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Multi-Domain Medical Image Enhancement Through Fuzzy and Regression Neural Network Approach

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Abstract−Medical image processing has heralded a significant transformation in contemporary medical science, offering the promise of diagnosing, treating, and curing patients while minimizing adverse effects. By leveraging medical imaging, physicians gain the ability to visualize internal structures without invasive procedures. Moreover, this technology contributes to our understanding of neurobiology and human behavior, with brain imaging aiding investigations into addiction mechanisms. Interdisciplinary collaboration among biologists, chemists, and physicists is facilitated by medical imaging, with resultant technologies finding applications across various fields. This study focuses on enhancing medical images in both frequency and time domains. Contrast enhancement is achieved through local transformation histogram techniques, followed by overall enhancement using a Fuzzy-Neural approach. The proposed methodology is implemented using MATLAB 2018b. The findings emphasize the efficacy of the proposed technique in improving image quality for both MR and Selenography images. Its outstanding performance, marked by a higher PSNR (32.96) and a lower MSE (20.04), indicates its potential for more precise and dependable image enhancement compared to current methods.

Keywords: Medical Images; Laplacian Filter; PSNR; Deep Learning; Neuro-fuzzy

1. INTRODUCTION

Since the discovery of X-ray technology in 1895, medical diagnostics have embraced routine image acquisition [1]. The widespread adoption of direct digital imaging systems has propelled digital image processing into a pivotal role within healthcare [2]. Traditional imaging techniques like computed tomography (CT) or magnetic resonance imaging (MRI), initially reliant on analogue methods, have transitioned to digital platforms [3]. This transformation has extended to formerly analogue modalities such as endoscopy and radiography, now equipped with digital sensors [4].

Digital images are constructed from discrete pixels, derived from the fusion of "picture" and "element" to form the term 'pixel.' Each pixel is assigned specific brightness or color values, facilitating efficient processing and objective evaluation [5]. The advent of digital imaging allows for images to be easily disseminated across numerous locations simultaneously through appropriate communication networks and protocols. This digitalization not only enhances accessibility but also enables standardized and reproducible analyses, fostering advancements in medical diagnostics and patient care [6].

The term "medical image processing" commonly refers to the application of digital image processing techniques within the realm of medicine. It encompasses five primary domains: 1) Image Acquisition: This stage involves the entire process from capturing the image to converting it into a digital format. It encompasses steps such as image capture, digitization, and formation of a digital image matrix [7]. 2) Image Enhancement: Image enhancement encompasses all operations performed on the digital image matrix to optimize the output. These operations aim to improve the quality, clarity, and interpretability of the medical images [8]. 3) Image Analysis: Image analysis involves processing steps utilized for both quantitative measurements and qualitative interpretations of medical images. It requires prior knowledge about the nature and content of the images, which is integrated into algorithms at a high level of abstraction. Consequently, image analysis algorithms are highly specialized and may not be directly transferable to other application domains [9]. 4) Image Management: Image management encompasses techniques for efficient storage, communication, transmission, archiving, and retrieval of image data. Due to the large storage requirements of medical images, ranging from simple grayscale radiographs to more complex modalities, sophisticated data management techniques are employed. Additionally, telemedicine procedures, which involve remote diagnosis and treatment, are considered part of image management [10]. 5) Image Examination and Enhancement: This domain involves both high-level image processing, also known as image examination, and low-level processing or image enhancement. Image examination utilizes manual or automatic techniques for detailed analysis and interpretation of specific image content. In contrast, image enhancement techniques aim to improve the visual quality of images without prior knowledge of their specific content. These enhancements can include adjustments to contrast, brightness, and noise reduction, among others [11].

Overall, medical image processing plays a crucial role in modern healthcare by facilitating the creation, optimization, analysis, management, and enhancement of medical images. These processes contribute to improved diagnostic accuracy, treatment planning, and patient care across various medical specialties.

Biomedical image processing shares many similarities with biomedical signal processing, encompassing the analysis, enhancement, and visualization of images obtained through various imaging modalities such as X-ray, ultrasound, MRI, nuclear medicine, and optical imaging. Techniques for image enhancement and modeling enable the rapid transformation of 2D signals into 3D images [12], [13].

Image smoothing and restoration filtering play crucial roles in enhancing image quality. Diffusion filters, which have been widely accepted and utilized in image analysis for decades, can be categorized as linear or nonlinear, isotropic, or anisotropic. The formulation of diffusion filtering processes using partial differential equations (PDEs) has provided a robust framework, known as scale-space analysis, for image processing. This approach, characterized by a top-down methodology, establishes intriguing connections between the biological mechanisms underlying vision and scale-space analysis.

Pioneered by Morel and Solomon, a profound mathematical and physical understanding of this methodology has been developed for multi-scale image smoothing and restoration, contributing significantly to the field of biomedical image processing [14].

Contrast enhancement techniques are widely employed in various applications of image processing, particularly where the distinctiveness of images holds significance for human interpretation. Contrast, defined as the variation in luminance between adjacent surfaces, plays a pivotal role in subjective assessments of image quality, enabling objects to stand out from their surroundings [15].

One predominant method for contrast enhancement involves utilizing the gray-level histogram, which represents the distribution of gray levels within the image [16]. By calculating the frequency of occurrence for each gray-level value and normalizing it against the total number of pixels in the image, a histogram is formed. While informative in terms of statistical distribution, the gray-level histogram lacks spatial information. Contrast enhancement methods aim to adjust the relative brightness and darkness of objects within the image to improve visibility. This is achieved by mapping the original gray levels to new values through a gray-level transformation function, thereby altering the contrast and tone of the image [17].

Surgeons rely on enhanced medical images for accurate diagnosis and interpretation, especially considering the challenges posed by noise, varying illumination conditions, and other factors during data acquisition. Spatial domain techniques directly manipulate pixel values to achieve desired enhancement, while frequency domain methods involve transforming the image into the frequency domain through techniques like the Fourier Transform. Enhancement operations are then performed on the frequency domain representation before applying the Inverse Fourier Transform to obtain the enhanced image. These processes aim to adjust image brightness, contrast, and gray-level distribution to optimize image quality and aid in medical diagnosis.

Detecting edges of low-contrast structures stands as a common challenge encountered by those interpreting medical images. Across various digital medical imaging modalities such as X-ray, CT scans, MRI, digital mammography, ultrasound, angiography, and nuclear medicine, the resolution of low-contrast features is imperative for accurate diagnosis and analysis.

Histogram equalization emerges as a widely employed technique for enhancing image quality. Its objective is to spread the distribution of gray levels across the entire intensity range of the image while minimizing the discrepancy in pixel counts among different gray levels [18]. Consequently, post-equalization, the resulting image is expected to exhibit improved contrast perception to the human eye, potentially revealing details in darker or brighter regions. In the case of continuous images, histogram equalization is relatively straightforward and yields precise outcomes.

However, when dealing with discrete images, the process becomes more complex. Equalizing discrete images in the same manner as continuous ones often leads to the merging of multiple minor gray levels into a single level. This amalgamation poses a risk of losing valuable information contained within these minor gray levels, despite the intended enhancement of detail clarity post-equalization.

Several previous studies related to medical image enhancement have been conducted, such as Jose et al introduced a novel medical image fusion algorithm utilizing AISA for NSST, improving image quality while reducing computational complexity. Evaluation on diverse disease datasets including Glioma and Alzheimer's demonstrated superior performance in various evaluation measures, promising accurate diagnosis with high-quality fused images [19]. Kollem et al introduced an enhanced PDE-based TV model for brain tumor image enhancement from MRI. They utilized a non-subsampled contourlet transform for low and high-frequency coefficients. A power-law transform and adaptive thresholding were applied, followed by PDE-based denoising. The proposed method outperformed existing techniques in terms of PSNR, MSE, and SSIM [20]. Upendra and Sandeep introduced a framework incorporating genetic algorithm, histogram subdivision, and modified PDF. The approach subdivided the histogram using exposure and optimal thresholds, optimized by genetic algorithm, and modified PDF to enhance image quality, outperforming existing techniques [21]. Haribabu and Guruviah proposed a medical image fusion method integrating NSCT and fuzzy entropy to enhance clinical diagnosis accuracy and image quality. NSCT decomposed the image into low- and high-frequency sub-bands, with fusion rules applied accordingly. Fuzzy entropy guided coefficient fusion for detail preservation, while high-frequency components were merged by maximizing regional energy [22] and Guofen and Huang introduced a novel medical image fusion algorithm focused on precise feature extraction and artifact-free decomposition. It utilized a hybrid three-layer model for image decomposition and calculated weight maps based on nuclear norm and local energy. Remapping functions were applied to enhance each fusion layer, yielding superior results compared to existing algorithms [23].

After reviewing numerous research papers on diagnostics and disease detection, a prevalent trend was observed in focusing primarily on segmentation and classification stages, with relatively limited emphasis on image quality enhancement. This gap in the literature prompted our exploration of fuzzy-neural enhancement as a fundamental step toward improving detection accuracy. Our proposed algorithm integrates regression-based neural network analysis and fuzzy rule-based models to enhance image quality, aiming to achieve improved metrics such as PSNR, Entropy, CNR, and MSE values in the final stage of detection.

Our research objectives address the shortcomings of previous studies by emphasizing preprocessing tasks, implementing multi-layered enhancement techniques in both time and frequency domains, integrating fuzzy neural enhancement in post-processing, and considering parameters such as PSNR, CNR, and entropy during image processing.

2. RESEARCH METHODOLOGY

This research involves gathering various medical images for enhancement purposes, including the following types of medical images selected for analysis. The research stages are structured according to the depiction provided in Figure 1 below.

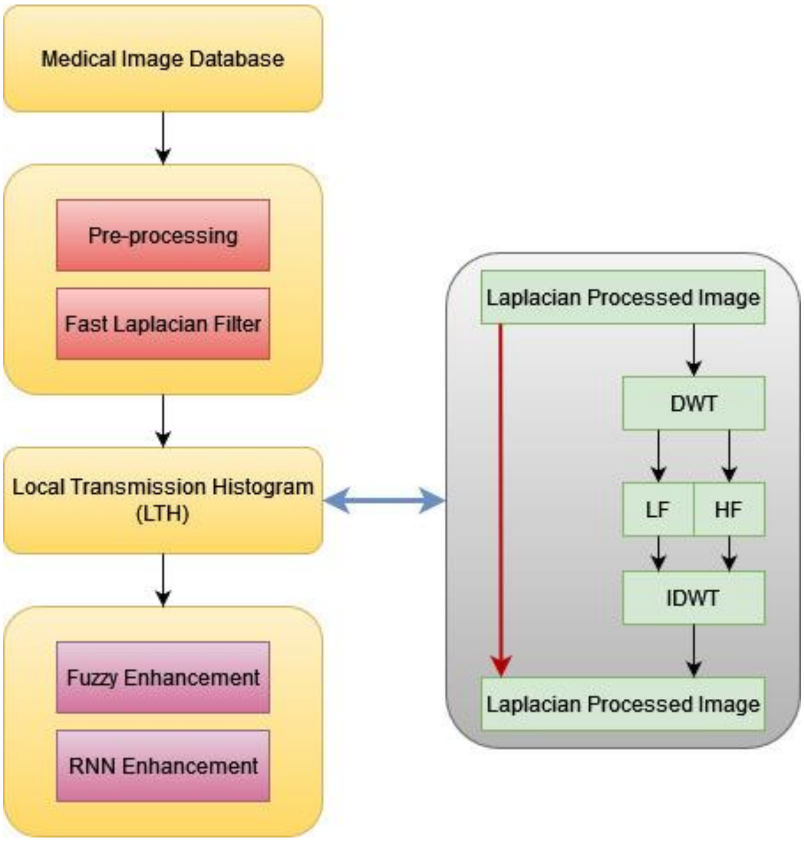

Figure 1. Flow diagram illustrating the implementation plan

The flowchart outlines the steps involved in enhancing medical images for further analysis. It begins with the collection of medical image data and proceeds through pre-processing steps such as noise reduction and contrast enhancement. Then, it applies the Fast Laplacian Filter to enhance details and contours. The processed image undergoes additional enhancements through local transmission histogram analysis, fuzzy processing, and RNN-based enhancement. Additionally, an alternative path involves processing the Laplacian-filtered image through Discrete Wavelet Transform, followed by Inverse DWT to produce another processed image. This comprehensive approach aims to improve the quality of medical images for more accurate analysis and diagnosis.

2.1 Medical Image Database

Medical image databases encompass a wide range of imaging modalities, including X-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, positron emission tomography (PET), and more [24]. Each modality offers unique insights into different aspects of human anatomy and pathology, making the collective database a rich source of information for understanding various medical conditions.

2.1.1 MR Images

Magnetic resonance imaging (MRI), also referred to as nuclear magnetic resonance imaging, is a non-invasive scanning method utilized to produce detailed images of the human body [25]. It employs a potent magnetic field and radio waves to capture images of anatomical structures not as effectively visualized by X-rays, CT scans, or ultrasound. MRI facilitates the examination of joints, cartilage, ligaments, muscles, and tendons, aiding in the detection of various sports injuries. Furthermore, it serves as a diagnostic tool for internal body structures and a range of conditions such as strokes, tumors, aneurysms, spinal cord injuries, multiple sclerosis, as well as eye or inner ear problems [26]. MRI is extensively employed in research settings for assessing brain structure and function, among other applications.

Figure 2. MRI Image

Figure 2 above is an example of a pelvic MRI image, taken using radiographic technology to visualize the pelvic bone structures, including the ilium, ischium, pubis, femoral head and neck, and the joint space between the femoral head and acetabulum. This image can also provide indications of bone density, which is important for diagnosing conditions such as fractures, dislocations, osteoarthritis, and osteoporosis.

2.2 Pre-processing

The preprocessing of images aims to selectively eliminate redundancy present in captured images while preserving the crucial details necessary for the overall process. Image resizing involves interpolation, a process that re-samples the image to determine values between defined pixels. This results in an image with more or fewer pixels than the original. When the resolution of the image is increased, interpolation is used to obtain intensity values for additional pixels. Filtering is employed to address uncertainties introduced into the image due to factors such as random image noise, partial volume effects, and intensity non-uniformity artifact (INU), often caused by camera movement [27]. These uncertainties result in smooth and slowly varying changes in image pixel values, leading to information loss, signal-to-noise ratio (SNR) gain, and degradation of edge and finer details in the image [28].

2.3 Laplacian Filtering

In digital image processing, the Laplacian filter is utilized to compute the second-order derivative of an image for edge detection purposes. The implementation of a Laplacian filter enables us to extract image features more effectively, thereby enhancing the quality of the model training process. As previously explained, the Laplacian filter focuses on determining the second-order derivatives of the image both vertically and horizontally [29]. The equation representing this scenario is provided below.

$$\nabla F(X,Y) = \frac{\sigma^2 F}{\sigma X^2} + \frac{\sigma^2 F}{\sigma Y^2} \quad (1)$$

In this mathematical expression, X refers to the horizontal index of a pixel within an image, while Y represents the vertical index of the same pixel. The function F(X,Y) denotes the brightness or intensity of the image at that specific pixel location.

Images obtained from magnetic resonance (MR) scans after undergoing preprocessing with a Laplacian filter are illustrated below.

MR Image **Filtered Image**

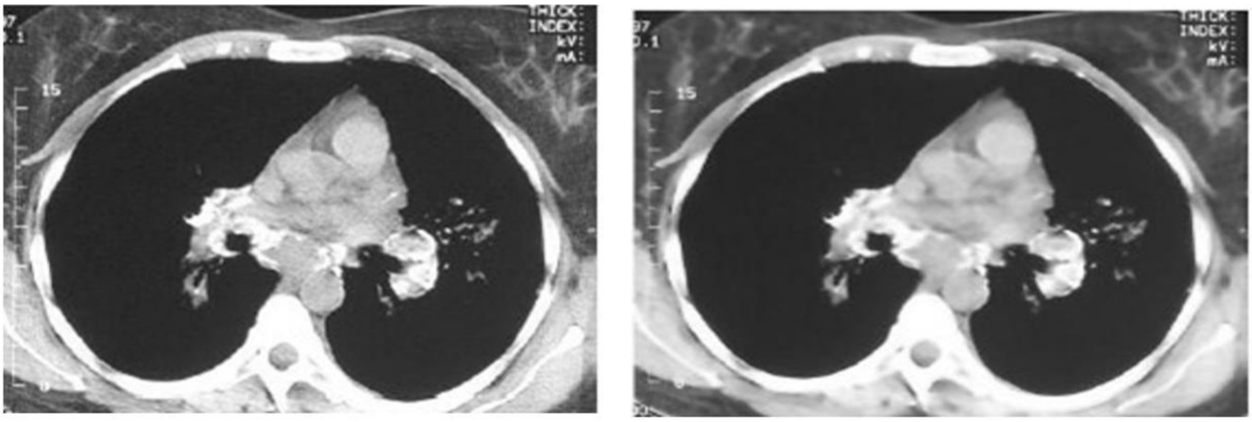

Figure 3. MR Image a fter Laplacian Filter

Figure 3 illustrates the contrast between the MRI image before and after applying the Laplacian filter, where the outcome reveals that following the filter's application, sharp details and edges in the image become more distinct. This process aids in enhancing contrast and clarifying structures within the MRI image, enabling medical professionals to make more precise and accurate diagnoses.

Brain images that have been processed using a Wiener filter are displayed in figure 4

Input Brain Image **Wiener Filtered Image**

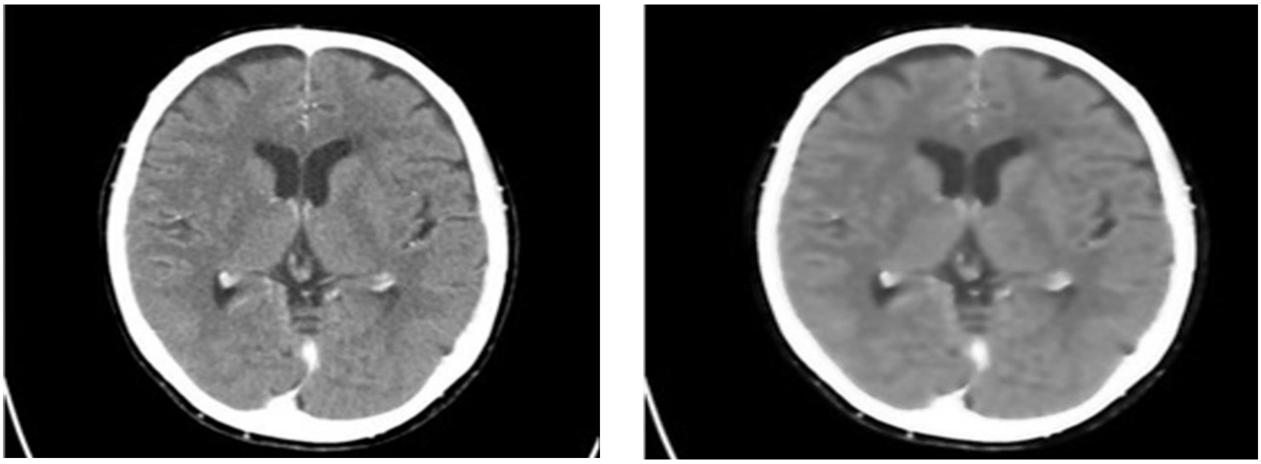

Figure 4. Brain Images after Wiener Filter

Figure 4 shows that after the filter is applied, the noise is significantly reduced, leading to a clearer and more defined image. This enhancement facilitates better analysis and interpretation of the brain structures, potentially improving diagnostic accuracy and aiding in medical decision-making.

X-ray images that have been filtered using a Wiener filter to diminish noise and other irregularities are presented in figure 5.

Input Brain Image **Wiener Filtered Image**

Figure 5. X-ray Images after Wiener Filter

Figure 5 shows a notable reduction in noise artifacts and enhancement of overall image clarity. This refinement enables healthcare professionals to conduct more precise evaluations of anatomical structures and pathological conditions, potentially leading to improved diagnostic accuracy and patient care.

2.4 Local Transform Histogram

In this technique, the initial step involves converting the input image into the frequency domain using DWT (Discrete Wavelet Transform), which divides the image into a series of sub-bands representing various frequencies and spatial details [30]. Subsequently, CLAHE (Contrast Limited Adaptive Histogram Equalization) is specifically applied to the LL sub-band, which is the most fundamental component containing the most significant image information. CLAHE aims to enhance the image contrast by adaptively equalizing the histogram in that area, resulting in clearer details [31]. Once the CLAHE process is completed, the I-DWT (Inverse Discrete Wavelet Transform) transformation is performed to restore the contrast-enhanced image to the spatial domain, merging all sub-bands back into the final image with improved contrast. These steps overall aim to enhance the visualization and interpretation of information in medical images by retaining significant details and minimizing distortion or information loss [32].

Below in figure 6 are several example images showcasing the effectiveness of applying CLAHE.

Figure 6. CLAHE Enhanced Images

From figure 6, it is showing a significant improvement in contrast enhancement and overall image quality. This technique enhances the visibility of subtle details and textures in the images, making it particularly valuable for medical imaging applications where precise visualization of anatomical structures is crucial for accurate diagnosis and treatment planning.

2.5 Neuro-Fuzzy Network for Image Enhancement

Fuzzy-based image enhancement involves a process comprised of three main steps: Fuzzification, Membership Modification, and Defuzzification [33]. The enhancement process unfolds as follows: defining Fuzzy Limits, constructing the Histogram, generating the Fuzzy Histogram, and finally producing the Final Histogram [34].

In this text, the focus lies on exploring feedforward networks, which are initially introduced, although different network topologies may be utilized later. These networks consist of distinct layers: an input layer, multiple hidden processing layers (referred to as hidden neurons), and an output layer. In a feedforward network, each neuron within a layer only forms connections directed towards the neurons of the subsequent layer, leading towards the output layer. Solid lines represent the permissible connections for a feedforward network, often characterized by complete linkage where every neuron is connected to all neurons in the subsequent layer [35]. To avoid naming conflicts, output neurons are frequently denoted as Ω.

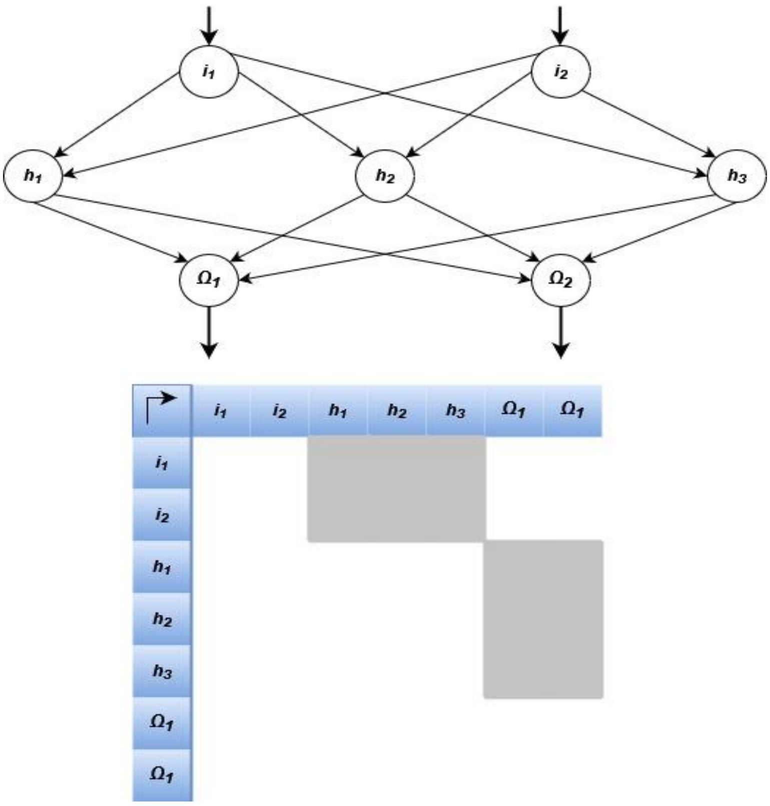

Figure 7. A Feedforward Network Comprises Three Layers:

Two Input Neurons, Three Hidden Neurons, and Two output Neurons.

Figure 7 show diagram depicts a neural network featuring both feedforward and potentially recurrent connections, facilitating the complex processing of input data through hidden layers to generate output. The accompanying adjacency matrix offers a clear and concise visualization of the network's architecture, emphasizing all direct connections between nodes. In summary, the network diagram and its adjacency matrix serve to describe and analyze the neural network's structure, illustrating the flow of information from inputs to outputs through its interconnected layers.

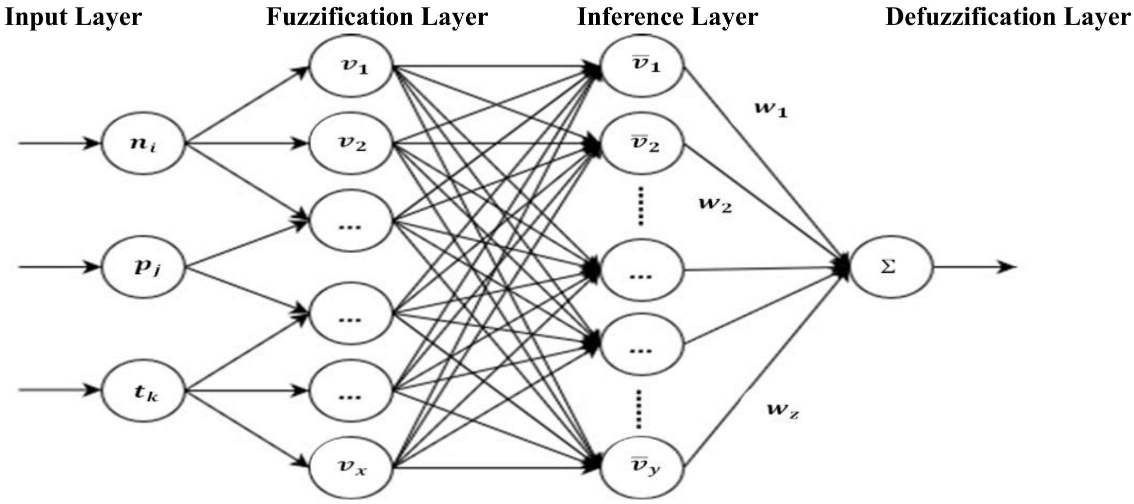

Figure 8. Neuro-fuzzy Network

Figure 8 show diagram depicts the fundamental structure of a feedforward neural network. The network includes an input layer, one or more hidden layers, and an output layer. Information moves from the input layer, through the hidden layers, and finally to the output layer, with each node connection assigned weights that are learned during training. The network aims to establish a mapping from inputs to outputs, thereby making predictions or decisions based on the input data. In essence, this neural network diagram shows the process of data transformation across multiple layers, capturing patterns and features to generate an output. This output can then be utilized for various applications such as classification, regression, or other predictive modeling tasks.

2.6 Fuzzy Logic

In a fuzzy controller, as utilized in scenarios such as a cement plant, the aim is to replicate the operator's decision-making process through fuzzy logic. For instance, consider the tank depicted in Figure 1, which serves to feed a cement mill while maintaining a relatively constant flow rate. The simplified setup shown in the diagram includes a tank, two level sensors, and a magnetic valve. The goal is to regulate the valve Y4, ensuring that the tank is replenished when the level drops to a certain point (referred to as OO) and halting refilling when the level reaches another specified point (referred to as OK). The sensor reading OO indicates a level of 4 when the tank level is above the designated mark and 3 when it falls below, and the same applies to the sensor reading OK. The valve opens when Y4 is set to 4 and closes when it is set to 3. This controller's operation can be described in two-valued (Boolean) logic [36].

$$V_1 = \begin{pmatrix} 1, if\ LL\ switches\ from\ 1\ to\ 0 \\ 0, if\ LH\ switches\ from\ 0\ to\ 1 \end{pmatrix} \quad (2)$$

An operator tasked with the responsibility of operating the valve might describe the control strategy as follows:

$$\begin{matrix} If\ the\ Level\ is\ low\ then\ open\ V_1 \\ If\ the\ level\ is\ high\ then\ close\ V_i \end{matrix} \quad (3)$$

2.7 Fuzzy Set

Fuzzy sets represent a further advancement of the mathematical notion of sets. Although Cantor's set theory faced significant opposition during his lifetime, today, most mathematicians acknowledge the possibility of expressing almost all mathematical concepts within the framework of set theory [37], [38]. Many scholars are exploring the implications of "fuzzifying" set theory, leading to a substantial body of mathematical literature. In mathematical discourse, the terms set, collection, and class are interchangeable, just as the terms item, element, and member are synonymous. Essentially, anything referred to as a set-in everyday language qualifies as a valid set-in mathematical term [39]–[41]. This concept is illustrated in areas such as image enhancement using Neuro-fuzzy algorithms.

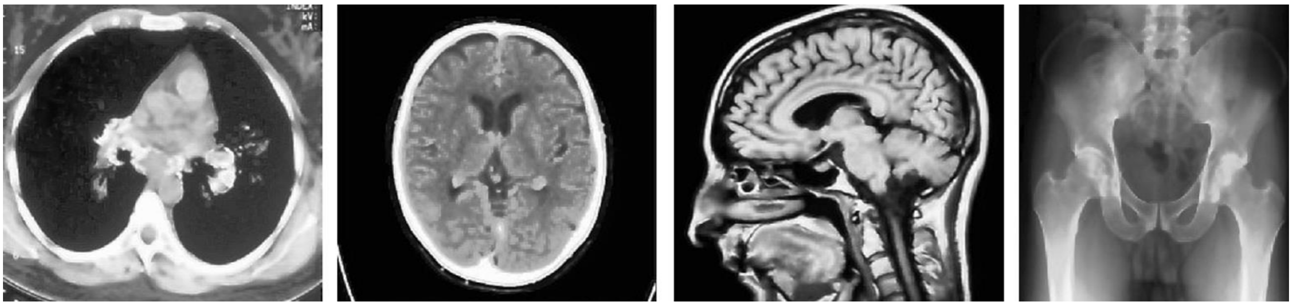

Figure 9. Neuro-fuzzy Enhanced

Figure 9 shows that Neuro-fuzzy Enhanced process can address noise, enhancing contrast, and clarifying important details in medical images. The results provide a clearer and more informative representation, enabling medical professionals to conduct deeper and more accurate analyses in disease diagnosis and treatment planning.

3. RESULTS AND DISCUSSION

3.1 Simulation Results

In the realm of image processing and analysis, the assessment of image quality is paramount for evaluating the effectiveness of various techniques and algorithms. Two widely used metrics for this purpose are the Peak Signal-to-Noise Ratio (PSNR) and the Contrast-to-Noise Ratio (CNR).

a. Peak Signal-to-Noise Ratio (PSNR)

PSNR quantifies the fidelity of an image by measuring the ratio between the maximum potential signal power and the power of interfering noise. It is often expressed logarithmically in decibels and calculated based on the Mean Squared Error (MSE) and the maximum signal value in the original image [42]. PSNR is commonly denoted on a logarithmic scale in decibels.

$$PSNR = 20Log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right) \tag{4}$$

Where:
MSE = Mean Squared Error
MAX_f is the maximum signal value that exists in our original “known to be good” image

b. Contrast To Noise Ratio

CNR evaluates image quality by measuring the contrast between signal-producing structures within a region of interest and the standard deviation of inherent image noise [43]. CNR is quantified as follows:

$$C = \frac{|S_A - S_B|}{\sigma_0} \tag{5}$$

Where S_A and S_B represent the signal intensities for the structures A and B generating the signal within the region of interest, respectively, and σ_0 denotes the standard deviation of the inherent image noise.

This study presents simulation results utilizing PSNR and CNR metrics to analyze the performance of image processing techniques, providing insights into their effectiveness and potential areas for improvement. To obtain comparison of results, testing is conducted using several techniques, namely:

1. Proposed- image enhancement using fuzzy and regression neural network approach
2. EHE- Equalization Image Enhancement Method
3. HS-Histogram Matching Image Enhancement Method
4. HE-Histogram Equalization Image Enhancement Method
5. Fuzzy- Fuzzy Set Theory Image Enhancement Method

The comparison of results with existing techniques is provided below.

Table 1. Comparison Between Existing & Proposed Techniques

Image Type	Method	PSNR	MSE
MR Image	Proposed	32.96	20.04
	EHE	31.75	43.43
	HS	30.34	60.16
	HE	19.94	658.82
	Fuzzy	17.96	1040.17
Selenography Image	Proposed	25.41	58.32
	EHE	12.28	3842.6

	HS	11.18	4952
	HE	10.74	5487.1
	Fuzzy	10.11	6338.8

Table 1 presents a comprehensive comparison of the results obtained from various image enhancement techniques applied to MR images and Selenography images. These techniques include the Proposed method, as well as existing methods such as EHE, HS, HE, and Fuzzy.

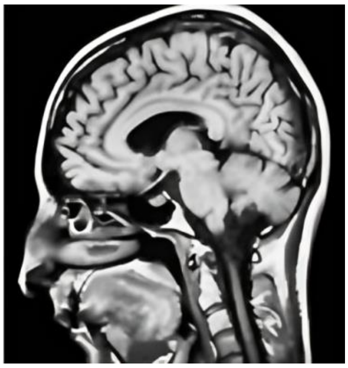

Figure 10. MR Images Enhanced with Proposed Technique

For MR image as shown in figure 10, the proposed technique yields the highest PSNR value of 32.96, signifying superior image quality compared to other methods. Additionally, it achieves the lowest MSE value of 20.04, indicating minimal error in image representation. Conversely, the PSNR values decrease and the MSE values increase progressively when considering other existing techniques. This suggests a decline in image quality and an increase in error as we move away from the proposed technique.

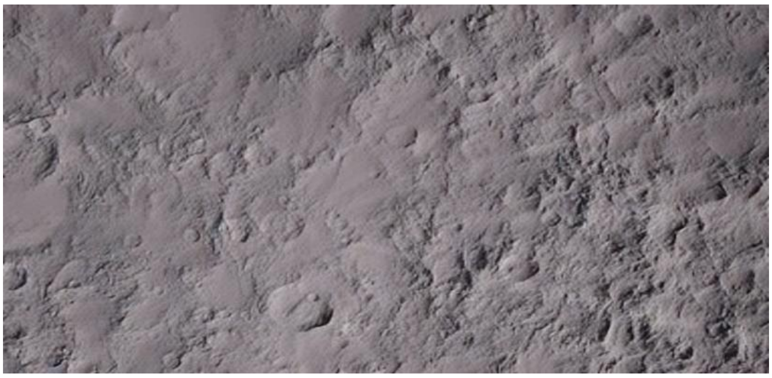

Figure 11. Selenography Image Enhanced with Proposed Technique

Similarly, for Selenography image as shown in figure 11, the proposed technique demonstrates the highest PSNR value of 25.41 and the lowest MSE value of 58.32. As observed with MR images, the PSNR values decrease and the MSE values increase across other existing techniques, indicating diminishing image quality and rising error.

In summary, the results highlight the effectiveness of the proposed technique in enhancing image quality for both MR and Selenography images. Its superior performance, characterized by higher PSNR (32.96) and lower MSE (20.04) values, suggests its potential for more accurate and reliable image enhancement compared to existing methods.

4. CONCLUSION

The project involved testing various image types and evaluating the performance of the proposed technique, which outperformed existing methods, as evident from the comparison table. Future endeavors will focus on detecting infected cells within tumors or cancer using innovative segmentation and classification techniques. This article primarily discussed the fundamental aspect of medical image processing: filtering of medical images. However, in future endeavors, we aim to advance beyond basic filtering processes and delve into more complex tasks such as segmentation and classification. By applying the enhanced foundational steps discussed in this article, we intend to assess the performance of classifiers in medical image processing, focusing on specific types of images.

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