Deep Neural Network Applications in Improving Medical Images for Spinal Tumors

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Abstract

This research aims to evaluate the performance of neural networks in enhancing medical images and to explore the possibility of applying them in improving the quality of medical images for tumors, thereby enhancing diagnostic accuracy and treatment effectiveness.
The study utilized a medical image of the lumbar spine MRI containing a tumor, to which Gaussian noise was added at levels of ***(0.01, 0.05, 0.10, 0.20).*** *Noise removal techniques were applied using three linear filters:* ***Mean Filter, Median Filter, and Gaussian Filter****, in addition to the pre-trained deep neural network (****DnCNN****) for noise removal and image quality enhancement. To achieve these objectives, the deep learning tool library in* ***MATLAB*** *was used. Two evaluation methods were employed: the first was the visual inspection of the enhanced images, and the second included image quality improvement metrics such as* ***PSNR****,* ***SSIM****, and* ***MSE****.*
*The results showed that the neural network (****DnCNN****) was able to improve the quality of medical images better than the other mentioned methods, achieving values of (****66.7711, 0.6886, 0.0013****) for (****PSNR, SSIM, MSE****) respectively at the low noise level of 0.01. It was observed that all the methods used faced challenges at higher noise levels. Thus, the results indicate that deep neural networks are effective in improving medical images and can be applied to enhance images related to spinal tumors, contributing to increased diagnostic accuracy and faster tumor detection, thereby improving healthcare.*
Keywords: *Deep Neural Networks, Medical Images, Improving, DnCNN, Denoised*

تطبيقات الشبكات العصبية العميقة في تحسين الصور الطبية للأورام الشوكية

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الملخص

يهدف هذا البحث إلى تقييم أداء الشبكات العصبية في تحسين الصور الطبية، واستكشاف إمكانية تطبيقها في مجال تحسين جودة الصور الطبية للأورام، مما يعزز دقة التشخيص وفاعلية العلاج، استخدمت الدراسة صورة طبية للعمود الفقري من النوع (MRI) في المنطقة القطنية تحتوي على ورم، حيث تم إضافة ضوضاء جاوس إلى الصورة بنسب (0.01، 0.05، 0.10، 0.20) تم استخدام تقنيات إزالة الضوضاء بواسطة ثلاثة فلاتر خطية، وهي Mean Filter وMedian Filter و Gaussian Filter ، بالإضافة إلى الشبكة العصبية العميقة (DnCNN) المدربة مسبقًا لإزالة الضوضاء وتحسين جودة الصور. لتحقيق هذه الأهداف، تم استخدام مكتبة أدوات التعلم العميق في MATLAB. كما تم استخدام طريقتين للتقييم: الأولى هي المعاينة البصرية للصور الناتجة عن التحسين، والثانية تشمل مقاييس تحسين جودة الصور مثل RPSN و SSIM و MSE .
أظهرت النتائج أن الشبكة العصبية (DnCNN) قادرة على تحسين جودة الصور الطبية بشكل افضل من الطرق المذكورة الاخرى حيث حققت (66.7711 ، 0.6886 ، 0.0013) لكلا من (PSNR ،SSIM ، MSE) على التوالي و عند نسبة ضوضاء المنخفظة (0.01) . ولوحظ أن جميع الطرق المستخدمة تواجه تحديات عند مستويات الضوضاء المرتفعة. وبذلك تشير النتائج إلى أن الشبكات العصبية العميقة فعالة في تحسين الصور الطبية، وقابلة للتطبيق في تحسين الصور الخاصة بأورام العمود الفقري، مما يسهم في زيادة دقة التشخيص وسرعة اكتشاف الأورام، وبالتالي تحسين الرعاية الصحية.
الكلمات المفتاحية : الشبكات العصبية العميقة ، الصور الطبية ، تحسين، DnCNN، ازالة الضوضاء .

1- Introduction:

Diagnostic medical imaging plays a crucial role in improving patient care. Imaging techniques such as X-rays, computed tomography (CT), positron emission tomography (PET), magnetic resonance imaging (MRI), and others are widely used in modern medical diagnosis and treatment. Consequently, large volumes of medical image data are generated, increasing the burden on hospital data management systems [1, 2]. AI has revolutionized the medical field, leveraging computer advancements and image processing techniques to enable faster and more accurate analysis of medical images. This "digital medicine" relies on artificial intelligence to perform tasks resembling human intelligence, such as problem-solving and learning. In the medical domain, AI techniques have evolved from basic commands to complex algorithms, significantly improving clinical diagnosis and leveraging vast amounts of medical data. This progress has had a notable impact on oncology and various other fields [3]. The spinal column and central nervous system are crucial for providing structural support and protecting the spinal cord. Injuries, fractures, and tumors affecting the spinal column can lead to severe complications, including paralysis and even fatality [4, 5]. When diagnosing spinal tumors, comprehensive imaging of the spine, along with medical history, clinical examination, and biopsy, is essential [6]. However, spinal diagnostic images often face challenges such as noise, distortions, and low contrast due to tissue diversity [7]. Improving image quality is crucial for accurate tumor diagnosis and better healthcare [8, 9]. Enhancing medical images involves tasks like noise reduction, contrast enhancement, and overall quality improvement. Deep learning techniques, particularly deep neural networks (CNNs), have shown promise in addressing these challenges and improving image accuracy in medical imaging [8]. Models are trained on known datasets to make predictions, and the acquired knowledge is utilized for diagnostic tasks on unknown datasets [10].

For instance, the DnCNN deep neural network specializes in noise removal, enhancing the clarity and diagnostic capability of medical images. This study aims to evaluate the performance of the DnCNN network in improving medical images of spinal tumors without the need for retraining, considering the scarcity of such images compared to traditional linear filters. The subsequent sections of this paper are organized as follows:

In Section 2, some previous studies in this field are presented. In Section 3, the methodology of study is presented, including a scientific background on methods of improving medical images, the concept of machine learning, deep learning, their basic components, as well as the data and techniques used in the study. The results are presented and discussed in Sections 4 and 5. Finally, a comprehensive summary of the results and discussion is provided in the last section, along with recommendations based on the main findings of the paper.

2_ Literature Review :

In a study by ***Abuya, T.K. et al. (2023),*** the researchers aimed to assess the effectiveness of different noise removal techniques for CT images, with a specific focus on Gaussian random noise. They proposed a method that combines an irregular Gaussian filter based on Adaptive Wavelet Transform (AGF) with a Deep Neural Network (DnCNN) for noise removal in medical CT images. The performance of this method was compared to other standard denoising filters using metrics such as PSNR, SSIM, and MSE. The results of the study demonstrated that the proposed method, specifically the DnCNN network, outperformed other filters in removing Gaussian random noise across various noise levels. This highlights the effectiveness of the DnCNN deep learning network and its developed methods in achieving high-performance noise filtering [11]. In a study by ***Günen, M.A. and Besdok, E. (2023),*** the researchers aimed to compare different denoising methods for hyperspectral images in remote sensing. The study evaluated five methods (DnCNN, NGM, CSF, BM3D, and Wiener) using the Pavia University hyperspectral dataset and four types of noise. The results indicated that DnCNN and BM3D performed the best across all four types of noise. CSF and Wiener had lower performance for specific noise sources, while the NGM method yielded the worst results. Although the employed tools were not effective in removing salt-and-pepper noise, they showed excellent results in removing Poisson noise. Notably, the DnCNN method achieved the best performance in removing Gaussian noise, emphasizing the importance of selecting an appropriate denoising technique to enhance the quality of hyperspectral images [12]. In a study by ***Rajni and Dahiya (2022),*** the aim was to experimentally analyze the application of noise removal techniques using deep neural networks based on the Transform Domain Cascaded Neural Networks in MATLAB. Quality metrics such as Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) were studied at different noise levels. Five different images were used as inputs for the analysis. The results showed that the PSNR and SSIM values decreased with increasing noise levels, indicating that increasing noise levels led to a deterioration in image quality [13]. In the study by ***Thakur, R. S. et al. (2021),*** a comparison of the performance of deep models in denoising various types of noise was conducted, as well as a comparison of dictionary learning models and Convolutional Neural Networks (CNN) in denoising Gaussian noise. The results showed that dictionary learning models performed lower in terms of PSNR compared to CNN models. The DnCNN model, built on residual learning and residual-in-residual learning, was used in the study of Gaussian noise denoising and achieved PSNR values that demonstrated promising performance. This model is considered the standard model for Gaussian denoising based on residual learning and has led to the development of many modern denoising methods [14]. In a study by ***Zhang , K., et al. (2016)***, the performance of some methods in image processing, specifically image denoising, was studied. The BM3D and TNRD methods were used, and the results showed that DnCNN-3 outperformed TNRD and BM3D. In terms of single image super-resolution, TNRD and VDSR were compared, and the results showed that DnCNN-3 outperformed TNRD and approached VDSR. In the field of JPEG image deblocking, DnCNN-3 was compared with AR-CNN and TNRD, and the results showed that DnCNN-3 outperformed AR-CNN in image quality [15].

3.Research Methodology :

3.1. Scientific Background:

There are different types of noise and interference in medical radiography images, including Poisson noise, Gaussian noise, pulse noise, and salt-and-pepper noise. Among these types, Gaussian white noise is considered the most common. Gaussian noise affects the image uniformly, reducing our ability to comprehend and analyze it. Therefore, processing and enhancing medical images are necessary to increase their quality and improve diagnostic accuracy [2, 16]. Gaussian noise follows a Gaussian probability distribution and spreads evenly throughout the signal. When Gaussian noise is added to an image, the original pixel values are distorted by adding random values that follow the same distribution. The spread of random values around the mean increases with a higher standard deviation [12, 17].

3.1.1 Methods for Medical Image Enhancement: The methods used to enhance medical images mentioned in this paper vary from traditional methods such as linear filters to more advanced and efficient methods, such as enhancing and improving medical images using deep neural networks.

3.1.1.1 Linear filters : they eere widely used in the early stages of image processing for enhancement and restoration. However, they have limitations in handling non-additive noise and non-linear statistical characteristics. These filters can cause blurring at edges and are not effective in removing Gaussian and mixed noise [18].

3.1.1.2 Machine Learning and Deep Learning: Machine learning is a branch of artificial intelligence, and deep learning is a subfield of machine learning that uses complex mathematical algorithms and multilayer computational units that resemble the process of perception in the human mind. These units include neural networks designed in various arrangements, such as recurrent neural networks, competitive neural networks, deep memory networks, and others [10, 19].

3.1.1.3 Basic Layers of Deep Neural Networks: A neural network consists of different layers: Neural networks consist of an input layer, hidden layers, and an output layer. In a single-layer neural network, there is only one hidden layer, while a multilayer neural network can have multiple hidden layers. A shallow neural network refers to a network with one hidden layer, while a deep neural network has two or more hidden layers. Deep neural networks are widely used in practical applications today [20, 21].

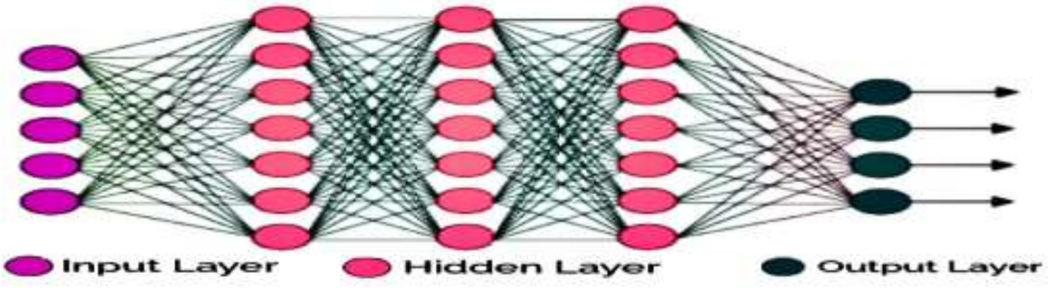

Figure 1: Basic Layers of Deep Neural Networks.

3.1.1.4 Convolutional Neural Networks (CNNs): CNNs are widely used in medical image processing and recognition. They extract features from input images to enhance computational efficiency and reduce parameters. CNNs can process both 2D images like X-rays and 3D images like MRI and CT scans [22, 23]. Image denoising models with CNNs aim to improve image quality and remove noise by extracting important features. Each layer applies a convolutional kernel and activation function, with the output serving as input for the next layer. This process iteratively transforms the image and extracts advanced features to enhance image quality and denoise the image [13].

3.1.1.5 Denoising Convolutional Neural Network (DnCNN): In recent years, deep learning techniques, particularly DnCNN, have shown significant advancements in image denoising algorithms, surpassing traditional methods [24]. DnCNN is a well-known model that utilizes deep learning and advanced network design to improve the quality of images corrupted by Gaussian noise [13]. The learning process of DnCNN involves multiple stages. Firstly, residual learning is employed, where the input image is passed through several layers to generate a residual image, aiming to capture the noise information within the input image. Batch normalization is then applied to normalize the input layer based on the learning rate, addressing changes in image features and mitigating overfitting in the hidden layers of the network [25]. DnCNN consists of 20 convolutional layers. The initial layer employs 64 filters with a size of 3x3x1, followed by rectified linear unit (ReLU) activation. Each of the subsequent 18 convolutional layers uses 64 different filters sized 3x3x64, accompanied by batch normalization and ReLU activation. The final convolutional layer employs a separate filter sized 3x3x64 for signal reconstruction [10, 14, 26].

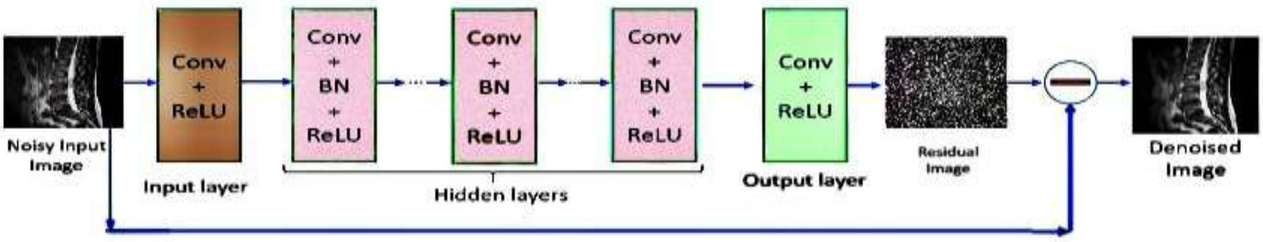

Figure 2: Basic Layers of DnCNN

3.2. Data and Techniques:

3.2.1 Data: The data consist of magnetic resonance imaging (MRI) images of the lumber spine region containing a tumor. The images are of high quality, and the input image size is modified to [630 630] as a double type. Initially, the images are converted to grayscale, and preprocessing steps are applied to remove noise [27]. Then Gaussian noise is added to the image sequentially with different ratios RN (0.01, 0.05, 0.10, 0.20). Filtering techniques and noise removal are applied each time Gaussian noise is added, both using traditional filters and the Denoising Convolutional Neural Network DnCNN.

3.2.2 .Technologies: The R 2019a MATLAB software is used, which includes libraries for image processing tools, including the Processing Images Toolbox. This toolbox contains both traditional and modern techniques for image enhancement, some of which are used in this paper, include:

3.2.2.1- Mean filter: Used for smoothing images and removing noise by calculating the average pixel values in the surrounding neighborhood. It is one of the simplest and most modest filters in digital image processing [10, 28].

3.2.2.2- Median filter: Used for image denoising by calculating the median value within a specified range of surrounding pixels and replacing the central pixel value with the median value. It works well in removing low-quality noise [28, 29].

3.2.2.3- Gaussian filter: This type of low-pass filter is effective in smoothing images, reducing noise, and can introduce blur while preserving important image features such as edges and corners [30].

3.2.2.4- Denoising Convolutional Neural Network (DnCNN) : This deep neural network is available in the Deep Learning Toolbox library in MATLAB and is also used for noise reduction in images. The DnCNN network has been pre-trained using natural images captured by a photographic camera [16]. The network is applied to the medical image after it has been contaminated with Gaussian noise at different levels, and the results are observed and evaluated.

3.2.2.5- Evaluation of Denoising Convolutional Neural Network (DnCNN) performance in noise removal: The performance of the Denoising Convolutional Neural Network (DnCNN) are evaluated for improving and denoising the medical image compared to the performance of linear filters (Mean filter, Median filter, Gaussian filter). The evaluation is conducted using the following methods:

A- Visual inspection: This involves displaying the original image, the noisy image, as well as the images after applying the filters and the deep neural network, and removing the noise from the image according to different noise levels.

B- Statistical measures: Statistical quality measures such as PSNR ,SSIM and MSE are used to compare the quality of the original image with the enhanced image using the Mean filter, Median filter, Gaussian filter, and the Denoising Convolutional Neural Network (DnCNN).

- PSNR (Peak Signal-to-Noise Ratio) : Is a measure that evaluates thequality of an image or video by calculating the ratio of signal to noise between the original and processed images. It is expressed in decibels (dB), with higher values indicating better image quality and closer resemblance to the original image.

-SSIM (Structural Similarity Index Measure) : Is a measure used to assess the structural similarity between two images. It quantifies the similarity in structure and fine details. SSIM values range from 0 to 1, with a value of 1 indicating identical resemblance between the original and enhanced images.

-MSE (Mean Squared Error) : Is a measure used in image processing and computer science to quantify the difference between two images. It calculates the average of the squared errors between pixel values in the two images. MSE is a numerical value that is zero when there is no difference between the images and increases as the difference between them grows ،27 ،24 ،10] [.28

***4 - Results*:**

The study focuses on enhancing a medical MRI image with a tumor in the spinal cord by removing Gaussian noise. The effectiveness of the DnCNN is evaluated and its superiority over traditional methods in improving medical images is assessed. The original image is contaminated with noise levels ranging from 0.01 to 0.20. Grayscale versions of these images are enhanced using Mean Filter, Median Filter, Gaussian Filter, and DnCNN.

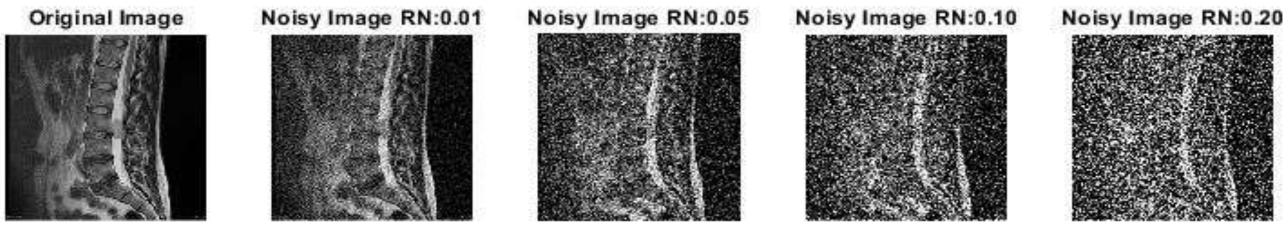

Figure (3): The original image and the image after adding noise with noise ratios

RN = (0.01, 0.05, 0.10, 0.20).

Then, the performance of the Denoising Convolutional Neural Network is evaluated compared to the performance of linear filters based on direct image inspection and the values of the metrics PSNR, MSE, and SSIM. The results are presented as follows:

4.1. Visual inspection of the images:

Figure (4) illustrates the impact of linear filters and the DnCNN on image quality after noise removal. The images demonstrate the substantial improvement in image quality achieved by both filters and the network. However, as the noise ratio increases, the DnCNN network exhibits a decline in image clarity, despite its superior performance in enhancing image quality.

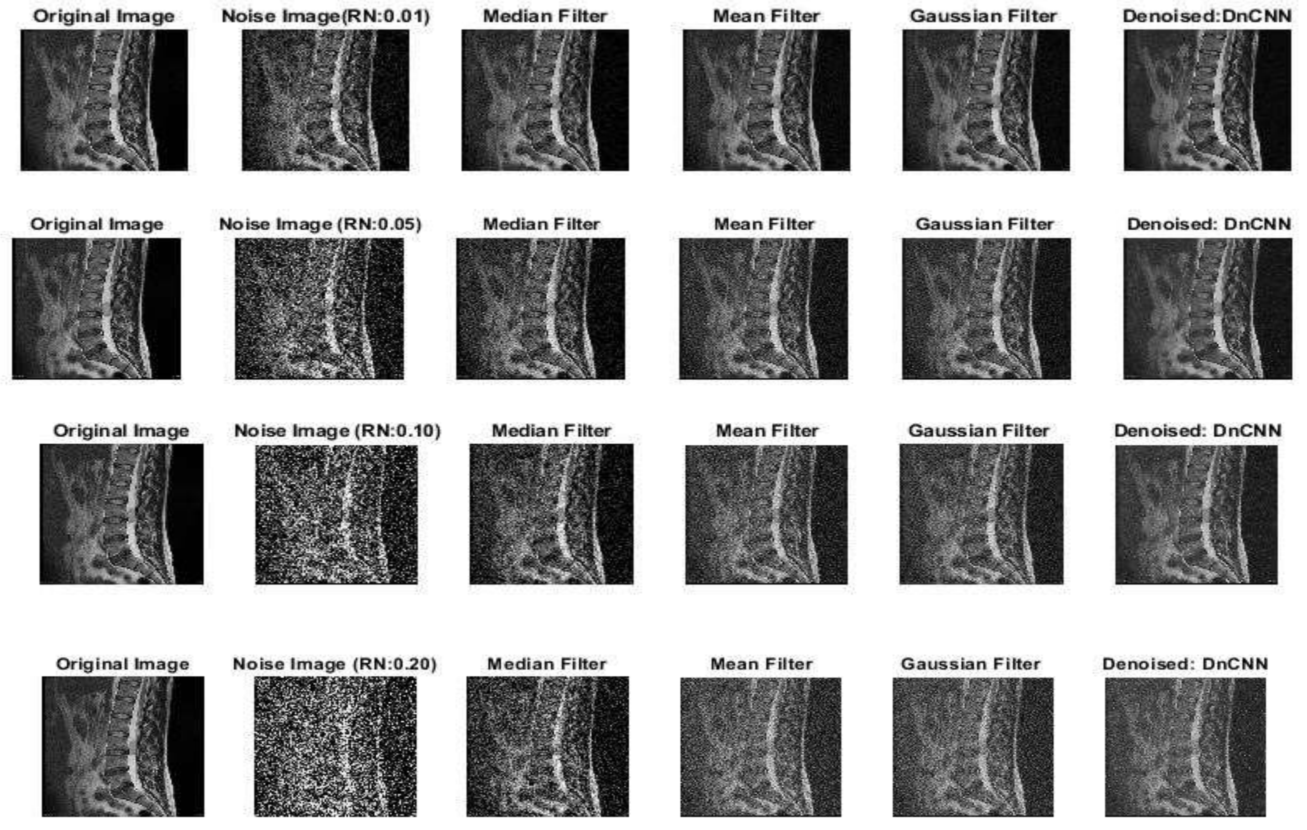

Figure (4): The effect of linear filters and the DnCNN on image quality after noise removal .

4.2. Statistical measures of image quality (SSIM, MSE, and PSNR):

In table (1), values of PSNR, SSIM, and MSE are displayed for the following methods (Median, Mean, Gaussian, DnCNN) at different noise ratios in the image.

Table (1): PSNR , SSIM and MSE to Evaluation of DnCNN and Linear Filters (Gaussian, Mean, Median)

Values of PSNR, SSIM, and MSE are displayed for the following methods (Median, Mean, Gaussian, DnCNN)				
PSNR				
Noisy Images	**)RN:0.01)**	**)RN: 0.05 (**	**)RN: 0.10(**	**)RN: 0.20(**
Median	52.8828	45.3789	40.6504	35.4160
Mean	56.5915	48.1167	42.8751	37.2588
Gaussian	62.0122	51.1141	45.0863	38.8861

DnCNN	**66.7711**	**55.0581**	**48.3100**	**40.9229**
Demonstrates the improvement in image quality achieved by filters and the DnCNN after noise removal. The DnCNN outperforms the other methods, exhibiting the highest PSNR values and thus preserving image quality more effectively. This superiority is particularly evident at lower noise levels.				
SSIM				
Noisy Images	**(RN:0.01)**	**(RN: 0.05)**	**(RN: 0.10)**	**(RN: 0.20)**
Median	0.5992	0.3152	0.2109	0.1341
Mean	0.6348	0.3753	0.2693	0.1865
Gaussian	0.6772	0.4378	0.3281	0.2377
DnCNN	**0.6886**	**0.5180**	**0.4181**	**0.2908**
The table displays the SSIM values for each method and different noise ratios. It indicates the effectiveness of each method, including DnCNN, in preserving structural similarity after noise removal, with superior performance at lower noise levels. The values suggest that the DnCNN method outperforms all other methods.				
MSE				
Images	**(RN:0.01)**	**(RN: 0.05)**	**(RN: 0.10)**	**(RN: 0.20)**
Median	0.0051	0.0107	0.0172	0.0290
Mean	0.0035	0.0081	0.0137	0.0241
Gaussian	0.0020	0.0060	0.0110	0.0205
DnCNN	**0.0013**	**0.0041**	**0.0080**	**0.0167**
The MSE values show the effectiveness of DnCNN and linear filters (Gaussian, Mean, Median) in reducing the difference between enhanced and original images. DnCNN achieved the lowest MSE value, indicating its superior performance, particularly at low noise levels.				

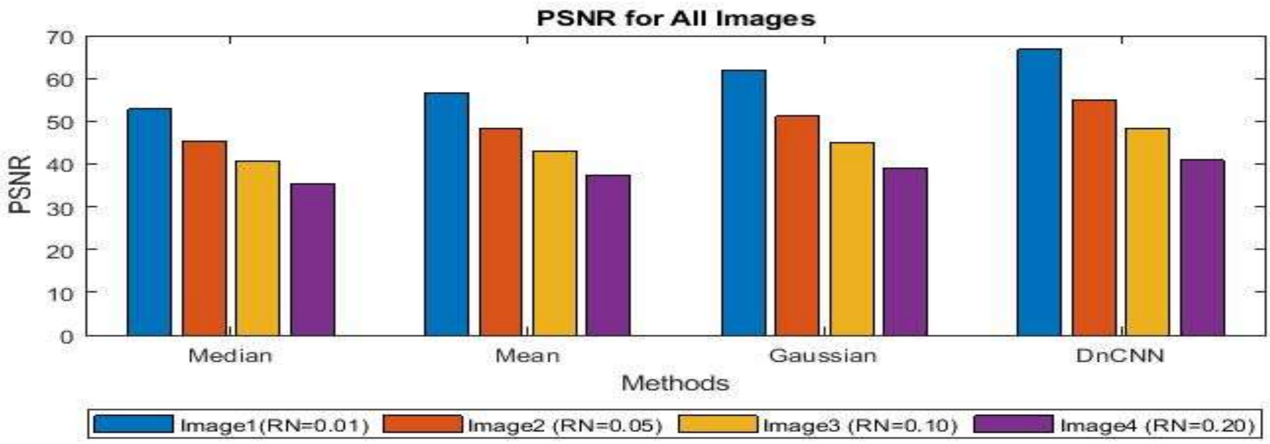

Figure (5): A chart illustrating the PSNR values for each method and different noise ratios.

Figure (5) depicts a graphical plot of the PSNR value, which represents the quality similarity between the enhanced image and the original image. Higher PSNR values indicate better quality and greater similarity to the original image. It is noteworthy that the image with a noise ratio of RN = 0.01 consistently exhibits the highest PSNR value, which decreases as the noise ratio in the image increases. Additionally, the DnCNN method outperforms other methods in achieving better values for preserving structural similarity.

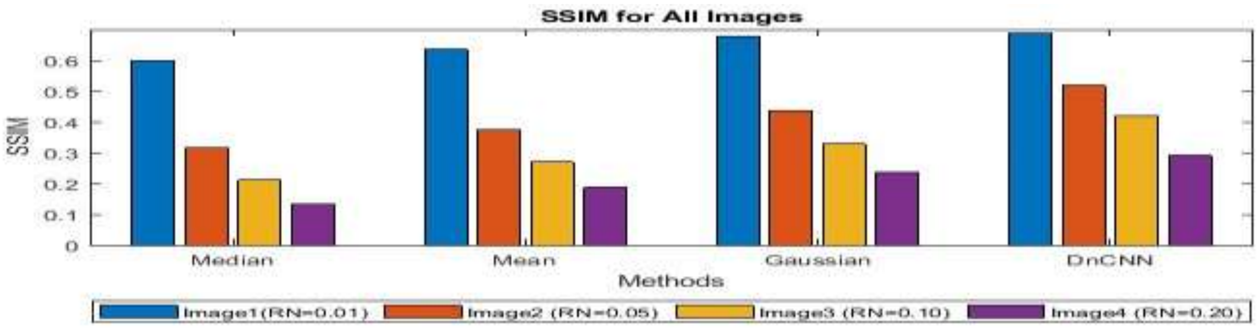

Figure (6): A chart illustrating the SSIM values for each method at different noise ratios.

In Figure (6), the SSIM value was plotted to measure the structural similarity between the enhanced image and the original image. A higher SSIM value indicates better preservation of structural similarity. It is worth noting that the image with a noise ratio of RN = 0.01 shows the highest SSIM value across all methods, and the SSIM value decreases as the noise ratio in the image increases. Additionally, the DnCNN method achieves better performance and outperforms other methods in preserving structural similarity.

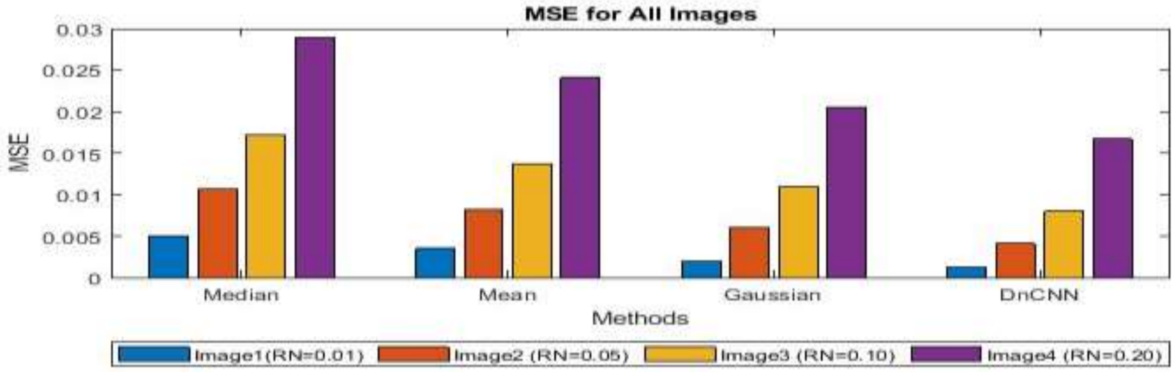

Figure (7): MSE Values for Each Method at Different Noise Ratios

In Figure (7), the MSE values represent the difference between the enhanced image and the original image. As the noise level increases, the MSE value also increases, indicating the impact of noise on the performance of filters and DnCNN. Notably, DnCNN consistently achieves the lowest MSE values, indicating its superior performance in reducing noise and improving image quality.

5- Discussion:

A study was conducted to evaluate the performance of the deep neural network DnCNN in denoising Gaussian noise from medical images. The evaluation was done using the PSNR , SSIM and MSE metrics. Additionally, by comparing the visual appearance of the images enhanced by the DnCNN neural network with those enhanced by other filters, the results showed that the DnCNN method achieved better performance in terms of the visual appearance of the enhanced image, as shown in Figure 4 of the Results section.

The results also revealed that the deep neural network DnCNN achieved the best values for all image quality metrics, including PSNR, SSIM, and MSE. It surpassed the Gaussian method, followed by the Mean method, and finally the Median method. In Table 1, the PSNR values demonstrated the superiority of the DnCNN method, ranging from 40.9229 to 66.7711, while the Gaussian values ranged from 38.8861 to 62.0122. The Mean method provided values ranging from 37.2588 to 56.5915, and the Median method exhibited the weakest performance with values ranging from 35.4160 to 52.8828. These findings shed light on the superiority of DnCNN in reducing Gaussian noise and improving image quality.

Similarly, the SSIM values showed that the DnCNN method achieved higher values ranging between 0.2908 and 0.6886, while the Gaussian values ranged between 0.2377 and 0.6772. The Mean method had values ranging from 0.1865 to 0.6348, while the Median method performed the weakest with values ranging from 0.1341 to 0.5992, as depicted in Graph 6. The SSIM values indicate the DnCNN's superiority in preserving important details and improving the structural similarity of the image.

Regarding the MSE values, the DnCNN method ranged between 0.0013 and 0.0051, while the Gaussian values ranged between 0.0020 and 0.0205. The Mean method had values ranging from 0.0035 to 0.0241, and the Median method performed the weakest with values ranging from 0.0051 to 0.0290. These results are consistent with studies conducted by Günen, M.A., Besdok, E., Abuya, and others, as well as the study by Thakur. The results show that all the methods used do not perform well at high levels of image noise, as evidenced by the higher values of both PSNR and SSIM for all methods and the lower values of MSE at a noise ratio of 0.01. Similarly, the lower values of both PSNR and SSIM and the higher values of MSE were observed at a noise ratio of 0.20, which is consistent with the results of the study conducted by Rajni and Dahiya. This indicates a negative impact of increased noise levels on the performance of all proposed methods.

Based on the presented results, it can be concluded that the DnCNN deep neural network is an effective tool for denoising medical images and improving their quality compared to conventional linear filters used, especially at low noise levels.

6- Conclusion:

This study concludes that the DnCNN neural network performs better in enhancing visual appearance and achieving superior values for quality metrics such as PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index Measure), and MSE (Mean Squared Error) compared to traditional filters like Gaussian, Mean, and Median. The results showed that DnCNN significantly improved the quality of medical image for spinal tumor (MRI image of size 630x630), achieving values of (66.7711, 0.6886, 0.0013) for (PSNR, SSIM, MSE) respectively at a low noise level of 0.01.

These findings demonstrate that using the DnCNN network leads to a noticeable enhancement in image quality, bringing processed images closer to their original counterparts, especially at low noise levels. Consequently, DnCNN is considered a reliable option for medical image processing applications. This research not only highlights the effectiveness of DnCNN but also provides a foundation for developing and improving denoising techniques to tackle the challenges posed by high noise levels, ultimately enhancing the overall quality of medical images in the future.

_ **Conflicts of Interest**: There are no conflicts of interest. .

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