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Research Article

A Fuzzy Neural Network System for Denoising Magnetic Resonance Images

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Abstract

Image acquisition is an essential step in image processing. When the image acquisition is done the image that is generated is subjected to Impulse noise, Gaussian noise etc. We have performed the image denoising on images inflicted with impulse noise. Image denoising is an essential step in all types of image processing. Traditional techniques reduce the noise in the image but it also reduces the quality of the image. Traditional filters like gaussian filter, median filter is analyzed which work in the spatial domain and filters working in the frequency domain are also considered like Butterworth filters, Weiner filter. A Deep residual Neural Network filter is proposed which is compared with the Fuzzy Neural Network denoiser. Their performance is compared on the metrics PSNR and SSIM. The Fuzzy Neural Network system improves the SSIM significantly compared to a deep residual neural network and a comparison is made with traditional image denoising methods. We also compare the performance of the deep residual neural network, Fuzzy Neural Network system and Median denoising algorithm on impulse noise has been compared. The performance of deep neural networks depends on the total number of examples used and the performance can be improved if we have more image pairs.

Keywords

Image Denoising, Deep Neural Networks, Fuzzy Logic, SSIM, PSNR

1. Introduction

When medical Image Denoising is done using different modalities various types of noise are introduced because of environment, acquisition method, transmission etc. Due to the presence of noise a lot of information content in the image is irrelevant. This has to be corrected to make the image interpretable. The image that is acquired is represented by

$$f = Au+\eta \qquad (1)$$

A->Physical system modelling the image acquisition process. Operator A can be a linear operator or nonlinear operator.

u->Unknown image to be reconstructed.

η->noise which can be Gaussian, Laplacian, Poisson, Rayleigh, Impulse.

A is a sub sampled Fourier transform in case of MRI imaging.

$$\mathrm{Min}L(u)=F(Au,f)\ +\lambda\Phi(W,u) \qquad (2)$$

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F(Au,f)->Gaussian noise, Poisson noise, Impulse noise. Salt and Pepper noise, Speckle noise.

Φ(W,u)->Regularization parameters.

Λ->provides balance between data fidelity terms and regularization parameter.

Image denoising is an essential step for doing further analysis of the image, Image denoising is done using approaches such as Wavelet based approach, BM3D, filtering in the spatial domain. The image can be significantly enhanced by using image denoising algorithms. When an image is denoised lots of features are lost such as the edges become less distinct resulting in loss of interpretability of the image. Recently Convolutional neural networks have been used to denoise images using different architectures and they have performed well. A survey of different Deep Neural Network based image denoising methods have been compared with there performance in recent years, How attention block can be introduced to perform image denoising have been compared [12].

2. Related Work

Different nonlinear filtering algorithms were applied and various types of noise were removed after introducing them with Salt and Pepper noise, Gaussian noise and PSNR, SSIM were compared for each type of filter [1]. A fuzzy logic-based filter is used which combines The Red Green Blue values of a particular patch and combines the fuzzy rules to denoise the image. Three fuzzy rules are generated with each other [2]. A Deep Learning Based image denoiser is proposed and the performance of the algorithm is compared with other algorithms such as Weiner filter and multi Layer perceptron, BM3D with different distribution of the noise in the image [3]. Different architecture of Deep convolutional neural networks is evaluated on image denoising and the PSNR, SSIM is calculated [4]. A multi-scale Gated Fusion network which has a merging layer combines the left and right block and a residual layer with a modified loss function [5]. A thorough Literature review has been carried out by authos for denoising images in the frequency domain, filtering, CNN-based, Generative Adversarial Networks (GAN)-based and Transformer-based approaches [6]. A fuzzy logic-based image denoising method on Ultrasound images is proposed and compared with various other such as median image denoising etc. and the method produces better results compared to the other techniques on SSIM, PSNR values [8]. A fuzzy derivative-based filter is proposed based on the nature of derivative in all the directions. Few fuzzy if then rules are proposed to denoise the image. The fuzzy if then rules are applied on a small window and we achieve Mean Squared Error which is better than the traditional filters. The neighbors of the image are considered and assigns values based on the membership function [9]. Then a 5x5 convolution template is applied and then the image is convolved with the original image to produce the denoised image. The deep residual network architecture is compared with various other deep neural architectures and traditional methods of image denoising. A quantitative and qualitative assessment is made on various datasets [11]. The deep residual neural network proposed is also compared with various other neural networks. Generative Adversial Neural Networks has been used to denoise the image. The popular U-net architecture has been used in the Generator and VCGNET19 architecture has been used as the discriminator and a custom loss function was used in the neural network which considers different types of image features [14]. Residual Attention Block has been used to denoise MRI images on various types of noise [7].

Filtering in Frequency Domain

Fourier transform of an image is represented by

$$F(s)= \int_{-\infty}^{+\infty} f(x)f(y)e^{-j2\Pi lx}\ e^{-j2\Pi ly}dxdy \tag{3}$$

We can then use thresholding to filter the noise. The common filters that are used for removing noise in the Frequency domain are (1) Low pass Filter (2) High pass Filter (3) Butterworth filter (4) Weiner filter. [This filter minimizes the mean squared error].

Low pass filter on frequency domain

$$\mathrm{HILP}(\mu, \lambda) = \begin{cases} 1, \text{if } \ D(\mu,\lambda) \leq fc \\ 0, \text{if } \ D(\mu,\lambda) > fc \end{cases} \tag{4}$$

D(μ, λ)-> Distance between the frequency rectangle and a point (μ, λ) in the frequency domain.

Wavelets

$$F(s) = \int_{-\infty}^{+\infty} |\psi(t)|^2 dt < ^{+\infty} \tag{5}$$

3. Wavelets Based Image Denoising

Wavelet analysis produces a time scale view of the system.

Continuous wavelet transform is the sum over entire duration of the signal, multiplied by scaled and shifted versions of the wavelet function.

Discrete Wavelet transform

In Discrete Wavelet transform there are two filters low pass filter and high pass filter. A one-dimensional DWT works on a 1-dimensional vector and creates a transformed vector of equal dimension.

Haar Wavelet transform:

Mother wavelet function:

$$\varphi(t) = \begin{cases} 1 & 0 \leq t < \frac{1}{2}, \\ -1 & \frac{1}{2} \leq t < 1, \\ 0 & otherwise. \end{cases} \tag{6}$$

Scaling function:

$$\varphi(t) = \begin{cases} 1 & 0 \leq t < 1, \\ 0 & otherwise. \end{cases} \tag{7}$$

Wavelets provide a time frequency localization of the signal using scaling and translation function. The benefits of using wavelets is that it leads to a better estimate of features. Wavelet features are used for denoising images. After the signal is converted to wavelet domain, thresholding would subsidize a particular frequency and the inverse discrete wavelet transform would provide a image with the subsidized frequency.

4. Deep Residual Networks for Image Denoising

Deep residual networks make an attempt to estimate the distribution of the noise. The deep neural networks have an array of convolution layers and they check for local features which they can change. In the final layer the estimated noise is subtracted from the original image. A Deep residual network has been proposed which uses skip connection between its layers and it was compared with traditional algorithms for image denoising the deep neural network shows significant performance gain in the tasks .We have used a very naïve deep residual neural networks for our image denoising task, and it performed significantly well, but the ANFIS neural network performed better in the metrics used to measure the *performance of the deep neural network.*

Architecture of Deep Residual Networks
1st layer: Conv 3X3, Batch Normalization
2nd layer: Conv 3X3, Batch Normalization
3rd layer, Conv 3X3, Batch Normalization
4th layer, Conv 3X3, Batch Normalization
5th layer, Conv 3X3, Batch Normalization
6th layer, Conv 3X3, Batch Normalization
7th layer, Conv 3X3, Batch Normalization
8th layer, Conv 3X3, Batch Normalization
9th layer, Subtract from 1st layer

The metric used as the loss function is the mean squared error. Training ran for 100 epochs with learning rate of 0.001.

Table 1. *Performance of deep residual network based image denoising.*

Original PSNR	PSNR denoised	SSIM original	SSIM denoised
43	14.4	0.1827	0.1827
43.64	14.76	0.185	0.190
43.6	14.34	0.155	0.156
43.73	14.76	0.10	0.10
43.30	13.15	0.18	0.19

Table 2. *Comparison of existing methods on image denoising.*

Author	Metrics	Technique
Tian, Chunwei & xu, Yong & Li, Zuoyong & Zuo, Wangmeng & Fei, Lunke & Liu, Hong. (2020) [5]	PSNR=31.74	Attention guided CNN for image denoising
Zhang, K., Zuo, W., Chen, Y., et al [8]	σ=15, psnr=31.73 σ=25, psnr=29.23	Deep CNN architecture with residual learning block.
LoveDeep Gondara [13]	SSIM=0.89	Medical image denoising using autoencoders
Ziyuan Wang, Lidan Wang, Shukai Duan and Yunfei Li [14]	PSNR=30.58 SSIM=0.9027	Image denoising based on deep residual GAN
Zhang et al (2017) FFDnet [15]	PSNR=32 with noise=15 PSNR=30 with noise=25	Gaussian Image denoising, super resolution and JPEG deblocking

5. Comparison of Image Denoising Methods

Table 3. Attention based image denoising.

Author	PSNR	Technique
R. G Pires et al [10]	Min=24.95 Max=35.02	Combining residual learning and attention

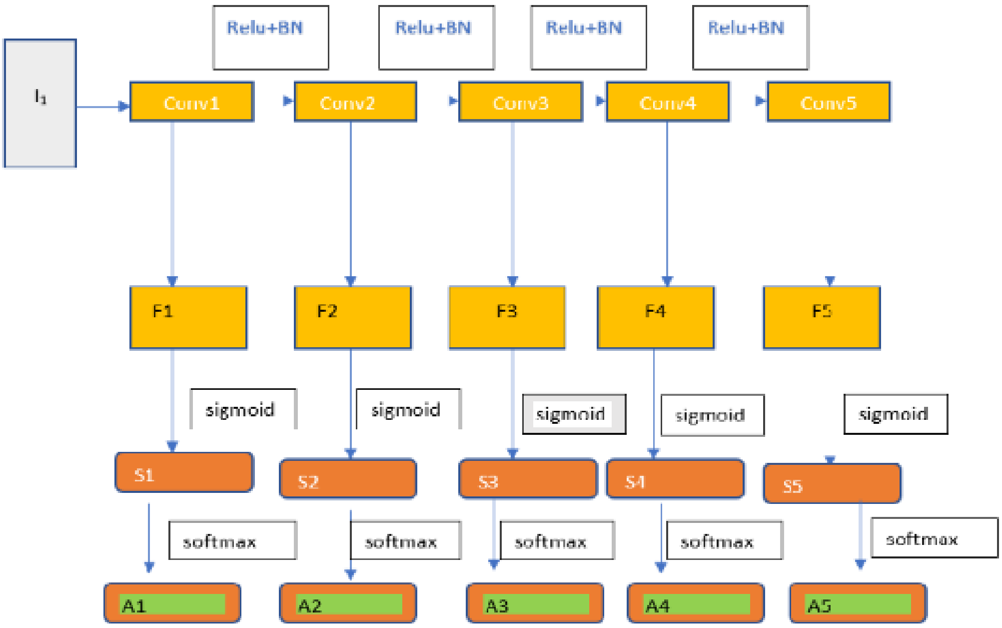


Figure 1. How attention masks are generated.

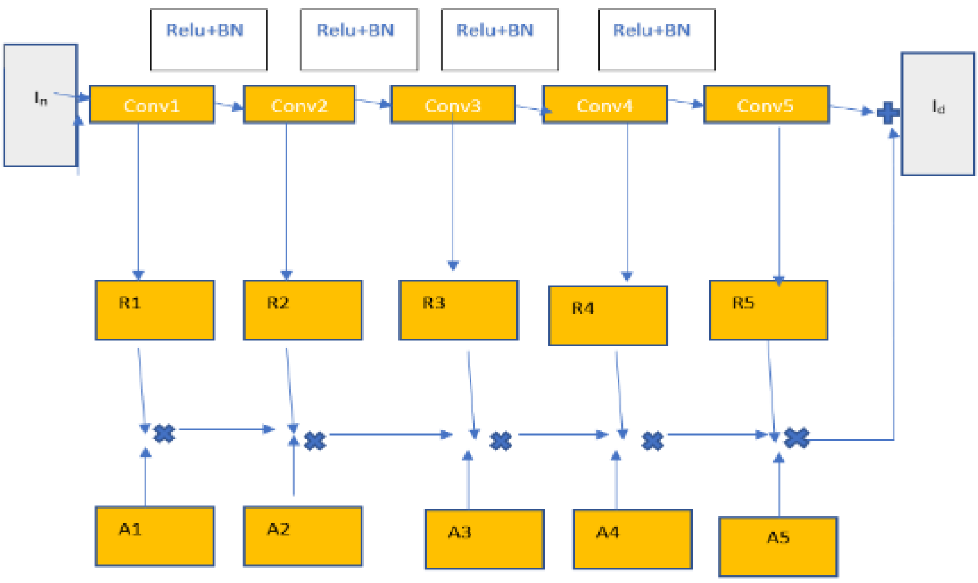


Figure 2. How the attention is added at each convolution block.

The attention computed from each block is multiplied with the convolution layer and we get a multiply block. The last layer the blocks are added to estimate the denoised image. This neural network architecture has shown state of the art results in Images inflicted with Gaussian noise, Poisson noise etc. There are 20 convolutional layers in the original Deep Neural Network for image denoising proposed by RG Pires et al [10].

6. Metrics Used for Estimating Image Denoising Performance

$$MSE=(1/mn)\sum\sum(xi-yi)^2 \quad (8)$$

Structural Similarity Index

$$SSIM(x,y)=\frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (9)$$

Peak Signal to Noise Ratio

$$PSNR=10\log10((L-1)^2/MSE) \quad (10)$$

L->maximum pixel value in an image

MSE->Mean Squared Error

Fuzzy neural network approach for performing image de-noising.

Fuzzy Neural Network for image denoising:

$$G=e^{((x-\mu)/\Sigma)^2/2}$$

$$W=W1*G+W2*G/(W1+W2)$$

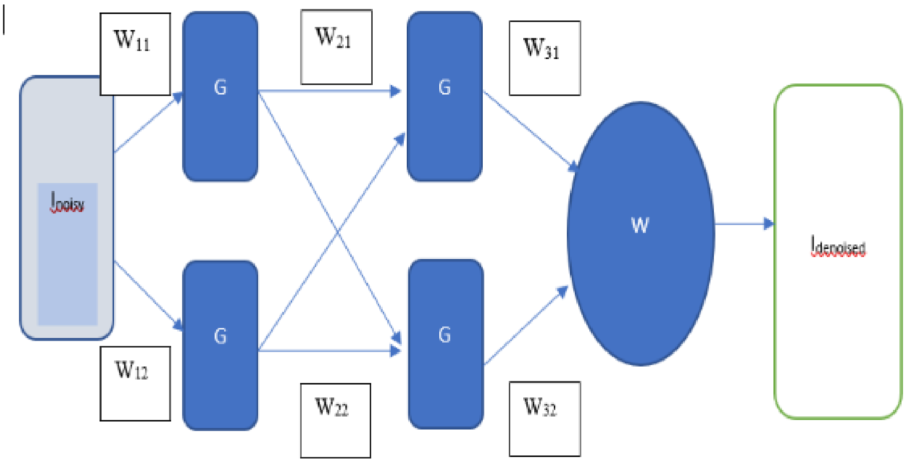


Figure 3. Fuzzy Neural Network architecture for performing image denoising.

The Fuzzy Neural Network architecture used is a multi layer deep neural network implemented in keras. The learning rate used was 0.001 and momentum of 0.8.

7. Training a Fuzzy Neural Network

$$\text{Loss Function}=\sum 1/2(xi-oi)2 \quad (11)$$

Weight change during learning phase is given by

$$\Delta W(t)=\eta\partial Ep(t)/\partial W+\alpha\Delta W(t-1) \quad (12)$$

The parameters of the gaussian membership function are updated using chain rule

$$\partial Ep/\partial mu=(\partial Ep/\partial x)(\partial x/\partial mu) \quad (13)$$

$$\partial Ep/\partial sigma=(\partial Ep/\partial x)(\partial x/\partial sigma) \quad (14)$$

Mu and sigma value change during learning phase is given by

$$\Delta Mu(t)= \quad \partial Ep(t)/\partial mu+\alpha\Delta Mu(t-1) \quad (15)$$

$$\Delta sigma(t)= \eta\partial Ep/\partial sigma+\alpha\Delta sigma(t-1) \quad (16)$$

η->learning rate

α->momentum term

When we train the Fuzzy Neural Network system we update the mean, standard deviation of the gaussian membership function and also the weights.

8. Results and Discussion

Table 4. Denoising performance using Median blur on 25% impulse noise.

PSNR (noisy)	PSNR (denoised)	SSIM (noisy)	SSIM (denoised)
35.87	35.16	0.0399	0.39
35.90	34.48	0.043	0.38
36.25	36.345	0.029	0.37
36.34	36.51	0.029	0.374
36.76	36.99	0.022	0.361

Table 5. Denoising performance using ANFIS on 25% impulse noise.

PSNR (noisy)	PSNR (denoised)	SSIM (noisy)	SSIM (denoised)
35.87	21.633	0.0399	0.27
35.909	21.08	0.043	0.30
36.25	22.82	0.029	0.21
36.34	22.69	0.029	0.204
36.76	23.364	0.022	0.2030

Table 6. Performance of Fuzzy Neural Network system with Salt noise of 5%.

Original PSNR	PSNR denoised	SSIM original	SSIM denoised
43.57	26.75	0.18	0.42
43.64	23.0	0.19	0.31
43.61	29.4	0.15	0.43
51	23.0	0.19	0.29
43	21.0	0.11	0.24

Table 7. Performance of Fuzzy Neural Network system with Salt noise of 10%.

Original PSNR	PSNR denoised	SSIM original	SSIM denoised
43.57	26.75	0.05	0.33
43.64	23.0	0.024	0.21
43.61	29.4	0.04	0.29
51	23.0	0.06	0.38

The PSNR values of the images after denoising are less but the Images details are improved as when denoising algorithm is applied few features are hidden, but the features which contribute more to the interpretability of the image is enhanced while using the proposed Neural Network architecture.

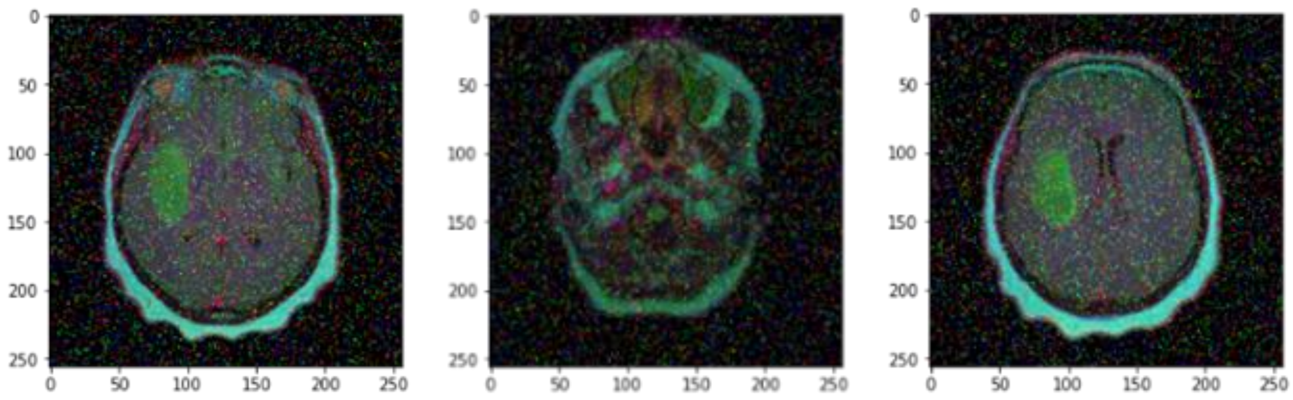
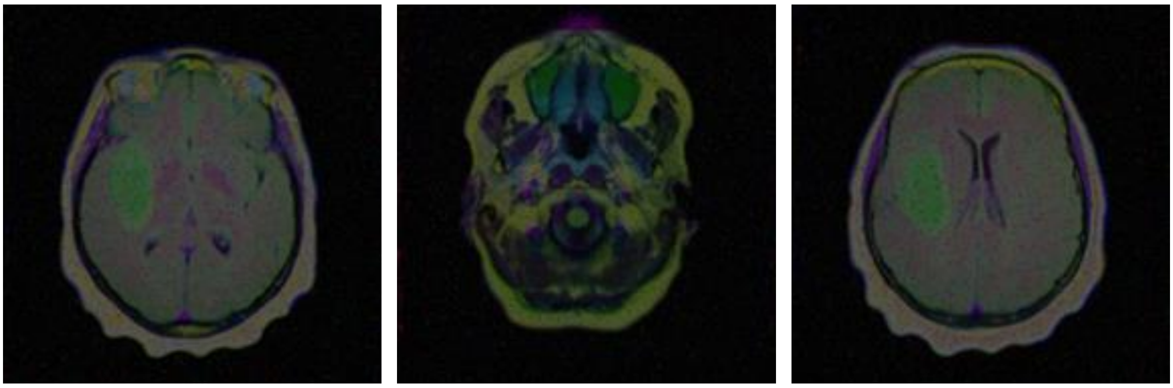


Image with noise



After denoising

Figure 4. *Images denoised using Fuzzy neural network with Salt noise of 5%.*

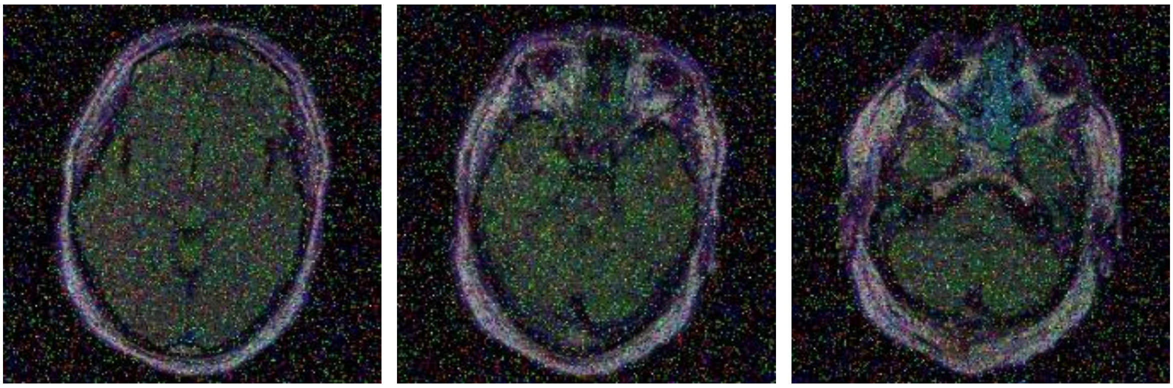
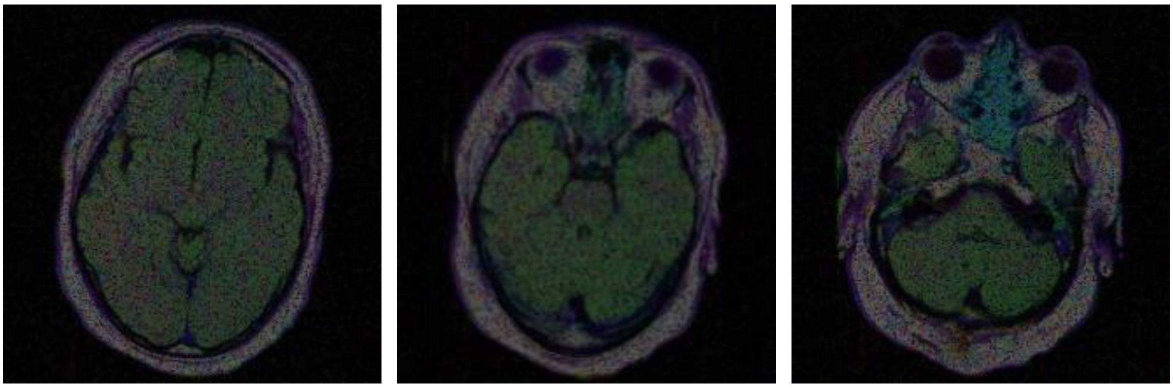


Image with noise



After denoising

Figure 5. *Image denoised using Fuzzy Neural Network with impulse noise of 10%.*

9. Conclusion

The fuzzy neural network performed significantly well for salt noise with different probability of noise inflicted. The denoised image had very good results in improving the SSIM of the image. The residual deep neural network also performed well in denoising images of very high percentage of impulse noise. The performance of the deep neural network can be improved if we use a deeper neural network. Image denoising has shown tremendous improvement for denoising images and these same algorithms can be applied for image inpainting and Image Demosaicing tasks. Traditional algorithms performs well when the type of noise is known but the deep neural networks can perform better when the noise is unknown.

Abbreviations

MSE	Mean Squared Error
PSNR	Peak Signal to Noise Ratio
SSIM	Structural Similarity Index

Author Contributions

Shubhajoy Das: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing

Debashis Das: Conceptualization, Resources, Data Analysis

Conflicts of Interest

The authors declare no conflicts of interest.

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