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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 crucial issue of reducing the size of medical photographs while preserving vital diagnostic information, especially the Regions of Interest (ROI). Because state-of-the-art lossless and lossy compression techniques are limited in their ability to execute an initial data reduction prior to further decomposing images, they typically cannot achieve great compression efficiency without the reduced image quality associated with lossy approaches. We create a unified hybrid compression framework that simultaneously models segmentation and compression in a single deep neural network in order to mitigate such problems. A CNN-based segmentation network that uses an autoencoder-based compression module with selective encoding (with near-lossless compression applied to the ROI areas for diagnostic quality & lossy in NROI regions to maximize storage gains) and coarse-level layers for medical image sub-stringing. Combining the two into a single architecture allows for the elimination of distinct processing steps and the use of integrated message-classification/constraint-based compression, which reduces computational complexity through improved compression performance while simplifying processing accuracy. Experiments using the BRATS MRI and CLEF MED X-ray datasets show that good performance across different modalities may be achieved using an effective yet general approach. The testing findings confirmed the excellent trade-off between picture quality and data reduction provided by this approach, achieving 56.07 dB for PSNR of ROI and 45.12 dB for NROI while retaining an overall compression ratio of 6.73.

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1. INTRODUCTION

The continuous increase in generated and shared medical data has made it more important to develop trustworthy methods for storing and transmitting medical images. X-rays and magnetic resonance imaging (MRI) scans are used for diagnosis, treatment planning, and long-term patient records. However, this enormous amount of data puts strain on network infrastructure and storage [1][2]. A solution to this issue is digital image compression, which tries to compress an image without losing visual information while maintaining the best quality and paying particular attention to the Region of Interest (ROI), which typically encodes diagnostically useful information.The trade-off between great compression efficiency and visual quality is especially crucial for medical applications [3][4].

The three primary streams of current medical picture compression technologies are lossless, lossy, and hybrid approaches. There exist lossless methods that have very low compression ratios but perfect visual fidelity as well. Lossy approaches produce visual artifacts that are unacceptable for medical diagnosis, even though they achieve better compression ratios. To overcome this trade-off, hybrid techniques are employed by fitting lossless compression in ROI regions and lossy compression in non-ROI regions, hybrid techniques aim to address this trade-off [5-6]. However, they come with an additional segmentation and compression step that reduces throughput performance and adds new complexity to the system. Also, nearly all of the existing approaches cannot change other medical imaging modalities by themselves without human editing or re-training when their capacity is required.The lack of unified, adaptive, and computationally efficient compression frameworks that can produce local-regional segmentation solutions while preserving diagnostic quality throughout the full dataset is the key research issue this work attempts to solve. This research presents a sophisticated hybrid neural network approach that results in segmentation and compression together in an end-to-end framework since we need a much larger and more intelligent solution. This approach, which is based on [7-9], uses an auto-encoder-based compression strategy with adaptive compression levels throughout the image, and CNN automatically detects the ROI. Overall, this eliminates the redundancies while enabling a faster and more automated all-in-one form processing pipeline through the pixel quality being focused only on clinically relevant regions. Here we assessed the proposed method on both proprietary datasets and benchmark datasets (CLEF MED 2009 X-ray, BRATS 2015 MRI).

The result demonstrate that the suggested approach achieves superior PSNR (56.07 dB and 45.12 dB, respectively) with a very high compression ratio (6.73), suggesting its effective potential in real-world medical image archiving and telemedicine applications. This study primarily contributes to the development of a single training framework that allows for adaptability to numerous modalities by combining features like segmentation and compression to achieve significant storage savings while maintaining diagnostic accuracy.By combining segmentation and compression into a single neural network architecture, we present an end-to- end hybrid compression system for medical images. The suggested system completes both tasks in a single run, increasing efficiency and scalability, in contrast to current methods that divide both processes and suffer from high complexity and low adaptability. In order to achieve large file-size reduction while maintaining high-fidelity visual quality where it is most crucial, the model uses lossy compression on non-ROI areas and near-lossless compression of diagnostically significant Regions of Interest (ROI) with lossless methods. Additionally, because the segmentation component is modular, it may be readily modified to accommodate different imaging modalities (such MRI and X-ray) by just reusing portions of it rather than retraining the entire network.

A vast amount of digital medical images has been produced as a result of the quick growth of medical imaging technologies including CT, MRI, and ultrasound. Numerous compression methods have been developed due to the increase in data and the desire to maintain diagnostic accuracy. These can be broadly classified into three categories: hybrid, lossless, and lossy [10]. Lossless compression algorithms guarantee that the information in the compressed image will be exactly the same as what was present before to compression after decompression. Although these techniques are useful for medical diagnostics, they are considerably too ineffective for compression. Lossy techniques (JPEG, JPEG2000, and fractal coding) provide a slight deterioration in image quality for comparatively greater compression ratios, which may be more beneficial for general applications than medical ones, where the identification of fine features is crucial and significant indicators of diagnosis [11–12]. The drawbacks of lossless and lossy approaches are addressed by a hybrid technique. One hybrid strategy is to use lossy compression for the NROI and lossless or almost lossless compression for the ROI in order to preserve diagnostically significant information. By incorporating techniques like SPIHT (Set Partitioning in Hierarchical Trees), Wavelet Transform, etc., these systems' performance has been enhanced. Recent years have seen an increase in the use of ANNs for segmentation and compression tasks in medical image processing due to their capacity to learn complex patterns. Since we concentrated on ROI-based techniques, we are aware that a number of models, including Auto-encoders and Multi-layer Perceptrons (MLP), were employed to eliminate redundancy and increase savings. ANNs were frequently used for either image feature extraction or classification in earlier research. However, there is currently no research for dynamic management of both ROI and NROI areas, and only a small number of them have used an ANN-integrated technique directly into the compression process [13–14]. Finally, this work suggests a deep learning-based hybrid compression framework that combines adaptive compression and ROI segmentation into an end-to-end model that comprehensively addresses all of the aforementioned issues with complexity, generalizability, and diagnostic reliability.

2. METHOD

The suggested approach provides a hybrid deep learning-based medical picture compression framework that simultaneously minimizes storage and transmission costs and satisfies the requirement for diagnostically significant areas to be concisely enclosed. It distinguishes ROI from NROI[15][16] by intelligently classifying picture segmentations and compression in the same pipeline. It strikes a good balance between image quality and compression ratio by combining ROI-near-lossless and NROI-aggressive lossy compression. In order to learn from significant portions of an image while it is being compressed, all of the designated neural networks are combined. This method enables us to create low-resolution medical images with a high degree of fidelity in crucial diagnostic domains, which is crucial for real-time diagnostic processes, telemedicine, and medical image archiving. Figure 1 shows a summary of the entire system pipeline, showing how data moves via the segmentation and compression units

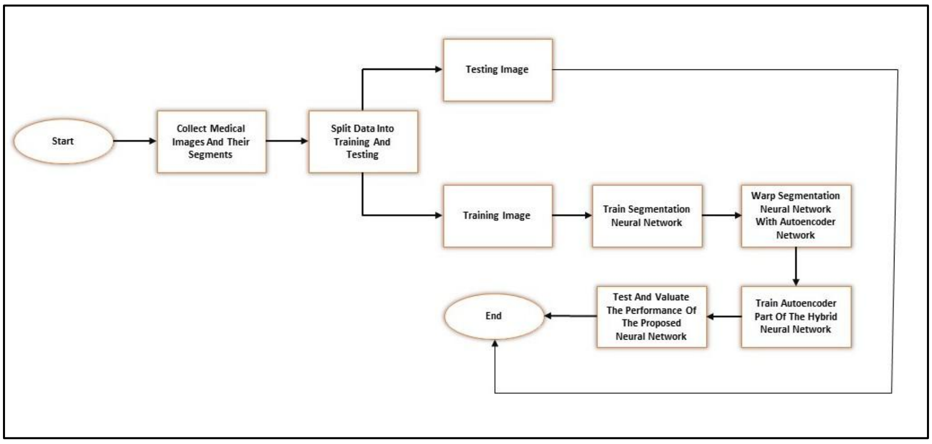

Figure 1. Framework of the proposed methodology
Source : Generated by the authors

The suggested network architecture, the Segmentation Autoencoder (Figure. 1), is made up of two closely related parts: an autoencoder and a segmentation network. We used U-Net, a well-known convolutional neural network architecture designed especially for biomedical picture segmentation, as the segmentation component. This generates a binary mask with each pixel representing the likelihood of being in ROI at the same spatial resolution as the input image. A 256 × 256 × 2 two-channel input tensor is created by concatenating this mask with the original grayscale image. After the input is concatenated, the aggregated vector is fed through an autoencoder that uses several learned convolutional and pooling layers to compress the image into a 32x32x1 bottleneck layer. Before recreating the image, the bottleneck representation is decoded. The network is separated into its encoder and decoder components. The encoder compresses the image while θ are model variables in terms of theta vectors θ, and the decoder uses the compressed representation to reconstruct the normalized version. The bottleneck layer's output is encoded using Huffman entropy coding to reduce redundancy and increase compression efficiency.

One of the fundamental components of this system's segmentation and compression is Artificial Neural Networks (ANN). The negotiated loss is defined in Equation (1) to represent the overall loss.

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

Here, B is the output of bottleneck layer and α=0.8 and β =0.2 are weight parameters given to ROI importance respectively. Definition of SSIM structure similarity index (SSIM) between I1 and I2 is defined as:

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

The constants C_1 and C_2 prevent division by zero, whereas μ and σ represent the mean and standard deviation, respectively. For effective compression, it limits the number of unique values in the bottleneck channel while encouraging the Region of Interest to maintain its comparable appearance. Unlike segmentation weights, which are fixed, the network is optimized with backpropagation [12]; therefore, segmentations should be always detected during training for compression. This architecture retains diagnostic information encoded into the compressed outputs and allows the system to learn generic features shared between many medical imaging modalities.The examination is based on four key metrics. The Peak Signal-to-Noise Ratio (PSNR) [22][23], was chosen as first measure provided by Equation (3), an approximate measure of the quality of reconstructed image.

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

MSE stands for Mean Squared Error between the reconstructed and original images [24] [25]. Equation (4) defines the MSE.

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

Here, MAXI stands for an image's maximum pixel value, and R and I stand for the original image and the reconstructed image (as used in Equation 1). As stated in Equation (5), the second metric is the Structural similarities Index Measure (SSIM), which highlights structural and visual similarities [26].

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

where μ, σ², and σ_IR represent the mean, variance, and covariance of the original and reconstructed images. Use the C_1 and C_2 constants to stabilize the division of two probability distributions. The third metric, known as the Compression Ratio (CR), can be defined using 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 indicate when the compression process began and ended. Finally, the Execution Time (T), described in measures the time required to finish the compression operation. Together, these metrics evaluate the system's capacity to lower storage needs without sacrificing diagnostic image quality. Tables, figures, and dataset comparisons are used in the following sections to discuss the results and interpretations.

3. RESULTS AND DISCUSSION

Experiments And Evaluation Results As well as detailed discussion of the proposed hybrid compression method for medical images Two benchmark datasets, the CLEF MED 2009 [17–19] and BRATS 2015 [20–21], are used with different parameter settings to evaluate. It essentially checks how well this particular system is capable of compression and visual quality, especially considering ROIs.

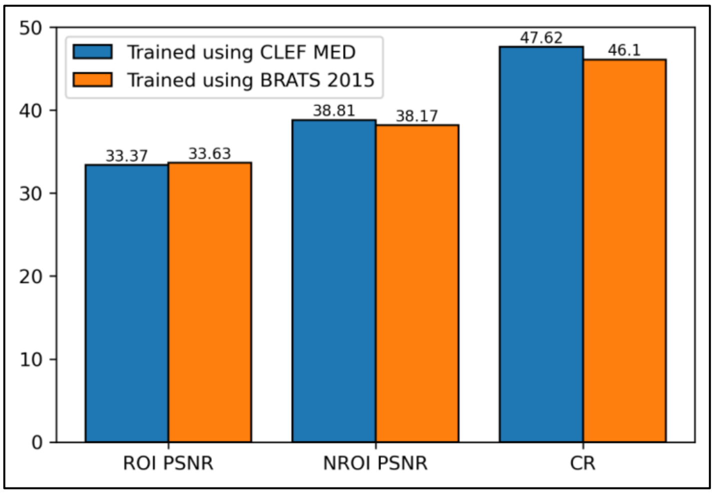

Figure 2. Validation results of the trained autoencoder using the CLEF MED and BRATS datasets.

Source : Generated by the authors

Figure 2 shows the Peak Signal-to-Noise Ratio (PSNR) values from the image that this novel hybrid compression method evaluated. A common metric for comparing the visual quality of compressed or reconstructed images to the original image is the Peak Signal-to-Noise Ratio (PSNR). According to Table [6], image 3 had the greatest PSNR among the several test instances in this investigation, which ranged from 31.11 dB to 38.94 dB. The similarity between the original and related decompressed images is indicated by the values' proximity to one, demonstrating how our suggested approach aids in both the preservation of important visual content and the provision of clinically significant diagnostic data required for medical imaging applications.When such data is usually limited to the ROI or its surroundings. However, in order to demonstrate the correctness of the will reduction approach, the specific PSNR numerical values are rather high.

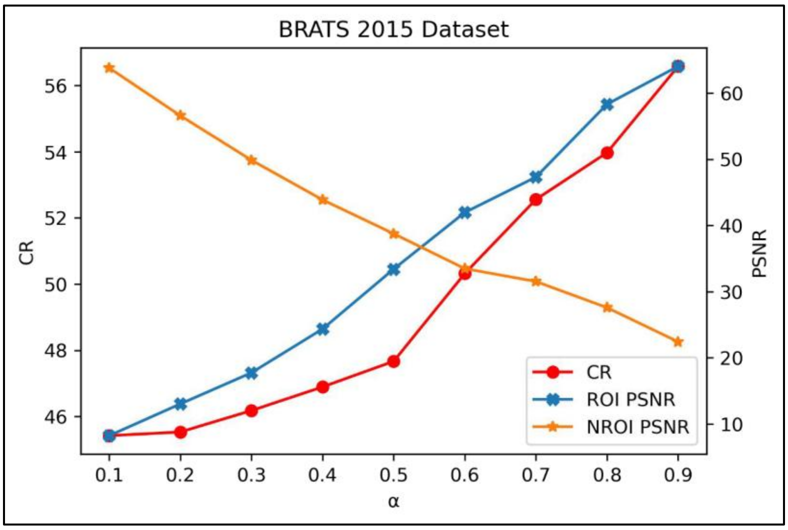

Figure 3. PSNR values of the ROI and NROI versus different values of ∝ using the BRATS 2015 dataset.

Source : Generated by the authors

One of the most crucial metrics that shows how successfully the compression method compresses the data is the compression ratio. Additionally, the ratios displayed range from 4.27:1 to 5.23:1, with Figure. 4 having the strongest ratio. The application of our proposed method for high-quality medical picture compression in key areas is supported by the MSE-based results. Because of its effectiveness and practicality, the method may be used in actual clinical settings where high-quality medical picture compression may be essential. The performance of the hybrid compression approach described in this research on the CLEF MED 2009 and BRATS 2015 datasets is shown in Table 1. Three measures are tested: Compression Ratio (CR), PSNR in ROI, and PSNR in NROI. The α values used to measure these indicators range from 0.1 to 0.9. The table shows that while the PSNR for NROI somewhat falls, the PSNR of ROI grows dramatically as α increases. This suggests that as α rises, ROI quality is preserved more effectively, leading to more aggressive lossy compression on the NROI. Because less aggressive compression is used in that ROI, the Compression Ratio (CR) deteriorates in relation to the global compression. Moreover, it is seen from the table results that for some specific ω values corresponding to α values, BRATS 2015 dataset yields significantly better compression ratios compared to CLEF MED 2009 dataset. This is because the BRATS dataset has a smaller ROI, which leads to more NROI and consequently, higher probabilities of lossy compression. This result demonstrates that the proposed compression method can be customized for different dataset characteristics exploiting a trade-off between efficiencies on compaction and image quality.

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

Source : Generated by the authors based on test result

4. CONCLUSION

Effective image compression methods that can maintain important visual information while reducing storage and transmission costs are required due to the growing reliance on medical imaging for everything from diagnosis to therapy. To perform aggressive lossy manipulations on an NROI while maintaining the ROI losslessly, a novel hybrid compression technique is suggested. Unlike traditional multi-stage approaches, the suggested approach combines segmentation and compression into a single end-to-end hybrid neural net. When suitable hardware resources, like as GPUs, are available, this architecture can decrease the execution time because it is well-suited to parallel processing.This approach's primary benefit is flexibility:

The entire method might be applied to medical pictures (X-rays, MRIs, CT scans) without retraining the autoencoder because the segmentation portion can be updated independently with transfer learning. Through experimental results, we show that the suggested technique can achieve competitive compression ratios while significantly increasing processing time while maintaining high visual quality in specific areas of interest. Next, we construct the suggested system, a high-performance generic solution for medical image compression in contemporary healthcare settings..

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