Journal for Technology and Science
Homepage : https://journal.antispublisher.com/index.php/IPTEKS/index
Email : admin@antispublisher.com

e-ISSN : 3047-4337
JOTECH, Vol. 3, No. 3, July 2026
Page 20-27

A Study on the Diagnosis of Cervical Magnetic Resonance Imaging Using Various Techniques

Tahseen Falih Mahdi
General Directorate of Missan Education, Missan, Iraq

Check for updates OPEN ACCESS

DOI : https://doi.org/10.61796/ipteks.v3i3.508

Sections Info

Article history:
Submitted: Mar 23, 2026
Final Revised: Apr 11, 2026
Accepted: May 20, 2026
Published: Jun 22, 2026

Keywords:
MRIs
Enhanced
analyses
algorithm
Processing images
Variation
Various techniques

ABSTRACT

Objective: *In this study, magnetic resonance images (MRIs) of the neck were examined and enhanced to help doctors clearly interpret and analyse the condition visible in the MRI scans.* ***Method:*** *Various techniques were employed to improve image quality and clarity, ultimately producing an excellent image with significantly clearer information compared to the original scan, These techniques lend a degree of clarity to the information provided by the image.* ***Results:*** *The results of the enhancements applied were significantly more positive compared to previous studies and the application of such techniques.* ***Novelty:*** *Furthermore, the success of these enhancements represents an important field and a focus of interest in many areas, particularly medicine, which is the most significant field.*

INTRODUCTION

Magnetic resonance imaging (MRI) is a crucial field in the detection and diagnosis of tumours and diseases, as it enables the planning and facilitation of treatment [1]. This technique is predominantly used to monitor the progression of diseases and to diagnose them; however, the images often provide poor resolution when identifying the affected area[2]. One of the most important applications of imaging is the identification of cancerous cells in most parts of the body, particularly brain tumours[3]. This can be described as challenging due to the presence of artefacts in the MRI images during the scanning process, the lack of homogeneity and clarity in signal intensity, as well as variations in signal intensity and ranges across different imaging devices[4][5]. Currently, in the field of medical studies, the separation of the skull and neck is a fundamental step in initial treatment[6]. MRI datasets, such as those addressing the challenge of segmenting brain tumours and other tumours, have already been segmented, recorded and compared with enhanced MRI[7]. However, MRI images are often distorted by field bias, leading to variations in signal intensity within the same tissues. In this context, the N4ITK software, designed by Tusseton, is used to correct these imaging artefacts[8]. In short, enhanced imaging and pre-processing techniques such as skull removal and distortion correction can be used, as well as very wide-range bias field correction to generate MRI data and information for the brain, the neck, and any other part to be imaged[9]. This study focuses on the improved effects resulting from certain techniques used, which the current study will present in detail[10]. Furthermore, MRI images of the brain are subject to noise to some extent[11]. Noise in MRI images affects subsequent analysis, as it becomes difficult to distinguish between normal brain tissue and the tumour region. Therefore, various noise removal techniques have been proposed in studies to obtain distortion-free brain MRI images [12]. Image registration is another essential step in pre-processing in medical imaging [13]. As brain MRI images are acquired using different methods or sequences, image registration is required to transform these images into a common coordinate system. In summary, pre-processing techniques, such as skull removal, noise reduction, bias field correction and registration, are widely used to prepare brain MRI data for the automatic segmentation and analysis of brain tumours. Deep learning models are then trained on this pre-processed data [14]. Pre-processing is essential for the automatic segmentation of brain tumours, as it directly influences the performance of deep learning models.

RESEARCH METHOD

1. AHE Enhancement Based on Otsu Segmentation

Digital image processing plays a significant role in the field of medicine, in particular, to enhance the quality of MRI and CT scans as unclear data cannot be properly diagnosed. Adaptive Histogram Equalization (AHE) is important in performing the local contrast enhancement of an image. However, whole image AHE may increase noise in insignificant regions. The Otsu segmentation technique is applied in order to locate areas of interest before they are improved.

a. Otsu Segmentation Algorithm

Otsu method is effective in that it determines the optimal threshold amount to cut the image into two or more. This limit is self-determined by reducing the contrast in certain areas and increasing it between areas. This simplifies the visualization of the brain region in MRI images since it is isolated by the background hence minimizing the impact of additional artifacts.

b. Enhancement Using AHE

Otsu identifies the area of interest in the picture and then applies the AHE technique on the picture. This technique splits the image in small sections and histogram modifications are then applied to the sections. This reveals features of the image that are difficult to see using conventional image-enhancing methods, such as tissue or small tumors.

c. Merging and Reconstruction

Once the area of interest is enhanced by AHE, it is reassembled with the other parts of the image. This action enhances the image in terms of displaying more details without compromising on the quality of other portions of the image. Otsu segmentation coupled with AHE is selective in enhancing contrast in areas of interest, minimizing the side effects of the global enhancement and raising awareness of complex facts that are significant to medical diagnosis. Improving medical images with Otsu segmentation and Adaptive Histogram Equalization (AHE) is an excellent method since it allows addressing and refining certain areas of interest. This combination facilitates the clarity of details and enhances both medical diagnosis and scientific research of image processing.

2. Un Sharp Mask Enhancement

Image processing is a crucial component of digital image processing, and the tools used to augment the quality of images are image augmentation techniques. The first process is the technique of Unsharp Masking (USM), which is commonly used in medicine, technology, and photography. This is based on the principle of edge sharpening in an image to enhance the clarity of complex details in an image. The principle of USM: This technique, despite the name, is meant to sharpen a picture, or, to be more precise, it is called unsharp because it is intended to remove the blurred image of the original one and only leave the edges. The original picture is obtained by capturing an image, which is then sharpened. The fundamental procedures of USM are as follows: before the edge information is added back into the original picture, it is first blurred using a Gaussian Blur filter to remove the complex detail and edge in question. The edge information is then reintroduced into the original image, which increases sharpness and detail. Though it is extremely basic, it finds application in fields such as medical imaging, digital image processing, and professional photography. This technique is adequately utilized to improve the quality of the image and minimize the negative effects.

3. Composed Between Background and Un Sharp Mask

Image enhancement using digital technology is a fundamental operation in various sectors such as the health sector, engineering, and photography. Unsharp Masking (USM) is a popular method in this sphere that enhances the edges and increases the level of detail. Nevertheless, it is possible that direct application can cause an increase in noise or even negative results. A compositing technique is utilized between the background image and the output of the Unsharp Mask filter to produce an enhanced image that integrates sharpness with visual harmony. The concept of compositing is based on the integration of: the original image (background), which provides fundamental information devoid of any enhancement; and the Unsharp Mask picture, which is the product of the sharpening process that subtracts the blurred version of the original image to accentuate the edges. Blending these two images in specific ratios (sometimes known as the Blending Factor) produces an enhanced image with clear details without losing the overall balance or increasing noise. How it works: blurring the original image by applying a Gaussian Blur filter to produce a smooth version; calculating the Unsharp Mask by subtracting the blurred version from the original image to highlight the edge components; and blending with the background, where the original image (background) is combined with the USM mask to produce the final enhanced image. This approach reduces artifacts such as over-sharpening, controls the degree of enhancement by changing the blending parameter (α), and maintains the visual balance between the natural background and enhanced details. It enhances medical images to highlight diagnostic details without losing less important areas. Medical images: enhancing radiology and MRI images while reducing noise. Photography: enhancing image details while preserving naturalness. Computer vision: enhancing the output of image and pattern recognition systems. Blending the background with the Unsharp Mask strikes a balance between increasing sharpness and preserving the original image quality. This strategy provides researchers and professionals with an effective tool for obtaining high-resolution images while minimizing the negative effects that may result from direct enhancement processes, see Figure 1.

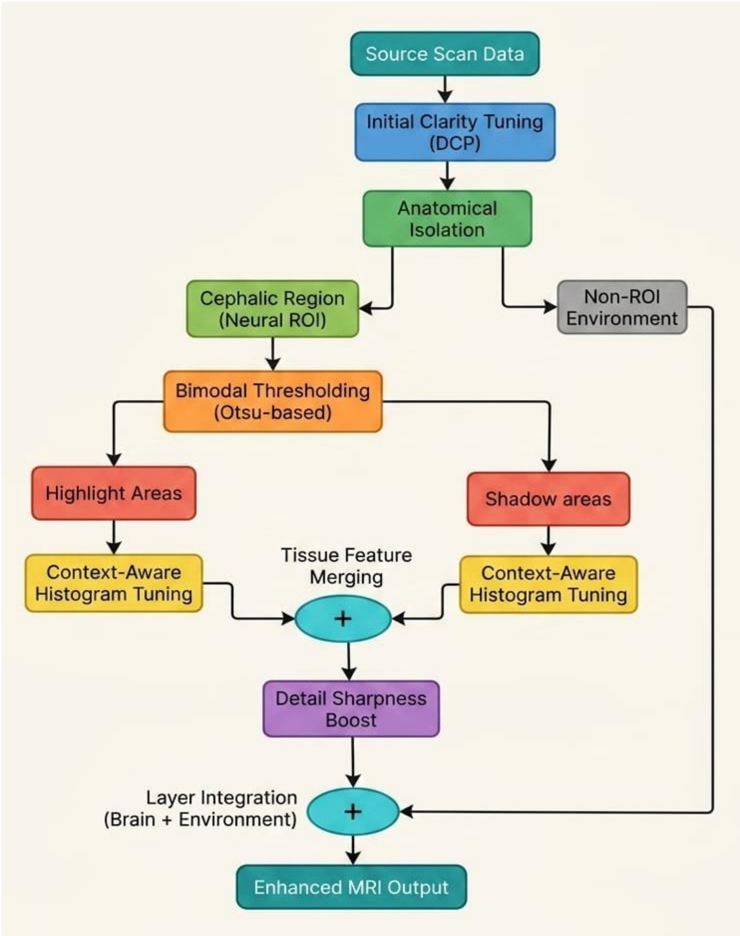

Figure 1. Proposed Method For Enhancement MRI Images

4. Mathematical Details of Image Enhancement Algorithm

a. Input Image: Load the original grayscale image.

In the first stage of the medical image processing workflow, we segment the image; this stage is considered pre-processing and involves image enhancement and standardisation, whereby we first resize the image to a standard format of 256×256 pixels, we then convert the image from its original 24-bit depth to an 8-bit greyscale format. This format supports image processing through these two stages; in the image enhancement process, we use several techniques, as indicated by the name in the image of the neck, Each technique works to improve intensity levels and utilises mathematical equations 1, 2, 3, 4 and 5. Ultimately, these processes complement one another, significantly enhancing contrast without causing distortion or blurring. These stages ensure rigorous pre-processing and optimisation, which produce medically excellent images in accordance with scientific standards. , thereby enhancing their quality and accuracy [15] [16].

$$h(i) = ni, for\ i = 0,1,2, \dots, (L-1) \quad (1)$$

$$p_x(i) = p(x = i) = \frac{n_i}{n} \quad (2)$$

$$cdf_x\ (i) = \sum_{j}^{i} = {}_0\, p\ (x = j\ ) \quad (3)$$

$$h(v) = round\ \frac{cdf(v) - cdf_{min}}{n - cdf_{min}} \quad (4)$$

$$\beta = \frac{M}{n}\left(1 + \frac{a}{100}(S_{max} - 1)\right) \quad (5)$$

RESULTS AND DISCUSSION

Magnetic resonance imaging (MRI) is considered a vital cornerstone of accurate medical diagnosis, and the images it produces require advanced processing and enhancement to improve contrast and image quality, thereby enabling an optimal diagnosis. In this study, several advanced techniques utilising eight algorithms were employed to enhance the images generated by the MRI scanner The neck was used as the examination site, as shown in Figure 2, and the algorithms were documented and summarised in Table 1.

The analysed results revealed a clear difference in the application of these algorithms, with the NMAHE algorithm recording the highest value for average gradient (AG = 5.65) This demonstrates the algorithm's success in enhancing image detail and edge sharpness. Similarly, the DCP algorithm achieved an effective reduction in distortion (PIQE = 52.10) as well as improved contrast (CEM = 0.76). Furthermore, the FCCE algorithm performed best in preserving the image structure when compared to the original image, with a score of (SSIM = 0.95).

From a graphical analysis perspective in Figure .3, the graphs illustrate a wide dynamic range of density distribution in the image, whereas in the original image the distribution is flat, reflecting poor contrast; the NMAHE and CLAHEWF algorithms shift the brightness intensity towards higher values to improve contrast balance, Similarly, the DCP algorithm distributes a wide-range probability to support contrast, whilst the SUG algorithm provides a balanced overall performance.

Table 1. Average quality assessment for (8 images).

METHOD	AG	CEM	SSIM	PIQE
ORIGINAL	3.120451	0.412350	1.000000	**68.41250**
SUG	5.210432	0.741250	0.824150	**55.21405**
NMAHE	5.651204	0.710294	0.798412	**62.10431**
CLAHEWF	4.610243	0.758410	0.612045	**81.34012**

DCP	3.784102	0.761045	0.841023	**52.10423**
FCCE	4.102431	0.698412	0.954102	**71.24015**
PACR	4.512043	0.541023	0.498412	**60.12403**
MCHE	4.410234	0.521043	0.698412	**58.98410**

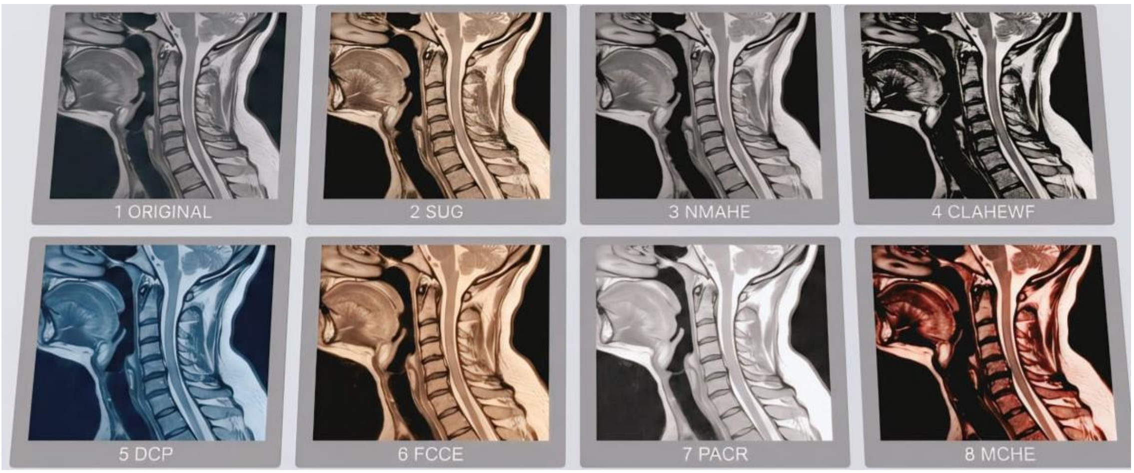

Figure 2. The original MRI image and the enhanced image.

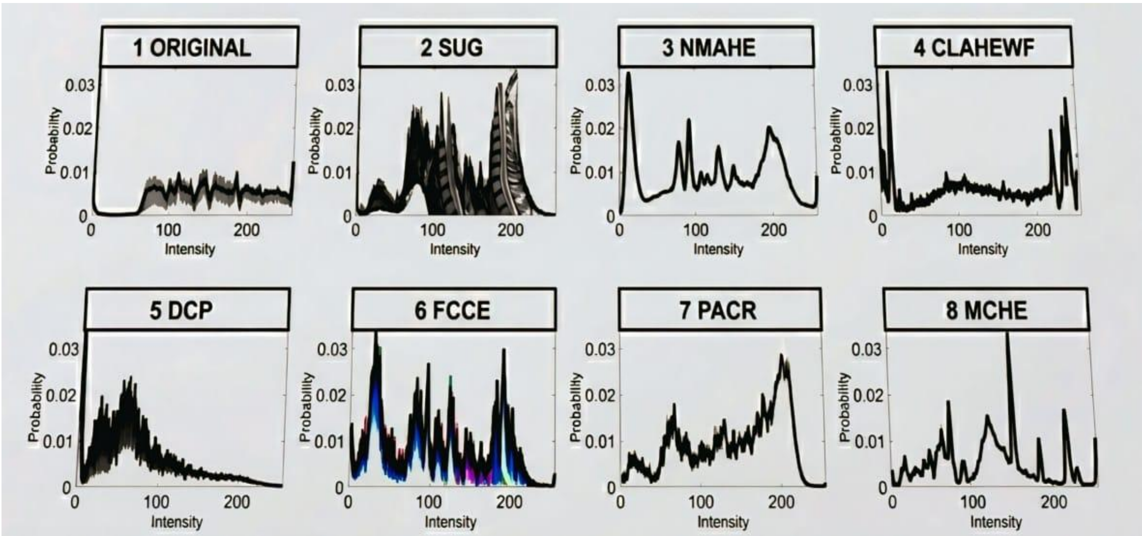

Figure 3. Graphs of the algorithms used.

CONCLUSION

Fundamental Finding : This study confirms that the selection of advanced algorithms depends on the equilibrium between sharpness, contrast and distortion levels in the image, in order to ensure the production of the best visual enhancement results. **Implication :** The integration of the techniques used in this work as sequential stages not only improves visualisation but also serves as a fundamental pillar for supporting image accuracy in delivering the best segmentation, tumour detection and tissue classification, thereby yielding excellent diagnostic and therapeutic results and reducing errors. **Limitation :** This study focuses on evaluating the effectiveness of integrated image enhancement techniques in achieving an optimal balance between sharpness, contrast, and distortion; however, the performance of the proposed sequential framework has not been extensively validated across different imaging modalities, clinical conditions, or large-scale datasets. **Future Research :** Future research should investigate the applicability and robustness of the proposed sequential enhancement framework on diverse medical imaging datasets and modalities, as well as explore the integration of artificial intelligence and deep learning approaches to further improve segmentation, tumour detection, tissue classification, and diagnostic accuracy.

REFERENCES

[1] J. Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Boston, MA, USA, 2015, pp. 3431–3440.

[2] Ö. Çiçek, A. Abdulkadir, S. S. Lienkamp, T. Brox, and O. Ronneberger, "3D U-Net: Learning dense volumetric segmentation from sparse annotation," in Medical Image Computing and Computer-Assisted Intervention (MICCAI 2016), vol. 9901, Cham, Switzerland: Springer, 2016, pp. 424–432.

[3] F. Milletari, N. Navab, and S.-A. Ahmadi, "V-Net: Fully convolutional neural networks for volumetric medical image segmentation," in Proc. 4th Int. Conf. 3D Vision (3DV), Stanford, CA, USA, 2016, pp. 565–571.

[4] R. Cui, R. Yang, F. Liu, and H. Geng, "HD2A-Net: A novel dual gated attention network using comprehensive hybrid dilated convolutions for medical image segmentation," Comput. Biol. Med., vol. 152, Art. no. 106384, 2023.

[5] X. Li, H. Chen, X. Qi, Q. Dou, C. Fu, and P.-A. Heng, "H-DenseUNet: Hybrid densely connected UNet for liver and tumor segmentation from CT volumes," IEEE Trans. Med. Imaging, vol. 37, no. 12, pp. 2663–2674, 2018.

[6] O. Oktay, J. Schlemper, L. L. Folgoc, et al., "Attention U-Net: Learning where to look for the pancreas," arXiv preprint arXiv:1804.03999, 2018.

[7] F. Isensee, P. F. Jaeger, S. A. A. Kohl, J. Petersen, and K. H. Maier-Hein, "nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation," Nat. Methods, vol. 18, no. 2, pp. 203–211, 2021.

[8] L. Xie, L. E. M. Wisse, J. Wang, et al., "Deep label fusion: A generalizable hybrid multi-atlas and deep convolutional neural network for medical image segmentation," Med. Image Anal., vol. 83, Art. no. 102683, 2023.

[9] I. Aboussaleh, J. Riffi, K. El Fazazy, A. M. Mahraz, and H. Tairi, "3DUV-NetR+: A 3D hybrid semantic architecture using transformers for brain tumor segmentation with multimodal MR images," Results Eng., vol. 21, Art. no. 101892, 2024.

[10] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in Medical Image Computing and Computer-Assisted Intervention (MICCAI 2015), vol. 9351, Cham, Switzerland: Springer, 2015, pp. 234–241.

[11] J. Chi, Z. Li, Z. Sun, X. Yu, and H. Wang, "Hybrid transformer UNet for thyroid segmentation from ultrasound scans," Comput. Biol. Med., vol. 153, Art. no. 106453, 2023.

[12] L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, "Encoder-decoder with atrous separable convolution for semantic image segmentation," in Computer Vision – ECCV 2018, Cham, Switzerland: Springer, 2018, pp. 833–851.

[13] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Honolulu, HI, USA, 2017, pp. 4700–4708.

[14] S. Panchal and M. Kokare, “ResMU-Net: Residual multi-kernel U-Net for blood vessel segmentation in retinal fundus images,” Biomed. Signal Process. Control, vol. 90, Art. no. 105859, 2024.
[15] H. Lan, D. Jiang, C. Yang, F. Gao, and F. Gao, “Y-Net: Hybrid deep learning image reconstruction for photoacoustic tomography in vivo,” Photoacoustics, vol. 20, Art. no. 100197, 2020.
[16] Z. Kuang, X. Deng, L. Yu, H. Wang, T. Li, and S. Wang, “Ψ-Net: Focusing on the border areas of intracerebral hemorrhage on CT images,” Comput. Methods Programs Biomed., vol. 194, Art. no. 105546, 2020.

***Tahseen Falih Mahdi (Correspondence Author)**
General Directorate of Missan Education, Missan, Iraq
Email: tahseenfalih@uomustansiriyah.edu.iq