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Performance Comparison of Different Digital and Analog Filters Used for Biomedical Signal and Image Processing

Hemanand Duraivelu*

*Corresponding author, Department of Computer Science and Engineering, S.A. Engineering College (Autonomous), Chennai, Tamil Nadu, India. E-mail: d.hemanand@gmail.com

Udaya Suriya Rajkumar Dhamodharan

Global Institute of Engineering and Technology, Tamilnadu, Ranipet, India. E-mail: u_suriya@yahoo.com

Pamula Udayaraju

Department of Computer Science and Engineering, SRKR Engineering College Bhimavaram, Chinamiram Rural, Andhra Pradesh, India. E-mail: udayaraju8910@gmail.com

S. Jaya Prakash

Associate Professor, Research Supervisor/School of EEE at Sathyabama Institute of Science & Technology, Chennai, Tamilnadu, India. E-mail: jayaprakash.eee@sathyabama.ac.in

Sasikumar Murugesan

Principal, C. Abdul Hakeem College of Engineering & Technology, Melvisharam-632509, Ranipet District, Tamil Nadu, India. E-mail: pmsasi77@gmail.com

Abstract

Getting highly accurate output in biomedical data processing concerning biomedical signals and images is impossible because biomedical data are generated from various electronic and electrical resources that can deliver the data with noise. Filtering is widely used for signal and image processing applications in medical, multimedia, communications, biomedical electronics, and computer vision. The biggest problem in biomedical signal and image processing is developing a perfect filter for the system. Digital filters are more advanced in precision and stability than analog filters. Digital filters are getting more attention due to the increasing advancements in digital technologies. Hence, most medical image and signal processing techniques use digital filters for preprocessing tasks. This paper briefly explains various filters used in medical image and signal processing. Matlab is a famous mathematical,

analytical software with a platform and built-in tools to design filters and experiment with different inputs. Even though this paper implements filters like, Mean, Median, Weighted Average, Guassian, and Bilateral in Python to verify their performance, a suitable filter can be selected for biomedical applications by comparing their performance.

Keywords: Digital Filters, Biomedical Data, Signal Processing, Medical Image Processing, Noise Removal, Preprocessing

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Introduction

Biomedical signals and images diagnose or detect specific pathological or physiological necessities. These signals and images that are characteristic or derived from diverse levels within the body are gathered from the body, including organ, cellular, and molecular levels. These signals possess EEG illustrating brain electrical activity, ECG reflecting heart electrical movement, EMG capturing muscle electrical activity, the electroneurogram transmitting nerve signals, and the electroretinogram measuring retinal reactions. These signals and images are pivotal in analyzing and comprehending physiological conditions and are acquired through technological instruments and sensors. The specialized advancement has led to wearable devices that authorize continuous monitoring, allowing early detection of potential health issues.

Similarly, these signals and images find utility in healthcare for analyzing biological systems. Signal processing attempts possess refining movements by eradicating noise, accurately outlining signal samples via analytical methods, extracting pertinent features and reducing measurements to discern function or dysfunction, and utilizing ML approaches to indicate forthcoming functional or pathological occurrences. Medical image processing is essential for doctors and radiologists to analyze diseases. When doctors take images inside the body, like MRI or X-rays, diverse things can produce images less precise, called "noise." This noise makes the pictures not show points and edges properly, which is terrible for discovering diseases. To help doctors to employ approaches to extract this noise and make the images more transparent. We use these approaches for pictures, such as MRI scans, C.T. scans, X-rays, and ultrasound images. Noise can produce it challenging to notice significant details. Noise can occur because of concerns with the supplies utilized to take images or problems during the procedure. Errors can cause noise during transmitting or keeping of ideas. Various types of noise coming from other things, like heat making noise in the sensors or pauses in light causing the noise. One example of noise is speckle noise in ultrasound images, generated by how sound waves scatter inside the body. Removing noise is crucial because it constructs ideas clearly for doctors to diagnose and find diseases. There are numerous ways to clear noise, but the primary purpose is to keep essential features like edges and boundaries clear.

Additionally, de-noising these medical images and signals increases the image quality. In medical industries, various filters are used to reduce noise and enhance the quality of the input medical data. Generally, two types of filters such as digital and analog filters, are used with biomedical signals and images to process the input data. Convolutional filtering techniques are not producing satisfactory results because it sometimes blurs the sharp edges. These filters have been widely used in recent years to overcome these issues. The digital filters are used to process the digital signals using microprocessors. It makes the filter more suitable for all types of applications. Digital filters are lower sensitivity to environmental factors like air, noise, and humidity. This filter is more flexible for advanced applications because the software programs entirely develop it. Its analyzing efficiency and high-speed filtering feature make the model more versatile. Likewise, analog filters are used to process the analog signals received from the various imaging signal processing modalities. It is designed with various hardware components like resistors, capacitors, and inductors. It generates a high dynamic range for high-level and low-level frequencies. It is easier to design and implement with the operational amplifier to handle the input medical image frequencies and signal data frequencies.

So, in this paper, various digital filters are examined to find the optimal model for medical image and signal processing. The following section discusses previous work on processing medical data. Then the performance of each digital and analog filter is briefed. Followed by the experimental result of the proposed filters is discussed, and finally, concluded with some ideas for future research works. This paper contributes:

- A detailed survey is carried out to understand the merits and demerits of various filters for preprocessing medical data.
- Some filters are randomly selected, implemented in Python, experimented, and the results verified.
- The obtained results are compared with one another to choose the best filter for medical image processing.

Literature Review

They have also employed a unified core sample-adaptive processing tool, allowing practical artifact handling across diverse types. This unified architecture seeks to deliver real-time compatibility while sustaining robust performance; limitations of the systems are the Load of computation explained by Kilicarslan and J.L Contreras-Vidal (2019). They have presented a wavelet-based denoising process to EEG signal de-noising, highlighting the significance of the wavelet transformation. While the suggested system offers significant merits, such as improved denoising and data preservation, probable limitations in the duration of complexity and trade-offs should be taken into consideration during its implementation discussed (Kilicarslan & Contreras-Vidal, 2019). Zhao et al. (2019) have advocated a pioneering resolution for the automated identification of noise-laden features in wearable ECG recordings by incorporating MFSWT and CNN. While the suggested approach showcases commendable excellence, such as enhanced accuracy and close advantage, reflections regarding the model's generalization and computational complicatedness should be noted during its application. Ferdous et al. (2023) presented an analysis report that evaluates diverse denoising techniques utilizing SNR measures and specifies the most appropriate algorithms for de-noising biomedical and speech signals, such as neural networks and CNN. The suggested strategies show merits like tailored denoising and high performance. Nevertheless, time of processing and complexity are the limitations, and N.N. gives better performance.

Khosla et al., (2020) have discussed and analyzed various functional neuroimaging approaches, emphasizing the unique neuroimaging capacities inherent in EEG signals. These EEG signals suggest benefits like a high temporal solution, cost-effectiveness, and portability. The study compares publicly available EEG datasets and other localized data acquisition methods through a thorough analysis. The suggested systems offer a host of merits and potential limitations that might impact their practical implementation. Kumar et al., (2021) have submitted a novel denoising technique that employs the stationary wavelet transform to improve the ECG signal quality that is contaminated by noise. Different denoising procedures are examined. Exhaustive evaluation through numerous metrics delivers a robust assessment of denoising implementation.

The computational complexity of the stationary wavelet transform may be elevated and reach more detailed denoising processes involving real-time processing abilities. Tay (2021) presents a valuable approach for enhancing sensor data quality via denoising. Construct an extended graph to model the WSN by leveraging principles from graph signal processing. This time-vertex graph helps capture correlations among neighboring sensor nodes across the temporal dimension. The merits of this system are Graph Signal modeling that allows a more accurate denoising process. Some of the limitations are complexity in computation and algorithm robustness. Celin and Vasanth (2018) has introduced a new method for categorizing ECG signals using different classification approaches. The approach involves preprocessing, peak detection, and classification methods. The primary purpose of this type is to organize the ECG signal database into normal or abnormal ECG signals. The proposed plan includes extensive preprocessing and feature extraction, improving classification accuracy. The main advantage of this technique is high performance and enhanced classification though the limitations are generalization and computational difficulty. S Celin and

Rajeev et al. (2019) proposed a robust denoising system incorporating LSTM-based Batch Normalization and RNN techniques to extract noise from lung C.T. images effectively. The main advantage of these approaches is the removal of noise and Optimized Batch Size, and the limitations are a dependency on the data. Chen et al. (2020) proposed a noise-resistant mode identification approach. This approach can identify the noise accurately with varying degrees of noise interference. Its advantages include correctness, versatility in case studies, and feasibility validation. The approach's limitations are the data variability and the algorithm's complexity. Ahmed et al. (2017) discussed a Hybrid IIR/FIR Filter Banks approach. This method improves denoising capabilities. The central excellence is minimizing the computation complexity, and the limitations are the various integrations of the system and the scope of applications.

Kilicarslan, and Contreras-Vidal (2019) used the Aircraft handling approach to manage challenging artifacts, particularly motion artifacts, via core samples and adaptive processing tools. The main merits of this system are versatility, efficiency, and streamlined processing, and the limitation is the diversity of aircraft and real-time constraints. The author has presented a study that suggests a two-stage speech enhancement technique that addresses reverberation and noise sequentially. This system delivers enhanced speech quality by even addressing the challenges posed by indoor environments. The main advantage of this system is improved quality of speech, and the limitation is the noise interactions. Kumar et al. (2023) explained CNN and LSTM systems. Both methods are used for denoising the ECG signal. The advantage of the proposed approach is the DL method's versatility and CNN superiority, and the limitations are the specific noise patterns.

Methodology

Filters for Biomedical Data Processing

The digital filter is a systematic process used to perform mathematical functions on images and signals to enhance them in certain aspects. At the same time, analog filters are called electronic filters and are used with electronic circuits for performing continuous analog signals. A digital filter comprises an analog-2-digital converter for sampling the signal, followed by a microprocessor and peripheral devices to store and filter out the coefficients. It uses some internal and external mathematical expressions to perform various functions on the data. A sample filter process model is shown in Figure-1. This section discusses the merits and demerits of various biomedical signal and image processing filters in detail. Filters are a more popular tool used for bioimage and signal processing. Generally, filters are used for smoothing, de-noise, and de-blurring the input data. Filters are mainly used to enhance the quality of the input original image. Based on the nature of the input data, the filters are chosen to perform the preprocessing tasks. The most common filters used in the image and signal process are the Mean filter, Sobel filter, Gaussian Filter, Non-Average filter, Median Filter, weighted average Filter, Bilateral Filter, and Trilateral Filter.

Mean Filter

It is a linear spatial filter used to reduce and enhance the noise and clarity of the input image. It is more beneficial to reduce the intensity variation among the neighboring pixels. That is, the pixels of each image are replaced with the mean value of the neighboring pixels. It replaces the center value of the window with the average value. The major advantage of the mean filter is that it sharpens the features of the input signals by filtering the noise. It is easier to deploy and smooth the input images. Though a mean filter helps enhance and reduce the image and noise, it has some drawbacks in working with low-frequency data. It has issues in analyzing the effects of the median filter. There is no error prorogation in the mean filter.

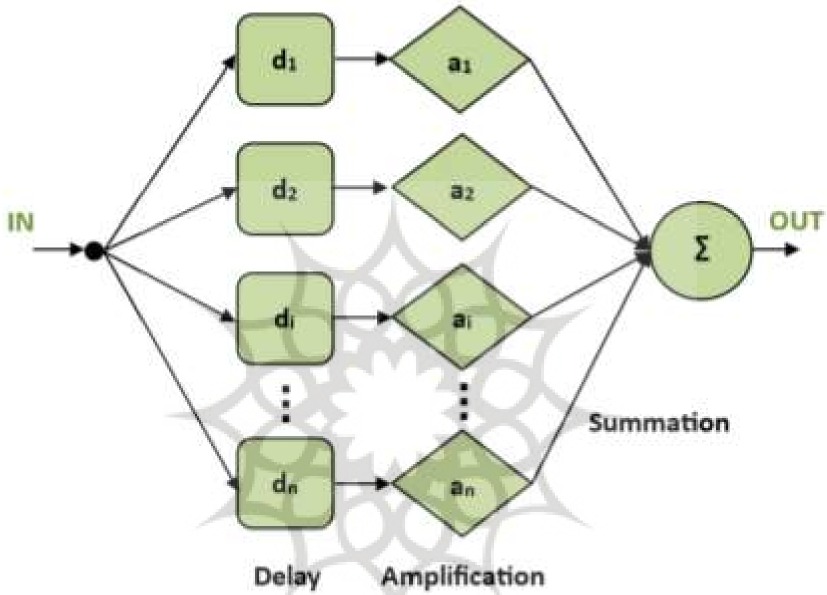

Figure 1. Sample Filter Process

A mean filter is a linear filter that follows the local averaging process on the data. For example, the average value of the neighbor pixels is calculated and replaced by all the pixel values (see Figure-2). It can also be expressed as:

Let $\boldsymbol{f}(\boldsymbol{i},\boldsymbol{j})$ is the noisy image // input image

The output image $\boldsymbol{g}(\boldsymbol{x},\ \boldsymbol{y})$ is obtained by

$$\boldsymbol{g}(\boldsymbol{x},\boldsymbol{y}) = \frac{\boldsymbol{1}}{\boldsymbol{n}} \sum_{(i,j)\in \boldsymbol{S}} \boldsymbol{f}(\boldsymbol{i},\boldsymbol{j}) \quad (1)$$

Where all the neighborhood pixels for the pixel $(\boldsymbol{x},\boldsymbol{y})$ are denoted as $\boldsymbol{S}$, and $\boldsymbol{n}$ denotes the total number of pixels taken from $\boldsymbol{S}$, and it is shown in Figure-2.

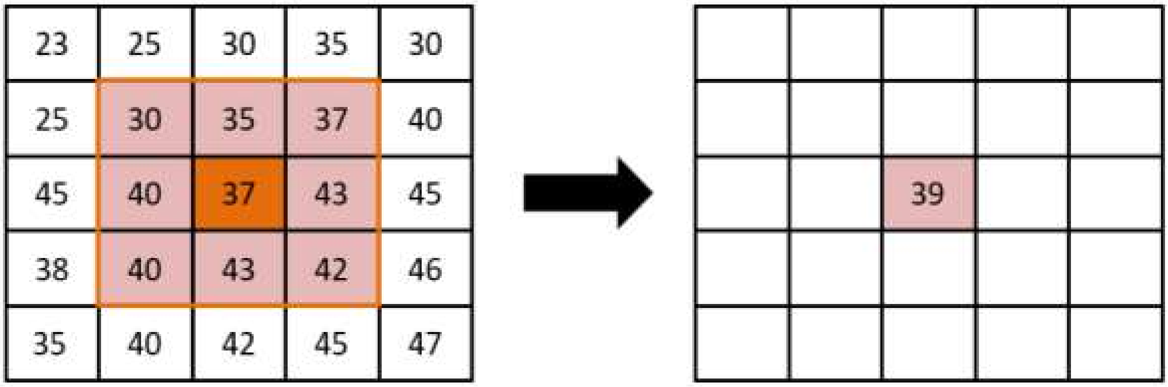

Figure 2. Mean Filter Process

Median filter

It is a non-linear filter, mainly used to remove the various types of noise in the input data. It is the most popular digital image processing technique used in many applications. The primary process of the median filter is to replace the entry by entry using the median values of the neighboring pixels. For example, if the window has an odd number of entries, the middle value of each entry is numerically sorted. More than one possible median is sorted if it has an even number. Median filters are popularly used in various applications such as image processing, signal process, and time series analysis. The significant advantage of applying a median filter is that it can eliminate the noise in the high-magnitude input data. In other words, a median filter is a process that replaces the pixel values by calculating the median value of the gray values of the selected region in the image. It is expressed as:

$$\boldsymbol{S(x,y)} = \underset{(i,j)\in A_{xy}}{\mathbf{median}}\{\boldsymbol{r(i,j)}\} \tag{2}$$

Where, $\boldsymbol{A_{xy}}$ denotes the region of the image and $\boldsymbol{r(i,j)}$ denotes the gray levels of the image. Generally, the median filter removes the salt and pepper noise from the image (similar to the Mean filter).

Weighted Average Filter

In medical image and signal processing, various filters are used to enhance the quality and characteristics of the input data. In that sense, the Weighted Average Filtering technique is used for de-noising, blurring, and improving the input data quality. The pixels of the windows are multiplied by different numbers. More weightage and preference are provided to the center value of the window. It is multiplied by the highest value in the window to compute the weighted average filter value. It makes the pixel contribute more than the other pixels in the masked window. Improving the quality of the image and signals is also more helpful. The main disadvantage of this filtering technique is that single pixels with more intensity values in the neighboring pixels affect the average value of the window. The filters with convoluted edge values produced the blurred edges. For example, the WAF is applied on the pixel indicated by *, and the 3 x 3 neighbors are used for noise estimation, as shown in Figure-3.

9	15	17	8
13	21*	14	14
16	18	15	16
7	15	17	8

7	8	7
8	10	8
7	8	7

Figure 3. Weighted Average Filter

Gaussian Filter

This type of filter is also used for noise reduction, image smoothing, and image enhancement. It is one of the linear spatial types of filter, which more effectively smoothing the images. The Kernel coefficient in the Gaussian filter decreases the distance from the kernel centers. Generally, the size of the Gaussian filter is odd, and the kernel matrix is symmetrically applied. The main drawback of this filter type is that it is ineffective in eliminating the salt and pepper noise.

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7	8	7
8	10	8
7	8	7

Figure 4. Gaussian Filter

The Gaussian filter with kernel function is computed using the following expression:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{-x^2+y^2}{2\sigma^2}} \tag{3}$$

The x, y represent the coordinates, and σ represents the standard deviation in the values.

$$GB[I]_p = \sum_{q \in S} G_\sigma (\|p - q\|) I_q \tag{4}$$

The $GB[I]_p$ is the blur obtained from the pixel p, and the RHS shows q, the sum of all pixel weights from the Gaussian function. The intensity q is represented as I_q.

Bilateral Filtering

A bilateral filter is a non-linear filter used to smoothen the input signal and image to get a clear output. Compared to conventional filtering techniques, bilateral filters have been widely used in many applications in recent years. It is formulated by replacing the weighted average value of its neighboring pixels. The bilateral filter is performed based on the two parameters, such as the size and contrast of the data. It is computed based on a non-iterative manner, making the model easier to perform. And it is more efficient in processing the largest of data. The bilateral filters' major drawbacks are that they cannot eliminate or reduce the slat and pepper noise in the input medical data. It has a problem accessing the multiple-frequency components of the images. Though it is more efficient in removing the noise from the large data set, it performs poorly in processing low-frequency data. The bilateral filter is formed in the following manner:

$$BF[I]_p = \frac{1}{W_p}\sum_{q\in S} G_{\sigma_s}(\|p-q\|)G_{\sigma_r}(|I_p - I_q|)I_q \tag{5}$$

The $\frac{1}{W_p}$ represent the normalization factor of the model. The space weight is defined as $\boldsymbol{G_{\sigma_s}(\|p-q\|)}$ and the range weight as $\boldsymbol{G_{\sigma_r}(|I_p - I_q|)}$.

The $\boldsymbol{\sigma_s}$ represent the size of the kernel, $\boldsymbol{\sigma_r}$ represent the minimum amplitude.

Results and Discussion

The filters explained above are implemented and experimented with four different kinds of medical images in Python. Breast mammograms, chest C.T.s, brain MRIs, and finger vein images are used in the experiment, and the performance is compared in terms of Mean Square Error (MSE) and Similarity Index (S.I.), given in Table-1. The images processed by different filters are given in Table-2. All the images are the output images obtained from the filter performance.

Table 1. Performance Evaluation

Image Number	Mean		WAF		Gaussian		Bilateral	
	MSE	SI	MSE	SI	MSE	SI	MSE	SI
Img-1 (FingerVein)	0.131	0.868	0.061	0.936	0.031	0.970	0.042	0.960
Img-2 (Breast Mammogram)	0.549	0.451	0.327	0.675	0.236	0.766	0.248	0.754
Img-3 (Chest CT)	0.586	0.414	0.582	0.419	0.191	0.812	0.273	0.729
Img-4 (Brain MRI)	0.293	0.709	0.293	0.709	0.262	0.740	0.253	0.749

Table 2. Results Obtained from Various Filters

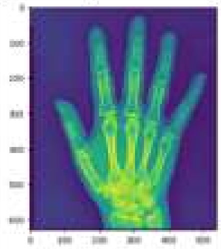
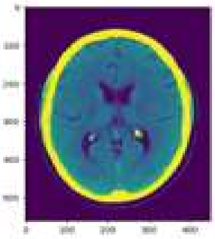
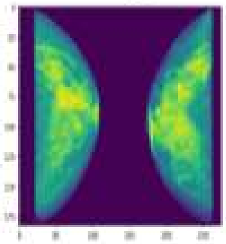
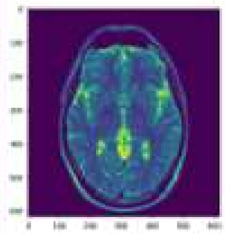
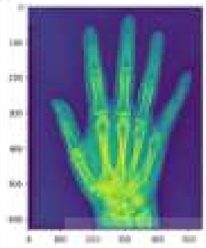
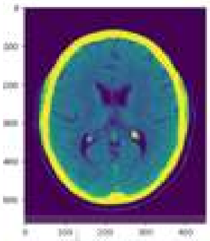
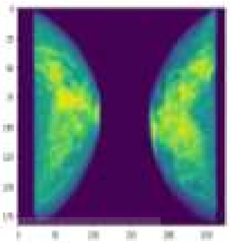
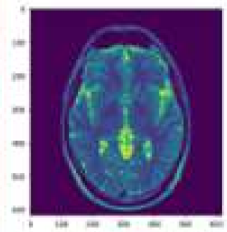
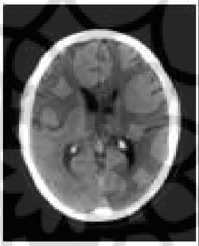
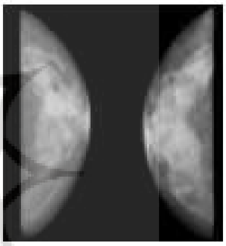
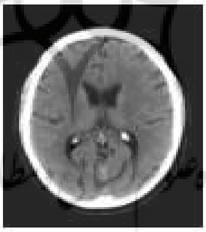
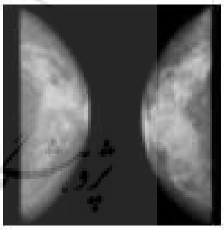
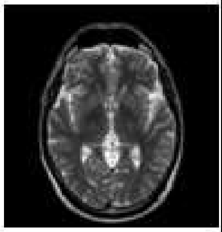
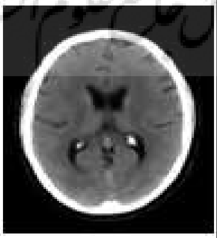
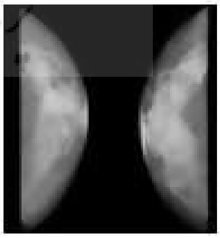
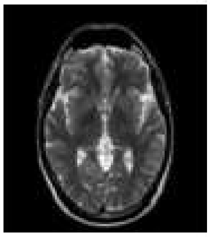
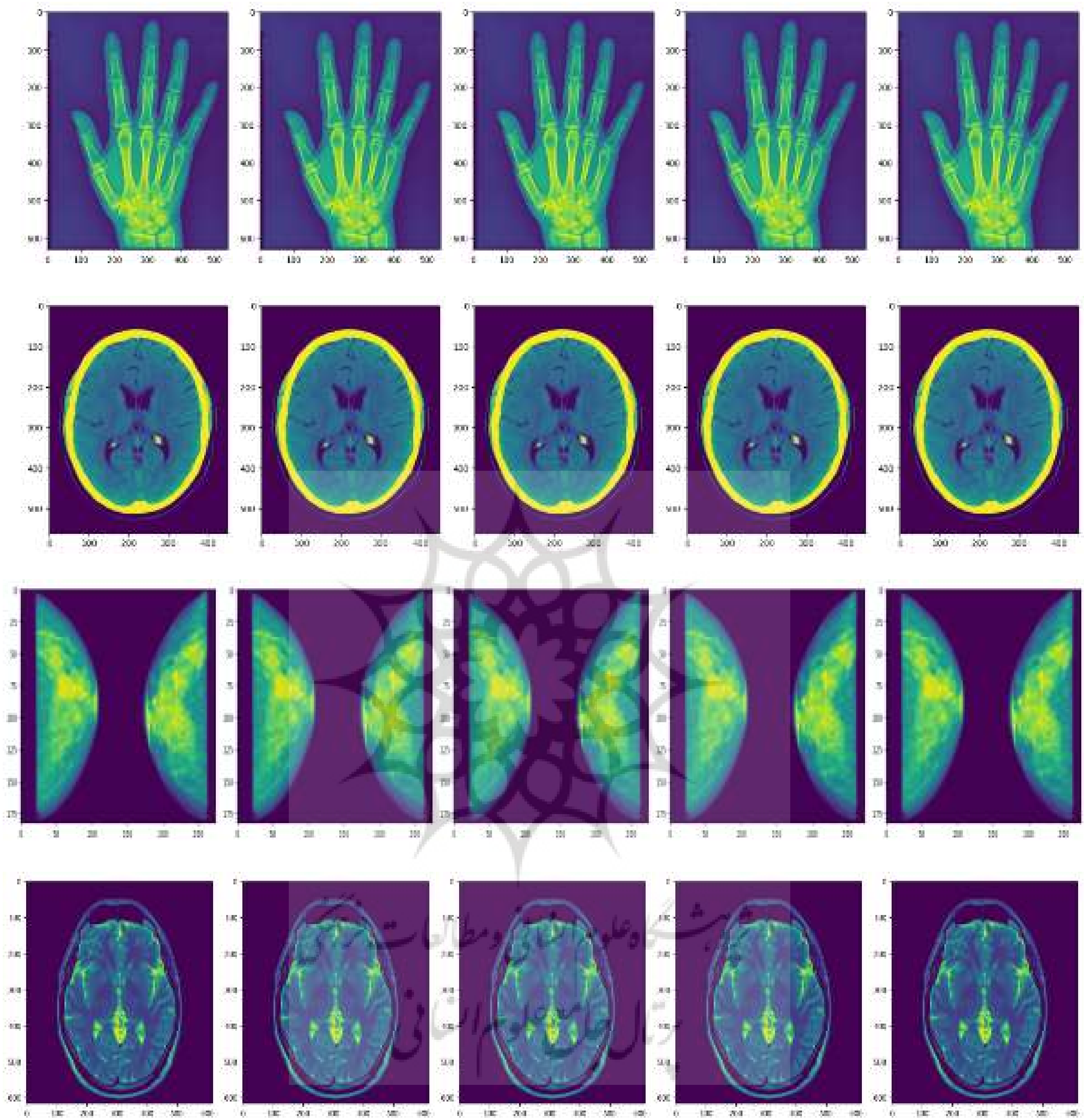
Filter Types	Finger Vein	MRI	Mammogram	CT
Mean filter's				
Average filter				
Median filter				
Gaussin Blur				
Bilateral filter				

Table 3. Mean Fitler [5 images from each category] put input image, and the corresponding output images.



Conclusion

This paper has aimed to discuss various digital filters used for medical image processing, to select the suitable one. Numerous filters are available in the computing industry concerning digital and analog data. Among all the filters, some of the filters, like mean, median, weighted average, gaussian, and bilateral filter, are considered into account. These filters are implemented in Python and experimented with the mammogram, MRI, CT, and finger vein images, and the results are verified. The performance of MSE and S.I. factors calculated for each filter concerning various images is verified. The results and performance factors obtained from the experiment show that the bilateral filter is highly suitable for medical image processing. Though the bilateral performance is good, it can not be used in the real time medical industry; hence, the performance is yet to be improved. In future work, the filters have experimented with more different kinds of medical images with variations, and their performance will be compared.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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