Indian Engineering Journal
ISSN: 2984-9047
Vol 4 Issue 1 (2026)

Medical Image Compression and CNN Performance: A Systematic Meta-Analysis

Mrs. C. Nandhini[1], Ms. M.Gokila[2], Dr. G.Vijaiprabhu[3]

[1]Research Scholar, PG and Research Department of Computer Science, Erode Arts and Science College, Erode, Tamilnadu,India. Email: ashonanthu@gmail.com

[2]Research Scholar, PG and Research Department of Computer Science, Erode Arts and Science College, Erode, Tamilnadu,India. Email:gokilaeasc96@gmail.com

[3]Assistant Professor, PG and Research Department of Computer Science, Erode Arts and Science College (Autonomous) Erode, Tamilnadu,India. Email: gvprabhu7@gmail.com

Abstract

A Modern medical imaging systems generate a large number of successive images, creating significant challenges for efficient storage and transmission. Imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), and fluoroscopy produce image sequences in which a considerable portion of the image content remains unchanged across successive frames. Conventional lossless compression techniques protect image quality but often achieve limited compression ratios, whereas lossy methods may eliminate clinically significant information. To address these limitations, this paper proposes a near-lossless compression framework designed for sequential medical images. The proposed method identifies static image regions and selectively encodes only the changing regions of interest (ROI) between consecutive images. Successive image subtraction is employed to identify non-zero ROI regions while assigning zero values to unchanged areas, thereby reducing spatial redundancy. Furthermore, a double-coding strategy is incorporated to enrich the overall compression efficiency. Unlike earlier approaches that process fluoroscopy images either individually or as conventional video streams, the proposed technique treats the entire image sequence as a coherent dataset to exploit temporal similarity more effectively. Experimental results obtained from fluoroscopy image datasets validate that the proposed approach achieves an improved compression ratio while maintaining diagnostically important image details. Comparative analysis with existing medical image compression methods shows the effectiveness and potential applicability of the proposed near-lossless framework for medical imaging storage systems.

Keywords: region of interest (ROI), Convolutional Neural Network, Medical Images, Computed Tomography, Compression Techniques.

1. Introduction

The most frequently occurring primary brain tumor is Meningioma, arising from the protective meningeal layers surrounding the brain and spinal cord. It represents approximately 37.6% of all primary brain tumor cases. These tumors can develop at any location within the cranial or spinal meninges and may present with diverse clinical symptoms. Although the majority of meningiomas are benign, a small proportion may show atypical (WHO Grade 2) or malignant (WHO Grade 3) features. Despite being generally non-cancerous, their growth can exert pressure on critical brain structures, leading to neurological complications and, in severe cases, life-threatening conditions. This underscores the importance of accurate and timely diagnosis along with effective treatment planning.

Magnetic Resonance Imaging (MRI) is the most widely used technique for the detection and evaluation of meningiomas. Its superior soft tissue contrast enables precise assessment of tumor size, location, and its relationship with adjacent brain or spinal structures. With recent advancements, there is an increasing need for systematic reviews and meta-analyses to evaluate the effectiveness of Convolutional Neural Network (CNN) models in meningioma MRI segmentation. Previous reviews have mainly focused on other brain tumors such as malignant gliomas and brain metastases. Therefore, this study specifically targets meningioma segmentation to compile existing evidence, identify research gaps, and guide the development of more reliable and standardized CNN models.

The primary aim of this review is to evaluate the accuracy, precision, and reliability of CNN-based methods for meningioma MRI segmentation. To achieve this, the methodological quality of relevant studies was critically analyzed to ensure the credibility of the findings. In addition, key factors influencing model performance—such as CNN architecture, variability in training datasets, and evaluation strategies—were examined. Overall, this systematic review and meta-analysis seeks to provide insights into current approaches and offer recommendations to enhance segmentation performance, accuracy, and standardization.

2. Literature review

The outstanding performance of learnt image compression approaches, which have lately outperformed the best manually designed lossy image coders and have the potential to be widely adopted, is discussed [5]. The authors stress how crucial it is to look at the architecture design of learnt image compression in terms of speed and performance for real-world use. Motivated by energy compaction in learnt picture compression, they suggest unequal channel-conditional adaptive coding. The researchers create a spatial-channel contextual adaptive model that improves coding performance without compromising speed by combining this uneven grouping model with pre-existing context models. Furthermore, He et al. present ELIC, an effective model that reaches cutting-edge compression and speed performance [6]. Learning-based image compression is now more feasible for future applications because to ELIC's incredibly quick preview and progressive decoding capabilities.

According to learnt image compression techniques—the majority of which are based on Convolutional Neural Networks (CNNs)—have demonstrated better rate-distortion performance when compared to conventional standards[7]. The quality of reconstruction is impacted by CNNs' inability to capture local redundancy and non-repetitive textures, according to the authors. Inspired by Vision Transformer (ViT) and Swin Transformer, Zou et al. combine global feature learning with local-aware attention techniques to solve this problem. They improve on the CNN and Transformer models by introducing a versatile window-based local attention block. Additionally, a new Symmetrical Transformer (STF) structure with transformer blocks in the encoder and decoder is proposed. Numerous tests show that their approach is more efficient and superior to cutting-edge methods [8].

A framework for end-to-end optimal lossy picture compression utilizing diffusion generative models is presented. Their method uses a conditional diffusion model for decoding, in contrast to VAE-based neural compression, which uses a deterministic neural network [9] decoder. Use “texture" variables that are synthesized at the time of decoding and introduce a "content" latent variable to condition the reverse diffusion process. Perceptual measurements can be used to adjust the performance of their framework. Numerous tests demonstrate that their method outperforms GAN-based models in terms of FID scores and performs competitively with VAE-based models in terms of distortion metrics [10]. Practicality is increased by training the diffusion with X parameterization, which produces high-quality reconstructions in a small number of decoding steps.

The important developments in medical image processing made possible by Artificial Intelligence (AI) solutions, especially deep neural networks, are reviewed. They concentrate on creating automated tools to help doctors diagnose conditions like bone cancer, breast cancer, brain tumors, and fractures. In addition to highlighting recent developments in deep neural network-based medical imaging [11], Mall et al.'s thorough study offers a summary of the literature, data sources, and potential avenues for future research.

An technique to image compression employing transform-based coding, encoding, and integer execution entropy was presented. Using color photographs, this method has been evaluated and contrasted with the current methods. First, the chrominance and luminance color components, or YCbCr, have been subjected to the Discrete Cosine Transform (DCT) method. Second, the YCbCr color components are quantized using a conventional quantization [12]. After the quantization process, the coefficients are subjected to zigzag scanning order. Finally, to achieve the best compression results, the image is encoded using an entropy encoder called an arithmetic encoder.

LindeBuzo-Gray (LBG), a vector quantization technique [13], has been employed to reduce the size of the codebook. An optimization issue solution is derived using a bio-inspired technique. To generate an effective codebook, the Lempel Ziv Markov Technique (LZMA) is coordinated with the Lion Optimization Approach

(LOA). The line optimization process is used to create an ideal codebook [14], and the LZMA approach is used to reduce its size. The study reports a compression ratio of 0.3425375 and a peak signal noise ratio of 52.62459.

3. Proposed work

3.1. Compression Technique

The compression scheme used in this work is discussed in this section. It relies on several key steps, including image separation into ROI and non-ROI areas, lossy compression for non-ROI, ROI detection by subtracting consecutive images, ignoring insignificant differences, and double-coding compression for ROI areas. Fig. 1 depicts the full suggested compression scheme. The ROI area is extracted from DICOM images, and the subsequent ones are subtracted in this figure. RLE and Huffman's methods are used, respectively, after ignoring insignificant variations, and CR values are then doubled. The compressed object is created by combining the outcomes of the Double-CR process with non-ROI sections that have been compressed using lossy compression techniques.

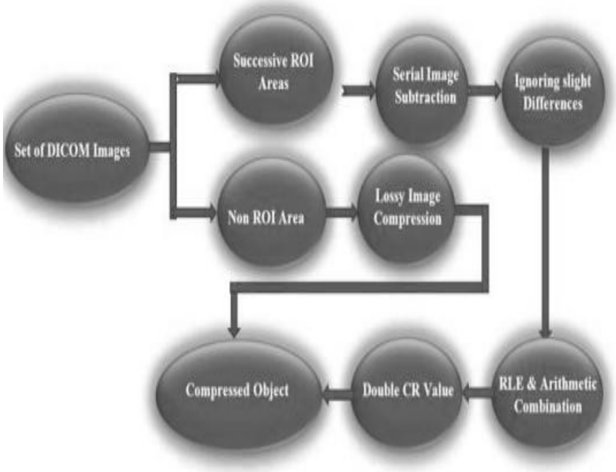

Figure 1: An overview of the suggested compression method for the DVF picture

This approach prefers to compress the differences between the subsequent images rather than compressing each individual image. The majority of the subtracted values will be zeros since the ROI area contains comparable areas, and the non-zero values are concentrated in the fluid-motion area. Figure 2 demonstrates that non-zero values are observed within fluid motion zones, while the majority of removed image data are transformed into zero values (black areas). Instead of the original values, the values within the fluid-motion area show the discrepancies between the corresponding values of the removed images.

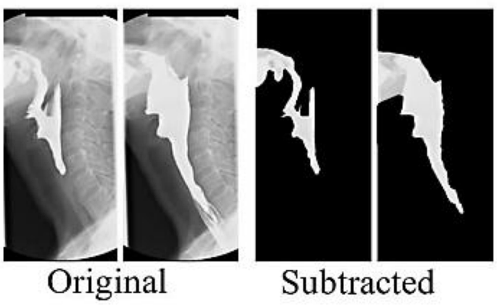

Figure 2: Values in the removed area of the image were changed to zeros.

There are two main steps involved in identifying picture changes across sets of DICOM images. Finding the differences between each image and the reference (the first image in the series) while taking into account motion variations from the patient's first case is the first step. Finding the difference between each of the next two photos while taking the patient test's update difference into account is the second step. There are benefits to each surgery; the first offers specific modifications to the patient's initial scenario. With more zeros in distinct photos and maximum similarity, the second one provides a greater CR by measuring the differences between too-close images. The correlation between DICOM images, which is determined using the Cross Correlation coefficient $r_{x,y}$ and the following function, justifies the last one:

$$r_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \mu_x)(y_i - \mu_y)}{\sum_{i=1}^{n}(x_i - \mu_x)^2 \sum_{i=1}^{n}(y_i - \mu_y)^2} \qquad (1)$$

Where n is the number of pixels in each image, μ_y, μ_y are the average of the pixel values in both images, and x_i, y_i are the pixel values from the removed images. Achieving the highest CR feasible for more effective compression performance is the main goal of this stage. Two distinct compression strategies are used in this paper. Since increasing CR regardless of included (nonrelative) information is the main aim, let's start with lossy compression for the non-ROI sections. The authors employed a rapid manner of Discrete Cosine Transform (DCT) to remove the bulk of zeros while maintaining value position for this type of compression, adopting one of the most recent developments of the standard Joint Photographic Experts Group (JPEG).

4. Medical Image Formats

Standardized information about how a computer file contains an image is provided by medical image file formats. The structure of picture data within the file and the way software can interpret pixel data for appropriate stacking and projection are both described by the image file format. There are primarily two kinds for medical image file formats. The first one, Dicom, is standardized as a diagnostic modality, and the second one aims to simplify and improve post-processing analysis.

4.1. Dicom

The National Electric Manufacturers Association and the American College of Radiology collaborated to create the Dicom standard. Nowadays, every medical imaging department uses the Dicom standard. Dicom was the first file format to realize that the definition of the medicine that produced the image could not be isolated from pixel information. Dicom supports image compression. Dicom provides compression methods for JPEG, JPEG_2000, JPEG_LS, MPEG_2, MPEG_4, and run length encoding (RLE).

4.2. Minc

The Montreal Neurological Institute (MNI) developed the Minc file format in 1992 in order to have a versatile file type for diagnostic imaging. The original version of Minc_1 was based on the Net_CDF standard. In order to overcome the limitation of helping with massive data documents and incorporate significant enhancements, Minc's production team decided to switch from Net_CDF to HDF_5. The latest version, Minc_2, was incompatible with the previous one.

4.3. Analyze.

In the late 1980s, Analyze_7.5 was initially developed at the Mayo Clinic in Rochester, Minnesota, as a format for the for-profit Analyze program. The "de facto" format for post-processing medical photographs was the norm. for almost ten years. Because it was designed for multidimensional data (volume), the Analyze format represented a significant advancement. A voxel raw data image file with the extension ".img" plus a header document of metadata with the extension ".hdr." comprise an Analyze 7.5 version.

4.4. Nifti

It appears that a National Institutes of Health team created the Nifti file extension in the early 2000s with the goal of developing a neuroimaging format that preserves the benefits of the Analyze standard while removing its drawbacks. Analyze does not support data types like unsigned-16_bit, but Nifti does. The majority of images are saved as a single ".nii" file that contains both header and pixel information, even though the header and pixel data must be kept in different files.

5. Result analysis

The purpose of this work's studies was to compress medical DVF photographs taken of the esophagus and pharynx. A variety of metrics, including PSNR, CR, and cross-correlation (Equation 1), were used to assess the experimental outcomes. The PSNR metric was developed to assess the quality of restored images following the deployment of various applications.

$$CR = \frac{Original\ Data\ Size}{Compressed\ Data\ Size} \qquad (2)$$

In image compression, lossy and near-lossless compression are typically used to assess the restored image. It relies on Mean Squared Error metrics (Equation 3) that quantify the variations between the original (O_{im}) and restored (R_{im}) pictures; for lossless compression, these metrics should be zero.

$$MSE = \frac{1}{M \times n} \sum_{i=1}^{N} \sum_{j=1}^{M} (O_{im} - R_{im})^2 \qquad (3)$$

$$PSNR = 20 \log_{10} \left(\frac{MAX_0}{\sqrt{MSE}} \right) \qquad (4)$$

in which MAX_0 is the original image's maximum pixel value. In lossless compression, where $MSE = 0,\ PSNR = \infty$, a greater PSNR (Equation 4) results in a larger similarity between the original and restored images. However, in various sources, a PSNR of 30 to 50 is deemed appropriate. Because of the large number of sequential values (0's), this research suggests using RLE instead of Huffman coding. On 65 sets of DVF pictures, the best and average PSNR values were obtained by applying various RLE and Huffman combinations. Sets of ignorable values in various photos show pixel value changes that are negligible or capturing faults. Although the majority of these values fall between 1 and 3, there are still some larger variations. The PSNR value drops as the produced CR rises when bigger differences are ignored, suggesting some distortion in the decompressed images. PSNR values were obtained by ignoring more than three decreases. PSNR and CR values, as well as 1–7, are explained in Fig 3. When more than three is ignored, the PSNR value falls in response to negligible increases in CR values.

In contrast adjustment, two 8-bit bytes are concatenated into one byte by converting them into 4-bit integers. By halving the size of the compressed data, this procedure doubles the compression performance as measured by CR values. The findings demonstrated that reducing an 8-bit byte to less than 4-bit values raises the complexity of the compression strategy and lowers the generated PSNR values. Conversely, there was no discernible increase in CR values.

Table 1: CR and $r_{x,y}$ values for two subtraction ways

DVF Images	Successive Diff.		Reference Diff.	
	CR	$r_{x,y}$	*CR*	$r_{x,y}$
1.	39	0.94	39	0.94
2.	40	0.96	40	0.92
3.	41	0.97	38	0.88
4.	45	0.95	37	0.91
5.	47	0.95	36	0.87
6.	48	0.96	37	0.9
7.	48	0.95	36	0.91
8.	49	0.97	35	0.92
9.	50	0.97	36	0.91

The suggested compression strategy produced better results when compared to previously published publications, achieving the best compression rate with a particular specified DVF (54.31). This work recorded a PSNR of 50.52 with a PSNR of 51.98 db, which is the average performance for all DVF picture sets examined. Table 1 lists the results of past medical picture compression studies that solely used near lossless image compression, ignoring lossy and lossless compression methods for face comparison.

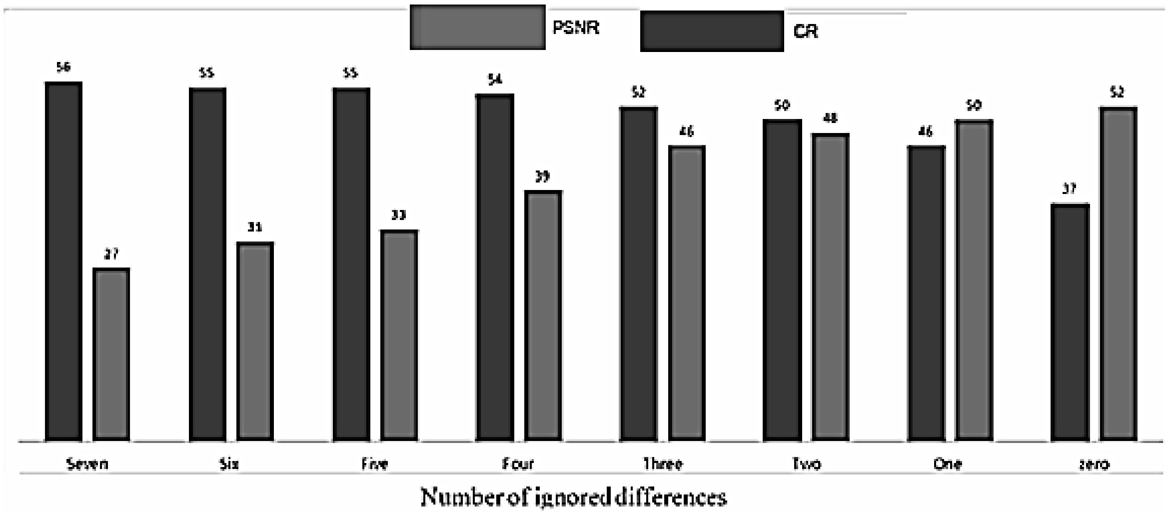

Figure 3: The quantity of overlooked variations and how they affect CR and PSNR

6. Conclusion

This article reviews various research efforts in medical image compression that have contributed to solving medical challenges and improving clinical capabilities. Some studies have used individual compression techniques, while others have adopted hybrid methods to achieve higher compression ratios without compromising efficiency. These approaches have significantly benefited the healthcare sector, and their contributions are highly valuable.

Despite extensive research, several challenges in this field still remain unresolved. Moreover, most previous work has primarily focused on two-dimensional medical images. As a result, there is a growing need to develop efficient compression techniques specifically designed for three-dimensional medical imaging.

References

[1] Singh, Upasana, and Manoj Kumar Choubey. "A Review: Image Enhancement on MRI Images." In 2021 5th International Conference on Information Systems and Computer Networks (ISCON), pp. 1-6. IEEE, 2021.

[2] S. A. B. Aziz et al., "A Performance Review for Hybrid Region of Interest-Based Medical Image Compression," IEEE Access, vol. 11, pp. 98025–98038, 2023, doi:

[3] 10.1109/ACCESS.2023.3312265.

[4] S. Jamil, M. J. Piran, M. U. Rahman, and O. J. Kwon, "Learning-driven lossy image compression: A comprehensive survey," Eng. Appl. Artif. Intell., vol. 123, p. 106361, 2023, doi: 10.1016/j.engappai.2023.106361.

[5] M. A. Rahman, M. Hamada, and J. Shin, "The impact of state-of-the-art techniques for lossless still image compression," Electron., vol. 10, no. 3, pp. 1–40, 2021, doi: 10.3390/electronics10030360.

[6] U. Singh and M. Kumar, "A Review: Compression on Medical Images," A Rev. Compression Med. Images Artic. Int. J. Eng. Tech. Res., vol. 11, pp. 103–109, 2022, doi:10.17577/IJERTV11IS040058.

[7] D. Gowda V et al., "A novel method of data compression using ROI for biomedical 2D images," Meas. Sensors, vol. 24, p. 100439, 2022, doi: 10.1016/j.measen.2022.100439.

[8] H. Abdellatif, T. E. Taha, R. El-Shanawany, O. Zahran, and F. E. Abd El-Samie, "Efficient ROIbased compression of mammography images," Biomed. Signal Process. Control, vol. 77, p. 103721, 2022, doi: 10.1016/j.bspc.2022.103721.

[9] B. Pervan, S. Tomic, H. Ivandic, and J. Knezovic, "MIDOM—A DICOM-Based Medical Image Communication System," Appl. Sci., vol. 13, no. 10, p. 6075, 2023, doi:10.3390/app13106075.

[10] He, D., Yang, Z., Peng, W., Ma, R., Qin, H., & Wang, Y. (2022). Elic: Efficient learned image compression with unevenly grouped space-channel contextual adaptive coding. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 5718-5727).

[11] Zou, R., Song, C., & Zhang, Z. (2022). The devil is in the details: Window-based attention for image compression. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 17492-17501).

[12] Yang, R., & Mandt, S. (2024). Lossy image compression with conditional diffusion models. Advances in Neural Information Processing Systems, 36.

[13] Mall, P. K., Singh, P. K., Srivastav, S., Narayan, V., Paprzycki, M., Jaworska, T., & Ganzha, M. (2023). A comprehensive review of deep neural networks for medical image processing: Recent developments and future opportunities. Healthcare Analytics, 100216.

[14] Yousif, R. I., & Salman, N. H. (2021). Image compression based on arithmetic coding algorithm. Iraqi Journal of Science, 329-334.

[15] Sowmyalakshmi, R., Waly, M. I., Sikkandar, M. Y., Jayasankar, T., Ahmad, S. S., Rani, R., & Chavhan, S. (2021). An Optimal Lempel Ziv Markov Based Microarray Image Compression Algorithm. Computers, Materials & Continua, 69(2).