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Adaptive Medical Image Compression Based On A Hybrid Neural Network With Built-In ROI Detection

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ABSTRACT

This study addresses the critical challenge of efficiently compressing the rapidly growing volume of medical images while preserving essential diagnostic details, particularly within the Regions of Interest (ROI). Traditional compression techniques, whether lossless or lossy, often struggle to balance high compression efficiency with image quality lossless methods offer limited data reduction, while lossy techniques risk removing vital clinical information. To overcome these limitations, a comprehensive hybrid compression framework is developed, integrating segmentation and compression within a single deep neural network. The system employs Convolutional Neural Networks (CNNs) to accurately segment medical images and identify ROIs, while an autoencoder-based compression module performs selective encoding applying near-lossless compression for ROI regions to maintain diagnostic fidelity and lossy compression for non-ROI (NROI) areas to maximize storage savings. This unified design eliminates the need for separate processing stages, reduces computational complexity, and enhances compression performance. The proposed framework was validated using the CLEF MED X-ray and BRATS MRI datasets, demonstrating high effectiveness and adaptability across different modalities. Experimental results achieved a Peak Signal-to-Noise Ratio (PSNR) of 56.07 dB for ROI and 45.12 dB for NROI, with an overall compression ratio of 6.73, confirming its strong balance between data reduction and image quality.

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1. INTRODUCTION

With the enormous development in the quantity of medical images being generated and transferred every day, the necessity for effective storage and transmission systems has become critical. Medical images such as X-rays and Magnetic Resonance Imaging (MRI) scans are vital for diagnosis, treatment planning, and long-term record keeping. However, the large volume of data places pressure on storage systems and network capacity [1][2]. Digital image compression is a crucial solution to this dilemma, attempting to minimize file sizes while retaining the integrity of visual information, particularly in the Region of Interest (ROI), which typically contains diagnostically essential details. The balance between compression efficiency and image quality is of critical importance in medical applications [3][4].

Existing solutions to medical image compression can be broadly classified into lossless, lossy, and hybrid methods. Lossless techniques maintain perfect image fidelity but offer limited compression ratios. Lossy techniques achieve higher compression but risk degrading visual quality, which is unacceptable for medical diagnosis. Hybrid methods attempt to resolve this trade-off by applying lossless compression to ROI regions and lossy compression to non-ROI areas [5-6]. However, these approaches often involve separate segmentation and compression stages, increasing system complexity and reducing processing efficiency. Furthermore, most existing systems lack the flexibility to adapt to different types of medical images without manual intervention or retraining across all components. The main issue addressed in this research is the lack of an integrated, adaptive, and computationally efficient compression framework that can automatically handle both segmentation and compression tasks while preserving diagnostic quality. Motivated by the need for a more streamlined and intelligent approach, this research proposes an end-to-end hybrid neural network that performs both segmentation and compression within a single architecture. The method leverages Convolutional Neural Networks (CNNs) for automatic ROI detection and implements an autoencoder-based compression mechanism that applies different compression levels across image sections [7-9]. This integrated strategy not only simplifies the processing pipeline but also improves performance by minimizing redundancy and focusing fidelity on diagnostically relevant areas. In this study, the proposed technique is evaluated on benchmark datasets (CLEF MED 2009 X-ray, BRATS 2015 MRI) and custom subsets. Results reveal improved PSNR values for ROI (56.07 dB) and NROI (45.12 dB), together with a high compression ratio (6.73), demonstrating the method's potential for real-world implementation in medical archiving and telemedicine. The main contribution of this work lies in the development of a unified deep learning framework that seamlessly integrates segmentation and compression, achieving substantial storage reduction while preserving diagnostic accuracy and adaptability across various imaging modalities.

This research provides an end-to-end hybrid compression framework for medical images that blends segmentation and compression into a single neural network architecture. Unlike previous approaches that divide both stages leading to increased complexity and limited adaptability, the proposed system executes both tasks in a single pass, enhancing efficiency and scalability. The model adopts a content-aware compression strategy by applying near-lossless compression to diagnostically critical Regions of Interest (ROI) and lossy compression to Non-ROI areas, ensuring excellent visual fidelity where it matters most while achieving significant file size reduction. Additionally, the segmentation component is modular, enabling easy adaptability to other imaging modalities such as X-ray and MRI without retraining the entire network.

The rapid proliferation of medical imaging technologies, such as MRI, CT, and ultrasound, has led to a huge increase in the amount of digital medical images. To handle the increasing data while maintaining diagnostic accuracy, various compression techniques have been suggested. These can be generically categorized into lossless, lossy, and hybrid compression approaches [10]. Lossless compression algorithms (e.g., Run-Length Encoding, Huffman Coding, Arithmetic Coding, and Lempel-Ziv-Welch) ensure that the decompressed image is identical to the original. These methods are vital in medical diagnosis but have limited compression efficiency. In contrast, lossy approaches (such as JPEG, JPEG2000, and Fractal Coding) obtain better compression ratios by permitting slight variations in image quality, which may not always be suitable for medical applications where fine details are crucial for diagnosis [11-12].To address the constraints of both lossless and lossy approaches, researchers have devised hybrid compression algorithms that combine the capabilities of each. A common hybrid strategy involves compressing the Region of Interest (ROI) using lossless or near-lossless methods to maintain diagnostic information while applying lossy compression to the Non-Region of Interest (NROI). Techniques such as SPIHT (Set Partitioning in Hierarchical Trees) and Wavelet Transform have been employed to enhance the performance of these systems. In recent years, Artificial Neural Networks (ANNs) have been widely utilized in medical image processing due to their ability to learn complex patterns, making them effective for both segmentation and compression tasks. Models like Autoencoders and Multilayer Perceptrons (MLPs) have been applied to eliminate redundancy and improve compression efficiency, especially when focusing on ROI-based methods. However, while some studies have used neural networks for feature extraction or classification, relatively few have integrated ANNs directly into the compression process, particularly in a way that dynamically manages both ROI and NROI areas [13-14].Eventually, study contributes a deep learning-based hybrid compression framework that unifies ROI segmentation and adaptive compression in a single end-to-end model, effectively addressing existing issues of complexity, generalizability, and diagnostic reliability

2. METHOD

The suggested methodology provides a hybrid deep learning-based system for medical picture compression, aimed to fulfill the necessity for maintaining diagnostically significant regions while minimizing storage and communication overhead. The method merges picture segmentation and compression into a single pipeline that intelligently distinguishes between the Region of Interest (ROI) and the Non-Region of Interest (NROI)[15][16]. Utilizing near-lossless compression for the ROI and more aggressive lossy compression for the NROI, the system attains an advantageous balance between picture quality and compression ratio. This method is done by a unified neural network that learns to recognize and prioritize essential image regions during the compression process. This method facilitates the generation of compressed medical images that preserve high fidelity in critical diagnostic regions, particularly significant in telemedicine, medical archiving, and real-time diagnostic systems. Figure 1 illustrates an overview of the complete system pipeline, depicting the data flow through the segmentation and compression units.

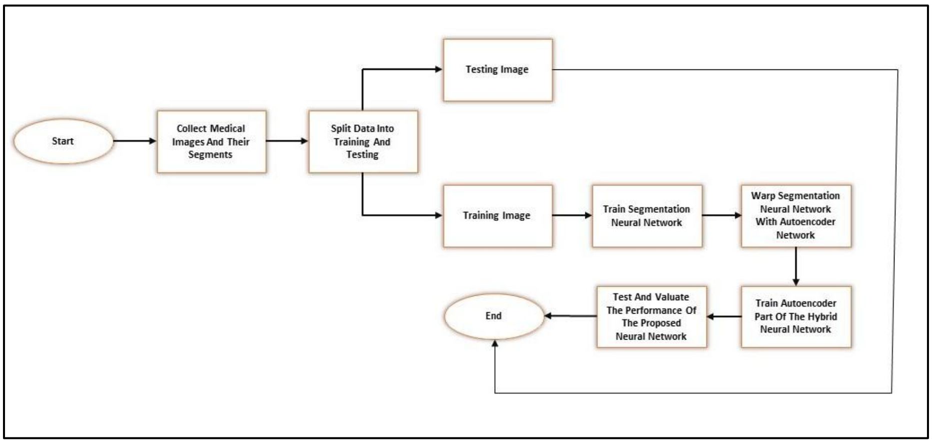

Figure 1. Framework of the proposed methodology

The network architecture has two tightly coupled components a segmentation network and an autoencoder. The segmentation component utilizes the U-Net architecture, a prominent convolutional neural network model for biomedical picture segmentation. It outputs a binary mask of the same spatial resolution as the input image, where each pixel denotes the likelihood of belonging to the ROI. This mask is concatenated with the original grayscale image to generate a two-channel input tensor of shape 256 × 256 × 2. The aggregated input is subsequently processed by the autoencoder, which compresses the image via a sequence of convolutional and pooling layers to a bottleneck layer of 32×32×1. The bottleneck representation is then decoded to reassemble the image. Upon completion of training, the network is divided into encoder and decoder components, with the encoder generating the compressed representation and the decoder reconstructing the picture from that representation. To improve compression efficiency, the bottleneck layer's output is encoded with Huffman entropy coding, minimizing redundancy in the compressed data.

Artificial Neural Networks (ANNs) are fundamental to segmentation and compression inside the proposed system. The training procedure is directed by a bespoke loss function that integrates structural similarity with entropy optimization. The aggregate loss is defined as:

$$\text{Loss}=1-(\alpha\cdot\text{SSIM}_{\text{ROI}}+\beta\cdot\text{SSIM}_{\text{NROI}})+\frac{|\text{unique}(B)|-1}{|B|} \tag{1}$$

Where B represents the output from the bottleneck layer, and α and β are weighting parameters with values of 0.8 and 0.2, respectively, to emphasize the significance of the ROI. The Structural Similarity Index (SSIM) for two image patches I_1 and I_2 is defined as follows:

$$\text{SSIM}(I_1,I_2)=\frac{(2\mu_1\mu_2+C_1)(2\sigma_{12}+C_2)}{(\mu_1^2+\mu_2^2+C_1)(\sigma_1^2+\sigma_2^2+C_2)} \tag{2}$$

In this equation, μ and σ denote the mean and standard deviation, respectively, whereas C_1 and C_2 are constants employed to stabilize the division. This loss function promotes the preservation of visual similarity in the region of interest while reducing the number of distinct values in the bottleneck for effective compression. The network is trained with the backpropagation technique, with the segmentation weights fixed to guarantee stability in ROI recognition during compression training. This design allows the system to generalize across different medical imaging modalities while maintaining diagnostic integrity in the compressed outputs.

Four key performance metrics are used in this evaluation. The first metric is Peak Signal-to-Noise Ratio (PSNR)[22][23], which quantifies image reconstruction quality and is calculated as shown in Equation (3):

$$\text{PSNR}=20\log_{10}(\text{MAX}_\text{I})-10\log_{10}(\text{MSE}) \tag{3}$$

where MSE is the Mean Squared Error between the original and reconstructed image[24][25]. MSE itself is given in Equation (4):

$$\text{MSE}=\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j)-R(i,j)]^2 \tag{4}$$

Here, I and R represent the original and reconstructed images, respectively, and MAXI is the maximum possible pixel value of the image. The second metric is the Structural Similarity Index Measure (SSIM), which measures visual and structural similarity [26], as defined in Equation (5):

$$\mathrm{SSIM}=\frac{(2\mu_I\mu_R+C_1)(2\sigma_{IR}+C_2)}{(\mu_I^2+\mu_R^2+C_1)(\sigma_I^2+\sigma_R^2+C_2)} \quad (5)$$

Where μ, σ^2, and σ_{IR} denote the mean, variance, and covariance of the original and reconstructed images. C_1 and C_2 are constants employed to stabilize the division.The third metric is the Compression Ratio (CR), defined in Equation (6):

$$\mathrm{CR}=\frac{\text{Original File Size}}{\text{Compressed File Size}} \quad (6)$$

This metric reflects how effectively the image is compressed. Equation (7):

$$T=t_{end}-t_{start} \quad (7)$$

Where t_{start} and t_{end} are the timestamps delineating the commencement and conclusion of the compression procedure. Finally, the Execution Time (T), defined in measures the time required to complete the compression process. These metrics collectively assess the system's capability to reduce storage requirements while maintaining diagnostic image quality. Results and interpretations are discussed in the following sections using tables, figures, and dataset comparisons.

3. RESULTS AND DISCUSSION

The experimental results and in-depth analysis of the proposed hybrid compression method for medical images. The evaluation is carried out using two benchmark datasets, CLEF MED 2009 [17-19] and BRATS 2015 [20-21] under varying parameter values. The goal is to assess the system's performance in terms of compression efficiency and the preservation of visual quality, particularly in the Region of Interest (ROI).

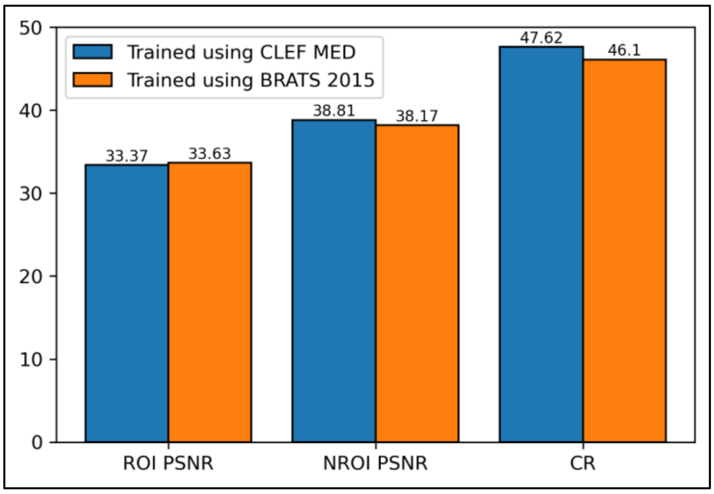

Figure 2. Validation results of the trained autoencoder using the CLEF MED and BRATS datasets.

Figure 2 presents the Peak Signal-to-Noise Ratio (PSNR) values obtained from the tested image using the proposed hybrid compression method. PSNR is a widely used metric that quantifies the visual quality of compressed or reconstructed images by measuring the difference between the original and compressed versions. In this study, the PSNR values ranged from 31.11 dB to 38.94 dB across different test cases, with the highest PSNR observed in image 3. These values indicate a high level of similarity between the original and decompressed images, reflecting that the proposed method maintains the essential visual features and diagnostic quality of medical images, especially in the Region of Interest (ROI). Such high PSNR values demonstrate the effectiveness of the compression strategy in preserving image integrity.

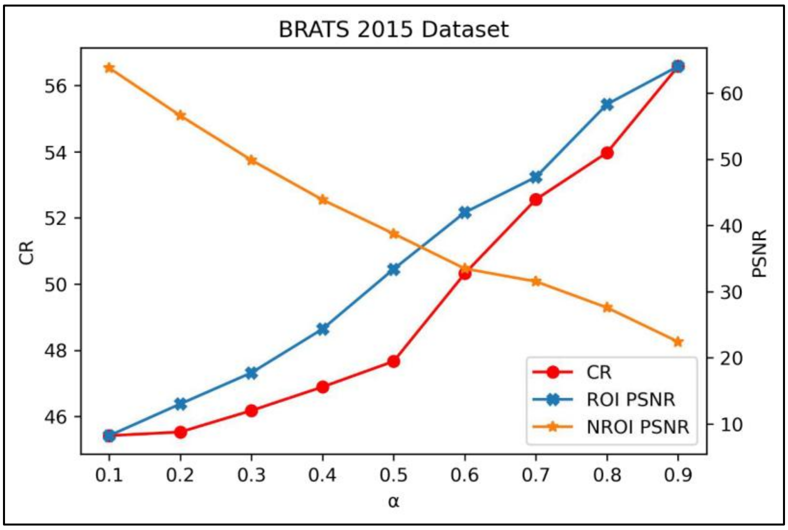

Figure 3. PSNR values of the ROI and NROI versus different values of ∝ using the BRATS 2015 dataset.

The compression ratios achieved by the same method for each tested image. The compression ratio is a critical performance metric that represents the efficiency of the compression algorithm in reducing data size. The reported ratios range from 4.27:1 to 5.23:1, with the highest compression achieved in image 4. These results confirm that the proposed method is capable of significantly reducing the storage size of medical images without compromising the quality of important regions. By balancing visual fidelity and storage efficiency, the method proves to be both practical and effective for applications requiring high-quality medical image compression.

The table1 presents the performance of the proposed hybrid compression method on two different datasets: CLEF MED 2009 and BRATS 2015. Three primary metrics are evaluated: PSNR (Peak Signal-to-Noise Ratio) for Region of Interest (ROI) and Non-Region of Interest (NROI), and Compression Ratio (CR). These metrics are examined under varying α values ranging from 0.1 to 0.9. From the table, it is evident that as α increases, the PSNR of the ROI increases significantly, while the PSNR for NROI decreases slightly. This trend suggests that increasing α prioritizes the preservation of ROI quality, allowing more aggressive lossy compression on the NROI. As a consequence, the overall Compression Ratio (CR) decreases because less aggressive compression is used in the ROI.

Additionally, the table indicates that the BRATS 2015 dataset achieves notably higher compression ratios compared to the CLEF MED 2009 dataset for corresponding α values. This is attributed to the smaller size of the ROI in the BRATS dataset, which results in a larger proportion of NROI and thus more opportunity for lossy compression. This finding highlights the flexibility of the proposed compression method in adapting to dataset characteristics while maintaining the desired balance between compression efficiency and visual fidelity.

Table 1. Effect of α on PSNR and Compression Ratio Across Two Medical Image Datasets

α	ROI PSNR (CLEF)	NROI PSNR (CLEF)	CR (CLEF)	ROI PSNR (BRATS)	NROI PSNR (BRATS)	CR (BRATS)
0.1	8.16	63.18	20.12	8.23	63.8	56.58
0.2	12.24	59.32	18.73	13.02	56.59	53.97
0.3	18.62	54.82	16.81	17.73	49.87	52.56
0.4	24.16	51.11	15.22	24.35	43.87	50.32
0.5	30.66	49.82	13.82	33.4	38.75	47.67
0.6	38.12	47.53	12.18	41.96	33.47	46.89
0.7	49.07	46.74	9.68	47.3	31.53	46.18
0.8	56.07	45.12	6.73	58.31	27.58	45.53
0.9	59.16	43.62	5.18	64.05	22.41	45.42

4. CONCLUSION

The growing dependence on medical imaging throughout diagnosis and treatment necessitates effective image compression methods that retain essential visual data while reducing storage and transmission expenses. A hybrid compression method was developed to maintain the Region of Interest (ROI) with near-lossless techniques while employing more aggressive lossy compression on the Non-Region of Interest (NROI). The suggested approach incorporates segmentation and compression into a singular hybrid neural network, in contrast to conventional multi-stage methods. This design facilitates parallel computing, therefore decreasing execution time when adequate hardware resources, such as

GPUs, are accessible. This approach's primary strength is in its adaptability; the segmentation component may be independently updated by transfer learning, enabling the method to accommodate diverse medical images such as X-rays, MRIs, and CT scans without necessitating the retraining of the autoencoder. Experimental findings validate the method's efficacy in preserving high visual fidelity in regions of interest, attaining competitive compression ratios, and markedly enhancing processing efficiency. The suggested system offers a versatile, high-performance solution for medical picture compression in contemporary healthcare settings.

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