A Hybrid Neural Filter (HNF) Based on Adaptive Median and Weiner Techniques for Reducing Speckle Noise of Ultrasound Liver Tumor Images

Deepak S Uplaonkar, Basavaraj Amarapur

Abstract*: *Pre-processing of image is considered to be an important aspect medical image analysis in order to enhance its quality. Noise reduction is performed for improvement in the visual quality and removing redundant image values. Ways of pre-processing of image are a necessity, for removing the noise and for quality enhancement of the image. Before applying any approach on medical images, measures used to pre-process seem to be vital for limiting the abnormalities' findings with no influence from background of the medical image. In this work, a filter is proposed based on Adaptive Median and Weiner Hybrid Neural Filter for noise reduction. The review of filtering techniques is implemented using MATLAB platform, followed by comparison of results with different filtering techniques to show the system effectiveness.

Keywords* : *Speckle Noise, Median Filter, Weiner Filter, Hybrid Neural Filter.

I. INTRODUCTION

In medical science field, various modalities are found that help in the human body visualization, in which there are popular images of ultrasound due to portability, appropriateness, harmlessness and less costly. The ultrasound images have a decline in their superiority because of varied aspects like wavelength scale roughness while acquisition [1]. Many types of noises have corrupted the medical images while capturing or transmission. It is important for acquiring the exact region of interest in encouraging perceptions that are precise for the application that has been given. It is tough for expelling noise from the images of medical with no prior knowledge of noise. This is the reason behind reviewing models of noise is vital in the process of image denoising [6]. Applications in Medical Ultrasound Imaging is found by image denoising wherever there is a requirement for appropriate image deception and analysis, and the noises found in an image that are digital in forensic science that can give rise to issues [9].

Restorative indicative system generally uses ultrasound imaging due to its non-intrusive property, application of minimal effort and framing of the ongoing imaging. The image of ultrasound can be adjusted, moved, and is moderately safe, these types of images comprise of speckle noise and artifacts leading to degradation of the organ reducing the contrast. Human perception is affected for recognizing pathological tissue [8]. High frequency waves of sound are utilised for viewing the internal body parts using Ultrasound Imaging. UI helps to evaluate, diagnose and treat the diseases [2]. The growth happening rapidly is due to the need for cost-effective, precise, fast and persistent treatment. Detecting and predicting imaging is becoming even easier by advancing the technology. Rapidly development occurs due to need for accurate and less intrusive treatment. n Radiologic imaging gear technological advancement has added to imaging utilisation [3]. While acqusing and transmitting, most of the images get corrupted by noise which is mostly modelled as Gaussian noise. Image denoising algorithm serves the purpose of noise reduction in the image and preserving it [5]. Many research works are conducted for noise reduction of speckle in images of ultrasound since a few years. Speckle noise was lessened with the help of temporal averaging which was the very first method [11]. It is way that is very simple and fast, but it creates images that are blurry with some lost details. Adaptive Weighted Median Filter (AWMF) has been introduced for reducing speckle that makes use of the weights of pixels that surround the filter [12]. It is used to suppress the noise of the speckle and the way is on the basis of the variable weight coefficient around every pixel. ASSF is introduced after filter of AWMF. ASSF filter is also makes use of the similar local ultrasound images statistics [7].

Methods of linear filtering such as spatial averaging have effect of blurring. Adaptive filtering methods on the basis of local statistics or spectral coefficients are good to preserve boundaries of object and features that are small with speckle size [10]. Nonlinear filters on grounds of Mathematical morphology are sensitive of size and shape. Morphological filters utilise mathematical morphological operations such as opening, closing, etc. [4] so, every filter has some limitations and it is important to design a filter for better outcome.

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The manuscript is arranged as: in Section 2 gives review on the survey of literature while section 3 lays explanation on the methods presented, where section 4 analyze the results of experiment for the dataset given. Finally, section 5 draws conclusion on work.

II. LITERATURE REVIEW

There have been many researches focusing on noise reduction in the ultrasound images in past few years. Let us review some of the works in this section

Ozyurt and et al. [13] have proposed a way for reducing the liver CT images categorization of time and maintaining the performance CNN. F-PHCNN has laid a proposal by utilising a perceptual hash function along with CNN, with the most crucial feature being the salient features. In the proposed F-PH-CNN approach, perceptual hash functions based on DWT-SVD has been utilised.

Kriti and et al. [14] have introduced a way to evaluate the performance of image texture along with its morphological features evaluated from the original and despeckled images ultrasound of the breast classifying breast tumours. They have utilised 100 images utilising six processed despeckling filters. Finally, classification is carried out using SVM classifier.

Sumit and Rabindra [15] have proposed ways of hybrid filters by introduction of computing AD and Butterworth band pass filter for overcoming the image over-filtering. Additionally, the proposed hybrid filter's performance and its parameters of design are increased by utilising PSO algorithm. Furthermore, the above study outcomes stated the effectiveness of the proposed filter as compared to HSA or other filtering mechanisms.

Subit and et al. [16] have introduced different equations of partial different for handling function of diffusion and the term fidelity as well. An energy functional was derived to study the associated evolution issues by utilising an approach of posterior regularization corresponding to the denoised image for recovery. Then it is evaluates the impact of the model with a few standard images of test and real images of ultrasound.

Hamid and Zahra [17] have presented an image of ultrasound way of despeckling on grounds of the maximum principle of likelihood that exploits the information that are not local to estimate pixels that are free of noise.

Alsinan and et al. [18] have indulged themselves in discussing about developing a way based on convolution neural network to segment the surface of bones from in vivo ultrasound images. The proposed design's novelty states that it uses feature maps' fusion and multi-modal images for abating sensitivity that takes place due to imaging artifacts and low intensity boundaries of bone. B-mode US images and t images that are local phase filtered in correspondence are utilized as multi-modal inputs for the fusion network that is proposed.

III. PROPOSED HNF BASED FILTERING TECHNIQUES FOR ULTRASOUND IMAGES

In this work, the hybrid neural filter is proposed for enhancing the image. The proposed model is based on Median and Weiner combined Neural Network for noise reduction. In this work, the output of median and wiener filter is applied to neural network as input to produce better outcome such as enhancing the image. At first stage ultrasound image is applied to median filter and wiener filter. At second stage the output from both will be applied to neural network and by reducing the MSE the enhanced image will be obtained. The discussion about Wiener filter, Median filter and neural network is explained in below sections. Figure 1 presents the block diagram of proposed hybrid Neural Filter.

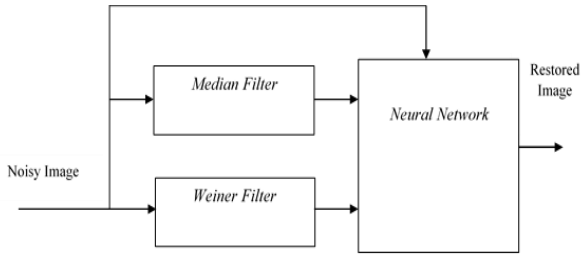


Figure 1: Block diagram of Proposed Hybrid Neural Filter

A. Speckle Noise

Noise of the speckle decreases the quality of image by putting a mask on the image structure which is vital to diagnose thereby impacting the visual interpretation of the radiologist. Speckle is a noise that is multiplicative in nature containing a structure that is a granular created because of echoes' superposition containing amplitudes and random phases. The noise of the speckle has a range of zero to maximum that depends on indulgence of echoes that are constructive or destructive in nature. Many different approaches have been presented so far as discussed in literature review to overcome the above said issue and in this work, Hybrid Neural filter-based algorithm has been projected for noise reduction of speckle obtained from US images.

B. Median Filter

It is simple filter of selection generating output of the pixels' median consisted in its filtering window. The median filtering technique is an operation that is crucial in order to achieve high filtering performance, particularly at high noise density; a median is also known as non-linear and order statistics filtering technique. The value of the median is attained by ascending or descending order arrangement of the values of pixels, then from middle pixel value the change in pixel is attained, However, if the considered pixel of an image that lies beside does not contain pixels, then it often replaces a pixel with the average of values of two middle pixel.

C. Wiener Filter

The Wiener filter aims at filtering out noise corrupting a signal. It has its base on an approach that is statistical. For a desired response of frequency, filters that are typical are designed. It has an approach towards filtering from a separate angle. One contains the spectral properties knowledge of the signal that is original as well as the noise, and one seeks the LTI filter with close outcome to that of the original signal.

D. Artificial Neural Network

The neural network is trained in such a way to provide the denoised images based on the output of Wiener and Median filter. ANN is inspired by biological neural networks.

The link of signal between the neurons is a real number and the output is calculated by functions that are nonlinear with its inputs' sum. The link that connects the neurons is called edges. Each neuron with its edges has weights, which adjusts as learning proceeds. The below figure 2 shows the structure of ANN.

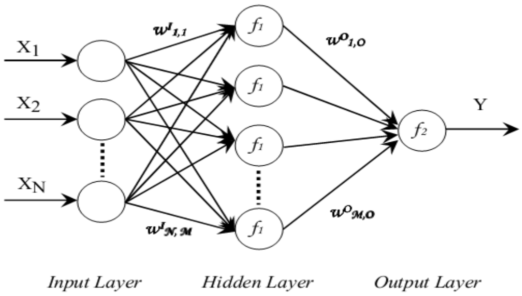
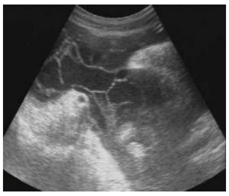


Figure 2: Structure of ANN

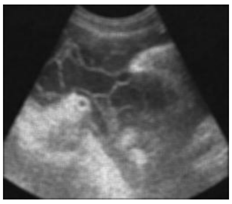
E. Mathematical Model of HNF based Filtering Technique

The mathematical model of HNF based filtering is categorized in to two phases. First one is speckle Noise Model and Second one is Neural based Hybrid filter. The below derivation shows the model of HNF filter,

Input Image: $I(u)$:



Speckle Noise: $I^n(u)$:



Speckle Noise Model:

The model of speckle noise in ultrasound images is signal reliant on and multiplicative type, which is defined as;

$$I^n(u) = I^o(u)m(u) \tag{1}$$

Where, $I^o(u)$ is the original Image, $I^n(u)$ is the noisy image, $m(u)$ is the multiplicative noise module, u is the pixel location. Now after applying log information to the model is given as;

1	0	0
1	1	2
0	1	1

$$\log(I^n(u)) = \log(I^o(u)) + \log(m(u)) \tag{2}$$

Hence the final model of speckle noise is represented as

$$I^n(u) = I^o(u) + I^o(u)^d * m(u) \tag{3}$$

Where, d is the parameter for representing ultrasound acquisition process with Gaussian distribution of 0 mean.

Neural system-based Hybrid Filter Model:

This stage consists of three stages such as Median, Wiener and Neural Network-based filters. At first stage, Noise image is applied with the Median and wiener filter. The output of both filters is applied to neural network with Noise and original image for training those images. The following function shows the procedure of HNF filter. In case of median filter, the noisy value of US image is substituted by the median range of the neighborhood, which leads to storage of the cluster's median value for replacing the noisy value, which can be presented as follow:

$$g(u,v) = median\{I^n(u-x, v-y), x, y \in w\} \tag{4}$$

Where, $I^n(u,v)$ is the noise Image, $g(u,v)$ is the Output Image. We can implement this filtering with the Mat lab function medfilt2. The image with 0 mean noises under normal distribution with noise variance of the median filtering is represented as

$$\sigma^2_{median} = \frac{1}{4sf^2(\bar{s})} \approx \frac{\sigma_x^2}{s+\frac{\pi}{2}-1} \cdot \frac{\pi}{2} \tag{5}$$

Where, σ_x^2 is the input noise variance, s refers to the median filtering mask size, $f(\bar{s})$ is the noise density. The noise variance of the average filtering is

$$\sigma_0^2 = \frac{1}{s}\sigma_x^2 \tag{6}$$

Procedure:

1. A 3 × 3 (or 5×5 etc.) region centered around the pixel (u, v) is taken
2. Values of the intensity values of the pixels in the region into ascending order is sorted
3. Middle value of the pixel is selected as the new value (u ,v)

1	0	0
1	85	2
0	1	1

↓

0 00 11 1 12 85

↓

Figure 3: Sample of 3*3 Median filter model

Figure 3 shows central pixel sample in 3 × 3 array that is considered to be an anomalously high pixel. It is the computational elimination approach is undertaken in order to eliminate pixel intensities median present in the array.

The obtained value replaces the central anomalous pixel, as in the filtered array underneath.

By reducing the noise of the pixel (u, v) the neighborhood size is 3*3. If $f - average > 0$, then the median value is $\overline{f(u,v)}$. If $f(u,v) < \overline{f(u,v)}$, then $\overline{f(u,v)}$ is the noise and $f(u,v)$ is the original image, where the median is given as

$$Median = \{f(u-1,v) + \cdots f(u,v) + f(u,v+1) + \cdots f(u+1,v+2)\} \quad (7)$$

The noise and image are uncorrelated and that optimizes the filter so that MSE is minimized

$$e = \sum_u \sum_v |I(u,v) - g(u,v)|^2 \quad (8)$$

The degradation model of wiener filter is represented as

$$g(u,v) = f(u,v).H(u,v) + I^n(u,v) \quad (9)$$

$$R(u,v) = g(u,v).H_{wiener}(u,v) \quad (10)$$

Where, $I^n(u,v)$ is the Additive Noise, $H(u,v)$ is the degradation function, $g(u,v)$ is the degraded image.

$$f(u,v) = \frac{1}{H(u,v)} \frac{|H(u,v)|^2}{|H(u,v)|^2 + \delta E_n(u,v)/E_f(u,v)} g(u,v) \quad (11)$$

$$f(u,v) = \frac{1}{H(u,v)} \frac{|H(u,v)|^2}{|H(u,v)|^2 + K} g(u,v) \quad (12)$$

The noise and image are uncorrelated and that optimizes the filter so that MSE is minimized

$$e = \sum_u \sum_v |I(u,v) - g(u,v)|^2 \quad (13)$$

Where, $I(u,v)$ is the Original Image, $g(u,v)$ is the Wiener filtering output. The MATLAB inbuilt “wiener2” is being used for implementation of wiener filtering. The Neural network is relied on error correction learning by comparing the output and the target values. The algorithm starts with initializing the weights randomly through the inbuilt function using MATLAB. Consider each input neuron $(i_u, u = 1 \ldots n)$ receive the input pixels/intensity I_u which sends these pixels to all neurons in the hidden layers of network. Now each hidden neuron $(h_v, v = 1 \ldots m)$ sums the weight of the input pixels (i_u) and the output pixel is calculated using the following derivation;

$$z_v = f(x_o + \sum_{u=1}^{n} x_{uv} i_u) \quad (14)$$

$$y = f(w_o + \sum_{v=1}^{m} w_v z_v) \quad (15)$$

Where, i_u is the input neuron, y is the output neuron, z_v is the sum of weighted input pixel, w_v is the input weight, w_o is the initial weight. Now, the error is calculated by comparing the output and the target which is defined as

$$\varepsilon = (O - T) f(y) \quad (16)$$

The output ε is used for correction of weight first and to update the weight at the end is represented as

$$\Delta w_v = \alpha.\varepsilon.z_v \quad (17)$$

$$\Delta w_0 = \alpha.\varepsilon \quad (18)$$

Now to update the weight of the pixels to obtain the output neuron y is calculated using the following functions

$$w_v(new) = w_v(old) + \Delta w_v \quad (19)$$

The process will stop until the error measure (MSE) is less than the target error or the epoch/iteration less than the maximum epoch/iterations. The value of iteration is set as 1000. Finally, for examining the proposed system’s performance, PSNR and MSE are utilized for comparing the error seen in between the image that is original and the image gone through reconstruction. A relationship inverse in nature exists within PSNR and MSE. So, the value of PSNR which is higher gives an indication that the image quality is higher.

$$PSNR = 10\log_{10}\left(\frac{M^2}{MSE}\right) \quad (20)$$

$$MSE = \frac{\sum_{U,V}[X(u,v) - Y(u,v)]^2}{U*V} \quad (21)$$

Pratt’s Figure of Merit:

The figure of merit is one of the important measures for verifying the quality of the image.

The FOM is evaluated using

$$FOM = \frac{1}{M_s} \sum m = 1^{M^K} \frac{1}{1+kc^2} \quad (22)$$

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Table 1: Input and Output of HNF Model

Input of ANN			Output of ANN
Noise Image Pixel	Median filter pixel	Wiener filter pixel	Original Image Pixel
0.1026964	0.100132217	0.08032256	0.077789
0.10366414	0.070575941	0.06450269	0.094024
0.07057594	0.070154787	0.06217472	0.102543
0.07015478	0.020939423	0.04794438	0.084684
0.01705015	0.003230467	0.02494239	0.016453
0.00323046	0.002205601	0.00558782	0.002385
0.00548009	0.002205601	0.00207776	0.004029
0.00289782	0.001614054	0.00189497	0.003944
0.00161405	0.001614054	0.00182936	0.001183
0.00462651	0.001614054	0.00207356	0.003417
0.00393585	0.002727055	0.00258364	0.003981
0.00483371	0.00283375	0.00259777	0.003922

Table 1 shows HNF filter input and results. The image size is 256*256, which means the number of pixels is 65,536 that is multiplied with total images present in the image database. Hence, we have tabulated very few from the total range of output from ANN.

IV. RESULTS AND DISCUSSION

Analysis of filtering techniques for US images of liver tumours has been discussed herein. A total of 43 US images were collected from hospital. Figure 4 presents sample images obtained from the total image database. The size of training image is 256*256 with three inputs, one hidden layer and one output.

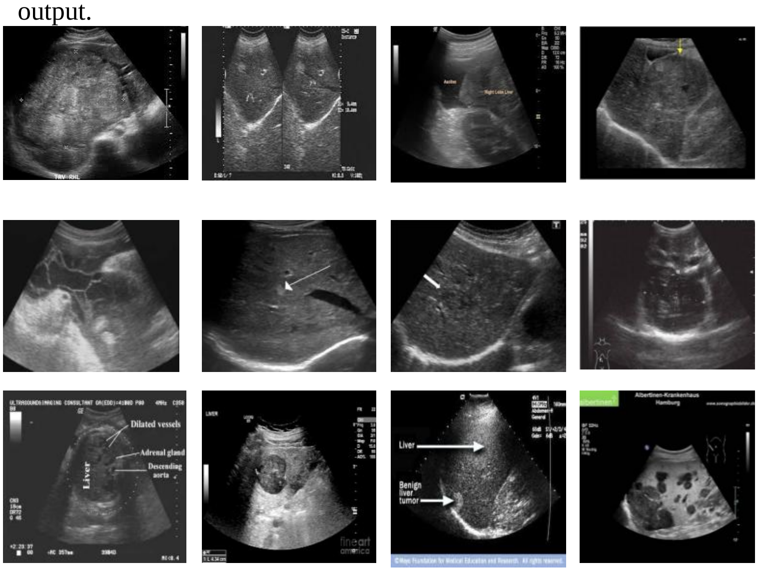

Figure 4: Ultrasound image database of Liver

Table 2: Comparison of PSNR for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters

	Mean	Median	AdMedian	Gaussian	Geometric	N L Diffusion	Weiner	HNF
'22.jpeg'	27.5441	27.6782	12.0385	27.5209	28.2865	18.3379	27.432	28.3043
'23.jpeg'	24.2418	25.8031	11.4805	26.6613	26.5877	18.3269	27.117	27.5243
'24.jpeg'	28.2195	28.9856	14.4368	29.8449	28.4828	18.8647	29.4365	30.3708
'25.jpeg'	22.4317	23.3106	13.9681	28.4466	27.2727	17.481	29.573	29.3804
'26.jpeg'	28.1954	26.0775	8.9973	25.0338	27.4473	18.4553	25.6043	26.4715
'27.jpeg'	28.7324	28.8288	12.3274	27.8487	29.8654	19.8166	28.1645	28.988
'28.jpeg'	27.7007	28.7657	12.7702	28.2894	29.7544	18.1242	28.0445	28.8696
'29.jpeg'	24.3504	24.3287	12.1702	27.5502	28.4065	18.0469	28.4094	28.695
'30.jpeg'	22.8855	24.3107	11.9328	26.8998	25.0887	17.8982	27.6273	27.8604
'31.jpeg'	23.4343	24.575	11.2728	25.9774	23.6358	15.8335	25.7385	26.3954
'32.jpeg'	21.3444	23.425	11.2046	25.583	22.68	13.7954	25.2977	25.6936
'33.jpeg'	24.3505	25.2095	12.8671	27.958	24.3681	16.1179	27.5884	28.3135
'34.jpeg'	22.2268	22.5341	8.0981	24.1234	22.3073	12.9651	24.7041	24.9833
'35.jpeg'	29.3063	29.5589	14.7389	29.9331	29.5818	19.58	28.8173	29.9261
'36.jpeg'	21.8434	22.1768	7.8215	24.0135	22.2476	13.4803	24.4475	24.6549
'37.jpeg'	26.3193	26.7053	10.7792	26.6164	25.9425	16.2608	26.446	27.3801
'38.jpeg'	26.7453	27.6865	14.5687	29.3362	27.856	19.0582	29.5904	30.174
'39.jpeg'	25.1763	25.9887	11.8878	26.8255	25.4786	16.5749	26.6298	27.4286
'40.jpeg'	24.9695	25.9302	11.9323	26.7788	25.5835	16.6334	26.6212	27.3725
'41.jpeg'	23.0859	23.9158	8.5508	24.0146	22.6878	13.7889	24.455	24.9339
'42.jpeg'	27.2308	27.8223	12.3613	27.673	27.3816	17.7061	27.9998	28.7749
'43.jpeg'	26.454	26.8213	12.38	27.8054	27.2828	17.7346	28.0408	28.7173

Table 2 presents comparison between PSNR for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters. It can be stated that the proposed HNF performs better in terms of PSNR comparing to other approaches. Thus for '23.jpeg' HNF have provided 27.5243 which is better comparing to other filters.

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The figure 5 shows the Comparison of PSNR for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters. Figure 5 presents effectiveness of the proposed model.

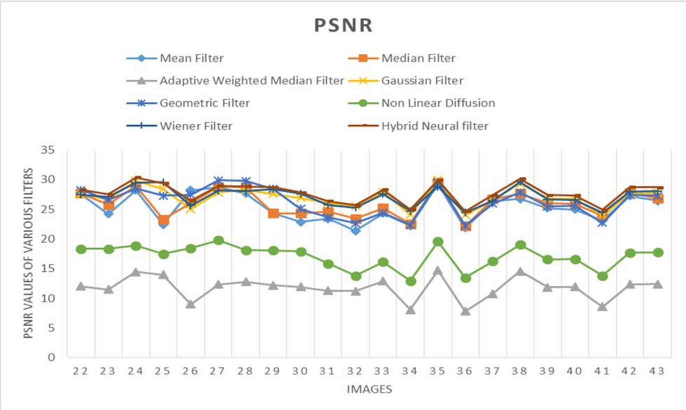

Figure 5: Comparison of PSNR for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters

The table 3 shows the Comparison of RMSE for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters. The proposed Hybrid Neural Filter shows better results with respect to PSNR when compared to other approaches. Thus for '24.jpeg' HNF have provided 0.030052 which is better comparing to other filters. The figure 6 shows the Comparison of RMSE for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters. It is clear that figure 6 shows the effectiveness of our proposed model.

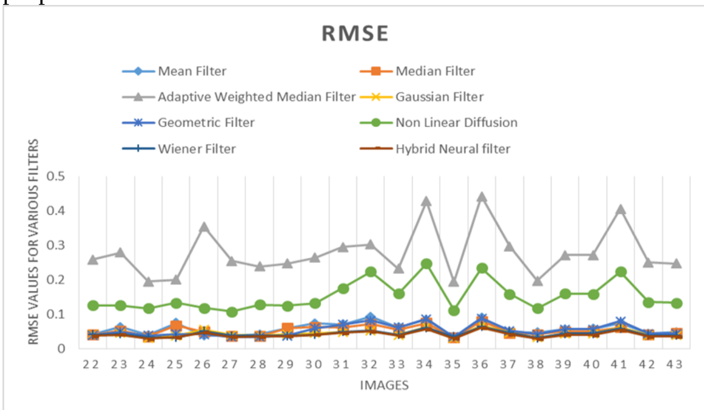

Figure 6: Comparison of RMSE for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters

Table 3: Comparison of RMSE for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters

	Mean	Median	Ad Median	Gaussian	Geometric	N L Diffusion	Weiner	HNF
'22.jpeg'	0.042823	0.041881	0.25867	0.041527	0.04045	0.12601	0.041924	0.037758
'23.jpeg'	0.063528	0.053296	0.27926	0.045895	0.050382	0.12659	0.043429	0.041627
'24.jpeg'	0.039859	0.036294	0.19553	0.032062	0.039337	0.11797	0.033471	0.030052
'25.jpeg'	0.075581	0.068307	0.20026	0.037815	0.043288	0.13364	0.033216	0.033961
'26.jpeg'	0.038925	0.049674	0.35492	0.056016	0.042426	0.11946	0.052455	0.047471
'27.jpeg'	0.038146	0.036725	0.25446	0.040096	0.034839	0.10789	0.038547	0.034669
'28.jpeg'	0.042544	0.037605	0.23857	0.038181	0.03484	0.12877	0.039332	0.035705
'29.jpeg'	0.060928	0.06104	0.24733	0.042057	0.038325	0.12575	0.03806	0.036882
'30.jpeg'	0.074856	0.06404	0.26492	0.045726	0.060122	0.13263	0.041513	0.041099
'31.jpeg'	0.070854	0.061212	0.2948	0.048875	0.071553	0.17637	0.049845	0.046367
'32.jpeg'	0.093372	0.071953	0.30268	0.051901	0.083018	0.22434	0.052801	0.051336
'33.jpeg'	0.062313	0.056252	0.23309	0.040271	0.062629	0.16082	0.041684	0.03863
'34.jpeg'	0.085338	0.075807	0.42762	0.065237	0.086702	0.24717	0.061146	0.057813
'35.jpeg'	0.035162	0.033425	0.19386	0.030877	0.035189	0.1123	0.035148	0.030588
'36.jpeg'	0.090071	0.080441	0.44192	0.067815	0.088929	0.23477	0.064989	0.062077
'37.jpeg'	0.049741	0.046852	0.29726	0.046843	0.052786	0.15913	0.047666	0.042663
'38.jpeg'	0.047725	0.042603	0.1971	0.033368	0.042917	0.11796	0.031976	0.030053
'39.jpeg'	0.057457	0.051275	0.27188	0.044484	0.057258	0.15985	0.045113	0.040967
'40.jpeg'	0.058781	0.051589	0.27212	0.044264	0.056856	0.15979	0.044629	0.04075
'41.jpeg'	0.07497	0.063134	0.40553	0.063001	0.081258	0.22449	0.059779	0.05529
'42.jpeg'	0.044633	0.041278	0.25071	0.040796	0.045031	0.13613	0.039116	0.035603
'43.jpeg'	0.048727	0.046604	0.24773	0.040555	0.045077	0.13426	0.039353	0.03644

The table 4 shows the Comparison of FOM for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters. Thus, the proposed hybrid Neural filter shows better results in terms of PSNR comparing to other approaches. The figure 7 shows the Comparison of FOM for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters. It is clear that figure 7 shows the effectiveness of our proposed model.

Table 4: Comparison of FOM for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters

	Mean	Median	Ad Median	Gaussian	Geometric	N L Diffusion	Weiner	HNF
'22.jpeg'	0.042823	0.041881	0.25867	0.041527	0.04045	0.12601	0.041924	0.037758
'23.jpeg'	0.063528	0.053296	0.27926	0.045895	0.050382	0.12659	0.043429	0.041627
'24.jpeg'	0.039859	0.036294	0.19553	0.032062	0.039337	0.11797	0.033471	0.030052
'25.jpeg'	0.075581	0.068307	0.20026	0.037815	0.043288	0.13364	0.033216	0.033961
'26.jpeg'	0.038925	0.049674	0.35492	0.056016	0.042426	0.11946	0.052455	0.047471
'27.jpeg'	0.038146	0.036725	0.25446	0.040096	0.034839	0.10789	0.038547	0.034669
'28.jpeg'	0.042544	0.037605	0.23857	0.038181	0.03484	0.12877	0.039332	0.035705
'29.jpeg'	0.060928	0.06104	0.24733	0.042057	0.038325	0.12575	0.03806	0.036882
'30.jpeg'	0.074856	0.06404	0.26492	0.045726	0.060122	0.13263	0.041513	0.041099
'31.jpeg'	0.070854	0.061212	0.2948	0.048875	0.071553	0.17637	0.049845	0.046367
'32.jpeg'	0.093372	0.071953	0.30268	0.051901	0.083018	0.22434	0.052801	0.051336
'33.jpeg'	0.062313	0.056252	0.23309	0.040271	0.062629	0.16082	0.041684	0.03863
'34.jpeg'	0.085338	0.075807	0.42762	0.065237	0.086702	0.24717	0.061146	0.057813
'35.jpeg'	0.035162	0.033425	0.19386	0.030877	0.035189	0.1123	0.035148	0.030588
'36.jpeg'	0.090071	0.080441	0.44192	0.067815	0.088929	0.23477	0.064989	0.062077
'37.jpeg'	0.049741	0.046852	0.29726	0.046843	0.052786	0.15913	0.047666	0.042663
'38.jpeg'	0.047725	0.042603	0.1971	0.033368	0.042917	0.11796	0.031976	0.030053
'39.jpeg'	0.057457	0.051275	0.27188	0.044484	0.057258	0.15985	0.045113	0.040967
'40.jpeg'	0.058781	0.051589	0.27212	0.044264	0.056856	0.15979	0.044629	0.04075
'41.jpeg'	0.07497	0.063134	0.40553	0.063001	0.081258	0.22449	0.059779	0.05529
'42.jpeg'	0.044633	0.041278	0.25071	0.040796	0.045031	0.13613	0.039116	0.035603
'43.jpeg'	0.048727	0.046604	0.24773	0.040555	0.045077	0.13426	0.039353	0.03644

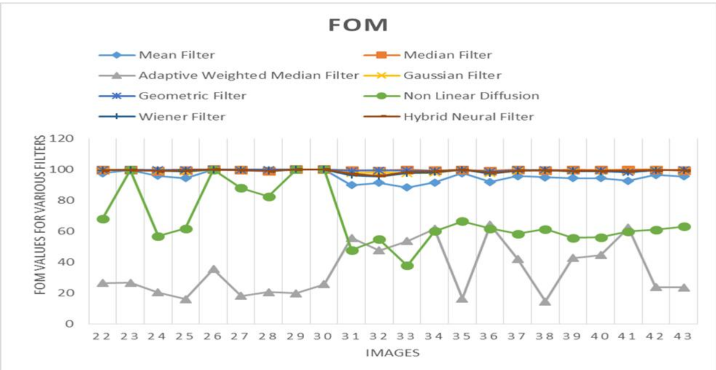

Figure 7: Comparison of FOM for Mean, Median, Adaptive Median, Gaussian, Geometric, Non-Linear Diffusion, Weiner and Hybrid Neural Filters

The proposed model shows better outcome than other filtering techniques for the evaluation metrics such as PNSR, RMSE and FOM. The proposed HNF outperforms all other filtering approaches such as mean, median, Gaussian, adaptive median, geometric, wiener and non-linear diffusion filters.

V. CONCLUSION

A hybrid neural filter has been shown in this work to remove noise of speckle from liver diseases images of ultrasound. The main concern of the model that is proposed is removing the noise of the speckle and enhancing the image. Hence, we have a new filter designed to cancel speckle noise. To enhance the noise, an effective way, an improved way of adapting Wiener filter, and median filter to remove speckle noise and neural network to remove noise share their contribution on this scheme for effective elimination of the noise. The results of the experiment show that the approach that has been proposed results in numerous algorithms that pre-exist the system effectiveness in terms of PSNR, RMSE and FOM parameters.

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