Medical Image De-Speckling Using Fusion of Diffusion-Based Filters And CNN

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***Abstract*— Ultrasound images, although significantly low cost when compared to the likes of MRI scans and Biopsy, these images have the disadvantage of being laden with Speckle noise, which is a multiplicative noise, making it less accurate and competitive to the level of details provided on MRI scans. Improving the quality of ultrasound pictures so that they may be used as a viable alternative to MRI scans entails using a combination of different denoising filters to remove noise, based on their individual qualities. Following that, after the initial denoising, CNN was used to perform learning-based denoising to maximize the removal of speckle noise in the images. To simulate a real-life scenario, 750 ultrasound images were contaminated with speckle noise. After a comparative analysis of various methods, this paper's proposed model of combining filters and CNN model achieves a PSNR of approx. 52.25 dB on denoising a speckle- corrupted ultrasound. By combining the best of both worlds of Hybrid filters and CNN denoising, the proposed model achieves solid efficiencies for reducing speckle noise in Ultrasound images, making it a strong alternative.**

Keywords*— *Image Denoising, filters, convolutional neural networks, PSNR, UQI, SSIM, Median Filter, Diffusion-based Filters, MATLAB, Speckle noise, Ultrasound imaging.

I. INTRODUCTION

Cancer is the largest cause of mortality worldwide, with millions of fatalities projected through 2020. Given the above statistics, it is overtly clear that successful detection of cancer is of utmost importance, and the impact that successful de-noising of said images holds unwavering importance. This is the aspect the proposed model focuses on. Segway into the different types of scans, the mainly accepted types of Image scans currently available would include MRI scans, CT scans, Biopsy reports, and Ultrasound images. MRI, abbreviated from Magnetic Resonance Imaging, scans produce detailed pictures of the inside of the body, by combining intense magnetic fields and radio waves.

The ultrasound image is created by waves bouncing off bodily structures [1]. The sound signal's amplitude (power) and the time required for the wave to travel through the body provide the data needed to create an image. The photos can help doctors diagnose and treat a variety of ailments and disorders. Ultrasound does not involve the use of radiation. Now that the characteristics of each type of image are known, it is clear that MRI images are superior with the least inaccuracies and noises, followed by Ultrasound images,

which have a higher ratio of noise. Although MRI stands as the ideal way to go forward, the cost of processing such an image becomes a huge disadvantage. Cancer diagnosis and treatment are generally very costly affairs, bearing a heavy load on the patient's pockets, and adding onto this cost if the prices for MRI Imagery is added, it becomes hard to bear. Hence a method, to make an Ultrasound image capable enough of accurate diagnosis, while being cost-effective seems like the method to go for, and that is what the proposed project tries to achieve.

To make ultrasound images stand at a similar ground as MRI scans, one needs to efficiently deal with noises and inaccuracies, which are abundant in such types of imagery. Clamor is an inevitable part of any image. As a result, diminishing noise in the scanned image is crucial for further analysis. Visual noise can be found in all such scanned images. An image with noise has a mottled, grainy, textured, or snowy appearance. Many factors impact the quality of an Ultrasound image.

The radiation dosage is one of the most significant parameters. The noise and outliers found in the image obscure many small features. As a result, image analysis, diagnosis, and interpretation rely heavily on noise reduction. During transmission and capture, as well as due to device malfunctions, noise can end up clouding an image. The noise will be quantified based on the number of corrupted pixels in the picture. Amplifiers or Gaussian noise [2], Salt and Pepper Noise, Shot Noise or Poisson Noise, and Speckle Noise [3] are all forms of noise found in CT scan/Ultrasound images. The most common cause of ultrasound image deterioration is speckle noise. There are a variety of ways for detecting and eliminating speckle noise. Every noise has its specific characteristics and downsides. As a result, careful examination of each noise is essential. When conversing around noise, certain terminologies hold the utmost importance.

The main objective, which is demonstrated through this paper is how with the fusion of a CNN-based De-noising model, when fused with other de-speckling filters, is capable

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of producing great de-noising results, when compared to the image processing methods being employed individually, versus a combination of the above. A combination of deep learning, with median and anisotropic filter, grants us a strong 52.25 PSNR, which is believed to increase with a higher training scale.

Within this paper, a section-wise deep dive is carried out on the various aspects. The strategies and resources utilised in the comparative approach are presented in section II. Within section III, which describes the various de-noising methods available, as well as the proposed de-noising method. For Section IV, comparative analysis and the results of these mentioned methods are documented and inferences are made for the same.

II. RELATED WORK

A relevant study [2] provides an overview of current noise reduction methods. It primarily conveys the importance of de-noising in medical images by stating and comparing various types of relevant noises such as gaussian, speckle noise and surveys how effective filters are to eradicate such errors.

An Enhanced Convolutional Neural Denoising Network [4] is a postulated innovative network (ECNDNet). To avoid fading and bursting gradient difficulties, ECNDNet employs residual learning strategies. The paper shows how Batch Normalization (BN) can also be used to speed up the convergence of the training model and essentially makes it easier to train the said network.

This publication [5] contains a total of 152 references, with 31 of them being research works on CNN image de-noising. A conscious attempt was carried out to incorporate all research publications related to CNN image de-noising in this study. The table shows that CNN was just recently employed by researchers for image denoising. This paper is an open comparative research project that allows for further experimentation and discovery, with many conveniences.

By de-noising, an image with CNN, the paper [6] investigates the new Deep Learning Toolbox feature released in MATLAB version R2019a. The advantage of employing a CNN model is that it optimises continually throughout network training, enhancing the weights of the convolutional kernel, whereas conventional image de-noising techniques have predefined parameters that cannot be modified during filtering.

The proposed approach [7] combines the noise reduction capability of the SavitzkyGolay smoothing (SGS) filter with edge-preserving capability of the SRAD channel to denoise ultrasonic pictures. The recommended hybrid channelling is tested on synthetic pictures, B-scan simulated images, and genuine ultrasound images.

A robust speckle reduction filter for breast ultrasound images is presented in this study [8]. Synthetic and clinical images were used to test the suggested framework. To construct a multiscale of images, the suggested approach uses the local Laplacian pyramid. The initial filtering was done with a Wiener channel. The new fast bilateral filter (NFBF) was therefore utilised to reduce speckle noise. In conclusion, the paper shows that the wavelet decomposition anisotropic channel was applied to decrease distortions. Simulated and scientific images were used to test the suggested framework.

III. METHODOLOGY

A. *Procuring and Cleaning of Datasets*

The proposed project trains over hundreds of images, therefore a collection of datasets with a strong number of Ultrasound Scans is necessary. For the same, a dataset containing ultrasound breast scan images was selected from Kaggle [9]. Once procured, the datasets need to be cleaned for redundant and corrupted images, to prevent halts and setbacks during the main part of the project. The dataset shall consist of images of similar scales and sizes, to maintain a cohesive functioning.

B. *Image pre-processing and Denoising*

Once a reliable dataset has been established, the project moves on to de-noising and pre-processing the dataset's images. As stated before, the goal is to achieve competing accuracies with the likes of MRI images. Therefore, de-noising needs to achieve strong PSNR values. The same can be achieved by using a hybrid combination of de-noising filters and then channelling the results into a CNN model. The CNN Model makes computing of multiple images quicker, and also learns simultaneously, helping achieve a strong de-noising action.

C. *De-noising Filters*

For de-noising the dataset, within MATLAB, first the images were de-noised using filters including the Median filter, Adaptive Median filter, Anisotropic filter, SRAD Filter, and Wiener Filter [10]. The principle of combining said filters was followed as shown in Fig. 1, trying several permutations of combinations [11], to achieve the best PSNR value possible. Post filtering, two CNN models were tested for de-noising, one pre-trained (DnCNN) and another trained with different amounts of images, coupling with the hybrid of filters mentioned above, reaching the goal of a good cleansing of images. All of the above was implemented on MATLAB, using appropriate libraries.

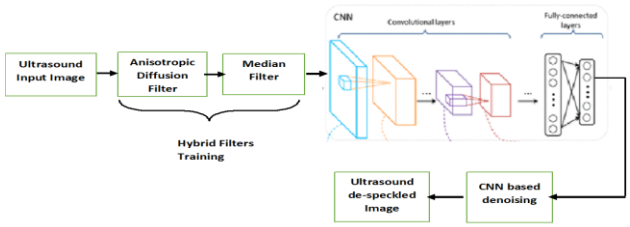

Fig. 1. The principle behind the proposed Implementation

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The speckle noise has a negative impact on possible following image processing activities. As a result, image denoising is critical in advanced image processing algorithms. Image denoising is the act of eliminating noise from a noisy image in an attempt to re-establish the original image.

1) Median Filter:

The median resulting value of a non-linear local filter is the central element of a sorted array of pixel values from the filter window. The filter is used to reduce the impulse noise since the median value is resistant to outliers.

2) Speckle Reducing Anisotropic Diffusion (SRAD):

SRAD filter [7], as a de-noising filter functions as an edge-sensitive diffusion method for speckled images. Its principle is similar to the conventional anisotropic diffusion, which operates as an edge-sensitive diffusion for images soiled by additive noise.

3) Anisotropic diffusion:

Anisotropic diffusion [12], alternatively referred to as Perona–Malik diffusion is a computer vision and image processing approach to reduce picture noise without losing key elements of the image content, such as edges, lines, or other features that are important for image interpretation.

4) Adaptive median filter:

For the restoration of grayscale pictures that have been heavily damaged by noise, an adaptive median filter is presented. It operates in two steps: first, it calculates the kernel's median value, and then it determines if the current pixel value is an impulse (salt and pepper noise) or not.

5) Convolutional Neural Network (CNN):

Even with a brief test period, CNN is an effective approach for modeling noisy and multi-modality pictures. The deep learning methodology is anticipated to benefit various image processing difficulties, such as de-noising and super-resolution jobs [13]. Some CNN models for medical image de-noising would include Detection/ reconstruction CNN, Pre-trained RLN [14], NN- DMRI [15], FB, DF-MFF & CNN [16] and SSDRN [17] other than DnCNN [18].

6) DnCNN :

The DnCNN is a fast deep learning model for estimating a residual picture from a Gaussian noise input image. Before generating the de-noised image, the DnCNN model [18] generates a residual image that is an approximation of the noise map. The difference here between the residual picture and the noisy input will then be used to generate a noise-free image estimate.

When residual learning plus batch normalisation are combined, the DnCNN model's training accuracy improves.

7) Wiener Filter:

This filter [10] is used to simulate a desired or target random process by filtering a reported noisy phase with linear time-invariant (LTI) filtering, assuming known stationary signal, additive noise, and noise spectra.

Fig. 2 indicates a key concept for the proposed method, by inferring the features of different classic denoising filters and certain frequently used CNN models for denoising (DnCNN). This algorithm demonstrates how the CNN models learn by running a combination of two filters in a continuous loop. We add speckle-

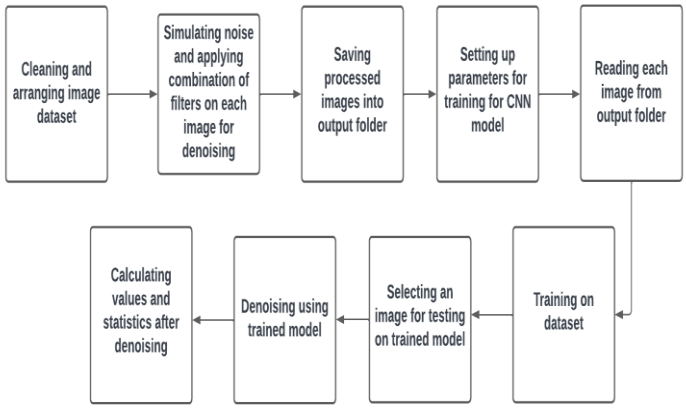

Fig. 2. Flowchart of Denoising using CNN and Hybrid Filtering

-noise to the dataset to mimic the real-world conditions of working with Ultrasound images, which are frequently plagued by this multiplicative noise. On top of that, the photographs are saved in a separate folder for CNN's training after going through the hybrid filter. When the training iterations on MATLAB are finished, the trained CNN model is used to analyse a test picture that already has a Hybrid filter applied. The for loop allows the model to cycle through hundreds of photos and effectively train and display its learning based on a powerful denoising output, as CNN learning is a continuous and optimizing process.

IV. RESULTS AND DISCUSSIONS

The image quality parameters that are used to quantify the exhibition of this proposed system are as per following:

- **Peak Signal to Noise Ratio (PSNR):** Between two unique photos, the PSNR [19] metric calculates the peak signal to noise ratio in decibels.
- **Universal Image Quality Index (UQI):** UQI [20] uses reduction in luminance distortion, correlation, and contrast distortion to assess the quality of the image.
- **Structured Similarity Index (SSIM):** This parameter creates a singular local quality score by combining local picture structure, brightness, and contrast [19].

With the hybrid filters, deployed onto a CNN training model, the noise in the images is reduced, so that the images could be comparable in accuracy with MRI scans and biopsy.

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D. Denoising using standard filters VS using CNN

Table I establishes an understanding of where CNN models and Traditional denoising filters stand by themselves, for all of the above Ultrasound images, PSNR values are calculated and a comparison is achieved.

Table I. Comparison of PSNR (in dB) of various simple filters using 15% speckle-noise:

Sr. No	Filters Used	PSNR Value
1	Median Filter	22.19
2	Adaptive Median	22.11
3	SRAD	22.21
4	Anisotropic Diffusion Filter	23.16
5	Wiener Filter	22.18

In table II, results are observed when de-noising an image containing 15% speckle noise, and by itself, and without prior training, the CNN models reign supreme due to their accessibility and flexibility when compared to traditional de-noising filters, which function just on certain characteristics.

Table II. Observation of PSNR (in dB) using CNN with speckle noise

Sr. No	Filters Used	PSNR Value
1	Proposed CNN Model (without training)	27.21
2	DnCNN [18]	27.93
3	BM3D [7]	26.13

E. Comparison of PSNR values using various CNN Models VS CNN models in combination with hybrid filters.

Table III. Observation of PSNR (in dB) of combining various de-noising filters onto the pre-trained DnCNN model.

Sr. No	Filters Used	PSNR Value
1	DnCNN + Anisotropic + SRAD + Adaptive Median	28.24
2	DnCNN + Anisotropic + SRAD	30.79
3	DnCNN + Anisotropic + Median	30.67

Table III indicates that these observations imply that, even on a pre-trained CNN model, when combined with hybrid filtering methods, yields better de-noising results that CNN or the filters by itself.

Table IV. Observed PSNR (in dB) of combining various de-noising filters onto the proposed CNN model, trained with different datasets.

Sr. No	Filters Used	No. of Images	PSNR Value
1	CNN + Anisotropic + SRAD	133	45.02
2	CNN + Anisotropic + SRAD + Median	133	44.54
3	CNN + Anisotropic + Median	133	45.51
4	CNN + Anisotropic + Wiener	133	44.69
5	CNN + Anisotropic + Median + Wiener	133	45.46
6	CNN + Anisotropic + Median + Wiener	205	47.83
7	CNN + Anisotropic + Median	205	48.33
8	CNN + Anisotropic + Median	400	50.32
9	CNN + Anisotropic + Median	500	50.55

Table IV describes how while training, initially tests around a various combination of filters for 133 and 205 ultrasound images were carried out and the combination of Median and Anisotropic Diffusion filters come across with the best values. So, keeping the combination of those two and CNN, the dataset size was increased from 133 and 205 to 250, 500 and 750, and a subsequent increase in PSRN was also observed.

Table V. As a strong PSNR value was yielded with the combination of Anisotropic and Median Filter, a higher number of images were used for training, and subsequent information was procured:

Sr. No	No. of Images Used	PSNR Value	SSIM Value	UQI Value
1	250	48.69	0.9531	0.9332
2	500	50.55	0.9686	0.9487
3	750	52.25	0.9499	0.9849

As observed from the PSNR values from Table V, it is overtly understood that the use of CNN for de-noising

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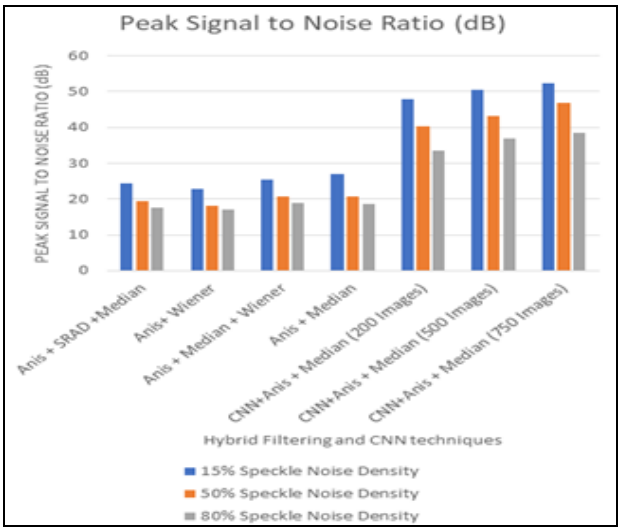
Breast's Ultrasound image is much better than the use of standalone de-noising filters such as median, SRAD, etc.

Table VI. Observed PSNR (in dB) for real-time ultrasound images

Sr. No	No. of Images Used	Speckle Noise in Percentage	PSNR Value	SSIM Value	UQI Value	Run Time
1	167 Realtime HD Ultrasound Uterus Fibroid images	15%	46.51	0.9810	0.9261	51min 17secs
2		50%	39.06	0.9947	0.9572	48min 14 secs
3		80%	30.93	0.9924	0.9412	49min 45secs

Table VI observes the model being tested on Real-time Ultrasound Uterus Fibroid images, captured from Philips Ultrasound scanner, to emulate a real-life scenario and showcase proposed model's strength, since the proposed model's accuracies were observed to be competitive so far as described in Fig. 3.



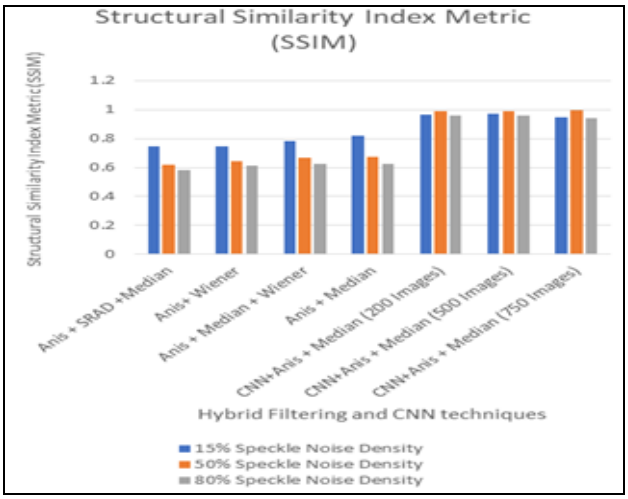


Fig. 3. Graphical representation: (a) PSNR performance for the proposed Fusion technique, (b) SSIM performance for the proposed fusion technique.

Table VII. PSNR, SSIM, UQI of Spatial filters for low, medium and high noise densities of Speckle noise.

15%), Medium (50%) and High (80%) Noise Densities **Image Used: Ultrasound Breast cancer**												
Filters	**Speckle Noise**											
	15%				**50%**				**80%**			
	PSNR (dB)	***SSIM***	***UQI***	***Run Time***	***PSNR (dB)***	***SSIM***	***UQI***	***Run Time***	***PSNR (dB)***	***SSIM***	***UQI***	***Run Time***
Median	22.19	0.719	0.889	0.25ms	19.76 19.76	0.601	0.616	0.28ms	17.05	0.566	0.571	0.29ms
Wiener	22.18	0.725	0.924	0.31ms	18.05	0.623	0.694	0.31ms	16.94	0.601	0.645	0.30ms
SRAD	22.21	0.684	0.963	0.29ms	14.91	0.512	0.612	0.28ms	13.78	0.482	0.587	0.32ms

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Anisotropic Diffusion	23.16	0.677	0.958	0.24ms	15.58	0.567	0.934	0.25ms	14.38	0.538	0.932	0.24ms
Anisotropic + SRAD + Median	24.39	0.745	0.993	0.33ms	19.45	0.619	0.931	0.35ms	17.7	0.583	0.932	0.35ms
Anisotropic + Wiener	22.76	0.748	0.959	0.30ms	18.02	0.642	0.937	0.31ms	17.07	0.614	0.921	0.32ms
Anisotropic + Median + Wiener	25.43	0.781	0.945	0.36ms	20.78	0.665	0.933	0.37ms	18.98	0.626	0.75	0.37ms
Anisotropic + Median	26.91	0.818	0.938	0.28ms	20.84	0.673	0.875	0.29ms	18.75	0.627	0.797	0.28ms
CNN + Anisotropic + Median (200 images)	47.86	0.963	0.933	54min 36sec	40.41	0.989	0.970	54min 33sec	33.63	0.956	0.947	59min 46sec
CNN + Anisotropic + Median (500 images)	50.55	0.968	0.948	2hr 44min 15sec	43.09	0.99	0.99	2hr 57min 22sec	36.87	0.96	0.88	2hr 33min 35sec

Table VII shows how the comparison study establishes a distinct array of statistics for the various methodologies while also demonstrating how the proposed model's de-noising is superior with PSNR, SSIM, and UQI values. The graphical representation illustrated by Fig. 3 clearly shows that the suggested fusion approach provides greater PSNR and SSIM than existing strategies.

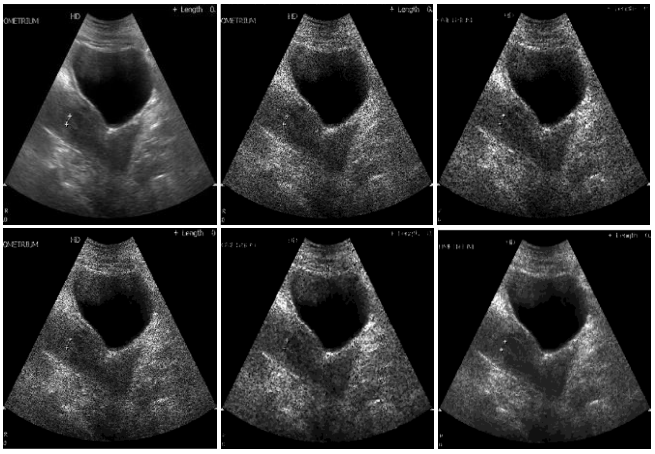

Fig. 4. Output Images of Individual filters, Hybrid Filters and Proposed Method:

a	b	c
d	e	f

(a) Real-Time HD Ultrasound Uterus Fibroid Image
(b) Simulated 50% speckle noise Ultrasound Image,
(c) Output Median Filter,
(d) Output of Anisotropic Diffusion Filter,
(e) Output of the Combination of Anisotropic and Median Filter,
(f) Output of Proposed Method using the combination of Anisotropic and Median filters, plus a CNN trained model.

The visual representation of each of the projected systems is shown in Fig. 4. The visual display of planned procedures reveals key outcomes.

V. CONCLUSION

The paper studies a proposed methodology where Convolutional Neural Network-based de-noising is combined with hybrid filters, essentially taking the best of two words, with the aim of bolstering the quality of Ultrasound Imagery, to have comparable accuracy, when pitted against costlier alternatives, that is MRI scans. The paper discusses various types of basic denoising filters available, tries out various combinations of said filters on Ultrasound Images having speckle noise, and figures out under what permutations, can the highest PSNR values be achieved. Based on comparative analysis, both from previously published literature and experiments, results were found supporting the proposed model, with strong PSNR values, which as seen from the observations, goes higher as the number of images in the dataset is increased, making it clear that the combination of denoising using hybrid filters and CNN model, is an efficient way of denoising on medical images, for a strong image pre-processing result.

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