

Selective Brain MR Image Compression Through Wavelet Optimization and Enhanced Convolutional Neural Network Model

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ABSTRACT- Tele-healthcare systems must store and transmit the digital data created by the various imaging modalities. For efficient handling of these data, compression techniques that provide a greater compression ratio with notable image quality are needed. This research proposes a selective image compression technique for brain MR images leveraging the energy compaction property of the wavelet coefficients and the feature extraction and learning capabilities of CNN. The procured images undergo a hybrid filter to eradicate the possible noise in the image. The Fuzzy C-Means technique optimized using the Greywolf optimization algorithm is used to segment the clinically relevant region from the rest of the MR image. Clinically significant areas are compressed using optimized zerotree wavelet transform to ensure the reconstructed image quality. The background information is compressed using enhanced CNN models to achieve a greater compression ratio. The algorithm put forward is implemented using MATLAB 2021a, and the algorithm completion is evaluated using the BRATS 2018 brain MR image dataset. The evaluation metrics show a commendable performance over the analyzed compression techniques with a PSNR of 42.11 dB, CR-29.3, and MSE of 14.37.

Keywords: Compression ratio, Convolutional Neural Network, CNN, image compression, selective image compression, zero tree wavelet transform.

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1. INTRODUCTION

Medical imaging systems generate massive amounts of data daily. High-resolution Magnetic Resonance Images (MRIs), Computed Tomography (CT scans), and X-rays require significant storage space. Telemedicine and telehealth systems transmit this data over the Internet reasonably and reliably. Consequently, image data compression is one of the primary study topics in the field of medical imaging.

Compression is achieved by minimizing the quantity of data needed to depict the image [18]. Compressing images facilitate to store and send vast volume of data, which is essential for

telemedicine, remote diagnostics, and data sharing between medical facilities and research institutes. By making medical imaging data accessible on devices with constrained storage or processing capacity, compression helps to bring healthcare to underprivileged populations.

Image file size can be reduced in lossy or lossless mode. Lossy mode minimizes the file size by removing less critical image data and, hence, results in some loss of quality [21,28]. Lossless or reversible compression reduces the file size without any loss of image quality or formation, ensuring the original data can be perfectly reconstructed [7,8,12].

Based on clinical relevance, brain MR imaging is distinguished as a region of interest (ROI) and a non-region of interest(non-ROI). The ROI refers to the specific parts of the brain MRI that are diagnostically important. These regions are typically the focus of the analysis, as they may contain abnormalities or critical structures relevant to patient diagnosis or treatment. Hence, ROI areas are compressed with minimal loss to preserve vital details for diagnosis [6,9,10].

Non-ROI comprises the parts of the brain MRI that are less critical or not directly relevant to the diagnostic purpose. These are the regions with uniform tissues that do not require detailed

analysis. Hence, non-ROI can be compressed more aggressively without compromising diagnostic integrity [2,22].

In medical image compression, the challenge lies in achieving high compression ratios while preserving diagnostically significant features and ensuring no loss of critical medical information. Selective image compression focuses on retaining essential information while reducing less relevant data, balancing efficiency and diagnostic utility. This research focusses on selective data compression employing optimized wavelet transform and convolutional neural network. The greywolf optimized-FCM technique is used to segment the clinically significant area from the less important areas in the image data.

The rest of the paper is arranged as follows. *Section 2* provides a thorough study of the suggested system, and *section 3* depicts the performance breakdown of the suggested approach.

2. DATA ANALYSIS AND TEST CASE SYSTEM

Recent decades have seen the development of numerous image compression algorithms based on different approaches, including transform, fractal-based, etc. Hybrid, lossless, and lossy compression methods have been developed.

Discrete wavelets transform (DWT) based image compression is a promising research area. DWT efficiently represents an image in the spatial and frequency realm. It splits the input image into sub-bands of varying information content [23,25]. By optimizing the threshold value for the sub-band coefficient selection, a reliable compression using DWT is possible while attaining an appreciable CR. Research [4,5,13,23,25,27] used DWT-based image compression techniques. Bruylants et al. [23] explained irreversible compression for images using wavelets. The volumetric image compression that supported JPEG 2000 was demonstrated by the suggested system. The suggested approach achieves a respectable bitrate and PSNR at the expense of a higher codec complexity. Due to the irreversible nature of DWT, IWT was used to accomplish the DICOM image's lossless compression. The drawback of the discussed algorithm is that as the distortion level increases, the PSNR value and the CR decrease. Talukder et al. [25] demonstrated a wavelet-centred compression system for grayscale images. The authors analyzed algorithm performance using hard and soft thresholding. Alkinani et al. [5] employed an optimized wavelet transform-based image compression approach. The authors used a modified version of the Haar wavelet to decompose medical image into sub-band details and approximations. This transformation facilitates effective compression by isolating significant image features. This study incorporates PSO to handle discontinuities that occur during thresholding in wavelet-based compression. By choosing the best threshold values for sub-bands, the PSO technique improves compression efficiency. This method tackles typical issues with wavelet-based compression, like thresholding-induced discontinuities.

Liu et al. [14] extended traditional 2D fractal compression techniques to 3D, enabling the algorithm to exploit spatial redundancies across multiple slices of MRI data. The authors divide the image volume into non-overlapping 3D blocks to capture self-similarities within the data. Optimal affine transformations are computed to map each range block to its best-matching domain block, ensuring accurate reconstruction during decompression.

Vikraman et al. [1] introduced an effective strategy for medical image compression by integrating advanced segmentation methods with optimized neural network architectures. This approach provides a well-balanced approach to diagnostic integrity and compression efficiency. Op-CNN is used to compress the segmented ROI while maintaining important diagnostic data. RNNs are used to compress non-ROI areas, enabling better compression ratios in less important locations. Parikh et al. [19] suggested HEVC coding as a irreversible compression method for medical photos. Using the permissible compression ratio determined by earlier research, the proposed method was contrasted with J2K. The results show a 54 per cent decline in storage needs compared to J2K. A small decrease in the compression ratio could significantly reduce computational complexity. The suggested approach increases the compressed file size by up to 1% in CT pictures, depending on the imaging modality.

A detailed literature review indicates the necessity of improved compression techniques with a higher compression ratio while ensuring recreated image quality.

3. PROPOSED IMAGE COMPRESSION METHODOLOGY

The workflow layout of the suggested compression model is shown in *figure 1*. The dataset's MRI images are first preprocessed, as seen in the figure.

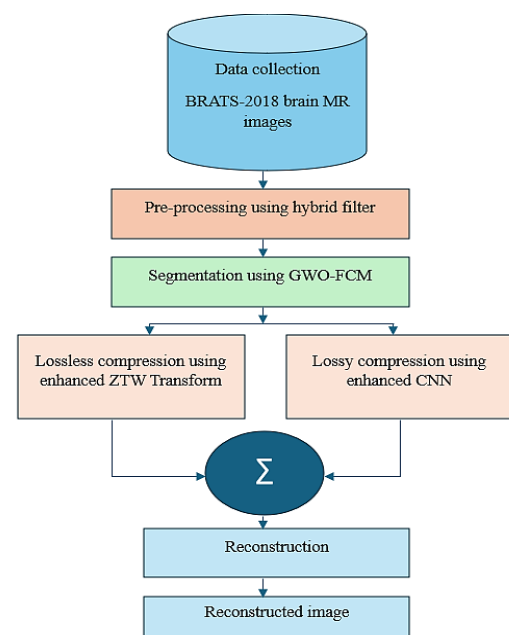


Figure 1. Proposed system process-flow diagram

A grey wolf optimized -Fuzzy C-Means (GWO-FCM) approach is used for segmentation. The enhanced Zerotree Wavelet (ZW) technique is used to apply reversible compression to the ROI image from the segmented image. This approach chooses the ideal threshold value using the GWO algorithm. Enhanced Convolutional Neural Network (ECNN) is used to compress the non-ROI image using lossy compression. The GWO method is used in ECNN to select the CNN weight values in the best possible way. In the reconstruction step, the compressed image is finally rebuilt.

3.1. Data Collection

The MR image data needed for the performance assessment of the suggested system is being collected from the public data source BRATS 2018. The resulting image was 256×256 pixels in size.

3.2. Image Preprocessing

Image preprocessing is required to remove artefacts and noise from MR images and enhance the relevant structures for selective image compression. In this research, a hybrid filter containing a mean, median, and Gaussian filter is used for preprocessing. Equation (1) describes a mean filter.

$$g(s, t) = \frac{1}{M} \sum_{s=-a}^a \sum_{t=-b}^b f[s, t] \quad (1)$$

Where M-indicates the total pixel considered, and s , and t indicates the pixel location.

Equation (2) describes a median filter, $g(s, t)$.

$$g(s, t) = \text{median}(f(s, t)) \quad (2)$$

Equation (3) describes a Gaussian filter, $GF(s, t)$

$$GF(s, t) = \frac{1}{2\pi\sigma^2} e^{-\frac{s^2+t^2}{2\sigma^2}} \quad (3)$$

The hybrid filter used in this research is a normalized hybrid form of the above three filters.

3.3. Segmentation Using GWO-FCM Algorithm

Fuzzy c-means (FCM) is a widely accepted segmentation algorithm [24,26]. The Graywolf optimization (GWO)algorithm is used to overcome FCM's drawbacks, such as tendency to trap in local minimum and sensitivity to noise.

The GWO algorithm mimics the hierarchy and predation behaviour of the greywolf pack [20]. As the apex predators, greywolves typically prefer to live in packs. Each group normally consists of 5–12 wolves, employing a rigid pyramid-style hierarchy in their management structure. Greywolves have a four-tiered hierarchical structure. The head wolf, the ideal solution, the pack's most potent and capable member, constitutes the first layer, called the α layer. These alphas in a wolf pack are responsible for deciding how to distribute food, engage in predation, and make other important decisions. The second-best solution is called beta (β) and forms the second

layer in the hierarchy. They support alphas and are under them. The beta wolf not only commands the other subordinate wolves but also ought to revere the alpha. The beta provides input to the alpha and reinforces the alpha's orders throughout the group [17]. Omega, the greywolf with the lowest rank, serves as the victim. All other dominant wolves must always yield to omega wolves. Deltas in this greywolf hierarchy are also called subordinates. They protect and guarantee the pack's safety and care for its ill, weak, and injured wolves. Under the direction of the head greywolf, the wolves seek and kill their prey using various techniques, including encircling, hunting, and attacking. According to the actual outcomes, this massive search algorithm focused on the top three grey wolves. GWO lacks an elimination mechanism, which means that even if a grey wolf travels to a poorer location than its current location, it must still arrive. As a result, this optimization method is more flexible and has a more powerful ability for global search.

The fitness function $x(P)$ is given in equation (4) and equation (5).

$$x(P) = \frac{1}{J(u, p)} \quad (4)$$

$$\text{where } J_{\min}(U, P) = \sum_{j=1}^n \sum_{i=1}^c u_{ij}^q d_{ij}^2 \quad (5)$$

Where P indicates the particle code and is given in equation (6).

$$P = \{p_1, p_2, p_3, \dots, p_n\} \quad (6)$$

The fitness function, $x(P)$, for a specific greywolf rises as the associated aim value J falls, indicating that the clustering effect is more advantageous.

3.4. ROI Compression Using Enhanced Zerotree Wavelet Transform

Image compression using zerotree wavelet transform efficiently encodes wavelet transformed coefficients by exploiting hierarchical and spatial redundancy within an image. DWT decomposes an input image into multiple frequency sub-bands that contain diagonal, vertical, horizontal, and image approximation. The Low-Low(approximation) sub-band is further decomposed into finer sub-bands in subsequent levels.

In the ZW transform, large coefficients are retained with higher precision, while the smaller coefficients are reduced to zero. Zerotrees allow encoding large regions of insignificant coefficients with minimal data, leveraging inter-scale redundancy. The optimal threshold value is calculated using the GWO algorithm.

Enhanced ZW transform based compression procedure is given below.

Step 1: Threshold, T_i , value initialization using equation (7).

$$T_i = 2|\log_2 C_{\max}| \quad (7)$$

GWO algorithm is used to select $C_{\max}$.

Step 2: Dominant pass

Significance of the coefficient is evaluated at this stage. Based on its significance zerotree root, isolated zero, significant positive, and significant negative is determined.

Step 3: The last subgroup's insignificant coefficients, which are not derived from the offspring or the zero tree, are taken into.

Step 4: In enhanced ZW, two different coefficients such as positive and negative are used for analysing the coding rules. The two coefficients are utilized for coding if the descendants are determined to be unimportant.

3.5. Non-ROI compression using Enhanced CNN

A convolutional neural network has multiple layers, including the input layer, convolutional layer, pooling layer, and fully connected layers. The preprocessed input image is given to the input layer. The input image's features are extracted by the convolutional layer using filters. The fully connected layer makes the final prediction, while the pooling layer minimizes computation by down sampling the image.

The proposed system convolves input data with the kernel to generate output feature maps. Equation (8) shows the mathematical representation of this transformation.

$$B_i^n = \sum_{j \in F_i} B_j^{n-1} \otimes \xi_{ij}^n + L_i^n \quad (8)$$

Where $\otimes$ indicates convolution operator.

ξ_{ij}^n - weight value of the i^{th} filter of the n^{th} convolution layer

L_i^n - bias of the i^{th} filter of the n^{th} convolution layer

B_i^n - is the activation map.

In equation (8) GWO optimally selects the weight values.

4. RESULT AND DISCUSSION

4.1. Performance Metrics

Proposed algorithm performance is evaluated based on compression ratio (CR), Mean Square Error (MSE), and Peak Signal to Noise Ratio (PSNR).

$$CR = \frac{\text{Original image size}}{\text{Compressed image size}} \quad (9)$$

$$MSE = \frac{1}{cd} \sum_{i=0}^{c-1} \sum_{j=0}^{d-1} [O(i,j) - C(i,j)]^2 \quad (10)$$

$$PSNR = 10 \log_{10} \left[\frac{255^2}{MSE} \right] \quad (11)$$

Figure 2 shows the images at the various stages of the proposed algorithm for the four test images. The images in the first column are input images. The segmented ROI images are shown in the second column. The third column shows the medically less critical non-ROI region, and the last column of images shows the reconstructed images.

Figure 3 shows the graphical representation of the algorithm performance for the five test images. CR indicates the reduction

in storage requirement. The ROI area has an impact on the CR value. For the suggested algorithm, the CR varies between 28.47 and 30.29, with an average of 29.33. PSNR signifies the worth of the decompressed image. For the analyzed images, the PSNR varies from 41.86 to 42.58, resulting in an average of 42.11dB, which is relatively high compared to the techniques considered in this paper. A lower MSE indicates a better coding-decoding method. The proposed technique yields a minimum MSE of 14.03, a maximum of 14.68, and an average of 14.37.

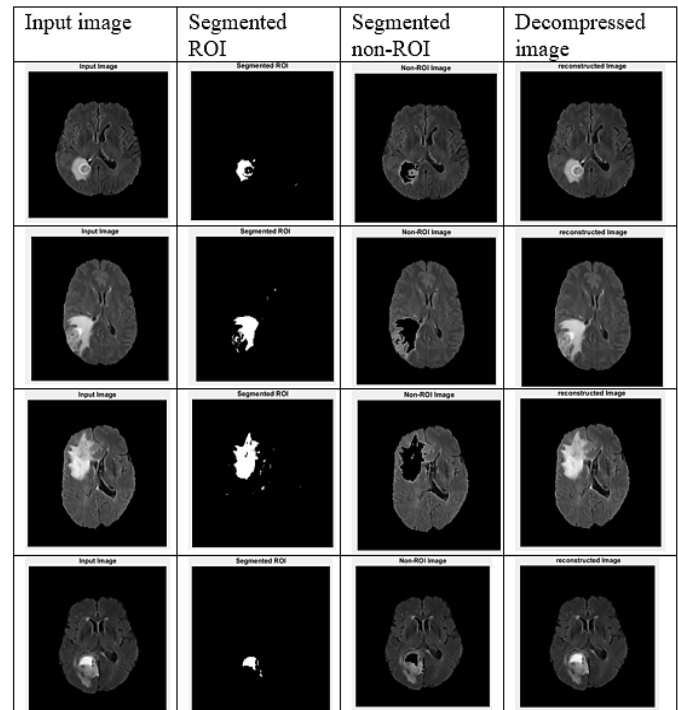


Figure 2. Outcomes of the proposed method

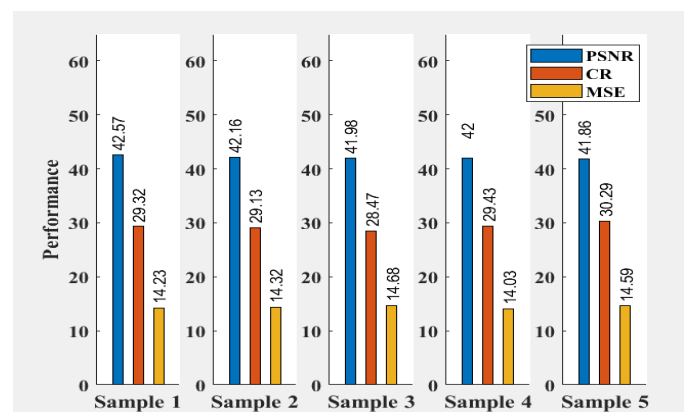


Figure 3. Proposed algorithm performance

4.2. Comparative Analysis of the existing Systems

Table 1 shows a comparative analysis of the suggested model's performance with popular methods such as the BWT-MTF, MIC-DWT-CNN, FODPSO, and HICOQF. By contrasting compressed images with originals, a statistic known as PSNR is used to assess the quality of the compressed images. Compared

to the analyzed approaches, the proposed e-ZW-ECNN system has better performance in PSNR and an improvement in CR value. In general, greater compression ratios are preferred to lower the amount of storage and bandwidth needed, but it's crucial to balance this with maintaining sufficient image quality for accurate medical analysis. The suggested approach has the lowest MSE (14.37), indicating that it can reduce reconstruction errors.

Table 1. Performance Comparison

Technique	PSNR (dB)	MSE	CR
BWT-MTF [16]	34.6905	22.0816	4.634
MIC-DWT-CNN [3]	35.11	23.21	25
FODPSO [15]	22.7223	-	2.13
HICOQF [11]	33.51	28.96	24.61
Proposed	42.11	14.37	29.33

5. CONCLUSION

The transmission and storage of digital data produced by the various imaging modalities are necessary for telehealth care systems. Compression algorithms with notable compression ratio and image quality are required for the effective storage and dependable transmission of these data. Using the energy compaction property of the wavelet coefficients and CNN's feature extraction and learning capabilities, this study suggests a selective image compression method for brain MR data. To eliminate any potential noise, a hybrid filter is applied to the acquired images. To separate the ROI from the non-ROI of the image data, the fuzzy C-Means technique optimized with the Greywolf optimization algorithm is employed. The optimized zerotree wavelet transform is used to compress clinically important areas to guarantee the quality of the reconstructed image. Comparative analysis of the proposed machine learning-based selective image compression technique with the analyzed papers shows that the algorithm has an appreciable result in CR, PSNR, and MSE values.

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REFERENCES

- [1] Vikraman, B.P., Jabeena, A., "Segmentation based medical image compression of brain magnetic resonance images using optimized convolutional neural network," *Multimed Tools Appl* 83, 26643–26661 (2024). <https://doi.org/10.1007/s11042-023-16559-4>.
- [2] P.V, B., A., J., "A brain magnetic resonance image compression technique using wavelet-based SPIHT algorithm and capsule autoencoder," *Multimed Tools Appl* (2024). <https://doi.org/10.1007/s11042-024-19213-9>.
- [3] R.K. Paul, S. Chandran, "A health care image compression scheme using discrete wavelet transform and convolution neural network," *J Eng Res.* (2022), <https://doi.org/10.36909/jer. ICMET 17163>.
- [4] M. Revathi, R. Shenbagavalli, and T. Nadu, "An efficient trapezoidal compression algorithm using wavelet transformation for medical image," *J. Math. Comput. Sci.*, vol. 11, no. 5, pp. 5565–5579, 2021, doi: 10.28919/jmcs/6000.
- [5] Monagi H. Alkinani, E. A. ZanatyandSherif M. Ibrahim, "Medical Image Compression Based on Wavelets with Particle Swarm Optimization," *Computers, Materials & Continua(CMC)*, 2021, vol.67, no.2. <https://doi.org/10.32604/cmc.2021.014803>.
- [6] B. P.V. and J. Afthab, "Region of Interest Based Medical Image Compression Using DCT and Capsule Autoencoder for Telemedicine Applications," *2021 Fourth International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, Erode, India, 2021, pp. 1–7, doi: 10.1109/ICECCT52121.2021.9616748.
- [7] P. Kumar and A. Parmar, "Versatile Approaches for Medical Image Compression: A Review," *Procedia Comput. Sci.*, vol. 167, pp. 1380–1389, 2020, doi: 10.1016/j.procs.2020.03.349.
- [8] .Sharma U, Sood M, Puthooran E, "A Block Adaptive Near-Lossless Compression Algorithm for Medical Image Sequences and Diagnostic Quality Assessment," *J Digit Imaging.* 2020 Apr;33(2):516-530. doi: 10.1007/s10278-019-00283-3. PMID: 31659588; PMCID: PMC7165212.
- [9] P. Sreenivasulu and S. Varadarajan, "An Efficient Lossless ROI Image Compression Using Wavelet-Based Modified Region Growing Algorithm," *J. Intell. Syst.*, vol. 29, no. 1, pp. 8. P. K. Sran, S. Gupta, and S. Singh, "Segmentation based image compression of brain magnetic resonance images using visual saliency," *Biomed. Signal Process. Control*, vol. 62, p. 102089, 2020, doi: 10.1016/j.bspc.2020.102089.
- [10] Sran, P.K., Gupta, S. and Singh, S, "Segmentation based image compression of brain magnetic resonance images using visual saliency," *Biomedical Signal Processing and Control*, 2020, 62, p.102089.
- [11] Magar, S.S., Sridharan, B., "Hybrid image compression technique using oscillation concept & quasi fractal," *Health Technol.* 10, 313–320 (2020). <https://doi.org/10.1007/s12553-018-00282-4>.
- [12] U. Habib, "Optimal compression of medical images," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 4, pp. 133–140, 2019, doi: 10.14569/ijacsa.2019.0100415.
- [13] P. N. Tackie Ammah and E. Owusu, "Robust medical image compression based on wavelet transform and vector quantization," *Informatics Med. Unlocked*, vol. 15, p. 100183, 2019, doi: 10.1016/j.imu.2019.100183.
- [14] S. Liu, W. Bai, N. Zeng and S. Wang, "A Fast Fractal Based Compression for MRI Images," in *IEEE Access*, vol. 7, pp. 62412–62420, 2019, doi: 10.1109/ACCESS.2019.291693.
- [15] A. Ahilan et al., "Segmentation by Fractional Order Darwinian Particle Swarm Optimization Based Multilevel Thresholding and Improved Lossless Prediction Based Compression Algorithm for Medical Images," in *IEEE Access*, vol. 7, pp. 89570–89580, 2019.
- [16] Devadoss, C.P., Sankaragomathi, B., "Near lossless medical image compression using block BWT–MTF and hybrid fractal compression techniques," *Cluster Comput* 22 (Suppl 5), 12929–12937 (2019). <https://doi.org/10.1007/s10586-018-1801-3>.
- [17] Peifeng Niu, Songpeng Niu, Nan liu, Lingfang Chang, "The defect of the Grey Wolf optimization algorithm and its verification method," *Knowledge-Based Systems*, Volume 171, Pages 37–43, 2019.
- [18] J. Hussain, Ali Al-Fayadh, Naeem Radi, "Image compression techniques: A survey in lossless and lossy algorithms," *Neurocomputing*, Volume 300, 2018, Pages 44–69, ISSN 0925-2312. <https://doi.org/10.1016/j.neucom.2018.02.094>.
- [19] S. S. Parikh, D. Ruiz, H. Kalva, G. Fernandez-Escribano, and V. Adzic, "High Bit-Depth Medical Image Compression with HEVC," *IEEE J. Biomed. Heal. Informatics*, vol. 22, no. 2, pp. 552–560, 2018, doi: 10.1109/JBHI.2017.2660482.

- [20] M. Q. Li, L. P. Xu, Na Xu, Tao Huang, Bo Yan, "SAR Image Segmentation Based on Improved Grey Wolf Optimization Algorithm and Fuzzy C-Means," *Mathematical Problems in Engineering*, 2018, [Online] <https://onlinelibrary.wiley.com/doi/10.1155/2018/4576015>.
- [21] Z. Zuo, X. Lan, L. Deng, S. Yao and X. Wang, "An improved medical image compression technique with lossless region of interest," *Int. J. Light Electron Optics* 126 (2015), 2825–2831.
- [22] M. Kaur, "ROI Based Medical Image Compression for Telemedicine Application," *Procedia - Procedia Comput. Sci.*, vol. 70, pp. 579–585, 2015, doi: 10.1016/j.procs.2015.10.037.
- [23] Bruylants, Tim, Adrian Munteanu, and Peter Schelkens, "Wavelet based volumetric medical image compression," *Signal processing: Image communication* 31: 112-133, <https://doi.org/10.1016/j.image.2014.12.007>
- [24] M. C. J. Christ and R. M. S. Parvathi, "Fuzzy c-means algorithm for medical image segmentation," *ICECT 2011 - 2011 3rd Int. Conf. Electron. Comput. Technol.*, vol. 4, no. 1, pp. 33–36, 2011, doi: 10.1109/ICECTECH.2011.5941851.
- [25] Talukder, K. H., & Harada, K., "Haar Wavelet Based Approach for Image Compression and Quality Assessment of Compressed Image," 2010, [Online] ArXiv. <https://arxiv.org/abs/1010.4084>.
- [26] Zhou, H., Schaefer, G., Shi, C. (2009). Fuzzy C-Means Techniques for Medical Image Segmentation. In: Jin, Y., Wang, L. (eds) *Fuzzy Systems in Bioinformatics and Computational Biology*. Studies in Fuzziness and Soft Computing, vol 242. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-89968-6_13.
- [27] M. Penedo, W. A. Pearlman, P. G. Tahoces, M. Souto and J. J. Vidal, "Region-based wavelet coding methods for digital mammography," in *IEEE Transactions on Medical Imaging*, vol. 22, no. 10, pp. 1288-1296, Oct. 2003, doi: 10.1109/TMI.2003.817812.
- [28] Rabbani, M., Jones, P.W., "Image compression techniques for medical diagnostic imaging systems," *J Digit Imaging* 4, 65–78 (1991). <https://doi.org/10.1007/BF03170414>.



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