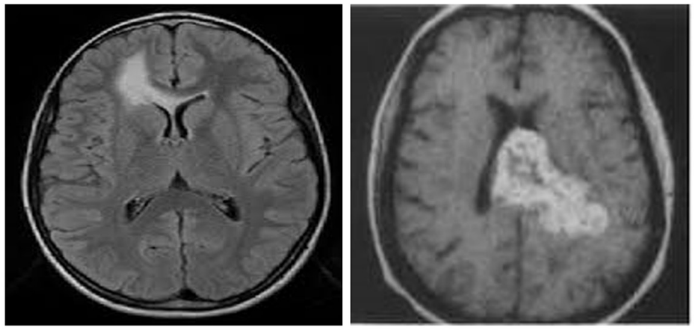


Fig. 7 – Images that has not been classified well after Denoising

Fig. 7 – Images that has not been classified well after Denoising

A sample image shown in Figure 5.7 has been taken into consideration for Gaussian noise with different noise levels □ = 1and □ = 2

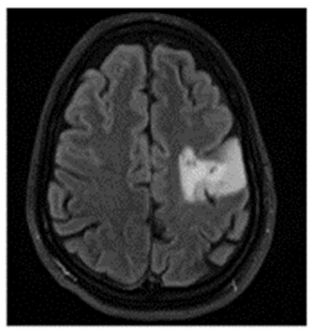


Fig. 8 – Images that has not been classified well after Denoising

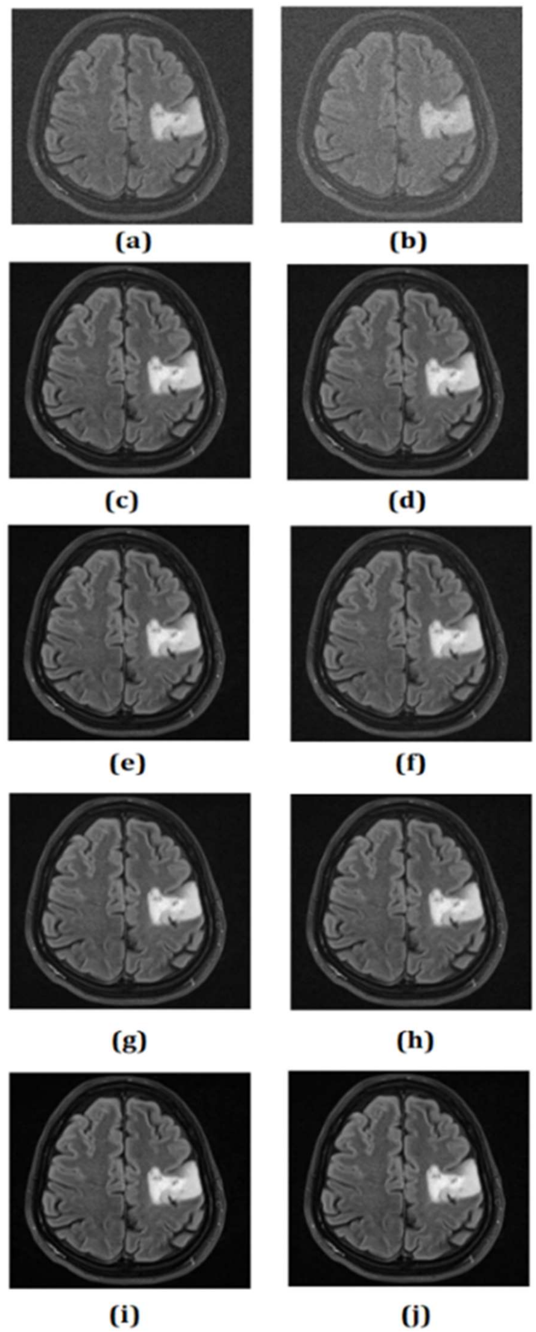


Figure 9 gives the denoising of the four methodologies DnCNN, UDnCNN, DUDnCNN and the HDnCNN-ILwith different noise levels taken into consideration for gaussian noise. From the images it is seen that the HDnCNN-ILhas given better results.

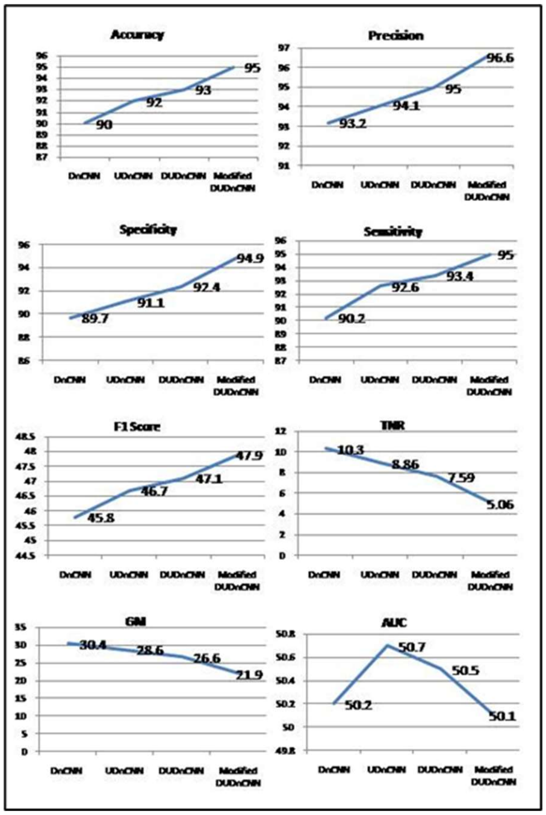


Figure 9 – Sample Output for Gaussian Noise removal using the four CNN model

(a) Noisy Image with □ = 1
(b) Noisy Image with □ = 2
(c) Denoised image for □ = 1 for DnCNN
(d) Denosied image for □= 2 for DnCNN
(e) Denoised image for □= 1 for UDnCNN
(f) Denosied image for □ = 2 for UDnCNN
(g) Denoised image for □= 1 for DUDnCNN
(h) Denosied image for □ = 2 for DUDnCNN
(i) Denoised image for □=1 for HDnCNN-IL
(j) Denosied image for □ =2 for HDnCNN-IL

The Performance Metrics PSNR (Peak Signal to Noise Ratio), SSIM (Structural Similarity) and MSE (Mean Square Error) for gaussian noise with two varientsof □ = 1 and □ = 2 the four CNN Models DnCNN, UDnCNN, DUDnCNN and HDnCNN-IL were given in Table 4. It is found that the HDnCNN-IL is giving a better performance under the noise influence of □ = 1 than □ = 2 but in all the cases the proposed HDnCNN-IL model has outperformed than all the other three existing models. Hence the proposed method has given a better performance and can be used for Denoising Medical Images efficiently.

	PSNR		SSIM		MSE	
	σ = 1	σ = 2	σ = 1	σ = 2	σ = 1	σ = 2
DnCNN	56.31	51.74	0.611	0.311	0.1519729	0.4354248
UDnCNN	61.77	56.75	0.699	0.399	0.0432281	0.1373767

DUDnCNN	69.05	63.45	0.715	0.461	0.0080807	0.0293706
HDnCNN-IL	**74.15**	**68.13**	**0.74**	**0.478**	**0.002499**	**0.009998**

Table 4 – Average PSNR, SSIM and MSE of the four CNN models for Gaussian noise with noise levels = 1 and = 2

It is found that the proposed HDnCNN-ILis giving a better performance under the noise influence of Sigma = 1 than sigma = 2 but in all the cases the proposed method has outperformed all the other three existing methods. Hence the proposed method has given a better performance and can be used for Denoising Medical Images.

The typical PSNR consequences of various strategies on the dataset are displayed in Table 4. As may be obvious, proposed HDnCNN-ILaccomplishes the best PSNR results than the contending techniques. Contrasted with the benchmarkproposed HDnCNN-IL, the techniques UDnCNN and DUDnCNN have a prominent PSNRacquire of around 74.15 dB. As indicated by the Table, barely any strategiescan beat DUDnCNN by more than 5.1 dB by and large. Incontrast, our proposed HDnCNN-ILmodel beats DUDnCNN by around 5 dBon both the two Sigma levels. Especially, even with a solitarymodel without realized noise level, our proposed HDnCNN-ILcan in any casebeat the contending strategies which is prepared for therealized explicit noise level. It ought to be noticed that bothUDnCNN and DUDnCNN outflank DnCNN by around 7.28dB and 5.46 dB when sigma = 1, also when sigma = 2 it will be 6.7 dB and 5.01 dB which is exceptionally near the assessed PSNRbound over proposed HDnCNN-IL.

Table 4 also records that SSIM also increased noticeably by the proposed HDnCNN-ILthan DnCNN, UDnCNN and DUDnCNN.

Table 4 also records that MSE, which decreased noticeably by the HDnCNN-IL than DnCNN, UDnCNN and DUDnCNN.

The graph shown in Fig.10,Fig.11 and Fig.12 depicts the correlation among average PSNR, average SSIM and average MSE between DCNN, UDnCNN, DUDnCNN and proposed HDnCNN-IL.models.

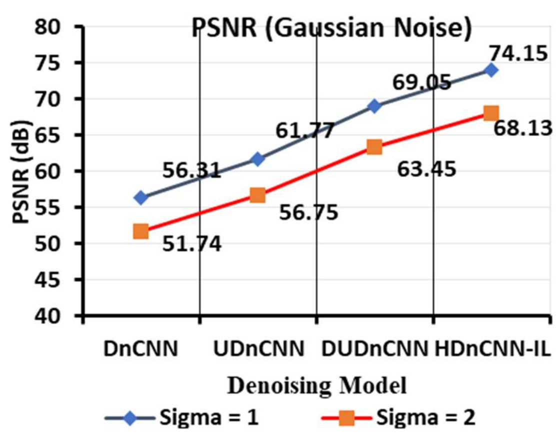


Fig. 10 The correlation among average PSNR between DCNN, UDnCNN, DUDnCNNand proposedHDnCNN-IL

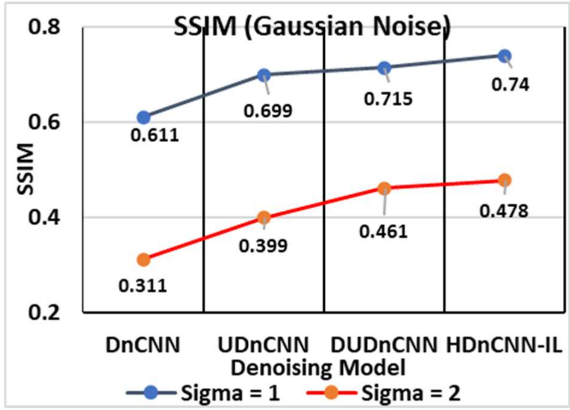


Fig. 11 The correlation among average SSIM between DCNN, UDnCNN, DUDnCNN and proposed HDnCNN-IL

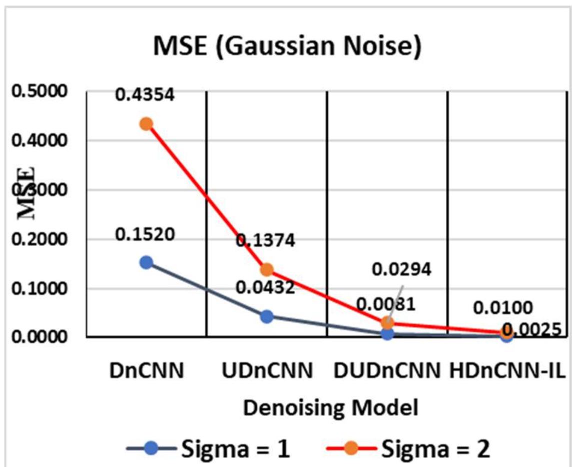


Fig. 12 The correlation among average MSE between DCNN, UDnCNN, DUDnCNN and proposed HDnCNN-IL

The Average PSNR, SSIM and MSE for Gaussian, speckle, poison and salt & pepper noises with noise level Set 1, which will experimented with 40 and 70 Epochs using the proposed HDnCNN-IL are listed in table 5.

Metric	PSNR		SSIM		MSE	
Epochs	40	70	40	70	40	70
Gaussian	74.1537	74.1496	0.73973	0.73957	0.002499	0.0025011
Speckle	98.628	98.6266	0.99913	0.99913	1.04E-05	1.04E-05
Poisson	102.353	102.353	0.99922	0.99923	7.02E-06	7.00E-06
Salt & Pepper	62.3957	62.3853	0.31761	0.31697	0.037609	0.0376917

Table 5 – Average PSNR, SSIM and MSEfor the four Noises with 40 and 70 Epochs by the proposed HDnCNN-IL

The graph shown in Fig.13 depicts table 4 graphically. From fig. 13we observe that both 40 and 70 epochs give approximately equal values for average PSNR, SSIM and MSE. Fig.14 and fig.15 depicts the value loss chart and step loss chart for Gaussian noise with □ = 1.

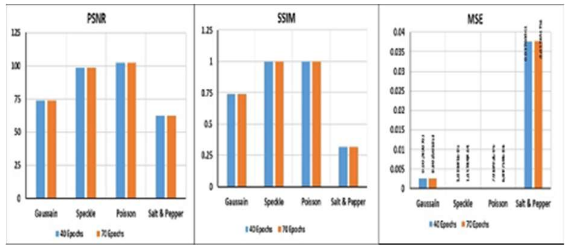
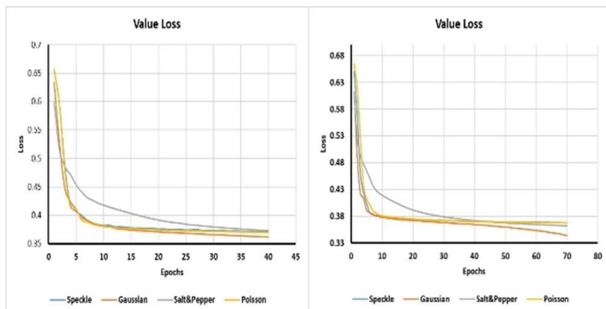
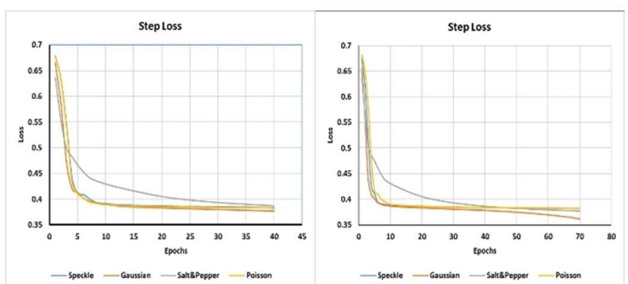


Fig.13 PSNR,SSIM and MSE of 4 different noises in the proposed method with 40and 70 Epochs



(a) *(b)*

Fig.14 ValueLoss Chart for four t noises with
(a) 40 Epochs (b) 70 Epochs



(a) *(b)*

Fig.15 StepLoss Chart for four different noises with
(a) 40 Epochs (b) 70 Epochs

Fig.16shows the visual result of sample original images considered for testing and its noisy versions with different noises such as Gaussian noise, Poison noise, Speckle noise and Salt & Pepper noise with noise level 1shown in table 1 and denoised versions by our proposed HDnCNN-IL model as well as the existing three CNN models.

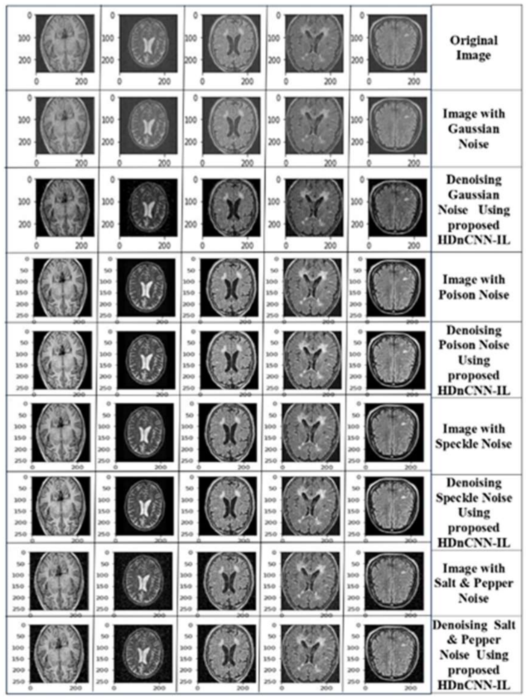


Fig.15 Sample output generated by the proposed HDnCNN-ILmodel for 4 different noise types

VI CONCLUSION

This paper has introduced an efficient Convolutional Neural Network basedapproach for Denoising medical images.The HDnCNN-IL model has given a better performance for Denoising Medical Images with Speckle noise, Poisson noise and Gaussian noise.From the experimentalresults it has been found that the proposed HDnCNN-IL has givena best PSNR value and SSIM value and low MSE for the value of □ = 1 than □ = 2 in thebrain images, but in all the cases the proposed method has outperformed all the other three existing methods.Compared with otheralgorithms this method has been found out to be faster, efficient, denoisingeffectively and was very easy to implement.Every image has given better results than the other three methods. Our experiments have proven the reliability of the proposed HDnCNN-IL model by having achieved an overall average accuracy of 95% of denosing the 200 MRI images as our dataset. Our model works well for Speckle noise, Poisson noise, Salt &Pepper noise and Gaussian noise and is shown in fig.12 based on the table 4.In future, the number of layers may be further increased, different activation functions may be used to improve efficiency of denoising images and also extend the work to denoise images with multiple noises as well. It may also extend to several general image denoising tasks.

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