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Image Denoising using a Combination of Spatial Domain Filters and Convolutional Neural Networks.

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Abstract*: Image denoising is one of the most pressing challenges in Image Processing. Spatial Domain Filters are long existing method for denoising that are simple and effective against different types of noises, but they do not take into account the recurring patterns. Furthermore, due to ever increasing demand for image denoising on various applications in technology, the computational and memory intensiveness along with their performance on various types of noises becomes extremely important. Recently Convolutional Neural Networks have turned out to be state-of-the-art methods for denoising. We put forward a system which integrates a deep CNN preceded by Block Matching along with traditional spatial domain methods for image denoising for both random structures of an image as well as recurring patterns. This system is evaluated over a large data set of grey-scale images and various noises and has state-of-the-art results.

***Index Terms*: image denoising, spatial domain filters, convolutional neural networks, block matching**

I. INTRODUCTION

Image Denoising is one of the most challenging and equally important problems in today's world since given our current image capturing devices and unfavorable situations such as low light photography and blurriness of the captured images. Spatial domain filters are perennial techniques which are simple and less memory intensive but are competent against different types of noises. The hunt for effective denoising methods is still an ongoing challenge. Despite the level of complexity of various algorithms, many techniques fail to achieve desirable level of applicability over their use and types of images over which they are proficient. Convolutional Neural Networks (CNN) are the most recent development in the world of Image Processing. They perform really well against varieties of noises but the training of the networks is time consuming and also their performance and regular textures with high resemblance are not up to the mark. Non-Local Filters are another set of technique that performs well on an image having patches of strong resemblance and however, they perform weak against images with less self-similarity within themselves Therefore, in this paper we attempt to combine Spatial Domain Filters along with Block Matching Convolutional Neural Network consisting of Hard Thresholding and Weiner Filter along with pre-trained Convolutional Neural Networks. We firstly attempt to remove the noise using Spatial Domain Filters. They perform extremely well on noisy images consisting of noise models such as: Gaussian noise model and uniform noise model. Secondly we attempt to denoise various images using Block Matching Convolutional Neural Network alone to check the performance. Lastly we use a combination of Spatial Domain Filters and BMCNN and compare their performances. Various Spatial Domain Filters are tested along with BMCNN on a various data sets of grey-scale images consisting of recurring patterns and irregular structures. After applying Spatial Domain Filters, we apply Hard Thresholding followed by Weiner Filters followed by Haar transform. Hard Thresholding is applied to suppress the noise which could've been left out after applying Spatial Domain Filter. Due to its low memory intensive nature Haar transform has been used for pattern recognition.

II. LITERATURE SURVEY

[1] Here they have introduced a combination of Convolutional Neural Network (CNN) based denoiser and a Nonlocal Filter (NLF) for images with texture similarities. Here the combination they have set up is modular unlike the traditional complicated neural networks. The system here makes use of standard nonlocal filters along with pre-trained CNN. The drawback of a NLF is that it doesn't give efficient results on images which lack self-similarity. It is seen from the work that the combination of the NLF with CNN gives better results than the currently available CNNF. The NLF used in the system is a liability in the case where images used doesn't have self-similarity. [2] Here they have studied weighted nuclear norm minimization (WNNM) with singular values assigned different weights. The WNMM is studied under varying weight conditions. And then WNNM is used for image denoising, WNNM exploits the image nonlocal self-similarity.

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The system shows increase in PSNR values and proves to be better than the existing system at that moment. But the system is too old and isn't fully compatible with our field of study.[9] Here in the proposed system there's a usage of Internal (denoising is one with the help of noisy patches in the same image) and External (denoising is done by a different clean image) denoising methods. The methods are chosen based on the noises in the image. Based on PatchSNR value a suitable technique is used for the denoising of image leading to improvements in the performance of the system.

[3] Here they propose a system which uses feed-forward denoising Convolutional Neural Network (DnCNN) which is capable of handling Gaussian noise of unknown level whereas the traditional methods can handle Gaussian noises only at a certain level. Here they propose making use of GPU to get the best out of DnCNN. From the experiment results its seen that the DnCNN is highly effective.

[4] Here in this proposed system the 2D image fragments are grouped into 3D arrays, the noise is attenuated without losing the unique features of the image. Then the blocks are reverted to original location. A Weiner Filter is applied on the image. The research work concludes that the results are on par with the stat-of-the-art denoising performance both on PSNR values and Visual Quality. This Paper also proposes a new method of denoising called BM3D which is a framework for diminution of additive white Gaussian Noise from the grayscale images.

[5] Here the purpose of the work is to log different types of Modern Image Filters and add insights on each one of them. The study explains the interrelation of the different filters and how it can work with the combination. The study talks about the possibility of enhancements in the filters alongside the drawbacks. The study helps in understanding the filters and acts as a guide for someone who wants to work on a specific Filter, i.e what drawbacks it has, how it can be altered and possibility of impactful enhancements.

[6] Here in the proposed system shape-adaptive discrete cosine transform (SADCT) is used. SADCT is highly complex and memory extensive. In the proposed system SADCT is used with the coexistence of Anisotropic Local Polynomial Approximation. They also use Hard-Thresholding and Weiner Filter, this technique of denoising works on grey-scale and color images, using this system they have made SADCT less memory extensive.

[7] Here in the proposed system Alternating direction method of multiplier (ADMM) is used. ADMM is known for its modularity. The system works on a plug and play scheme which are based on bounded denoisers. The combination of plug and play scheme and ADMM resulted in a superior performance of the system with comparison to the state-of-the-art algorithms existed at the time of work.

III. PROPOSED METHODOLOGY

A. Spatial Domain Filters

We evaluate various Spatial Domain Filters over a wide dataset of grey-scale images to choose the efficient filter which is also compatible with CNN. Firstly, we manually add noise to images and apply Spatial Domain Filters separately and apply BMCNN separately and also we apply a combination of Spatial Domain Filters and CNN. We do this by applying Spatial Domain Filters over the images and keeping a record of the PSNR values and also to later compare it with the results.

B. Block Matching Convolutional Neural Network

BMCNN is a combination of Hard Thresholding, Weiner Filters and Haar Transform coupled with pre-trained CNN. The Weiner Filter is a restorative method for deconvolution. If the image is noised by a low pass filter, then image restoration is possible by inverse filtering. Since we're adding additive noise inverse filtering is sensitive to additive noise we need to use Weiner Filter which provides optimal balance between the techniques of inverse filtering and noise smoothing, it eliminates the additive noise and inverts the blurring concurrently. We use pre-trained CNN since the training of CNN's time consuming. This allows our methodology to be modular and reusable. Lastly we compare the PSNR values obtained in all the three cases and find the most optimal method. We have chosen DnCNN for BMCNN as DnCNN is a pre trained Neural Network which has shown great potential in image denoising. Various image denoising problems can be implemented by using this method. As, Zhang[3] has shown DnCNN yields outstanding outcomes for the three image denoising methods : Blind Gaussian Denoising SISR and JPEG Deblocking.This Method turns out to outperform methods like BM3D [4], WNNM[2] in relation to Gaussian Denoising .

In our system a noisy input image is fed the input image is hard threshold (The coefficient. below the threshold value is set to zero) and then a Weiner filter is used which inverts blurring and removes additive noise. The image is then passed to Haar filter, they are the most basic wavelet, Haar can be used to extract selective features of an image. Now after this the system makes use of BM3D for denoising, which extracts the images in patches, the patches are denoised using a pre-trained CNN patch by patch, Here the system still has few noisy patches without any significant change, Now the patches which were denoised before are used as reference for denoising the patches which still holds noise in it. We get noise free patches, which are then combined together to form the Denoised output image.

C. Convolutional Neural Networks(CNN)

Convolutional Neural Networks are a main category of Artificial Neural Networks which are mainly used for image classification, image recognition.

Each input image is distributed through a series of convolutional layers with corresponding filters. The Filtered Image are then fed into the convolutional layers of which consists of nested kernels and feature maps. There are various activation functions and we can choose any one of them based on the task. One of the most popularly used Activation Function is the Rectified Linear Unit(ReLU). In CNN's,The Activation Function is used mostly in the Nonlinearity Layer. Fig 1 shows the results of the ReLU activation function over a range of values.

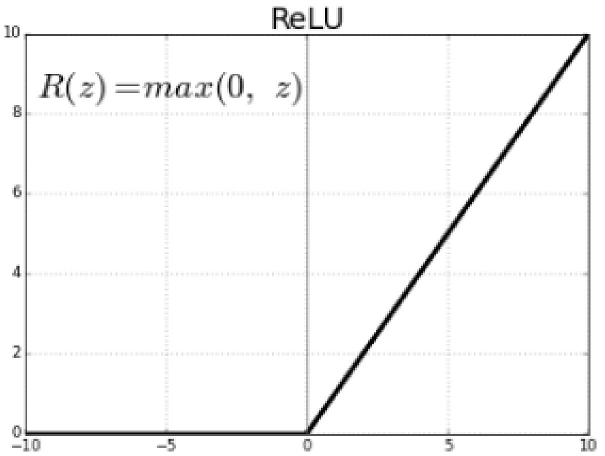

Figure 1: Results of ReLu over a range of values

Another major part of the CNN architecture is the Pooling Layer which is used to decrease the spatial dimensions on the Network but leaves the depth of the CNN unchanged. The two widely used types of Pooling are: Max Pooling and Average Pooling.

Fig 2 is the overall structure of the CNN over a cross sectional view. It shows the Convolutional Layers along with the Fully Connected Layers majorly used for classification.

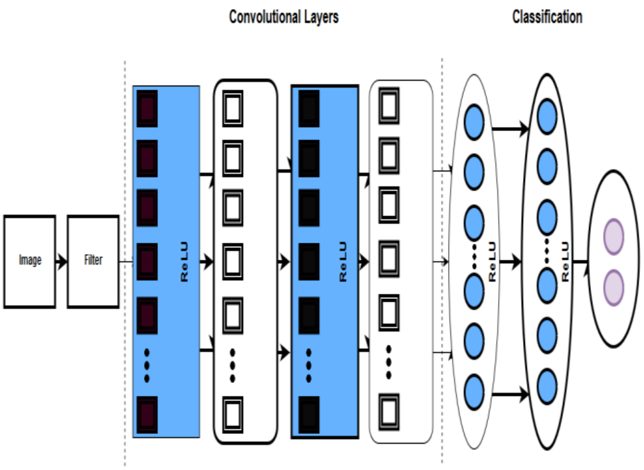

Figure 2: Architecture of CNN

The main goals of the Pooling layer are to provide spatial variance so that the system can recognize an object even though it's appearance is varied across the image.

In the Fully Connected Layer, the output of the last Convolutional layer is flattened and each MLP of the layer is connected to every other node of the other layer or this particular part of the CNN is fully connected. The operations in the FC layer are pretty much as same as with any other ANN.

IV. BLOCK DIAGRAM AND EXPLANATION

Figure 3 is a representative of the overall structure of the Block Matching Convolutional Neural Network. The noisy image is taken as input and Hard-Thresholding is performed on the image with a constant block size and set of parameters. Then Weiner Filtering is performed with pre-set parameters. Frequency Transform Matrices are computed with the help of Hard-Thresholding and Weiner Filters for producing estimate of PSNR values of Images. Image Denoising is performed using BM3D framework which works on patches and Non-Local Self Similarity.

The output of the BM3D is then passed to a pre-trained CNN which is helpful for analyzing images with regular structures and patterns. The Results are then compiled to produce the PSNR value of image denoising using BMCNN.

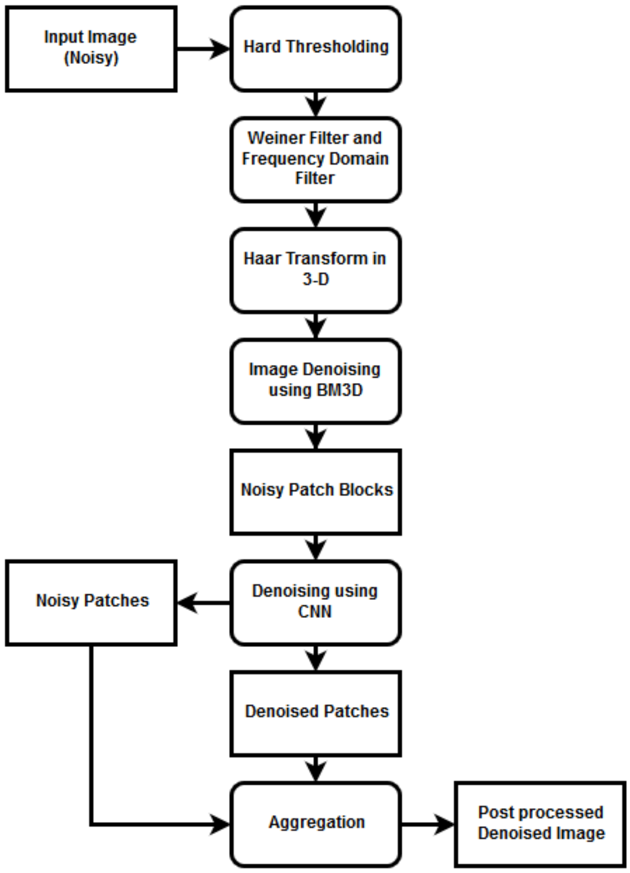

Figure 3: Methodology of BMCNN Image Denoising

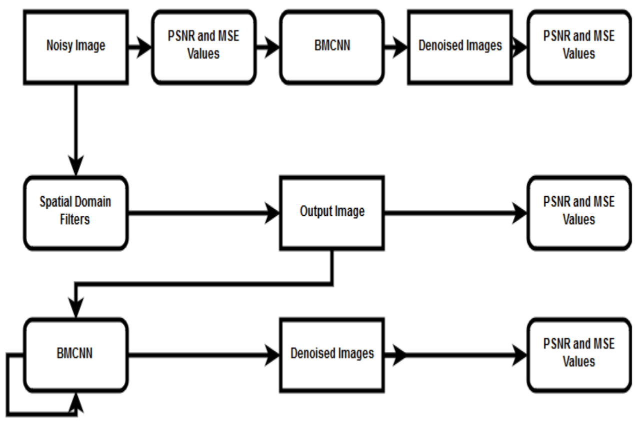

Figure 4: Overall Methodology to compare PSNR Values after Image Denoising using various techniques

Figure 4 is a representative of the combination of Spatial Domains and BMCNN.

Firstly, the input image is solely evaluated against Spatial Domain Filters to test their authenticity and performance against the accepted benchmarks. Next, the input images are tested against BMCNN to evaluate the performance of BMCNN on the noisy images and their PSNR Values are recorded. Finally, the input images are passed to a combination of Spatial Domain Filters and BMCNN and their PSNR Values are recorded and compared to the PSNR Values obtained by applying BMCNN and Spatial Domain Filters alone and the results are tabulated.

V. IMPLEMENTATION

TABLE I
COMPARISON OF VARIOUS FILTERS ON VARIOUS NOISES ON THE BASIS OF PSNR VALUES (dB)

	Arithmetic Mean	Harmonic Mean	Median	Min	Max
Gaussian	20.23	20.18	20.19	15.8	16.75
Salt and Pepper	22.44	16.46	22.46	17.48	-
Speckle	21.93	20.55	21.90	19.78	20.01
Poisson	25.90	26.18	26.72	18.25	12.87

*variance for the appropriate noise is 0.02

TABLE II

COMPARISON OF BMCNN ON VARIOUS TYPES OF FILTERS

	Gaussian	Salt and Pepper	Speckle	Poisson
BMCNN	80.03	81.25	79.86	83.77

TABLE III

COMPARISON OF SDF+BMCNN ON VARIOUS TYPES OF FILTERS

	Gaussian	Salt and Pepper	Speckle	Poisson
Arithmetic Mean+BMCNN	82.65	82.80	80.47	83.61
Median+BMCNN	77.03	86.79	77.15	81.79

Table I shows the output of Spatial Domain Filters applied on images riddled with various types of noises. The Respective PSNR Values are noted.

Table II shows the output of BMCNN applied on images riddled with various types of noises. The Respective PSNR Values are noted.

Table III shows the output of Spatial Domain Filters and BMCNN applied on images riddled with various types of noises. The Respective PSNR Values are noted.

VI. RESULTS AND OUTPUTS

Firstly, we apply Spatial Domain Filters on Noisy Images to obtain the PSNR Values of the denoised images. Figure 5 is the output obtained after applying Harmonic Mean Filter on an image riddled with Poisson Noise.

Next, we apply BMCNN on Noisy Images to obtain the PSNR Values of the denoised images using this particular technique. Figure 6 is the PSNR valued obtained after applying BMCNN on a noisy image riddled with Salt and Pepper Noise. Figure 7 is the output obtained after applying BMCNN on a noisy image riddled with Salt and Pepper Noise. Figure 8 is the output obtained after applying BMCNN on a noisy image riddled with Speckle Noise. Figure 9 is the PSNR Values obtained after applying BMCNN on a noisy image riddled with Salt and Pepper Noise.Finally, we apply Spatial Domain Filters on Noisy Images and then we apply BMCNN on the resultant images. Figure 10 is the output obtained after applying Median Filter followed by BMCNN on Noisy image consisting of Salt and Pepper Noise. Figure 11 is the Output of Arithmetic Mean Filter and BMCNN on Speckle Noise.

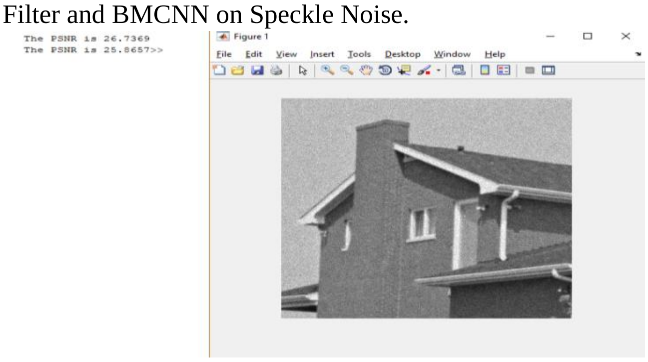

Figure 5: Harmonic Mean Filter on Poisson Noise
Here, we have applied Poisson noise on an image on which a Harmonic filter is used.

```
 PSNR before denoising= 66.52 dB

 MSE before denoising= 0.01450
BASIC ESTIMATE, PSNR: 6.13 dB
FINAL ESTIMATE (total time: 2.1 sec), PSNR: 66.52 dB

 PSNR after denoising= 81.25 dB

 MSE after denoising= 0.00049
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Figure 6: PSNR Values of BMCNN on Salt and Pepper Noise
Here we have recorded the PSNR and MSE after denoising an image with salt and pepper noise using BMCNN.

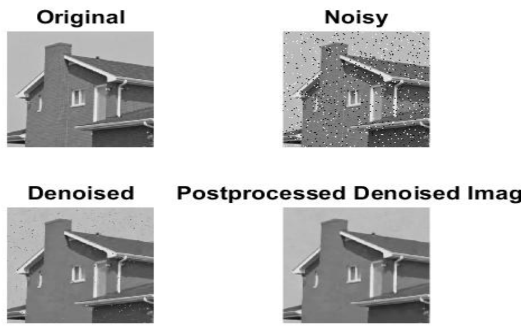

Figure 7: Output of BMCNN on Salt and Pepper Noise
Here we have the output of the denoising process of an image with salt and pepper noise using BMCNN.

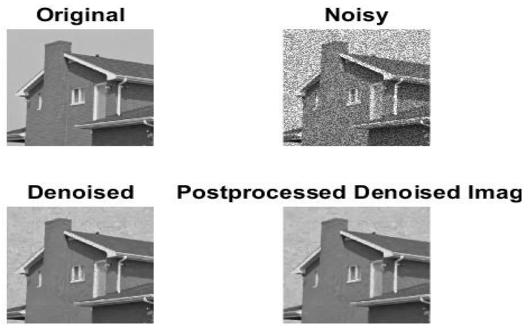

Figure 8: Output of BMCNN on Speckle Noise

Here we have the ouput of the denoising process of an image with speckle noise using BMCNN.

```
 PSNR before denoising= 66.14 dB

 MSE before denoising= 0.01580
BASIC ESTIMATE, PSNR: 6.10 dB
FINAL ESTIMATE (total time: 2.5 sec), PSNR: 66.14 dB

 PSNR after denoising= 79.70 dB

 MSE after denoising= 0.00070
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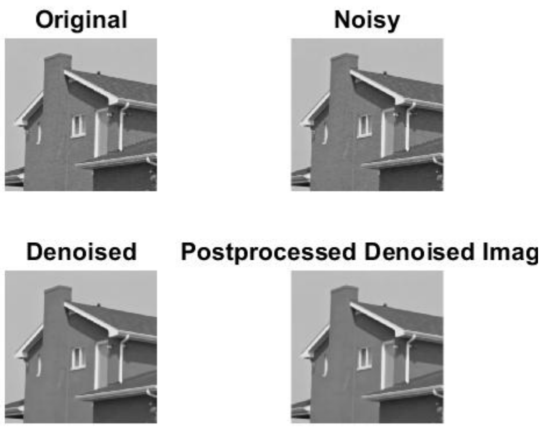
Figure 9: PSNR Values of BMCNN on Speckle Noise

Here we have recorded the PSNR and MSE after denoising an image with speckle noise using BMCNN.

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PSNR after denoising= 86.79 dB

MSE after denoising= 0.00014
```

Figure 10: Median Filter and BMCNN on Salt and Pepper Noise

Here, we have applied Salt and Pepper noise on an image on which a median filter is used and then denoised using BMCNN. The PSNR and MSE outputs are recorded.

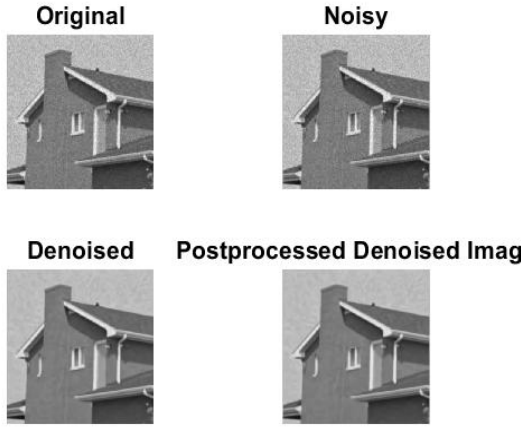

Figure 11: Output of Arithmetic Mean Filter and BMCNN on Speckle Noise

Here, we have applied Speckle noise on an image on which a mean filter is used and then denoised using BMCNN.

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PSNR after denoising= 80.48 dB

MSE after denoising= 0.00058
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Figure 12: PSNR Values of Arithmetic Mean and BMCNN on Speckle Noise

The PSNR and MSE outputs of an image with speckle noise after applying mean filter and denoising using BMCNN.

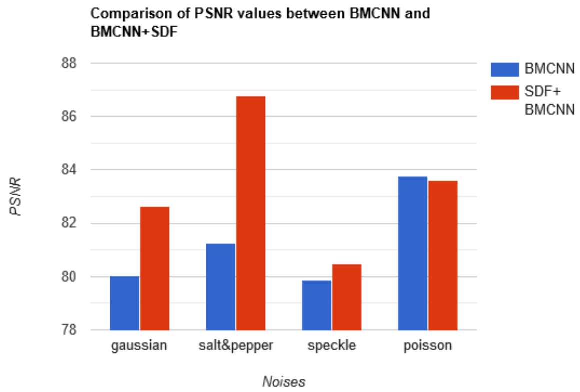

Figure 13: Comparison of PSNR values between BMCNN and BMCNN+Spatial Domain Filters.

Figure 13 showcases the different PSNR Values obtained from the two techniques of Image Denoising: BMCNN and BMCNN + Spatial Domain Filtering.

Each PSNR Value is obtained by performing image denoising by adding a particular type of noise to an image which is uniform throughout the procedure. The same tests are performed by using different images to test their validity. From the experimental results, the usage of Spatial Domain Filters along with Block Matching Convolutional neural network tested on different types of noises yielded better results than the traditional methods in existence.

VII. CONCLUSION AND FUTURE WORK

Our proposed system of Spatial Domain Filters and modified BMCNN performs well on Salt and Pepper noises and Speckle noises. It performs on par with the traditional BMCNN for Poisson noise and it performs well on Gaussian Noise based on the choice of the Spatial Domain Filter used. The choice of the Spatial Domain Filter affects the overall PSNR Values obtained after applying Spatial Domain Filters and BMCNN. Hence, our proposed system performs better than the traditional BMCNN Method and Spatial Domain Filters and provides Higher Magnitude of PSNR Values for Various types of noises as well. Also, since our system combines BMCNN and Spatial Domain Filters which are not computationally expensive and is also not memory intensive. All in all, this

system provides a higher degree of performance without a significant increase in the complexity or memory and processor requirements.Furthermore, Our system provides a promising future in the field of image processing. The future enhancement could comprise of application of various image denoising techniques such as Wavelet Shrinkage and other such frequency domain filters along with BMCNN. BMCNN as a whole can be modified to add various other technique along with DnCNN or an entire new neural network structure could be used altogether. As was shown in the Results Section, the choice of Spatial Domain Filters plays a huge role in the overall end result. Hence, further enhancements could include testing over various other Spatial Domain Filters and other techniques can be used as a combination.

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