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A SPECKLE DENOISER: DEEP CONVOLUTIONAL NEURAL NETWORK FOR MR IMAGE DENOISING

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Abstract— Image de-noising is used to enhance the quality of images because while acquiring images they are degraded by different noises. Medical images get corrupted by gaussian and speckle noises in general. In this paper, Noisy image is obtained by adding either Gaussian noise or speckle noise of range 5 to 50. For MR brain tumor image de-noising purpose, deep learning models like pretrained DnCNN, and proposed deepCNN are considered. The performance of deep learning models are evaluated in terms of parameters like PSNR, SSIM, MSE, and MAE. The proposed DeepCNN model gives better performance in achieving denoising than other method due to usage of batch normalization, ReLU, and 17 convolutional layers so that the training process gets speeded up, the denoising performance is boosted and over fitting problem is also avoided by doing augmentation of the datasets.

Keywords— Speckle denoiser, DeepCNN, deep convolutional neural network, DnCNN, Image denoising, Noise removal CNN.

I. INTRODUCTION

Filtering methods [1] are generally preferred for reducing noise in an image. Gaussian noise [2] is evenly distributed over the image and has a normal Gaussian distribution function. Speckle noise mostly occurs in medical images as a multiplicative noise and has gamma distribution. Due to the fast inference and good performance, discriminative learning methods have been widely used for image denoising. However, these methods mostly learn a specific model for each noise level, and require multiple models for denoising images with different noise levels. DnCNN is a pretrained Convolutional Neural Network (CNN) [3], [4] for image regression problem. It contains an input layer, convolutional layers, Batch normalization layer, rectifier linear unit layer, max pooling layer, dense or fully connect layer, and finally regression layer. Usually, it is also called as a multilayer neural network. The structural design of a CNN [5-7] is planned to get the benefit of the 2D arrangement of an input image. This is attained with local networks and weights monitored by a certain method of pooling [8] which effects translation invariant features. CNN models (DnCNN) for MRI Brain tumor image de-noising is chosen because of three reasons. First, a very deep architecture of the CNN increases the flexibility and capacity for exploiting the image characteristics. Second, the CNN speeding up the training process and improves the performance of denoising due to sparsity [9], weight sharing, batch normalization, and Rectifier Linear Unit. Third, Parallel computing capabilities of CNN on modern powerful Graphical Processing Unit (GPU) is used to improve the run-time performance.

II. ARCHITECTURE OF DEEP LEARNING MODELS

In this section, the architecture of both models pretrained DnCNN and Proposed DeepCNN are discussed.

A. Pretrained DnCNN model

There are many pretrained convolutional neural networks for regression problems and image classification [10], [11]. The DnCNN [12] is a 20 convolutional layers depth pretrained model for performing image de-noising task. It contains total of 59 layers including one input layer, 20 convolutional layers, 19 ReLU layers, 18 batch normalization layers, and one regression output layer. The architecture of DnCNN model is shown in Fig 1.

In this architecture model, the pooling layers are avoided. This model has three different types of layers as shown in Fig 1. The Conv+ReLU is the first convolutional layer, which is used after the input layer (patch size, patch size, channels). In this, the convolutional layer is followed by activation layer, ReLU. All convolutional layers use filters of size 3 x 3 x channels (of size 64 filters) to generate 64 feature maps. Here channels=1 for gray image and 3 for RGB image. The Conv+BN+ReLU is a combination of three layers, convolutional, batch normalization, and ReLU layer. In the proposed model, this combination is repeated 18 times between first Conv+ReLU layer and last convolutional layer, Conv20. 64 filters of size 3 x 3 x 64 are used and batch normalization layer is added between Convolutional layer, and ReLU layer. The Conv is the last convolutional layer channels number of filters of size 3 x 3 x 64 are utilized to reproduce the output. The final layer in the model is the regression layer to calculate the Mean squares error.

Due to batch normalization, ReLU, and 17 convolutional layers, the training process gets speeded up, boost the denoising performance and over fitting problem is also avoided by doing augmentation of the datasets. So the proposed DeepCNN model gives better performance in achieving denoising than other methods.

B. Proposed deep learning model (DeepCNN)

Architecture of Proposed DeepCNN model is same as DnCNN architecture. But it is a 17 convolutional layers depth model and has 50 layers including one input layer, 17 convolutional layers, 16 ReLU layers, 15 batch normalization layers, and one regression output layer. The input layer used for DnCNN is an image of patch size 50 x 50, whereas patch size 61 x 61 can be used as the input layer image size in DeepCNN. Moreover, it offers favorable results when extended to numerous traditional images denoising tasks.

One important issue of the model architecture is to fix proper depth for better performance and efficiency. The depth of the model is dependent on effective patch size and noise level in the image. Usually high noise level image denoising task requires large effective patch size. Here the proposed DeepCNN model learns to estimate the residual image. The residual image contains information about the image distortion. The denoised image is obtained by subtracting residual image fom original image.

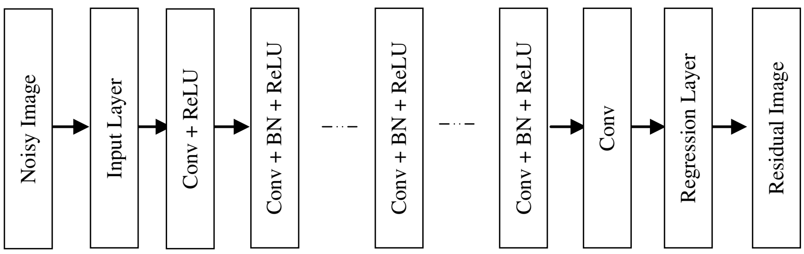

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Fig. 1 The architecture of DnCNN model

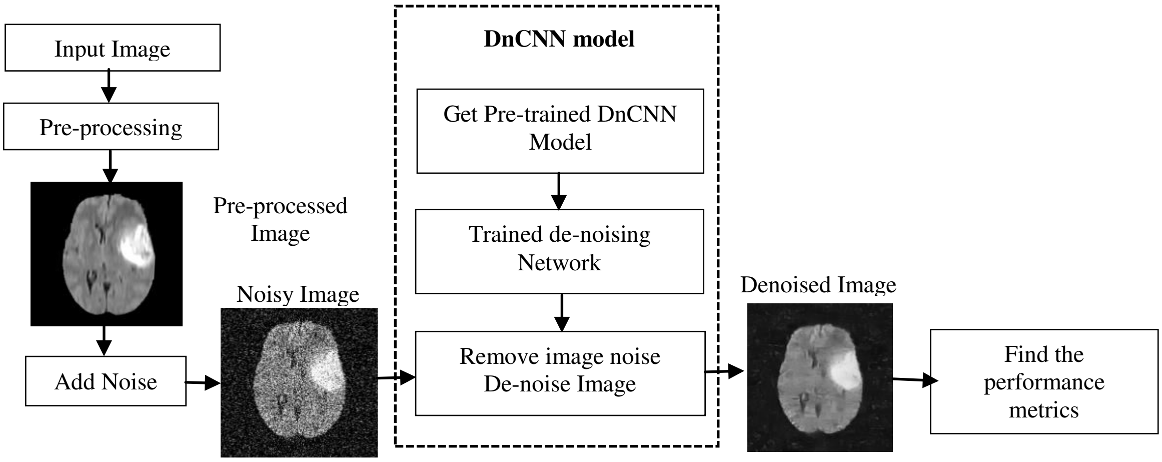

Fig 2 Frame Work of image de-noising with Pretrained Convolutional Neural networks (DnCNNs).

III. METHODOLOGY

In this section, Methodology for image de-noising using pretrained DnCNN and Proposed DeepCNN are discussed.

A. *Image de-noising using DnCNN*

Figure 2 details the application of DnCNN for image de-noising. In the framework, one of the pre-trained convolutional neural network (DnCNN) is considered for de-noising. The DnCNN is well trained on millions of natural images database ImageNet. Load this well optimised weights of DnCNN pretrained model as network or model then, pass the DnCNN network and a noisy 2-D image to reduce the noise. Then the performance metrics are calculated from the de-noised image. The image shows the workflow to denoise an image using the pretrained DnCNN network.

The simplest and fastest solution is to use the built-in pretrained de-noising neural network, called DnCNN. However, the pretrained network does not offer much flexibility in the type of noise recognized. Here the network or model DnCNN is not trained with our data images because the DnCNN pretrained model is directly considered for noise removal.

The pretrained DnCNN network is used to remove Gaussian noise without the challenge of training a network. Removing noise with the pretrained network has the following limitations:

- Noise removal works only with 2-D single-channel images. If there are multiple color channels, or 3D images, noise can be removed by treating each channel or plane separately.
- The network recognizes only Gaussian noise, with a limited range of standard deviation.

To overcome limitations of this frame work, to get more flexibility and improve the de-noising performance, the network has to be trained using predefined layers and customize de-noising neural network.

B. *Image de-noising using proposed DeepCNN*

A model is trained to detect a larger range of Gaussian noise standard deviations from grayscale images, starting with predefined layers. To train a de-noising model using predefined layers, the steps followed are

- Create an image data store that stores original images.
- Create a de-noising image data store that generates noisy training data from the

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original images in the image data store. Here noise level, patch size and channel format are specified, so that the size of the training data matches the input size of the network.

- Get the predefined DnCNN layers as network or model.
- Define training options to train the model. The training options are adaptive momentum estimator (adam) optimizer, Maximum Epochs 30, Initial learn rate 0.0001, Mini batch size 16.
- Train the network, specifying the de-noising image data store as the data source.

For each iteration of training, the de-noising image data store generates one mini-batch of training data by randomly cropping original images from the image data store, then adding randomly generated zero-mean Gaussian white noise to each image patch. The standard deviation of the added noise is unique for each image patch, and has a value within the range specified by the noise level of the de-noising image data store. After the network has trained, pass the network and a noisy image to de-noise image. The training workflow and denoising workflow are shown in Fig 3.

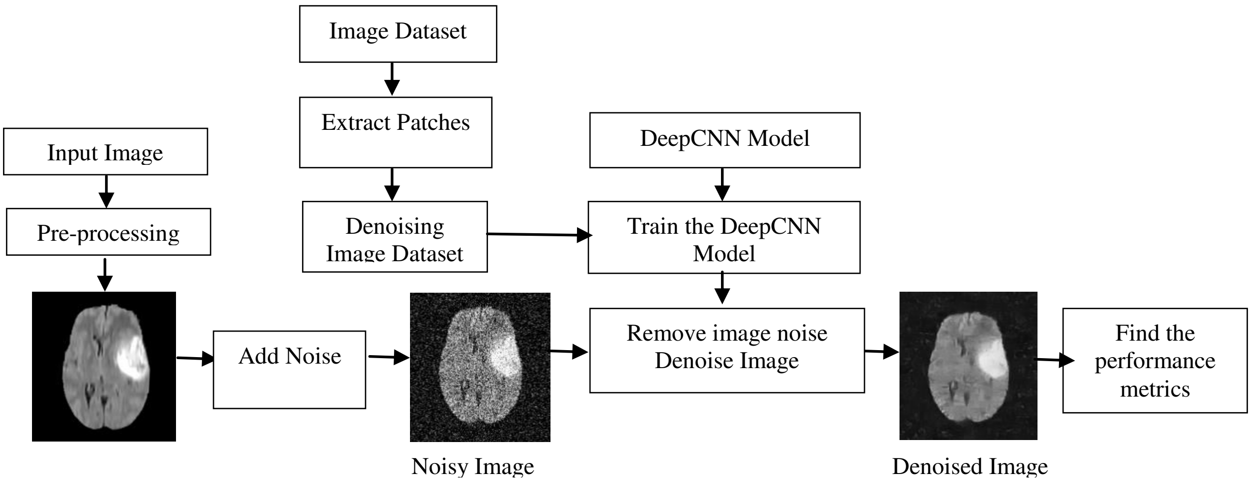

Fig. 3 Frame Work of image de-noising with Proposed DeepCNN.

BraTS 2018 database is considered to prepare the image datastore size of 400 images and used for training the DeepCNN model. Patches are extracted with an effective patch size of 61 at the rate of 64 patches per image. De-noising image data store is prepared by using these patches with gaussian noise of noise level range from 5 to 50. DeepCNN model is then trained to this dataset to perform the de-noising task. The noisy image is applied to the DeepCNN-model to reduce the noise in the image.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, images considered for denoising task are corrupted in two ways. Firstly, image is corrupted by adding gaussian noise with wide range of noise level from 5 to 50. Second, image is corrupted by adding speckle noise with wide range of noise level from 5 to 50. The experimental results of both cases are obtained using Pretrained DnCNN, and proposed DeepCNN Model and The performance metrics evaluated for image denoising are PSNR, SSIM, MSE, and MAE. The entire denoising work is

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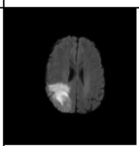
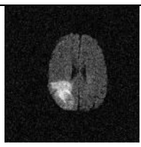
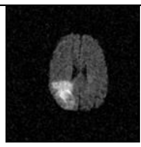
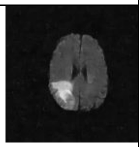
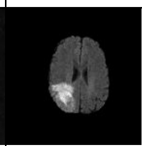
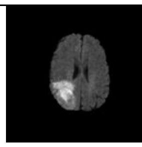
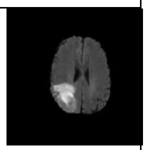
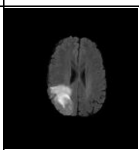
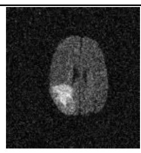
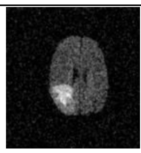
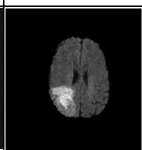
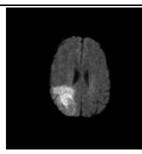
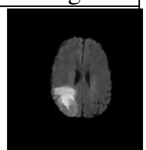
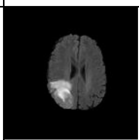
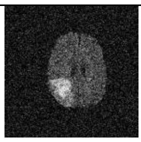
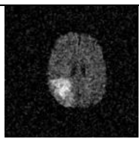
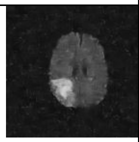
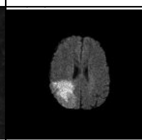
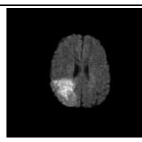
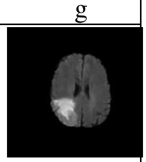
executed on the system with specifications of core i5, 7th generation Intel processor with 8GB RAM and GPU of 4GB NVIDIA graphic card.

Figure 4a and 4b show original image and noisy image which is formed by the addition of gaussian noise with noise range from 5 to 50. Denoised images obtained using pretrained DnCNN model and proposed DeepCNN model are shown in figure 4c and 4d respectively. From figure 4, the DeepCNN gives clear de-noised image visually than that of pretrained DnCNN. Figure 4e shows noisy image which is formed by the addition of speckle noise with noise range from 5 to 50. Images f and g show the denoised images obtained using pretrained DnCNN model and proposed DeepCNN model respectively. From this, the DeepCNN gives clear denoised image visually than that of pretrained DnCNN. Over all the proposed DeepCNN model gives the better performance in image denoising task.

Table 1 presents the performance metrics obtained by proposed DeepCNN and pretrained DnCNN models for varying levels of Gaussain noise for de-noising. It is clear that with increasing noise content the PSNR, SSIM Values decreases. For one instant noise level sigma equal to 20, the de noising performance metrics of DeepCNN like PSNR, SSIM, MSE, and MAE are 20.6564, 0.1412, 559.042, and 20.6937 respectively. From the table 1 the proposed DeepCNN model shows superior performance when compared to pretrained DnCNN. Hence DeepCNN seems to be the better suitable method for reducing noise when the image is corrupted by various noise level of gaussian noise.

S.No	Noise Level	Denoising images						
		With Gaussian noise				With Speckle noise		
1	σ=5							
		a	b	c	d	e	f	g
2	σ=10							
		a	b	c	d	e	f	g
3	σ=15							
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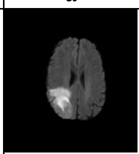
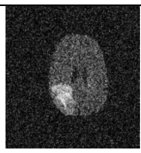
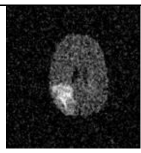
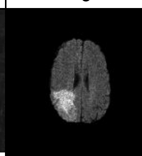
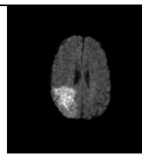
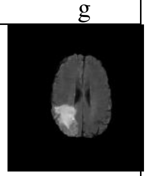
4	σ=20							
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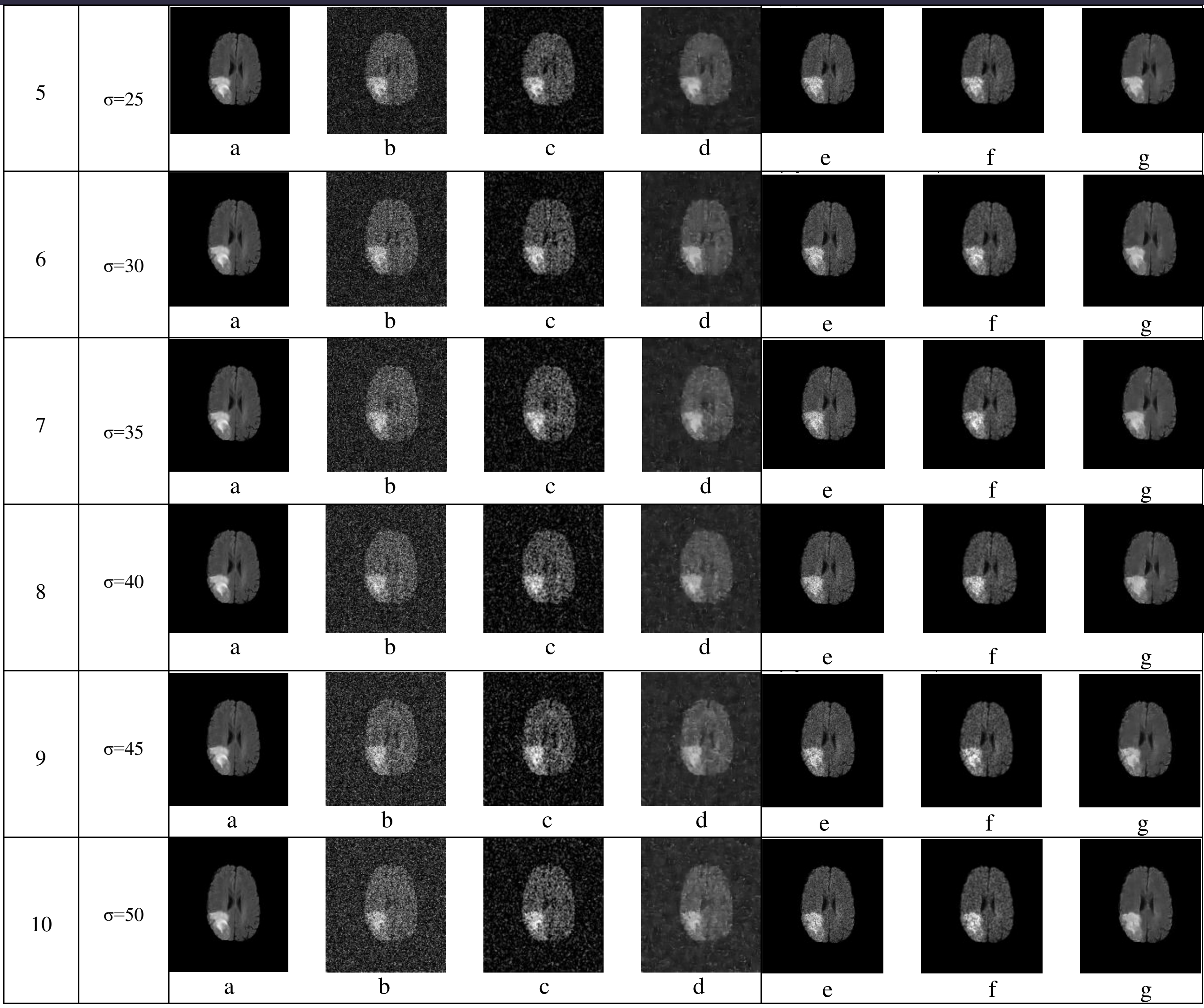

Fig. 4 a) Original image b) Noisy Image corrupted by gaussion noise with noise level range from 5 to 50. c) Denoised image by DnCNN d) Denoised image by DeepCNNe) Noisy Image corrupted by speckle noise with noise level range from 5 to 50.
f) Denoised image by DnCNN g) Denoised image by DeepCNN

TABLE 1 PERFORMANCE METRICS OF PROPOSED DEEPCNN AND PRETRAINED DNCNN WITH GAUSSIAN NOISE OF VARIES NOISE LEVELS.

S.No	Noise Level	Method	PSNR (dB)	SSIM	MSE	MAE
1	σ=5	DeepCNN	**28.9274**	**0.2385**	**83.242**	**7.9241**
		DnCNN	25.3215	0.1931	192.5861	12.122
2	σ=10	DeepCNN	**25.3826**	**0.1978**	**192.6814**	**12.112**
		DnCNN	22.4189	0.1631	375.0291	16.8145
3	σ=15	DeepCNN	**22.39**	**0.1587**	**375.0389**	**16.7951**
		DnCNN	20.6479	0.1391	559.042	20.6937
4	σ=20	DeepCNN	**20.6564**	**0.1412**	**559.042**	**20.6937**
		DnCNN	19.439	0.119	738.3465	23.6042
5	σ=25	DeepCNN	**19.448**	**0.125**	**738.3745**	**23.7842**
		DnCNN	18.5059	0.1099	911.2204	26.3927
6	σ=30	DeepCNN	**18.506**	**0.1169**	**917.2244**	**26.4804**
		DnCNN	17.6692	0.1029	1.10E+03	29.3711
7	σ=35	DeepCNN	**17.6741**	**0.1031**	**1.11E+03**	**29.2791**
		DnCNN	16.8921	0.0968	1.20E+03	31.5921
8	σ=40	DeepCNN	**16.9834**	**0.0979**	**1.30E+03**	**31.6065**
		DnCNN	16.4132	0.0924	1.48E+03	33.4921
9	σ=45	DeepCNN	**16.5299**	**0.0934**	**1.45E+03**	**33.4439**
		DnCNN	15.9954	0.0861	1.61E+03	35.6172
10	σ=50	DeepCNN	**15.9539**	**0.0851**	**1.65E+03**	**35.6019**
		DnCNN	15.5281	0.0805	1.82E+03	37.3686

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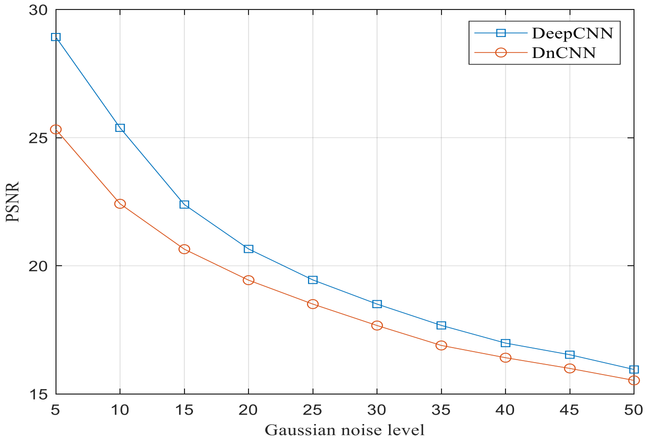

Fig. 5 Plot of PSNR values and gaussian noise level.

TABLE 2 PERFORMANCE METRICS OF PROPOSED DEEPCNN AND PRETRAINED DNCNN WITH SPECKLE NOISE OF VARIES NOISE LEVELS.

S.No.	Noise Level	Method	PSNR (dB)	SSIM	MSE	MAE
1	σ=5	DnCNN	36.625	0.9547	14.1444	0.556
		DeepCNN	**39.4316**	**0.9705**	**7.4118**	**0.5178**
2	σ=10	DnCNN	34.4705	0.9368	23.2292	0.7523
		DeepCNN	**37.6716**	**0.9611**	**11.1152**	**0.6611**
3	σ=15	DnCNN	33.2209	0.9256	30.9734	0.7869
		DeepCNN	**36.5237**	**0.9568**	**14.4782**	**0.6599**
4	σ=20	DnCNN	32.1186	0.9131	39.9225	0.9878
		DeepCNN	**35.7782**	**0.9512**	**17.1894**	**0.7507**
5	σ=25	DnCNN	31.3743	0.9066	47.386	0.9893
		DeepCNN	**35.2188**	**0.9476**	**19.5525**	**0.7425**
6	σ=30	DnCNN	30.7113	0.8992	55.2009	1.1387
		DeepCNN	**34.5764**	**0.9436**	**22.6695**	**0.8119**
7	σ=35	DnCNN	29.916	0.8905	66.2944	1.3151
		DeepCNN	**34.1029**	**0.9392**	**25.2807**	**0.882**
8	σ=40	DnCNN	29.259	0.8872	77.1217	1.3396
		DeepCNN	**33.3072**	**0.9344**	**30.3642**	**0.9056**
9	σ=45	DnCNN	29.1481	0.8839	79.1169	1.4303
		DeepCNN	**33.2201**	**0.9336**	**30.9789**	**0.9426**
10	σ=50	DnCNN	28.7149	0.8776	87.4166	1.5094
		DeepCNN	**33.041**	**0.9299**	**32.2837**	**0.9595**

Figure 5 shows the variation of PSNR with different gaussian noise level ranging from 5 to 50 for pretrained DnCNN and proposed DeepCNN. The proposed DeepCNN shows a highest PSNR and decreases with increasing gaussian noise level.

Table 2 presents the proposed DeepCNN and pretrained DnCNN models along with the varying noise levels of speckle noise for de-noising task. It is clear that with decreasing noise content the PSNR, SSIM Values increases. For one instant noise level sigma equal to 10, the de-noising performance metrics of DeepCNN like PSNR, SSIM, MSE, and MAE are 37.6716, 0.9611, 11.1152, and 0.6611 respectively. From Table 2 the proposed DeepCNN model shows superior performance when compared to pretrained DnCNN. It's concluded that the DeepCNN is the better suitable method for reducing noise when the image is corrupted by varying noise level of speckle noise.

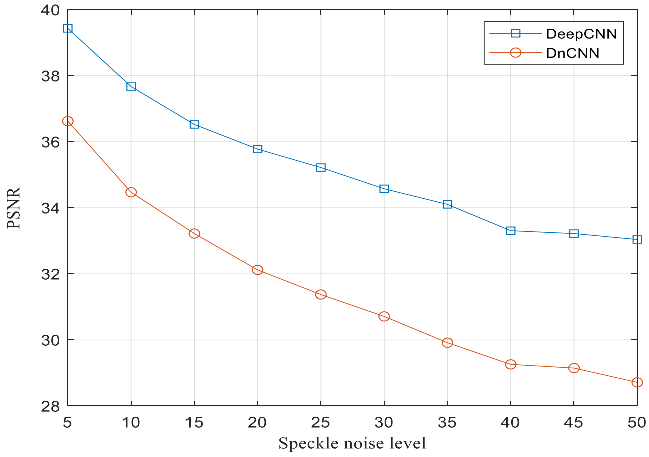

Fig. 6 Plot of PSNR values and speckle noise level for various methods.

Figure 6 shows the variation of PSNR with different noise level ranging from 5 to 50 for pretrained DnCNN and proposed DeepCNN. The proposed DeepCNN shows a highest PSNR and decreases with increasing speckle noise level.

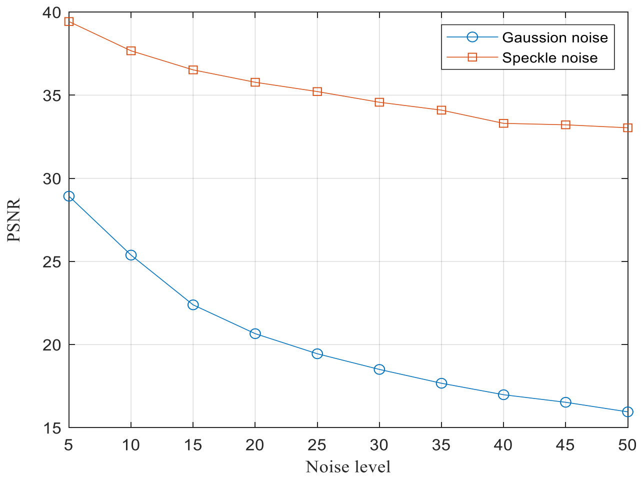

Fig. 7 PSNR performance of proposed DeepCNN for Gaussian and speckle noise.

When DeepCNN performs de-noising task with speckle and gaussian noises level ranging from 5 to 50, the DeepCNN is able to handle speckle noise very well in the entire range.

V. CONCLUSIONS

The performance of PSNR for gaussian noise corrupted image is improved to 14.24% for the proposed DeepCNN model with a noise level of 5. An improved performance of 7.66% is achieved by the proposed model when speckle noise with an addition of noise level 5 is taken. For a Gaussian noise with known noise level of 15 the proposed DeepCNN model shows an improvement of PSNR by 8.39%. Hence, the proposed DeepCNN model appears to be better for reducing noise when image gets corrupted by either speckle or Gaussian noise with known or unknown noise levels. In addition, the proposed DeepCNN preserves the structural information of the image by observing the SSIM values from the results.

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