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Denoising and Quality Improvement of Mri Images Using Hybrid Filters and Deep Neural Network Based Northern Goshawks Optimization Algorithm

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Abstract:

Purpose: The main purpose of this work is to enhance the quality of the MRI images by removing the noises. This provides details about the diseases without any doubt and improves the robustness.

Theoretical Structure: In the study of musculoskeletal magnetic resonance imaging, picture denoising and image quality improvement are essential. Electric current is transmitted and received through an electromagnetic coiled wire by radio and magnet communication devices used in magnetic resonance imaging (MRI) systems. Loud noises are produced when the flow of current causes coils to expand. This could have led to the acquisition of noise in the MRI pictures. These days, studies have shown that non-local means (NLM) approaches appear to be far more effective and dependable than traditional local statistical filters such as average filters when Rician noise is introduced.

Methodology: In order to denoise the MRI images for this investigation, we combined and applied a non-local means filter with a Non-subsampled Shearlet transform (NLM-NSST) model. To further improve the appearance of MRI imagery, have implemented the Northern Goshawks optimization (NGO) technique with a deep neural network (DNN).

Findings: The MATLAB software manages the execution of the work on the MRI picture database. When compared to earlier investigations, the suggested study successfully denoises the MRI pictures and enhances the image quality.

Research and Practical Implications: Through this work, we found that it will provide minute details about the disease to physicians and thus improvise the clinical findings.

Originality/Value: This work help in providing the details about improving the MRI scan images for analyzing the diseases with the parameters such as SNR, PSNR, accuracy, MSE, and time consumption.

Keywords: Denoising of MRI image, non-local means, Non-subsampled Shearlet transform, Deep neural network and Northern Goshawks optimization algorithm.

1. Introduction:

Over the past few decades, there has been a noticeable advancement in the rapidly advancing field of medical imaging technology. There are various different imaging techniques, each with its own set of principles and occurrences. The majority of the procedures are made to be suitable for use in the appropriate investigation of particular organs or diseases. Computed tomography, radiography, ultrasound, and magnetic resonance imaging are a few medical imaging modalities [1]. Like every approach, every modality has unique benefits and drawbacks. These lead to the conclusion that MRI has greater benefits for both normal and diseased tissues. Because MRIs have a better resolution, they can be used to examine minute details in a variety of organs. Additionally, the MRI's contrast was higher than the CT modality's. It is widely used to identify sclerosis, leukodystrophy, and abnormalities of the brain [2].

However, because it fails to capture the essence of genuine imagery, the noises found in them are not representative of those found in real imagery. The imaging techniques used during collection and processing may have resulted in image distortion and noise addition. Frequently, thermal noise is introduced because of the significant amplitude of the blood oxygen level during MRI scanning [3]. This explains the deterioration in the MRI scans' visual quality. The process of feature extraction is also impacted by the deterioration of image quality. To avoid these problems, it is necessary to ignore the noise, a procedure called as denoising an image. Although it is important to maintain the image's fine details, like edges, during the denoising process, a number of researchers used a variety of denoising techniques while maintaining the fine details. The majority of these techniques use neighbor pixel analysis as well as detection and restoration of noisy pixels in the images to suppress noise [4]. This work propsoed a novel denoising and quality improvement of MRI images using hybrid filters and deep neural network based northern goshawks optimization algorithm.

The remainder of the work is arranged in accordance with this; section 2 contains the literature review for the suggested work. Section 3 outlines the proposed denoising and image enhancing methods. Section 4 presents the comparison research and the experimental analyses. Section 6 provides a summary of the work.

2. Related works:

Gassenmaier et al. [5] first described dynamic contrast-enhanced gradient echo magnetic resonance imaging, which was used to accomplish edge enhancement and iterative denoising. Conduct the volume interpolated breath exams. Every imaging report is reviewed by both radiologists separately with regard to noise levels. For the analysis of image quality enhancement, 50 photographs were chosen. Although there has been an improvement in quality, noise levels have increased.

A deep learning (DL) model was proposed by Higaki et al. [6] for improving the quality of CT and MRI images. The quality of the image was enhanced by reducing both noise and artifacts. Under each category, a few features based on studies were described. The raw input was being reconstructed into image information by the deep convolutional neural networks. This model predicts behaviors more easily than linear processing, but it was unable to enhance the quality of the images.

Deep image prior based unsupervised MR image denoising network was introduced by Zhu et al. [7]. The encoder network was utilized to extract the low-resolution picture features, while the decoder network assisted in restoring the high-resolution information. Although the Rician and speckle noises could not be reduced, the edge and texture information was adequate to produce the image quality analysis.

Ramesh Patil et al. [8] looked into the brain MR images of infants and the performance of their image quality improvement model. The knee, bladder, heel, and skull are frequently treated with MRI images that contain common noises including salt, speckle noise, and additive noise combined with Gaussian noise. The quantitative results indicated that the diagnosis accuracy and Gaussian noise management were both good. There was an increase in computational complexity.

Huang et al. [9] proposed two filling procedures with the new unsupervised pseudo-siamese network for denoising and image quality improvement. The noises affect the accuracy of image segmentation, identification, and edge detection. Using a network loss function increased the results' similarity. Application of non-adaptive parameters has a limited influence and necessitates additional training data.

3. Proposed Methodology:

The proposed framework for denoising MRI images and enhancing image quality is described in this section. In order to denoise MRI pictures, the NLM-NSST model was combined. We have employed the NGO-DNN m to improve MRI picture quality even more.

3.1 Non-local mean filter-based NSST for image denoising:

The NLM filter is described in the section above for image denoising. This is the MR image smoothing configuration for the NLM filter. A noteworthy issue with this design is that a few of the filter parameters lack deterministically established values. Because these values can theoretically be set more precisely through experimentation, we focused on the non-subsampled Shearlet transform (NLM-NSST) model method, which will forecast and recommend an appropriate value setting [10]. We use the NLM-NSST approach to identify the optimal filter parameter combination based on various cost function assessments.

In order to eliminate undesired noise and maintain the fine structure of MRI images, we have employed the NLM-NSST model. The two main processes are enhanced non-local means filtering and picture denoising. The pre-filtering procedure eliminates any remaining noise while preserving the image's edges. Figure 1 explains the suggested NLM-NSST model for MRI image denoising.

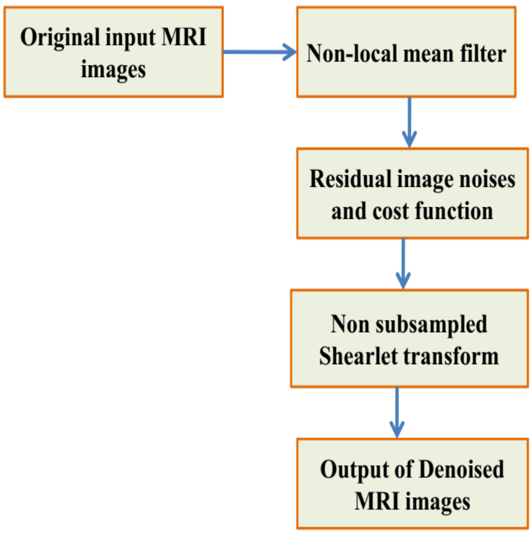


Fig 1: MRI image Denoising using NLM-SST

The NSST is one of several discrete Shearlet transforms possessing the special property of shift-invariance. This is a Shearlet transform that yields results with multi-scale and multi-dimensional expansion qualities by combining non-subsampled shearing (NSS) and non-subsampled Laplacian pyramid (NSLP) filters. The NSLP filters are used to decompose the MRI noisy input pictures into four stages across their higher and lower frequency sub-bands. Assuming that the sub-bands and the image have the same dimensions. The broken down function of the NSLP is expressed as,

$$N_{x+1} = \left(FH_x \prod_{y-1}^{x-1} FL_x \right) I_n \tag{1}$$

The Laplacian filter coefficient and input picture are denoted by I_n and N_{x+1} in the equation below. Using the low band and high band filters, the scaling parameters *x* and *y* are FH_x and FL_x. In contrast, NSS captures a high-pass image and functions as a band-pass filter [11]. Meyer-based shearing filters are used to leverage the NSLP four-level decomposition sizes based on various directions. The NSS adjustments obtain the Shearlet coefficient by the use of discrete Shearlet transform (DST) performance. The threshold's parameter is expressed in the equation below.

$$TH_{x,y} = \frac{\vartheta^2_{x,y}}{\vartheta^2_{x,y,m}} \tag{2}$$

Whereas, $\vartheta^2_{x,y,m}$ with m^{th} factor variance of the x^{th} and y^{th} sharing direction. Utilizing the Monte Carlo methodology, assess the variances. Utilize the higher values of the coefficients $TH_{x,y}$ and eliminate the lower value $TH_{x,y}$ to perform the reverse transformation of the Shearlet. As a result, an inverse operation is carried out and the threshold coefficient is restored in which I_n recovered images are represented as ignored factors. The MRI images are successfully denoised by the use of the (NLM-NSST model.

3.2 Image quality improvement:

This section illustrates the deep neural network based Northern Goshawks optimization (NGO) algorithm to improve the image quality.

3.2.1 Deep neural network:

Compose and extract the features for the building of architecture. The fully connected DNN is interpreted by one input layer, which is fully connected to the hidden layers. The DNN model is shown in Figure 2. To produce feature vectors, optimize the features [12]. Obtain the hidden layers as shown below, based on the input layers;

$$g_{1(i)} = \sum_i m_{1(i,j)} w_i + c_{1(i)} \tag{3}$$

Wherein the outcome of the hidden layer is denoted as, and where the DNN bias and weights are $c_{1(i)}$ and $m_{1(i,j)}$

$$g_{O(i)} = AF(g_{1(i)}) \tag{4}$$

Wherein, the initialization function of the DNN is $AF(.)$. Utilizing DNN, mark and incorporate the data design. By needing the optimizing DNN, the characteristic vector are improved.

Complete the training phase quickly in order to complete the DNN's predominant tweaking. Enhance speed and efficacy are the features of extraction. In order to determine the fitness value, minimize or maximize the necessary optimization. The cost function is defined by the expression below.

$$Z(m,c) = \frac{1}{L}\sum_{i=1}^{L} l\left(q^{ti}, q^{i}\right) \tag{5}$$

Whereby with an L-loss of *l*, are the original cost, the evaluated cost, q , q^i and *Z,* the mean value of the cost function. Predict the loss function as the difference between the prediction models based on this. The gradient descent method is minimized by obtaining weights and biases using the cost function *Z*. The cost function is minimized using gradient descent in the following formula.

$$m = m - \beta \frac{\partial}{\partial m} Z(m) \tag{6}$$

$$c = c - \beta \frac{\partial}{\partial c} Z(c) \tag{7}$$

Updates the weights and bias and reduces the cost function as $P(M)$. The values are computed using the formula below.

$$P(m) = \sum_{k} \left\| m_k \right\|_E^2 \tag{8}$$

Based on this, k and $\|\cdot\|_E^2$ stand for the governing coefficient and Frobenius, the. The resultant penalty sparsity of the hidden layer is $P(m)$.

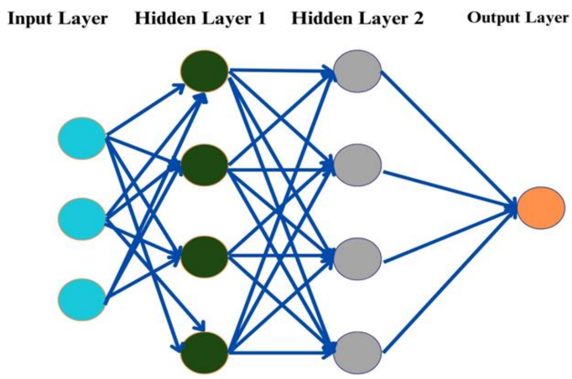


Fig 2: Structural diagram of DNN

***<u>3.2.2 NGO based DNN for image quality improvement</u>*:**

The population-oriented technique known as NGS is predicated upon the traits of northern goshawks. Its population is thought to be the answer for image quality enhancement and offers values for the parameters that are taken. With the computational approach, the NGS population component is viewed as a vector that creates the matrix [13]. The solutions' beginning is dispersed at random throughout the searching space. The sample matrix is presented as follows:

$$A = \begin{bmatrix} A_1 \\ \vdots \\ A_k \\ \vdots \\ A_M \end{bmatrix}_{M\times N} = \begin{bmatrix} a_{1,1} & \cdots & a_{1,l} & \cdots & a_{1,n} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ a_{k,1} & \cdots & a_{k,l} & \cdots & a_{k,n} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ a_{M,1} & \cdots & a_{M,l} & \cdots & a_{M,n} \end{bmatrix} \tag{9}$$

In this work, the amount of solutions is *A*, and the anticipated the mixture is at the k^{th} place. The parameters of the l^{th} parameter in the k^{th} the mixture are. The overall number of individuals with a population is *N*, and each of the factors are designated as n. The challenge the mixture is regarded as the member, a proposed solution can be designed in a format based on vectors as,

$$ob(A) = \begin{bmatrix} ob_1 = ob(A_1) \\ \vdots \\ ob_k = ob(A_k) \\ \vdots \\ ob_M = ob(A_M) \end{bmatrix}_{M\times 1} \tag{10}$$

The goal functions matrix of the ob result obtained is and the k^{th} proposed solution of the objective function as ob_k. This objective function determines the best way for identifying the results of image quality enhancement and is altered with every repetition and modified appropriately.

(i) Exploration

The level entails randomly choosing prey and attacking it instantaneously, improving exploration power in searching area. This entails an international hunt and is expressed as,

$$S_k = A_i, k = 1,2,....., M, i = 1,2,...., k-1, k+1,....., M \quad (11)$$

$$a_{k,l}^{New,R1} = \begin{cases} a_{k,l} + s\left(S_{k,l} - J \quad a_{k,l}\right), & ob_{R_k} < ob_k \\ a_{k,l} + s(y_{k,l} - R_{k,l}), & ob_{R_k} \geq ob_k \end{cases} \quad (12)$$

$$A_k = \begin{cases} A_k^{New,R1}, & ob_k^{New,R1} < ob_k \\ A_k, & ob_k^{New,R1} \geq ob_k \end{cases} \quad (13)$$

Where, S_k as prey position when the k^{th} GHS has been chosen as. The corresponding goal function is, and arbitrary number is *i* that falls within the range of 1, *M*. Its k^{th} solution's new spot $a_{k,l}^{New,R1}$ as its l^{th} dimension. This phase's GHS goal function is and the chance integer ranges from 0 and 1. *J* is an arbitrary number, meaning it can be between one or two.

(ii) <u>Exploitation</u>

The prey attempts to flee from the NGS when an assault is being carried out. In this situation, the NGS pursues the prey in a tail and chase phase. The stalking procedure will be successful as the NGS are faster than the prey. This will improve the algorithm's local search. In the meantime, hunter activity occurs within the radius of *G* and is quantitatively expressed as,

$$a_{k,l}^{New,R2} = a_{k,l} + D(2s-1)a_{k,l} \quad (14)$$

$$G = 0.02\left(1 - \frac{t}{T}\right) \quad (15)$$

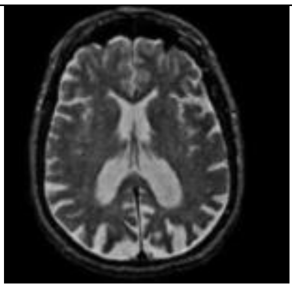
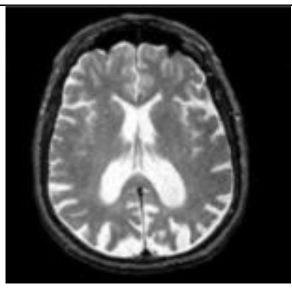
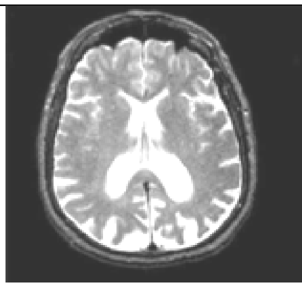
$$A_k = \begin{cases} A_k^{New,R2}, & ob_k^{New,R2} < ob_k \\ A_k, & ob_k^{New,R2} \geq ob_k \end{cases} \quad (16)$$

The most recent repetition is *t*, and the greatest number of iterations is *T*. The work's new revised answer position k^{th} is $A_k^{New,R2}$. Here, $ob_k^{New,R2}$ as phase's primary role. The NGO-DNN model to enhance the performance of image quality.

4. Experimental Analysis

This section describes the performance analyses of our proposed method as well as the comparison analysis in a broader perspective. The dataset used for the performance analyses is also thoroughly detailed, along with the parameter values. The MRI brain imaging dataset is gathered from many patients in the database (https://sethu.ac.in/bramsit/). It provides information on the early stages of brain illnesses. An experiment is carried out on MATLAB using the system specifications of Intel core CPU with 64 GB RAM and NVIDIA GeForce GTX 1080 Ti graphical processing unit (GPU). Figure 3 depicts the sample MRI scans as well as the results of the DNN and NGO-DNN procedures. The first column in the picture shows the original MRI images, column 2 shows the outcome after using the NGO-DNN alone, and column 3 shows the results of our proposed NGO-DNN.

Figure 3: Sample images, outcomes of DNN and proposed model

MRI original images	**DNN**	**Proposed**
		

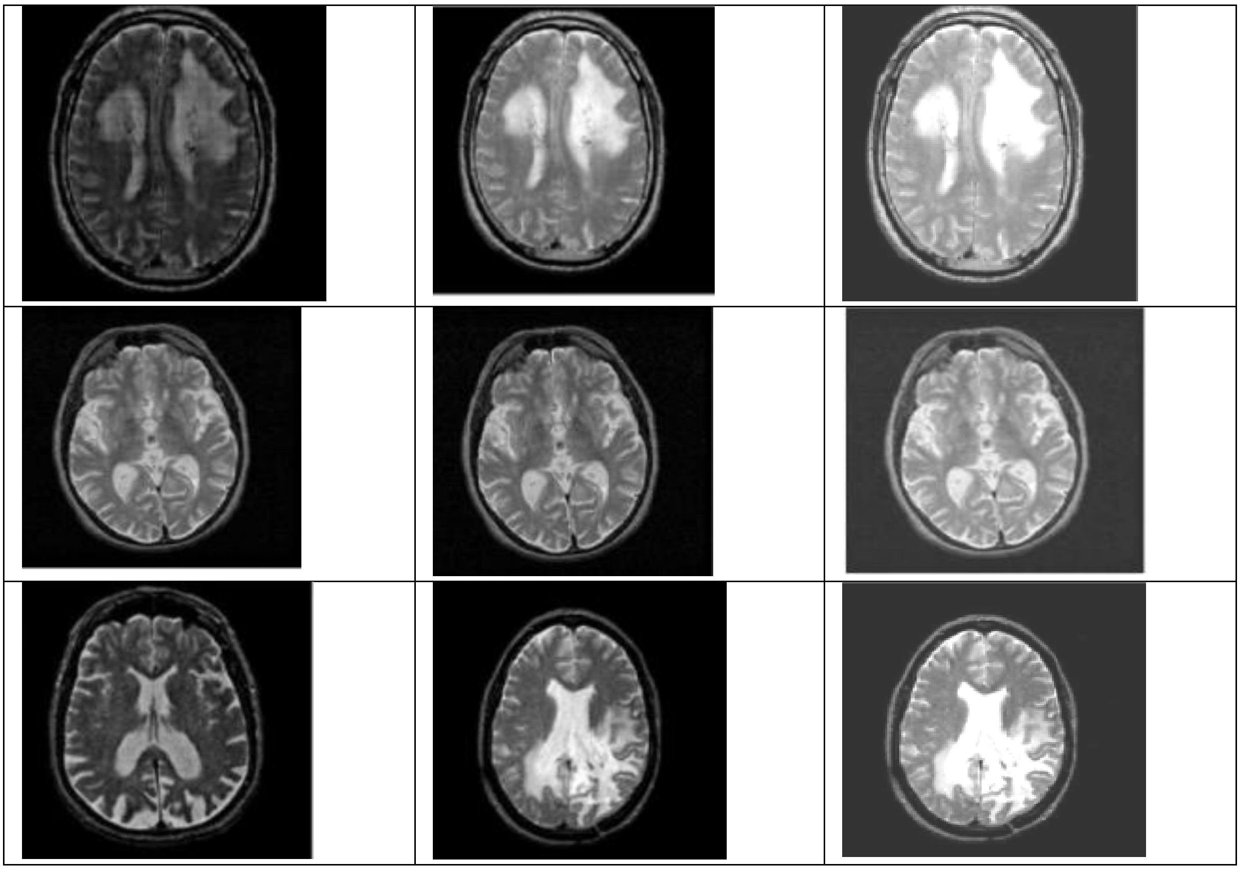


Figure 4 depicts the proposed work's training and testing accuracy. We have used 80% of the dataset for training and 20% of the dataset for testing. Training is an important proposal for teaching the proposed approach how to remove noises from photos. It is also utilized for identifying Rician noise, salt and pepper noises, and speckle noises. Following training, the system will distinguish Rician noise, salt and pepper noises, and speckle noises, and testing will be carried out to see how well the approach identifies the noise and remove it for future use. The NGO-DNN technique has a training performance of 99% at the 300th epoch and an accuracy for testing of 98.2% at the 300th period. The algorithm's accuracy decreases over shorter epochs and increases with higher periods.

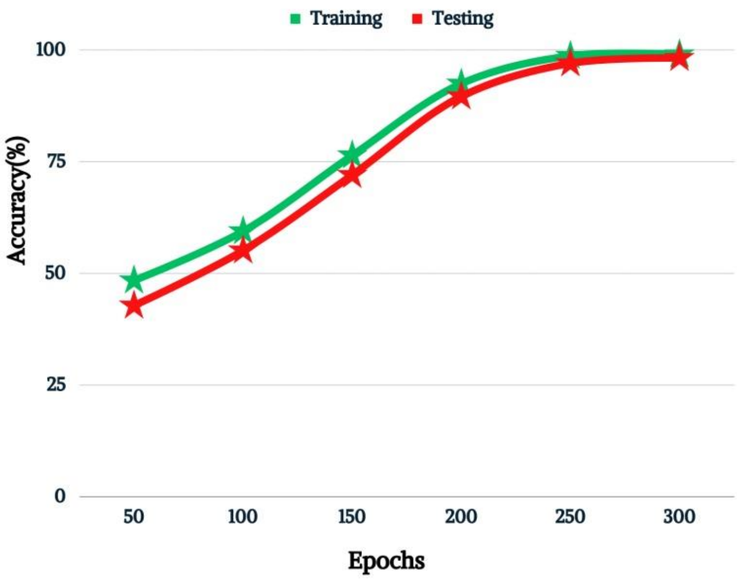


Fig 4: Training and testing accuracy of the proposed NGO-DNN work

Table 1 lists the state-of-the-art outcomes for several noise variance ranges in relation to MSE. The comparative examination of several noise variance ranges with respect to PSNR is explained in Table 2. Compared to other current approaches like NLM, Gaussian filter, Non-local mean filter, and Mean filter, the suggested method yields lower MSE and SNR output.

Table 1: The most recent outcome of different noise variance ranges in relation to MSE

Techniques	**Variance ranges for noise**				
	0.02	***0.04***	***0.06***	***0.08***	***0.10***
Gaussian filter	206	332	441	521	612
NLM	193	205	353	684	887
Mean filter	85	242	430	515	652
Non-local mean filter	83	169	321	362	525
Proposed	70	153	264	342	492

Table 2: The most recent outcome of different noise variance ranges in relation to PSNR

Techniques	**Variance ranges for noise**				
	0.02	***0.04***	***0.06***	***0.08***	***0.10***
Gaussian filter	38.67	23.75	24.77	17.07	18.99
NLM	30.07	34.74	25.76	17.86	19.40
Mean filter	21.44	20.33	25.33	24.56	23.62
Non-local mean filter	30.56	28.18	25.08	26.70	18.67
Proposed	10.78	15.98	20. 77	15.34	16.19

Figure 5 illustrates the comparative analysis of different sounds according to SNR levels. In this investigation, denoised noises such as Rician, speckle, salt, and pepper noises are analyzed using the latest techniques such as Gaussian, mean, median, and the proposed NLM-NSST model. In terms of Rician, speckle, salt, and pepper noises, the suggested method produces fewer signals to noise ratio outputs than the other picture denoising filters like Gaussian, mean, and median filters.

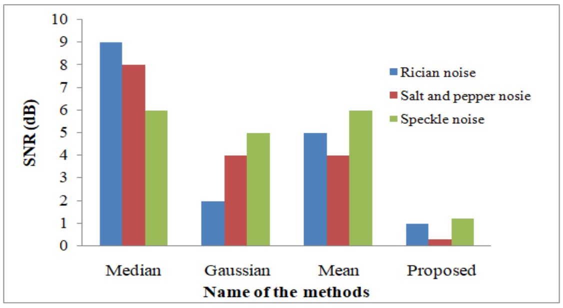


Figure 5: Comparative study of various noises based on SNR values

The performance analysis based on the picture enhancement step run time is shown in Table 3. Support vector machines (SVM) [30], artificial neural networks (ANN) [31], deep residual networks (DRN) [32], deep neural networks (DNN) [33], and the suggested technique all have different run times. Modern algorithms like SVM, ANN, DRN, and DNN use run times of 3.39, 2.96, 2.76, and 3.78 seconds, respectively. When compared to previous ways, the suggested solution has a lower temporal complexity because it uses a shorter run time of 0.4 seconds.

Table 3: The state-of-art of run time performance

Methods	**Time in seconds**
SVM	3.39s
ANN	2.96s
DRN	2.76s
DNN	3.78s
Proposed	0.4s

After being identified by the proposed approach and other approaches like SVM, ANN, DRN, and DNN, the noise removal accuracy is assessed to determine how well the proposed approach removes the Rician noise, salt and pepper sounds, and speckle noises. Figure 6 shows the resulting accuracy of suggested and alternative methods. As the epoch rises, as illustrated in the image, so does the noise reduction accuracy of the suggested and alternative procedures. As illustrated in Figure 7, the suggested work achieves 98.2%, SVM 97%, ANN 92%, DRN 87%, and DNN 82% of noise removal accuracy.

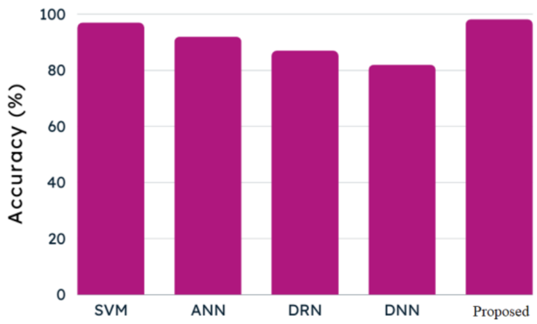


Fig 6: Overall accuracy of suggested and state-of-art works

5. Conclusion:

The proposed work is based on NGO-DNN for post-denoising picture enhancement and NLM-NSST-based filtering for noise reduction from MRI medical images. We employed NSST to lower the temporal complexity of NLM and effectively remove noise from the images. Subsequently, the quality of the denoised images was enhanced through the application of the NGO-DNN algorithm-based technique. This improves the quality and reduces the possibility of giving patients ineffective treatment. Lastly, the pictures' contrast was improved. When the suggested work was compared to cutting-edge methods like SVM, ANN, DRN, and DNN in terms of run time complexity, it was found that the suggested methodology significantly reduced the complexity. Comparing our suggested approach's MSE and PSNR values to those of other filters, like NLM, Gaussian, Non-local mean, and Mean, revealed that they were likewise in the required range. Therefore, with a removal accuracy of 98.2%, we may deduce that our proposed method improves the quality of MRI images while also removing distortion.

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