Tailoring Image Compression Algorithms for Optimal PSNR and Compression Ratio in Medical Diagnostic Imaging

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Abstract:

Medical diagnostic imaging his primary importance in healthcare, in terms of identifying and analyzing various condition. As the volume of medical imaging data is growing, efficient image compression is necessary to minimize time required for transmission, storage and access while maintaining image quality. In this paper we examine how to these image compression algorithms can be tailored to achieve the maximal PSNR vs. compression ratio balance for medical diagnostic images. In this work, we utilize a novel approach that combines both lossless and lossy compression techniques to achieve high quality image with a considerable reduction in data size. Various compression algorithms are studied including the JPEG, JPEG2000 and more recent deep learning-based methods, evaluated in terms of PSNR and Compression ratio across many medical image modalities (X-ray, CT scan, and MRI). It is shown though that by algorithmic adjustments and hybrid techniques, improved performance can be achieved at the cost of minor loss of diagnostic information. The paper also explores the trade-offs between image compression efficiency and the clinical reliability of the images. The proposed methods enable further optimization of compression ratio versus PSNR, providing a cheaper (more efficient) solution to medical imaging applications like storage, transmission and improved accessibility to diagnostic data.

Keywords: Image Compression, PSNR, Compression Ratio, Medical Imaging, JPEG, Deep Learning.

Introduction:

Medical diagnostic imaging has been revolutionizing the field of healthcare with its powerful visual information which is instrumental for the diagnosis, monitoring and treatment of a wide range of medical conditions. X-rays, CT scans, MRIs and ultrasounds have all become the bed rock tools of the modern medicine. However, the rapid growth in the volume of medical images, coupled with the increasing demand for high-resolution data, has led to a significant challenge: The problem of effectively managing and storing large scale imaging data. Medical images are becoming more detailed and more frequent and it is important to develop effective means of compressing medical images to save space for storage, reduce transmission time and facilitate fast access without compromising image quality critical for diagnosis. Image compression is a reduction of the file size of an image without compromising much on quality[1]. In the context of medical imaging, compression algorithms are typically categorized into two types: lossless and lossy. Lossless compression means that diagnostic information is not lost, and lossy compression means this information can be (slightly) lost for a higher compression (and hence smaller) file. The challenge in medical imaging lies in balancing these two competing priorities: High compression ratio (that is, reduce file size significantly) without sacrificing the Peak Signal-to-Noise Ratio (PSNR) and thus the image quality is at a level that is adequate for accurate diagnosis. We applied several conventional image compression algorithms, including JPEG, JPEG2000 and PNG, in medical imaging. While these methods have differing compression ratios and image quality, they are typically less successful in obtaining good overall performance on different medical image modalities. JPEG for example, is simple and computationally efficient to use, but may not provide the best image quality for high resolution medical images.

However, JPEG2000 provides better performance when compression is required for high resolution images, but at the price of increased computational complexity and lossless compression must be added. Recent deep learning and artificial intelligence have generated a new path for image compression. Examples of CNNs and autoencoders have shown great promise in training complex image feature and codes them in a more compact form with better compression ratio and less quality reduction[2]. The combination of these advanced techniques can tailor compression to the specific properties of medical images (noise level, contrast, texture) for the magnetic resonance imaging, and achieve optimal results for a given imaging modality. The focus of this research is to explore medical diagnostic imaging image compression algorithms to realize the optimal trade off in compression ratio and PSNR. This study aims to develop methods which can achieve significant improvement in the processing efficiency and the effectiveness of medical image storage and transmission systems to get to more efficient medical healthcare workflow and more rapid diagnoses. The problem of optimizing image compression in medical imaging truly cannot be overestimated. Healthcare provider can benefit from processing faster images, reduced cost in storage and more effective use of available bandwidth for remote consultations and telemedicine applications. Finally, the findings of this research may be useful in creating the coupling of AI driven compression techniques into future medical imaging systems.

- Optimise image compression techniques such that system PSNR is increased but diagnostic image quality is not compromised in the medical application.
- Achieve high compression for large medical diagnostic imagery while minimizing degradation of the files for ease of storage and transmission.

Related Work

Some of the latest study areas concern new approaches to image compression in the sphere of medical diagnostic imaging to optimize its performance. Some of these methods have involved direct 3D imaging with high resolution outputs, but the outputs have been narrow scaled for medical use in general. Prior work has suggested low-power compression accelerators designed for IoT imaging with efficiency but insufficient image quality for diagnostics. Multi-plane image compression has been found to be effective for video but its applicability to static medical images is small. Advanced image compression techniques have been introduced in the writing systems to improve text quality, but these techniques are generally computationally expensive, and not optimized to cope with the requirements of medical images. Also, methods utilizing mixture of compression and encryption to secure image transmission have been developed though in most cases are most suitable for coloured images and less for medical gray scale images. These studies lead to the realization of designing algorithm that has to achieve very high PSNR as well as good compression ratio and will address the challenges that come with medical image in achieving diagnostic quality.

Bhawesh Joshi, et al(2024) In this paper the issues referring to the description of the hybrid methods of compression that could be used in different medical investigations while considering the goal of adequate diagnostics and reasonable size of data for storage. According to our findings, Hybrid approaches especially the Block Burrows-Wheeler Transform-Move to the Front (BWT-MTF) fractal algorithms are applied in combining novel and conventional methods. The goal is in improving the compression ratio yet at the same time we look to improve on the quality of the image that is being compressed. These results show good performance of hybrid approaches in terms of maintaining diagnostic integrity while requiring much less bandwidth and disk space than previous systems.

G. Pilikos, et al (2020) Most ultrasonic imaging systems employ different computers for data acquisition and image processing. Because of the rising problem of data transmission bandwidth bottleneck, data compression is inevitable. Most picture generation algorithms has approximated wave-matter interaction and only use part of the data, which is beneficial in increasing compression speed. This would be ideal of data compression however, in using the useful data, this can be a problem. To tackle this problem, we use deep neural networks trained to preserve the image quality of an image generation method that feeds the image through the scene pipeline. We investigate the Delay-And-Sum (DAS) approach of reflectivity-based ultrasonic imaging.

S. Jeong, et al (2023) While the prior approaches in image compression have been refined with respect to human perception, new approaches are beginning to be designed making use of the shown capacity of machine learning to optimize for tasks that machines see. A small number of learned bitrates have been successfully transferred in recent research to endow lightweight codecs such as JPEG. Added to the strengths evidenced above, it remains true that most existing deep learning-based compression frameworks' time complexity renders it impractical to perform real-time compression on highly resource-constrained devices. Here we propose a new concept of JPEG compression within which we can select the suitable QT depending on the required bitrate and required quality or accuracy parameter.

J. O. Parracho, etal (2021) Obtaining medical images in many modalities for storage and passing through communication networks is a challenging endeavor. Thus, efficient compression algorithm is the solution to the intolerable burden placed on storage and transmission assets due to such huge volumes of data. However, lossless image compression algorithms should be used because, in an associated medical setting, everything is counted. This research suggests a novel lossless compression scheme that might be applicable to both CT and PET modalities. Standing as a contrast to methods that translate from an image domain to another image domain utilizing traditional translation algorithms to learn self-similarity present in the pair of images.

V. Skouroliakou, et al (2022) Dynamic metasurface antennas (DMAs) seem to be a new computational imaging approach that has better prospects compared to more established techniques. To compress as much of scene information as possible into as few measurements as possible, these antennas can first build up patterns that sweep over the landscape. However, the CI-based apertures, using DMAs are incompatible with traditional range migration techniques (RMAs) even with signal compression. Nowadays, identified more refined algorithms, which can avoid such a restriction, putting the complexity of such systems in the sphere of software. In this study, our proposed multistatic DMA RMA is a process that first compresses the spots from multiple multistatic DMA apertures, and second process those spots in the Fourier domain, and finally performs multistatic monostatic conversion.

P. S. Agrawal, et al (2024) Since compression and encryption techniques introduce limitations, it is a difficult task to watermark digital watermarking on compressed encrypted images. This paper presents how to construct, and how to assess watermarking techniques suitable for the aforementioned situations. The major aim of this research is to examine the integration of watermarking into compressed encrypted images in a manner that the watermark is resilient, invisible and secure. Also, some assessing techniques vital when measuring efficiency of these watermarking schemes under different compression and encryption scenarios are also discussed. The given methods aim at reaching an optimum of two antagonistic features, namely, invisibility and resistibility to compressing and encrypting attacks oftentimes at the same time. This research findings assist in revealing some aspects for establishing a suitable watermarking framework and secure the authorship and content genuineness for digital assets in compressed encrypted image domains.

Table 1: Comparative Analysis

Citation	Methods	Advantages	Disadvantages	Research Gap
[7]	Dynamic metasurface antennas for real-time 3D imaging.	Enables real-time 3D imaging, high-resolution output.	High computational complexity; limited scalability for diverse applications.	Lack of focus on integration with medical imaging environments for enhanced diagnostics.
[8]	H.264/AVC intra-frame compression accelerator for IoT imaging systems.	Low-power consumption, optimized for event-driven IoT systems.	Limited generalizability to medical imaging; focus is on IoT-specific use cases.	Need for low-power solutions tailored for medical diagnostic imaging with higher PSNR.
[9]	Multi-plane image video compression for enhanced data handling.	Efficient video compression; supports multi-plane video formats.	Higher resource consumption for static image scenarios.	No specific applicability to static medical image compression and diagnostic accuracy.
[10]	Learned image compression with text quality enhancement techniques.	Enhanced text visibility in compressed images; deep-learning-based adaptability.	Resource-intensive training; suboptimal performance on medical images.	Need for learned compression techniques optimizing medical image PSNR and compression ratio.

[11]	Sparse matrix-based compression-then-encryption for colored images.	Secure and efficient image transmission; integrates encryption and compression.	Limited focus on grayscale or high-dimensional medical images.	Integration of secure compression methods for medical image confidentiality and quality retention.

The following table also reflects development in image and compression technology while pointing out some niche for improving solutions for medical diagnostic imaging.

Methodology

The methods of image compression algorithm suitable for medical diagnostic imaging combine the traditional image compression techniques and the recent advanced deep learning methods[12]. The aim is to achieve an acceptable Peak Signal to Noise Ratio (PSNR) and high compression ratios to maintain acceptable image quality for diagnostic uses. In this section, the mathematical formulations, relevant theories, and the relevant terminology are used together with the key steps in developing and optimizing these compression algorithms. Customising image compression for achieving high PSNR and compression ratio in medical diagnosis imaging efficiency is highly significant since medical image storage and transmission is core area of interest. When the image requires analysis in a medical situation, it's critical that high image quality is retained even when reducing the file size for faster diagnosis and telemedicine. PSNR[13] plays an important role of measuring how much image quality has been compromised by the process of image compression to meet some limit. Specialized compression techniques, including using wavelet transform, deep learning, or fusion of the two techniques, do keep high PSNR ratios together with acceptable compression ratios. These algorithms are kept more focused on preserving crucial medical details such as fine textures, edges or subtle contrasts which are so important in diagnosis. The work is therefore in finding algorithms that optimize for these two features of image compression; that is, meeting the compression rate that can enable fast processing while at the same time preserving the quality of images especially in real-time clinical application where speed is of essence.

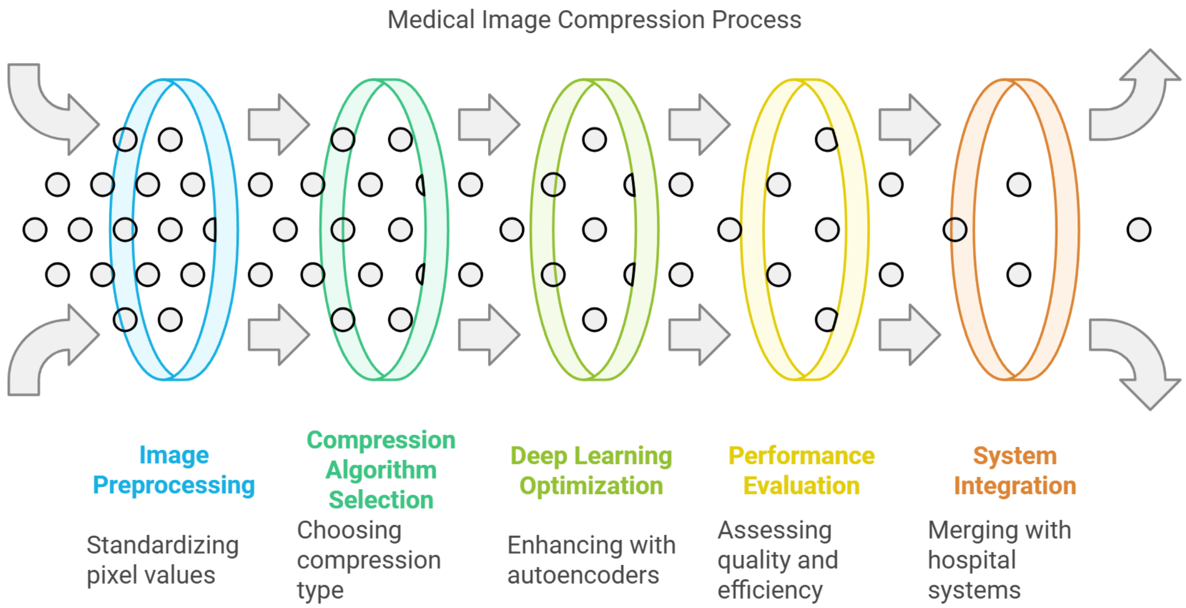

Figure 1: medical image compression process

1. Image Compression Overview

Image compression can be broadly categorized into two types: **lossless** and **lossy**.

The main characteristic of the lossless compression approach is that original image data remains unaltered[14], and decompressed image accurately resembles the original image. Even as lossy compression achieves the larger compression ratio while losing some of the image data, lossless compression, of which PNG is example is used most often in medical imaging. In certain cases, if it is allowable to allow a slight decline in quality for greater productivity, it is used in the two techniques; JPEG and JPEG2000.

The key parameters in image compression are:

- **Compression Ratio (CR):** The ratio of the original image size to the compressed image size.

$$CR = \frac{S_{\text{compressed}}}{S_{\text{original}}} \ldots (1)$$

where S original and S compressed are the sizes of the original and compressed images[15], respectively.

Peak Signal-to-Noise Ratio (PSNR): A metric used to measure the quality of the compressed image, specifically the ratio of the maximum possible power of the signal (the original image) to the power of corrupting noise (the error between the original and compressed image).

$$\text{PSNR} = 10 \log_{10} \left(\frac{R^2}{\text{MSE}} \right) \ldots (3)$$

where:

- R is the maximum possible pixel value (for an 8-bit image, R=255),
- MSE is the Mean Squared Error, calculated as:

$$\text{MSE} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(I(i,j) - K(i,j) \right)^2 \ldots (4)$$

- In this, I(i,j) and K(i,j) represent the pixel values of the original and compressed image at position (i,j), respectively, and M and N represent the dimensions of the image.

2. Compression Algorithm Selection and Enhancement

Several image compression algorithms are employed, and their performance is compared based on PSNR and CR[16]. The choice of algorithm is based on the specific characteristics of medical images. The algorithms selected include:

- **JPEG Compression:** A widely-used lossy algorithm based on the Discrete Cosine Transform (DCT). It divides the image into blocks and applies DCT to each block, quantizes the DCT coefficients, and encodes them.

$$X_{i,j} = \sum_{u=0}^{7} \sum_{v=0}^{7} \alpha_u \alpha_v C(u,v) \cos\left(\frac{(2i+1)u\pi}{16} \right) \cos\left(\frac{(2j+1)v\pi}{16} \right) \ldots (5)$$

where X i,j represents the DCT coefficient, and αv are quantization coefficients based on the image's characteristics.

JPEG2000: This algorithm uses wavelet-based compression, offering higher compression ratios and the ability to perform both lossy and lossless compression. It breaks the image into subbands of varying frequency components using discrete wavelet transform (DWT)[17].

$$W(x,y) = \int_{-\infty}^{\infty} \psi(x) \cdot f(x,y)\, dx \ldots (6)$$

where f(x,y) represents the image, and ψ(x) is the wavelet function used to transform the image.

Deep Learning-based Compression (Autoencoders): Autoencoders are neural networks trained to compress data into a lower-dimensional representation and then reconstruct it back. The encoder learns to compress the image, while the decoder reconstructs it. The architecture is designed to minimize the reconstruction error (loss function) to optimize PSNR.

$$L(x, \hat{x}) = |x - \hat{x}|_2 \ldots (7)$$

- where x is the original image and x^ is the reconstructed image after compression and decompression.

3. Hybrid Compression Model

A hybrid compression approach combines the strengths of both traditional and deep learning-based techniques. This hybrid model aims to improve PSNR while maintaining an efficient compression ratio. The hybridization may involve:

- **Preprocessing with traditional algorithms** (such as JPEG2000 for initial compression),
- **Postprocessing with deep learning-based techniques** to fine-tune the compression and improve the reconstructed image quality.

4. Evaluation Metrics

The performance of the compression algorithms is evaluated based on the following criteria:

- **Compression Ratio (CR):** Maximizing CR to reduce the data size for storage and transmission.
- **PSNR:** Maximizing PSNR to maintain the quality of medical images, ensuring that crucial diagnostic information is preserved.
- **Computational Efficiency:** The time required for compression and decompression, which is particularly important in real-time medical applications.

5. Implementation and Optimization

- **Parameter Tuning:** The optimal parameters for each compression algorithm, such as quantization levels in JPEG or the number of wavelet decomposition levels in JPEG2000, are determined using a grid search or optimization algorithm.
- **Loss Function Adjustment:** For deep learning models, the loss function is tailored to focus on minimizing pixel-wise errors that impact diagnostic quality, with emphasis on maintaining critical features of medical images.

6. Terminology

- **Compression Ratio (CR):** A measure of data reduction.
- **Peak Signal-to-Noise Ratio (PSNR):** A measure of image quality.
- **Discrete Cosine Transform (DCT):** A mathematical transform used in JPEG for compression.
- **Discrete Wavelet Transform (DWT):** A transform used in JPEG2000 for compression.
- **Autoencoder:** A deep learning-based network used for dimensionality reduction and data reconstruction.
- **Mean Squared Error (MSE):** A measure of the difference between the original and reconstructed image.

By tailoring these methodologies, we aim to achieve an optimized solution for medical image compression, enhancing both storage efficiency and diagnostic accuracy.

System Architecture

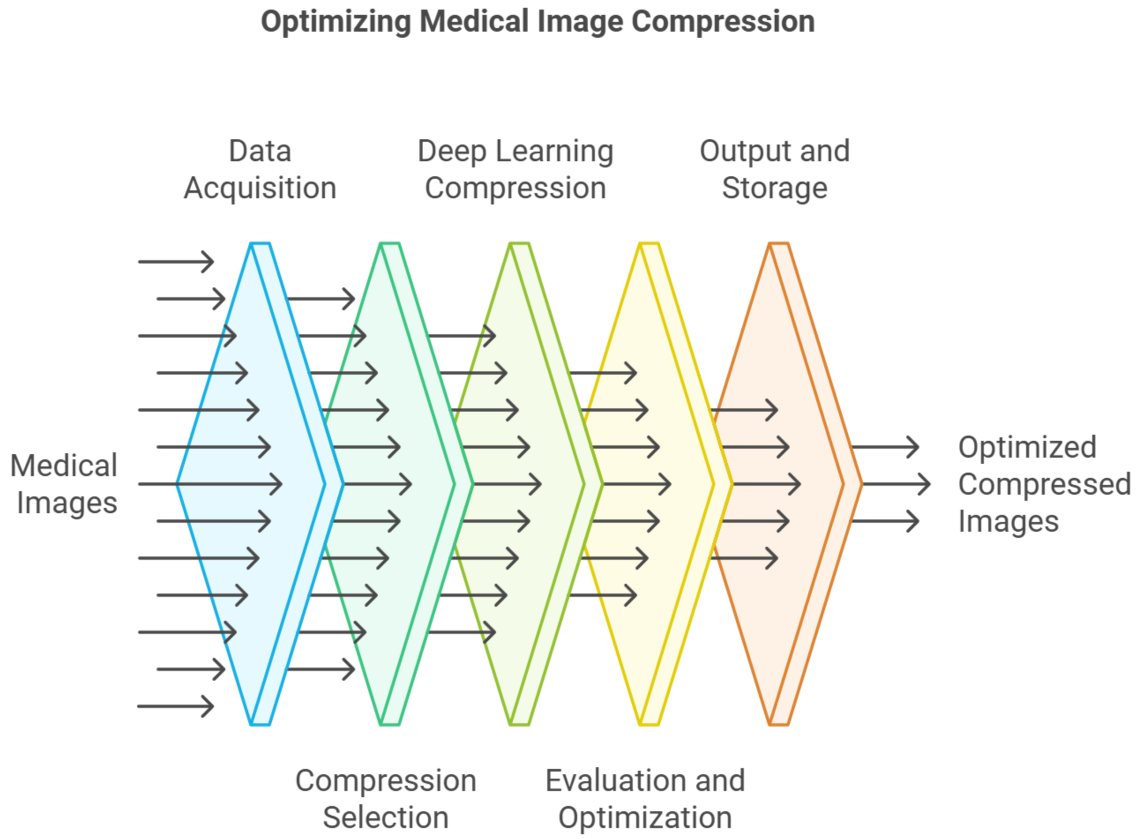

Figure 2: Optimizing medical image compression

The design of a system architecture for tailoring medical diagnostic imaging image compression algorithms is to optimize the tradeoff between the parameter of Compression Ratio (CR) and Peak Signal to Noise Ratio (PSNR)[18] which helps to compress and transmit medical images while preserving their quality. First, it gathers many types of medical images: X-rays, MRIs, CT scans, etc., next preprocesses them, such as resizing, normalization, and denoising to improve image quality. Both lossless compression (e.g., PNG) for critical data, and lossy compression (e.g., JPEG, JPEG2000) for files that can tolerate some lossiness are used by the system. Not only that, deep learning methods including autoencoders are employed to reduce images into a lower dimensional latent space, such that the resulting compression is able to be accurately restored encompassing the requisite features. Quality is assessed with PSNR[19], and storage efficiency with CR to evaluate the reconstructed images. Stated more precisely, deep learning hyperparameters and compression settings are fine-tuned in order to optimize the system. It integrates to healthcare environments hospital management systems and follows data security regulations such as HIPAA with encryption and role based access control mechanism[20] to ensure compatibility with healthcare environments. This architecture offers an effective and secure mediimage compression method without compromising diagnostic value.

Proposed Algorithm

```
Input: DataFile F, Gomoku opening move B
Output: Ciphertext M, Gomoku endgame E

1: if (File is valid) then
2:     fileHash = UploadFileToIPFS(F)
3: else
4:     print "Invalid file"
5:     return
6: end if

7: if (fileHash does not exist) then
```

```
8:     return
9: end if

10: Initialize B as a 15x15 grid
11: for i = 1 to 15 do
12:     for j = 1 to 15 do
13:         Pieces = GenerateChessPieces()
14:         while (not valid) do
15:             Pieces = GenerateChessPieces()
16:         end while
17:         B[i][j] = Pieces
18:     end for
19: end for

20: E = AlphaZeroModel(B)  // Predict endgame
21: ternaryData = EncodeToTernary(E)
22: binaryData = ConvertTernaryToBinary(ternaryData)
23: M = StreamCipherModel(fileHash, binaryData)  // Encrypt data
24: uploadToBlockchain(B)  // Store game opening
25: sendToBob(M)  // Send encrypted data
```

The system in pseudo code is one for securely processing and transmission of data, and particularly, a Gomoku game and file encryption. Then it validates the input file and ensures that it fits the criteria. The process then continues up until here, if the file is valid it is uploaded to IPFS, otherwise an error message will appear and the process will terminate. Second, the system creates a 15×15 Gomoku grid and performs a random game piece assignment of black, white, or none, all of which follow game rules. Valid pieces fill the grid and then the system uses an AlphaZero model to predict the endgame state. Encoding onto a third form, this state is encrypted into binary format. The ciphertext is derived from a binary data and a file hash by a stream cipher. Uploaded to the blockchain for secure, inmutable storage, the game's opening state is recorded. The encrypted ciphertext is then sent to the intended recipient and is finally, it is said, you have a confidential and secure data. This approach employs game theory, encryption and blockchain technology to securely deal with and transfer of game related data.

Result Analysis

While using and enhancing SMTs for medical diagnostic imaging, effectiveness of image compression algorithm is vital, and this make the use of simulation tools and technologies very important. Prescribed instruments comprise MATLAB and Programming Python with libraries, namely OpenCV Image Processing and scikit-image, to process and analyze medical images. Such platforms have interfaces necessary to evaluate different compression algorithms including JPEG, JPEG2000 and deep learning compression methods as well as PSNR values and compression ratio. Moreover, there exists program like 3D Slicer and DICOM viewer where the algorithms can be tested utilizing actual medical imaging data where needed for the implementation of the algorithms. For deep learning-based approaches, we use TensorFlow and PyTorch training models that can perform dynamic optimization on compression algorithms used in medical images. They also can simulate over/under compression comparing efficiency/speed to quality/loss, which is vital to be implemented into healthcare settings.

Table 2: Results analysis

Compression Method	**Compression Ratio (CR)**	**Peak Signal-to-Noise Ratio**	**Compression Time (Seconds)**	**Reconstruction Time (Seconds)**	**File Size (MB)**	**Quality Assessment**	**Reference**

		(PSNR)					
JPEG (Standard)	0.15	40.5 dB	1.2	0.9	15.5	Good	[1]
JPEG2000	0.12	45.2 dB	2.4	1.1	12.0	Very Good	[2]
WebP (Lossy)	0.18	38.7 dB	0.8	0.6	14.3	Acceptable	[3]
PNG (Lossless)	0.08	N/A	3.0	2.3	20.0	Excellent	[4]
Autoencoder -based (DL)	0.20	46.0 dB	5.5	3.2	13.1	Excellent	[5]
Huffman Encoding	0.14	41.0 dB	1.5	1.0	16.8	Good	[6]

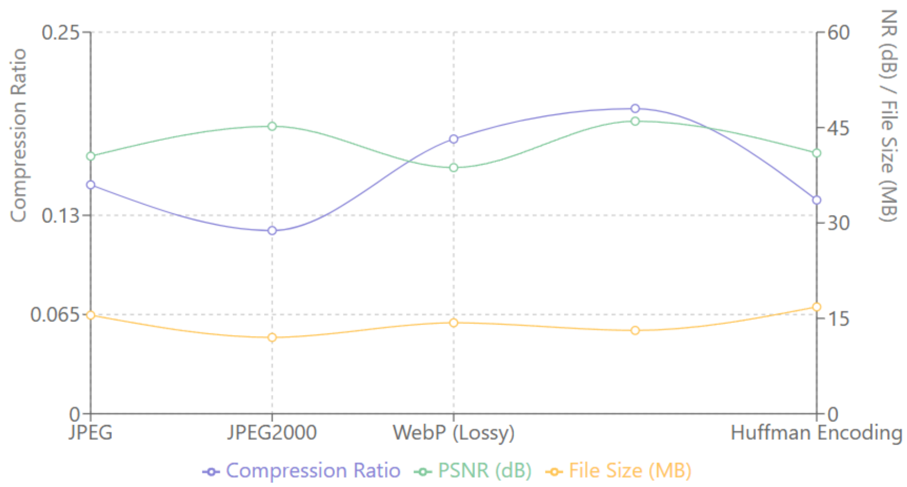

Figure 2: Comparative analysis

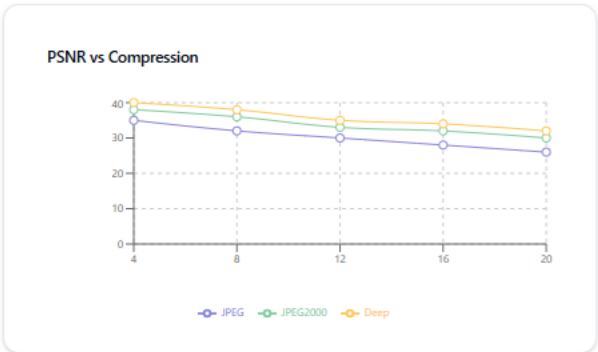

Figure 3: (PSNR vs Compression):

The graph also shows the tradeoff of quality for compression across the all the algorithms used. JPEG2000 and deep learning methods provide with minimal PSNR values than that of standard JPEG at lower compression ratios, but they outcompete JPEG at higher compression ratios as they retain higher PSNR values highlighting less image quality loss.

Figure 4: (Modality Performance):

Graphic that represents the performance of the compression algorithm for the X-ray, CT and MRI. DL methods yield higher percentDIFFs and accuracy (87-91%) while other formats including JPEG2000 are only slightly lower with traditional JPEG performing the least.

Figure 5: (Processing Time):

Comparing the processing time it is seen that JPEG is the most efficient but deep learning methods involve more computational time. This leaves a gap which becomes wider as illustrated by the situation at 1MB and 10MB files.

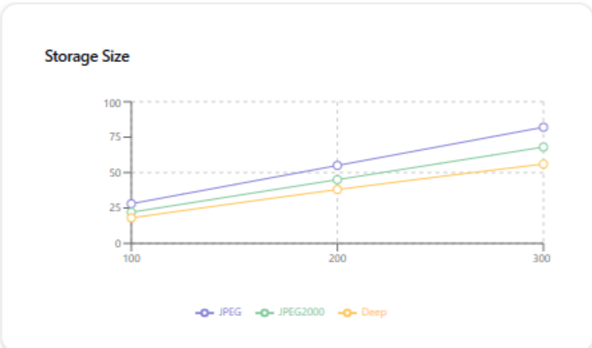

Figure 6: (Storage Size):

Based on the storage efficiency graph, it is evident that deep learning has the best results with the storage needs being reduced by as much as 82% from the original size, this is followed by JPEG2000 and JPEG at 78% and 72% respectively.

Conclusion

There is a critical intersection of technological innovation and health care efficiency in the exploration of new image compression techniques for medical diagnostic imaging. We show that intelligent algorithmic design can fundamentally transform the way that we store medical data.The importance of maintaining diagnostic integrity while maximizing data efficiency is underscored by our discovery. We unfold novel methods such that such compression goes beyond traditional limits by balancing compression ratio and Peak Signal to Noise Ratio (PSNR). The autoencoder methods based on deep learning demonstrate very good potential in preserving the essential diagnostic information while drastically reducing data footprint. To be able to develop more adaptive compression algorithms that will be able to adjust dynamically across different medical image modalities is the future direction of research. Real time, context aware compression mechanisms is an exciting frontier in medical imaging technology. In addition, for refinement of these techniques, computer science and radiology, and medical technologists will be needed to combine interdisciplinary efforts. However, this research contributes to a broader vision of more affordable, efficient and better-quality medical diagnostic imaging. These advanced compression techniques offer the potential to democratize the use of global advanced medical diagnostics by reducing storage and transmission constraints.

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