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Research Article

Medical Images Denoising using Filters and Neural Network: Comparison through Implementations

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Wide variety of medical images are degraded by different types of noise such as Impulse noise, Gaussian noise, Poisson or a mixed of all. These noise disruptions typically result from sensor malfunctions, transmission issues, or environmental factors [1]. They provide an essential basis for clinical diagnosis and treatment. Unlike natural photographs, medical images often contain significant signal-related noise during their creation, resulting in lower contrast and more visible noise [3].No single method or procedure is effective for noise removal hence care should be taken before cleaning noisy area of image. Factors such as type of image (CT scan, Ultrasound, MRI etc) and type of noise such as (Gaussian, the impulsive and speckle noise etc) should be identified and based on the type of input, an appropriate method should be selected. For accurate segmentation of medical images through the automatic means,it is necessary to remove the noise from the images. There are many methods such as learning based (traditional methods) and non-learning based methods(using various types neural networks).To measure the denoising accuracy, parameters like Signal-to-Noise Ratio (SNR), Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) are used. This paper discusses the results obtained through the various methods and their comparison in terms of PSNR,SSIM. Removing noise is crucial for accurate segmentation of medical images. These noise-less images are to be treated as pre-processed images for the segmentation task.

Keywords: Filters,DenoisedAutoencoder,MRI,PSNR,SSIM,NVIDIA,GPU,Pytorch

I. INTRODUCTION

Acquiring internal details of human body through the various methods such as computed tomography (CT), X-rays,Positron Emission Tomography (PET), MRI (magnetic resonance imaging) etc is called Medical Imaging. It is used by clinical experts for diagnosis and analysis. But due to sensors errors and camera angles ,images get noise in it and that lead to poor image quality. Following types of noise can be found in images like Gaussian noise,salt and pepper,noise of lines and stripes.Ali Awad proposed a new method for removing random-valued impulse noise, Gaussian noise, or a mixture of the two from images, involving an initial stage to remove strange values followed by multiple subsequent stages using principal component analysis to gradually remove the remaining noisy components [1].Neural networks based and deep learning based methods such as denoising autoencoding and convolutional neural networks (CNNs) are used to remove noise level in images.CNNs are trained on noisy and noiseless dataset for the reduction of noise from images.MRI images with noise are denoised using few top level filters such as non-lecal means(NLM), Bilateral, block-match and 3D filtering (BM3D) and Total variation (TV).Recently Denoising diffusion probabilistic models (DDPMs) have been successful for image generation,image resolution enhancement and MRI reconstruction. It uses two step processes :forward process and reverse process [3].

A deep learning model called Fast and Flexible Denoising Network (FFDNet) is presented by Lyu et al. [4] with the goal of providing quick and adaptable image noise reduction. The proposed model maintains efficient computation performance and achieves competitive results in the of noise reduction field. The idea of using deep neural networks as preconditions for image reconstruction tasks, such as noise reduction, has been studied by Ulyanov et al. [5]. The authors prove that a randomly initialized deep neural network can effectively remove noise from images, retaining their core architecture without the need for supplementary training data.

The self-supervised learning technique for image denoising, called Noise2Self, was proposed by Batson and Royer [6].The method makes use of the notion that an image can be used in its noisy label, enabling the model to directly learn denoising from noisy images. In real-world image denoising, where the noise characteristics are unknown, Zhai et al. [7] tackled the difficulties. For efficient denoising, the authors suggest neural adaptation networks (NANs), which can be adjusted to various noise levels and distributions.

This paper explains the non-learning (filters) and learning(neural networks) methods for noise removal from MRI images and calculates various key performance indicators such as structural similarity index measure (SSIM) and peak signal-to-noise ratio (PSNR).It also shows the result of the Notch filter for the removal of periodic noise from X-ray images. Along with this ,it also shows the result of the denoised autoencoder for noise removal from medical images.The proposed model is trained on locally available COVID and non-COVID datasets. Denoised autoencoder-based results are superior to the use of filters[9].

The rest of this paper is divided into various sections that goes into detail about things like the architectures, methods, and implementations of Basic filters, and how denoised autoencoder has improved results over filters. The final section is the conclusion of the paper.

II. DENOISING METHODS

Image noise refers to random changes in brightness or color that can reduce the clarity of medical images. To improve image quality, image denoising methods are used to transform the original noisy image into a cleaner version by reducing or removing the noise. These methods can be categorized into two main types: spatial domain methods, which focus on directly manipulating images directly, and transform domain methods, which involve changing the images into a different format before processing it[1].

1. Spatial Domain Denoising Method:

There are two types of image denoising methods in the spatial domain ,1-filtering techniques and 2-variational denoising methods. Spatial filtering methods make use of linear and non-linear filters in order to remove noise to the greater extend. Non-linear based filters like median filters tries to retain edges by replacing pixel values with median values of adjacent pixels. These methods are popularly used in medical imaging to reduce noise levels by keeping important details intact.

2. Variational denoising methods:

Methods of variational denoising improve image clarity by minimizing noise levels while preserving key visual details. According to Y. Xiao and K. Huang(2025),These methods employ previously obtained images to direct the denoising process and refine an energy function, thereby allowing for the estimation of the most accurate clean image. The key to these methods is selecting an appropriate "prior" model, such as gradient prior or sparse prior, which helps in effectively distinguish between noise and actual image content.

3. Total Variation (TV) Regularization:

Total variation regularization is a technique used in image processing that helps reduce noise while retaining important details, like edges, sharp. According to Y. Xiao and K. Huang(2025),The proposed method works on the idea that natural images usually have smooth areas where pixel brightness changes gradually. This method can effectively clean up images by minimizing the total variation, which measures how much the pixel values change however it may sometimes make flat areas look overly smooth, leading to a loss of contrast.

4. Nonlocal Regularization:

Nonlocal regularization is a method used in image processing to reduce noise by observing similar patches (small areas) through the image, rather than just the nearby pixels. According to Y. Xiao and K. Huang(2025),Unlike local mean filtering, which averages only the surrounding pixels, nonlocal filtering averages all pixels in the image, giving more weight to those that are similar to the pixel being processed. This method helps maintain clarity and detail in the images after filtering, making it more effective for various types of noise, such as Gamma, Poisson, and Gaussian noise.

5. Sparse Representation:

Sparse representation is a technique used to express complex data, like images, using some basic elements or features, such as edges and textures. This approach is effective because it recovers high-dimensional signals with only a few measurements as long as the signals are sparse or nearly sparse. It has practical applications in medical imaging, such as brain CT and MRI scans, where it helps improve image quality and to combine information from different imaging modalities.

6. Transform Techniques:

Transform domain methods are techniques used in image processing that originated from Fourier transform, which analyzes signals in terms of their frequency components. In recent years, few of the techniques such as the cosine transform, wavelet methods, block-matching, and 3D filtering have been developed and improved further to enhance image analysis features. These methods make use of the unique features of images and the diverse characteristics of noise in different transformed domains, hence facilitating more efficient noise removal and image improvement.

7. Transform Domain Filtering:

The transform domain filtering method involves converting a noisy image into a different domain in order to improve it. In this new domain, noise is isolated and eliminated by examining image features, including the depiction of fine details (higher frequencies) and background interference (lower frequencies).This technique consist of two primary categories: data-adaptive methods, which adapt the process to the data at hand but are computationally expensive, and non-data-adaptive methods, which function without making data-specific adjustments.

I. Data-adaptive Transform:

The main drawback of data-adaptive transformation methods is their significant demand for computer resources and longer processing time consumption. The model's performance is degraded by its reliance on analyzing image parts using sliding windows and also by the need for high-quality, noise-free data, which can be difficult to obtain. It is almost impossible to get an image without any form of noise even after transformation.

II. Principal Component Analysis (PCA):

Principal Component Analysis (PCA) is a statistical method used to simplify complex data by breaking it down into more manageable parts for easier analysis. The proposed approach divides related data into uncorrelated components, enabling the identification of patterns (the low-rank component) and the separation of noise (the sparse component). In medical imaging, PCA is utilized to enhance image quality, such as in perfusion MRI and diffusion-weighted MRI, by minimizing unwanted noise while preserving critical information.

III. Non-data-adaptive Transform:

a. Spatial-frequency Domain:

Images are cleaned up using spatial-frequency domain filtering methods, which focus on the various frequency components of the image data. These methods operate by permitting low-frequency signals – which keeps vital image information – to be transmitted while attenuating high-frequency signals, which generally signify noise. In medical imaging methods such as PET and MRI, this filtering improve image quality by removing unnecessary noise while keeping important details of the images.

b. Wavelet Domain:

The wavelet transform technique is used to break down data into multiple sub-parts. It allows to simplify the tasks of analysis and processing of images. The process correctly eliminates noise while maintaining required image features. Thus proving it a valuable tool for medical imaging applications. The success of this method depends on selecting the correct wavelet basis; using an inappropriate or incorrect one can lead to poor image cleaning results.

c. Block-Matching and 3D (BM3D) Filtering:

The BM3D method reduces noise in medical images by grouping similar small image areas, referred to as patches, into three-dimensional blocks. These blocks are then processed in the wavelet domain to filter out noise. Finally, the cleaned patches are combined to recreate the entire image. However, as the level of noise increases, BM3D's effectiveness decreases, leading to potential distortions, especially in smooth areas of the image. BM4D is an advanced version that works with 4D data, allowing for better handling of volumetric images by considering both local and non-local relationships between the data points.

Deep Learning based Image Denoising Methods:

Deep learning-based denoising techniques optimize a loss function on the training dataset to train the model when training data sets including pairs of noisy and related clean images are available. According to Y. Xiao and K. Huang(2025),This deep learning technique comes under the category of supervised learning. When there insufficient pairs of noisy and clean images for training, researchers can use semi-supervised learning, which relies on a few paired images, or unsupervised learning, which only uses noisy images. Deep learning (DL) has various architectures, such as deep neural networks and convolutional neural networks (CNN), that are applied in medical image denoising. Examples of these applications include using unsupervised methods for denoising PET images and employing techniques like Generative Adversarial Networks (GAN) for low-dose CT images. There are very limited studies on the Denoising Diffusion Probabilistic Models (DDPM).Hence it is the choice of researchers to explore, and it is giving promising results. However the drawback of DDPM is that it needs lot of processing power.

III. DIFFERENT MEDICAL IMAGE MODALITIES:

1. Computed Tomography (CT):

CT images are created by taking multiple X-ray images of an object from different angles, which helps to capture detailed information about the internal structures[12]. Each pixel in a CT image represents the attenuation coefficient, which indicates the extends to which how much the X-rays are absorbed by different tissues in the body. However, noise can cause variations in these values, making it harder to detect subtle tissue differences, which is crucial for accurate disease diagnosis and prevention. Noise in CT images can be reduced by increasing the number of detected photons, which means increasing the radiation doselevel. However, to cut the noise in half, the dose should be quadruple, which raises safety concerns because higher radiation exposure can increase the risks for patients. Researchers are focused on minimizing noise while keeping radiation doses low, and they study different types of noise, such as quantum noise from limited photon detection and electronic noise from the device's components, using statistical models to understand and manage these issues. In CT imaging, random noise can come from two main sources: quantum noise, which occurs due to the limited number of photons detected, and electronic noise, which arises from the device's electrical components. Quantum noise is often modeled using a Poisson distribution, while electronic noise follows a Normal distribution. To reduce these noises, various reconstruction algorithms, like filtered back projection and iterative reconstruction, are used, along with post-processing techniques that help improve image quality while managing the noise levels.

2. Magnetic Resonance Imaging (MRI):

Magnetic Resonance Imaging, or MRI, generates detailed images of body tissues and organs by employing a strong magnetic field and radio waves. According to Y. Xiao and K. Huang(2025),Hydrogen atoms in a person's body become magnetically aligned when they are exposed to a magnetic field. Following the disturbance of atomic alignment by a radio wave, the atoms return to their normal state and release energy, which is then used to produce gray-scale images showing the magnetization pattern inside the body. Raw MRI images are complex data that comes from applying a mathematical technique called the Fourier transform, enabling the visualization of hydrogen atom distribution. The predominant form of noise in these images is Rician noise, and its level fluctuates according to signal power. Tt shows characteristics similar to those of Rayleigh noise In low-light intensity regions and in high-intensity regions, it looks like to Gaussian noise. The presence of this noise leads to unpredictable variations, hence complicating it further the process of identifying the specific features of images. The statistical methods can be used to represent noise in MRI images.The noise level is calculated using the square root of the sum of the squares of two independent Gaussian random variables, showing that it can vary due to various factors. The noise follows a stationary Rician distribution, indicating its intensity remains steady across various image regions (or voxels), which may impact the image's clarity and overall quality.

3.Positron Emission Tomography(PET):

PET scans is a medical imaging technique that helps medical professionals to visualize the functioning of various body parts, with a focus on metabolic processes. Throughout the entire procedure, trace quantities of radioactive materials are inserted in to the patient. The computer are used creates 3D images based on where these substances accumulate. Most of the noise comes from random changes in how photons, or light particles are detected. This noise can be divided into true coincidences, random coincidences, and scatter coincidences. Random coincidences can be measured and removed from the data, but scatter coincidences, which come from real events, are harder to deal with. They create uncertainty in diagnostic images, making it more difficult to interpret the results.

4.Ultrasound:

To create real-time images of the body's tissues,ultrasound technique is used.This technique uses high-frequency sound waves, which are above the range of human hearing. A typical ultrasound system includes a transmitter that sends out sound waves and a receiver that displays the image. As sound waves travel through different types of tissues, like soft tissue or bone, they bounce back at different speeds, creating contrast in the images that helps doctors identify various materials and structures within the body[14].

IV.FILTER'S ROLE IN NOISE REMOVAL

The filtering techniques used in medical imaging should be conservative in the following terms.

1-Information in images should not be removed or altered.[15]

2-All the Information needed for physicians should be intact.For example,noise in in utlrasound imaging sometimes shows mobility of certain structures hence useful for diagnosis. It should be preserved and not be removed.

3-No new information should be added. Sometimes these newly added artifacts are misinterpreted as anatomical features hence incorrect diagnosis is made.

V. VARIOUS TYPES OF NOISE IN MEDICAL IMAGES

1. Gaussian Noise:

Gaussian noise is a prevalent form of statistical noise found in digital images, including those from medical imaging techniques like X-rays, MRIs, CT scans, and ultrasounds. It is characterized by random fluctuations in pixel values that adhere to a Gaussian (normal) distribution, which is defined by its mean and standard deviation.

Gaussian noise follows a normal distribution, with the most of values concentrated around the mean (typically zero), and fewer values showing significant deviations from it.

It is mathematically represented as:

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

Where

P(x) is the probability density function.

μ is the mean (frequently set to zero for noise).

σ is the standard deviation (calculates the spread of the noise).

Methods for controlling Gaussian Noise:

Filter-based methods such as Gaussian filters,Median Filters,Median Filters,Wiener Filters and Wavelet Transform Denoising.Its apperance is shown below.

Fig.1 a)Clean X-xay b)X-Ray with Gaussian Noise

2. Impulsive noise:

Impulsive noise, alternatively termed salt and pepper noise, emerges from sudden signal disruptions or imaging system malfunctions. This noise phenomenon creates a random pixel intensity distribution characterized by unexpected white and black pixel insertions.These noisy images often have dark pixels in lighter regions and light pixels in darker regions. The noisy pixels are randomly assigned either a salt (white) or pepper (black) values.

It is mathematically represented as follows:

$$I_{\text{noisy}}(x, y) = \begin{cases} 255, & \text{with probability } P_{\text{salt}} \\ 0, & \text{with probability } P_{\text{pepper}} \\ I(x, y), & \text{with probability } 1 - P_{\text{salt}} - P_{\text{pepper}} \end{cases} \tag{2}$$

Where

With probability $P_{salt:}$ The pixel is set to the maximum value (255, which represents white)

With probability P_{pepper}: The pixel is set to the minimum value (0, which represents black).

With probability $1–P_{salt}–P_{pepper}$: The pixel retains its original value, i.e., no noise is added.

Its apperance is shown below with respect its clean image.

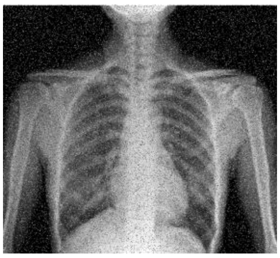

Fig.2 a)Clean X-ray b)X-Ray with pepper and Salt Noise

3. Rician noise:

Rician noise represents a specialized statistical noise phenomenon predominantly observed in magnetic resonance imaging (MRI) signal processing. This noise arises from complex signal characteristics involving independent Gaussian-distributed noise components in the real and imaginary signal domains.This noise is signal-dependent, meaning it changes according to the intensity of the underlying image signal. Unlike Gaussian noise, which is symmetrically distributed around the mean, Rician noise creates a bias in the magnitude image, particularly in areas with low signal-to-noise ratio (SNR). This makes it more difficult to accurately recover the original signal.

For a given pixel intensity I in the presence of Rician noise, the probability density function (PDF) is given by:

$$P(I \mid I_0, \sigma) = \frac{I}{\sigma^2} \exp\left(-\frac{I^2 + I_0^2}{2\sigma^2}\right) I_0\left(\frac{I I_0}{\sigma^2}\right) \tag{3}$$

where:

- I: Observed noisy intensity.
- I_b: True (original) signal intensity.
- σ: Standard deviation of the Gaussian noise in the real and imaginary parts.
- $I_0(\cdot)$: The modified zeroth-order Bessel function

Its appearance is shown below.

Fig. 3 a)Clean X-ray b)X-Ray with racian noise

4.Poisson noise:

Poisson noise, alternatively termed shot noise, and it is a statistical noise phenomenon arising from particle-based signal generation in medical imaging systems. The noise model emerges from individual event counting processes involving photons or electrons.

For a signal intensity I, the probability of observing a value k due to Poisson noise is as per below equation:

$$P(k; I) = \frac{I^k e^{-I}}{k!} \tag{4}$$

where:

k: Observed pixel intensity (a non-negative integer).

I: True pixel intensity.

e: Base of the natural logarithm.

k!: Factorial of k.

Its appearance is shown below.

Fig. 4 a)Clean X-ray b)X-Ray with possion noise

5. Periodic noise :

Periodic noise in X-ray images is a form of organized noise that appears as consistent, repeating patterns, such as horizontal, vertical, diagonal lines, or grid-like overlays on the image. Unlike random noise types like Gaussian or Poisson noise, periodic noise results from systematic disruptions occurring during the image capture process[16].

The following section discusses the notch filter for removing periodic noise from x-ray image.

A notch filter is a custom defined filter used in signal or image processing to block or reduce specific frequencies while allowing others to pass. The frequency power spectrum of image is calculated using Discrete Fourier Transform(DFT).The Points of spike/energy burst is manually selected and removed those frequencies from image and the inverse transform is calculated to restore noiseless image.

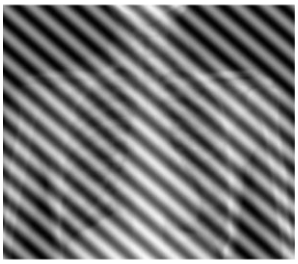

Fig. 5 a)Periodic Noise b)After aplying Notch filter

VI. DENOISING MRI IMAGE USING VARIOUS FILTERS:

The results of filters-based denoising method after applying it to the noisy MRI image are shown below pictorially as well as in tabular form with SSIM values.

First the clean MRI image is shown below and then subsequently results of various filters applied on noisy MRI image are shown.The filter names are stated on the top of all images.

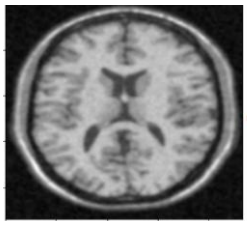

Fig. 6: Clean MRI Image(Reference Image)

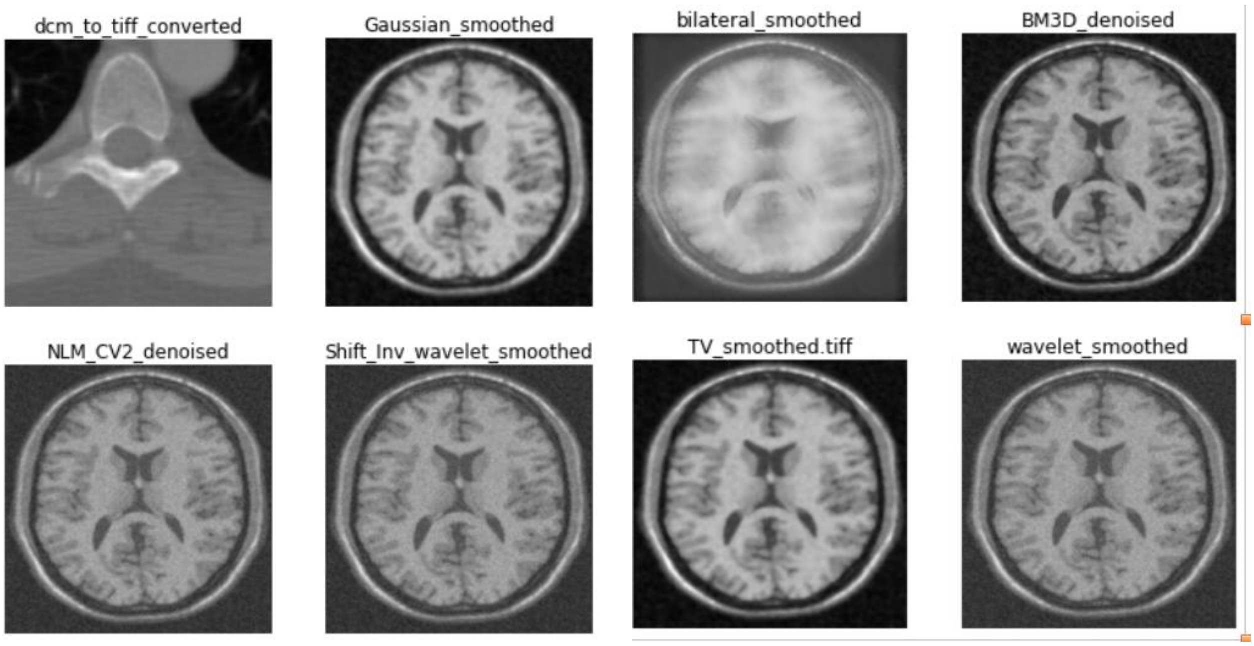

Fig. 7 Comparison between the reference MRI image and images denoised using filter-based denoising methods.

Denoising results are measured using below parameters.

Performance Metrics:

1-Peak Signal to Noise Ratio:(PSNR)

It measures the ratio between the maximum original signal and MSE(Mean Square Error).Higher PSNR values signify better image quality.

2-Structural similarity index measure (SSIM):

It measures perceptual differences (such as luminance, contrast,structure) of two similar images.

Higher SSIM values indicate better image quality (0-1).

Table 1. Performance measurements between Filters

Image & Type of Filter	**SSIM Value**
MRI Clean,Wavelet Smoothed	0.399
MRI Clean,Bilateral Smoothed	0.479
MRI Clean,BM3D Denoised	0.671
MRI Clean,Gaussian Smoothed	0.617
MRI Clean,MRI Noisy	0.394
MRI Clean,NLM-CV2 Denoised	0.401
MRI Clean,NLM-skimage Denoised	0.394
MRI Clean,Shift-Invariant Wavelet	0.400
MRI Clean,TV Smoothed	**0.690**

Highest SSIM value(in between 0-1) is shown in bold text hence TV smoothed filter produces the clearest MRI image. The higher the SSIM value,the better the image quality.

VII. PROPOSED METHODOLOGY

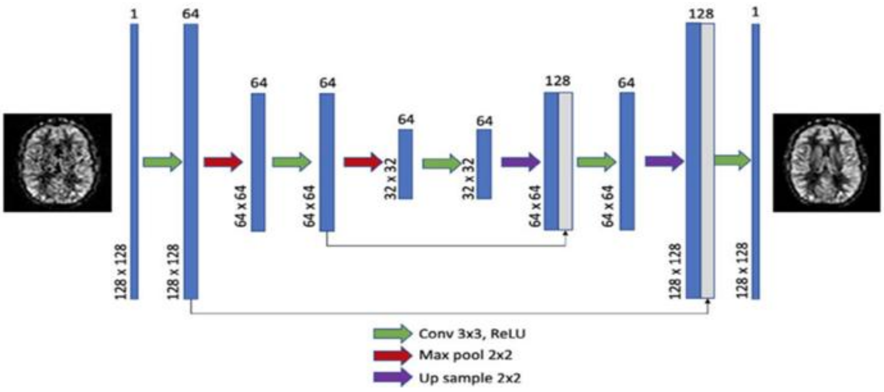

FIG. 8: ARCHITECTURE OF DENOISED AUTOENCODER

A noisy image is provided to Autoencoder as a input for getting denoised image as a output and it generates denoised image by removing noise from given input. It is trained on noisy and noise free datasets[17].

VIII. RESULTS AND DISCUSSIONS:

The following table shows the results of the filtering -based methods and Denoised Autoencoder(Specialized architecture of Neural Network) in terms of PSNR after denoising a noisy MRI image. PSNR values are obtained through the python based implementation of PSNR formula. It is noted that Denoised Autoencoder is best suited for removal of specific noise from image.

Table2. Performance measurements with Filters & denoised autoencoder(Neural Network)

Denoising Method	PSNR Value
Median Filter	56.058
Gaussian Filter	57.058
Average Filter	57.213
Bilateral Filter	57.405
Proposed(Denoised Autoencoder)	**68.10**

The highest PSNR value is shown in bold text hence the denoised autoencoder produces the clearest MRI image.The higher the PSNR value ,the better the image quality.

IX. DATASET AND IMPLEMENTATION:

Dataset is obtained from kaggle with name SARS-COV-2 CT-Scan Dataset. It consist of 1252 CT scans that are positive for SARS-CoV-2 infection (COVID-19) and 1230 CT scans for patients non-infected by SARS-CoV-2, 2482 CT scans in total.Denoised autoencoder is trained on these datasets with 40 epoch on NVIDIA Titan X GPU.

All above results are obtained on jupyter-notebook using pytorch version 2.1.0+cu121 along with other required python libraries like numpy,matplotlib etc.

X. CONCLUSION:

In this study,it was noted that noise removal from medical images using a neural network gives much improved output as compared to traditional methods such as filters. To achieve better results ,we used a denoised autoencoder and to evaluate the results,we used the PSNR and SSIM parameters. In the process of noise removal,It noted that texture of image is changed, for example in ultrasonic images,fetus movement causes some noise hence it should be preserved instead of removal.

XI. FUTURE SCOPE:

Although the denoised autoencoder has generated quite good results but there is still a wide scope for the improvement in terms of image quality. Denoising Diffusion Probablistic Models is not only good for realistic contents creation but also good for denoising images hence it should be explored to obtain much clearer images than denoised autoencoder.

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