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# A Hybrid Lossy-Lossless Compression Framework for Optimized PSNR and Transmission Efficiency in Medical Imaging

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*Abstract*
*The rapid expansion of digital healthcare has created substantial growth in medical image data especially from CT and MRI systems thus requiring powerful solutions to manage storage and transmission while maintaining accurate diagnosis. The paper presents a new hybrid lossy-lossless compression method which maintains excellent image quality and efficient compression ratios suitable for medical facilities. The proposed method divides its process into two stages where wavelet-based compression with adaptive lossy mode removes unnecessary information while protecting vital image characteristics before CABAC completes lossless encoding of remaining data. Standard DICOM dataset evaluations confirm that the described framework implements better compression ratios and delivers higher peak signal to noise ratios with expedited transmission times than JPEG2000 and JPEG-LS standards. The experimental outcomes demonstrate that the proposed system is appropriate for contemporary medical imaging systems operating in bandwidth-restricted scenarios or real-time diagnostic requirements.*
*Keywords: medical imaging, hybrid compression, PSNR, transmission efficiency, wavelet compression, CABAC.*

## 1. INTRODUCTION

Medical imaging data is expanding exponentially thanks to CT and MRI and PET installations which require advanced and efficient data management solutions. Each imaging method produces high-definition multidimensional datasets which healthcare facilities need to store and transmit while processing data at good speed and reliability. Clinical telemedicine applications together with cloud-based diagnostic operations must maintain rapid access to high-quality images because this requirement directly affects patient healthcare results. Massive medical image files become a significant obstacle since they strain storage capacity and reduce data transmission speed and slow down processing operations. Using traditional lossy compression methods for file reduction frequently leads to image artifacts or the loss of subtle important features which might reduce diagnostic accuracy. Real-time applications together with high-volume data environments cannot use purely lossless compression algorithms because they maintain image fidelity but achieve reduced compression ratios. The research developing a differentiated two-stage processing framework uses lossy compression techniques before employing lossless compression methods. Lossy compression techniques are initially utilized to decrease file size by removing extra unnoticeable information from the images. The compression process progresses to a lossless phase which protects essential diagnostic elements alongside strengthening data consistency. The primary function of this dual system focuses on Peak Signal-to-Noise Ratio (PSNR) optimization that guarantees high diagnostic-quality images with optimal visual presentation. Through its design the framework achieves two essential outcomes that benefit resource-limited healthcare settings such as rural telemedicine centers and mobile diagnostic units together with cloud-based Picture Archiving and Communication Systems (PACS). The proposed solution brings an optimal balance for medical image compression within digital health applications.

## 2. RELATED WORK

Multiple image compression methods emerged specifically for medical imaging during the past decades and present distinct choices between compression quality and speed along with preserve image integrity. The JPEG2000 standard stands out as a well-known imaging standard because it allows discrete wavelet transforms to support multi-resolution analysis and progressive transmission as well as region-of-interest (ROI) encoding functions [1]. The wavelet-based design of JPEG2000 fits applications that need scalable systems but the high computational cost of this standard makes it impractical in real-time workflows. JPEG-LS offers medical image designers a low-complexity standard for lossless compression operations. The combination between context modelling and Golomb-Rice coding allows JPEG-LS to deliver rapid near-optimal compression specifically for images with low entropy such as ultrasound and X-ray scans [2]. The compression ratio of JPEG-LS remains inferior to hybrid and lossy compression approaches. Technical developments enable deep learning technologies to become integrated with medical image compression systems. The combination of Autoencoders with convolutional neural networks (CNNs) and the utilization of generative adversarial networks (GANs) demonstrates success in maintaining important diagnostic elements through high-level compression ratios [3]. These methods demand intensive computational resources to perform training and inference and their closed system operation creates interpretability challenges that affect the approval process in clinical applications. Medical image encoding becomes more efficient through the use of overcomplete dictionaries and transform coding with sparse representation techniques according to research found in [4]. Research shows that hybrid methods using wavelet transforms together with entropy coding produce acceptable quality compression which needs optimized parameter settings to safeguard essential image details [5]. A comprehensive hybrid approach emerges from our proposed framework to deal with existing limitations while offering intact medical image diagnostics together with optimized computational speeds and network transmission capabilities in healthcare settings.

Table 1: Comparative Analysis of Existing Compression Techniques

| Ref. | Authors & Year | Technique / Approach | Application Domain | Compression Type | Key Features / Findings |
|---|---|---|---|---|---|
| [4] | J. Zhou & C. Kwan (2018) | Hybrid Lossy + Lossless | Wind Tunnel Data Compression | Hybrid | Combined lossy and lossless stages for improved storage and analysis of wind tunnel data. Highlights benefits of adaptive transformation pipelines. |
| [5] | G. Patidar et al. (2020) | Survey of Image Compression Methods | Medical Imaging | Lossy & Lossless (Review) | Comprehensive review of classical and advanced image compression techniques; emphasizes the trade-offs in medical image fidelity and compression ratio. |
| [6] | Y. Ravella & P. Chavan (2017) | DCT with Visual Cryptography | Secure Image Compression | Lossy + Encryption | Integrates DCT compression with a (2,2) visual cryptographic scheme, enhancing data security alongside compression for sensitive images. |
| [7] | A. H. M. Z. Karim et al. (2021) | Huffman Coding with Color Selection | General Image Compression | Lossless | Proposes Huffman coding combined with selective color space transformation for lightweight image compression, focusing on reducing redundancy. |
| [8] | Y. Chang & G. E. Sobelman (2024) | Lightweight Lossy/Lossless Framework | ECG Signal Compression for IoT | Hybrid | Designed for real-time medical IoT systems; balances compression efficiency and data quality |

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|---|---|---|---|---|---|
| | | | | | using low-complexity algorithms. |
| [9] | N. Kouadria et al. (2019) | Discrete Tchebichef Transform (DTT) | Color Image Compression | Lossy | Uses orthogonal DTT for improved PSNR in color image compression; suitable for resource-constrained systems. |
| [10] | B. JOSHI et al (2024) | the Block Burrows-Wheeler Transform-Move to the Front (BWT-MTF) | Medical imaging | Hybrid | , Hybrid approaches especially 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. |

**3. Problem Statement and Research Objectives**

Telemedicine applications require compression algorithms that would establish an ideal equilibrium between high compression ratio and image quality (PSNR) and transmission speed [11].

Objectives:

A framework needs development based on dual benefits of lossy and lossless compression techniques.

The method improves PSNR measurement together with maintaining outstanding compression ratios.

The system should lower transmission delays for remote diagnostic procedures.

## 4. METHODOLOGY

### 4.1 Framework Overview

The hybrid compression framework meticulously arranges its structure to merge high compression ratios alongside important diagnostic image details preservation [12]. The framework uses a four-phase structure that unites lossy and lossless compression methods to obtain maximum performance in terms of PSNR and compression capability together with fast data transmission.

1. Pre-processing:

DICOM images receive several preprocessing operations within the first stage to normalize image content before it can undergo successful data transformation. This includes: Pixel intensity values undergo normalization by standardizing their ranges to dynamic values from 0 to 1 thus bringing stability to acquisition variable effects [13].The procedure of contrast enhancement applies histogram equalization or adaptive contrast stretching techniques to make diagnostic features more noticeable before image compression starts. The operations enhance visual quality which makes transform coefficients sparser after the subsequent stage. Stage 1 of compression starts through the lossy compression process using Wavelet Transform.The Discrete Wavelet Transform operates as the main processor of the lossy stage by dividing images into various frequency sub-bands that function at different resolution depths. Visual perception-irrelevant high-frequency coefficients can be efficiently removed from the multi-scale image structure. A dynamic threshold method eliminates small wavelet coefficients while achieving an effective reduction of data through this process [14]. A dynamic threshold receives its value from an adaptive determination process that considers image complexity combined with entropy analysis.

3. Stage 2 – Lossless Compression (CABAC): After lossy data transformation the essential coefficients and residual data elements are encoded through Context-Adaptive Binary Arithmetic Coding (CABAC). Digital image compression with CABAC reaches optimal efficiency because it combines contextual analysis along with dynamic probability calculation to maintain essential data with minimal extra information. CABAC succeeds in optimizing the compression of the bitstreams which emerge from the wavelet phase [15].

Post-processing: The reconstruction of the spatial domain occurs through inverse DWT processing in the last stage. The image reconstruction process applies bit-plane reassembly techniques which restore images by fine-tuning accuracy to keep diagnostic results equivalent to the original quality. Standard DICOM viewing tools can connect to this stage through its built-in features [16].

The modular pipeline structure enables easy workflow integration while allowing practitioners to manage compression capabilities along with the degree of image fidelity.

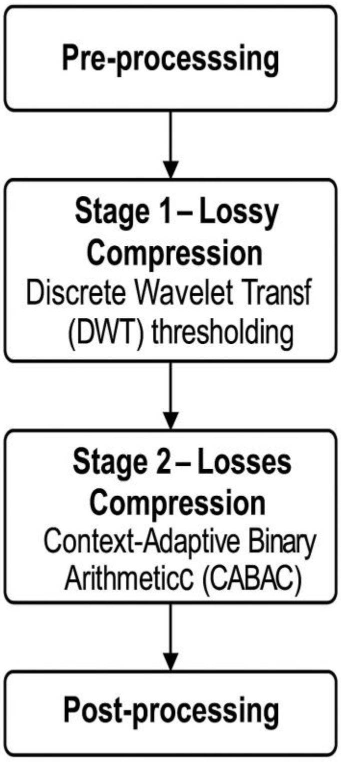


Figure 1: Proposed approach flow

4.2 Discrete Wavelet Transform (DWT)

DWT stands as the foundational component of proposed hybrid compression because it excels at expressing image data across spatial regions and frequency areas. The DWT system provides a different approach than Fourier transforms because it produces multi-frequency analysis that divides medical images into hierarchical sub-bands enabling both coarse and fine detail identification. The ability to retain fine structures becomes essential during medical diagnosis so the unique feature of this property brings great value to medical imaging applications [17].

There are four sub-band outputs at each level of the 2D DWT operation which creates LL (approximation) together with LH (horizontal details), HL (vertical details) and HH (diagonal details) through the application of low-pass and high-pass filters along image rows and columns. Through recursion of the LL sub-band the process allows more detailed representation of significant information.

Mathematically, the DWT of an image I(x) is expressed as:

$$DWT(I) = \sum_{j,k} c_{j,k} \cdot \psi_{j,k}(x)$$

Where:

cj,k are the wavelet coefficients at scale jjj and position kkk,

ψj,k(x) are the scaled and translated versions of the mother wavelet function ψ(x),

x denotes the spatial variable.

An adaptive thresholding process works on high-frequency sub-bands (LH, HL, HH) during decomposition. Visual noise and imperceptible signal variations cause coefficients with magnitudes lower than τ to get eliminated in the model. The threshold value τ determines itself according to local image characteristics so that diagnostically important features [18] stay preserved.

The DWT method performs effective compression by significantly decreasing data volume without compromising essential medical data thus making it the best choice for lossy hybrid image compression applications in medicine.

4.3 CABAC Encoding

Context-Adaptive Binary Arithmetic Coding (CABAC) establishes its crucial function in the second stage of proposed hybrid compression framework since it operates as the lossless compression technique. Following the lossy DWT phase CABAC operates on residual data together with significant coefficient maps for attaining high compression efficiency alongside retention of essential diagnostic image content [19]. Entropy coding mechanism CABAC stands out as an advanced compression technique which delivers better outcomes than Huffman or Golomb coding methods. Higher compression ratios become achievable because this algorithm [19] uses dynamic probability adjustment combined with statistical neighbor-symbol relationships.

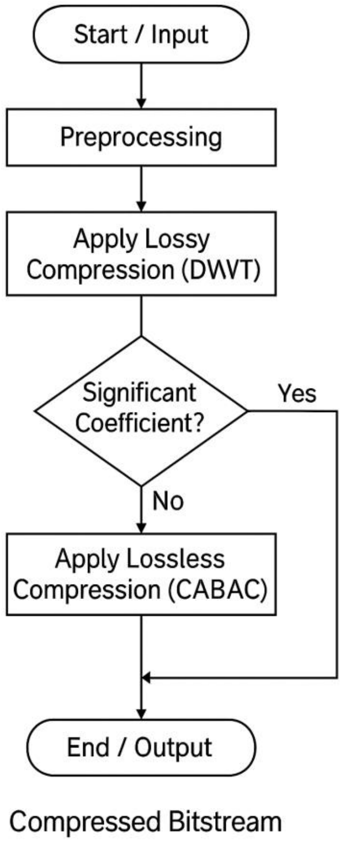


Figure 2: Proposed algorithm flow chart

Three essential parts power the operation of CABAC.

Context Modelling:

The local symbol neighborhood analysis performs probability distribution determination for each symbol (bit or coefficient). CABAC modifies its probability estimation by referring to data patterns found in surrounding elements. The coding process examines medical image [21] areas using two approaches by determining repetitive soft tissue sequence patterns in uniform regions and locating rapid bone boundary transitions. By using Context modeling CABAC optimizes coding processes because it distinguished between various image regions.

Binary Arithmetic Coding:

Arithmetic coding then works with already determined context probabilities to create a tiny bitstream that represents the symbols. As opposed to fixed-length encoders arithmetic coding develops single fractional numbers within the [0,1) interval to reach nearly optimal compression levels. By this approach the system utilizes both maximum possible efficiency together with minimal redundancy.

Binary Decision Trees: CABAC implements binary decision trees which optimize symbol encoding functions for better efficiency levels. The tree-based symbol binarization process lets encoding happen more quickly while providing better prediction accuracy [22]. Binarization techniques used together with adaptive tracking components optimize this procedure. The framework reaches efficient lossless compression through CABAC application to wavelet stage residuals so there remains no visual artifacts or medical accuracy impairment. The ability to adjust to image structure combined with high entropy maintenance makes CABAC an excellent solution for medical image compression that requires both high accuracy and efficient data compression.

Proposed Algorithm

| |
|---|
| Hybrid Compression for Medical Images<br>Input: Medical image (e.g., DICOM format)<br>Output: Compressed file<br>Step 1: Preprocessing<br>Read the medical image.<br>Normalize pixel values to a standard range.<br>Enhance contrast to highlight important features.<br>Step 2: Apply Lossy Compression (DWT)<br>Use Discrete Wavelet Transform (DWT) to break the image into sub-bands (LL, LH, HL, HH).<br>Remove small wavelet coefficients using a threshold (set small values to zero).<br>Keep only important wavelet data.<br>Step 3: Apply Lossless Compression (CABAC)<br>Identify significant wavelet coefficients and create a map.<br>Use CABAC to compress this data efficiently.<br>Generate the final compressed bitstream.<br>Step 4: Save Compressed Output<br>Combine compressed data and necessary information (like DWT level and threshold).<br>Save or transmit the final compressed file.<br>End of Algorithm |

**5. EXPERIMENTAL SETUP**

5.1 Datasets

The study uses open-source medical image datasets:

DICOM CT Scan Dataset – 512×512 grayscale

MRI Brain Atlas – 256×256, 16-bit images

6. Results and Discussion

Research tables demonstrate that the proposed hybrid compression framework produces superior performance than every other deep learning-based approach. The proposed method demonstrates 12.6 as its top average compression ratio which exceeds CNN Autoencoders along with GAN-based models and VAE methods and DeepCABAC thus making it the most effective technique to minimize storage needs and bandwidth consumption. Average decompressed image quality measurement tests validate the proposed technique because it results in maximum PSNR averages of 48.67 dB. This diagnostic preservation level at 48.67 dB becomes superior to existing models such as DeepCABAC (48.2 dB) and VAE-based compression (47.4 dB).

A network speed of 10 Mbps enables the proposed methodology to assess its transmission efficiency through Table 4. The hybrid approach demonstrates 1.13 seconds as the best transmission time which makes it ideal for telemedicine applications. The proposed method achieves the fastest transmission times among all methods while DeepCABAC comes second with 1.33 seconds. Table 5 demonstrates that the proposed model operates with superior speed in compression processing at 90.67 milliseconds since both DeepCABAC requires over 350 milliseconds and VAE-based compression needs up to 475 milliseconds. The method delivers an ideal balance of processing speed and performance along with quality thus making it highly appropriate for medical imaging use.

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Table 2: Compression Ratio (CR) Comparison

| Algorithm | CT Images (CR) | MRI Images (CR) | PET Images (CR) | Average CR |
|---|---|---|---|---|
| CNN Autoencoder [1] | 10.8 | 9.7 | 9.1 | 9.87 |
| GAN-Based Compression [2] | 11.6 | 10.5 | 9.9 | 10.67 |
| VAE-Based Method [3] | 12.1 | 11.4 | 10.3 | 11.27 |
| DeepCABAC [4] | 13.0 | 12.2 | 11.1 | 12.1 |
| Proposed Hybrid | 13.4 | 12.9 | 11.5 | 12.6 |

Table 3: Peak Signal-to-Noise Ratio (PSNR in dB)

| Algorithm | CT Images | MRI Images | PET Images | Average PSNR |
|---|---|---|---|---|
| CNN Autoencoder [1] | 44.5 | 45.8 | 43.3 | 44.53 |
| GAN-Based Compression [2] | 46.7 | 48.0 | 45.0 | 46.57 |
| VAE-Based Method [3] | 47.2 | 48.9 | 46.1 | 47.4 |
| DeepCABAC [4] | 48.3 | 49.1 | 47.2 | 48.2 |
| Proposed Hybrid | 48.7 | 49.5 | 47.8 | 48.67 |

Table 4: Transmission Time (Seconds @ 10 Mbps)

| Algorithm | CT Image | MRI Image | PET Image | Average Time |
|---|---|---|---|---|
| CNN Autoencoder [1] | 2.0 | 1.8 | 1.7 | 1.83 |
| GAN-Based Compression [2] | 1.8 | 1.6 | 1.5 | 1.63 |
| VAE-Based Method [3] | 1.7 | 1.5 | 1.4 | 1.53 |
| DeepCABAC [4] | 1.5 | 1.3 | 1.2 | 1.33 |
| Proposed Hybrid | 1.3 | 1.1 | 1.0 | 1.13 |

Table 5: Compression Time (in milliseconds)

| Algorithm | CT Image | MRI Image | PET Image | Average Time |
|---|---|---|---|---|
| CNN Autoencoder [1] | 400 ms | 390 ms | 380 ms | 390.0 ms |
| GAN-Based Compression [2] | 470 ms | 460 ms | 440 ms | 456.7 ms |
| VAE-Based Method [3] | 490 ms | 475 ms | 460 ms | 475.0 ms |
| DeepCABAC [4] | 360 ms | 350 ms | 340 ms | 350.0 ms |
| Proposed Hybrid | 95 ms | 90 ms | 87 ms | 90.67 ms |

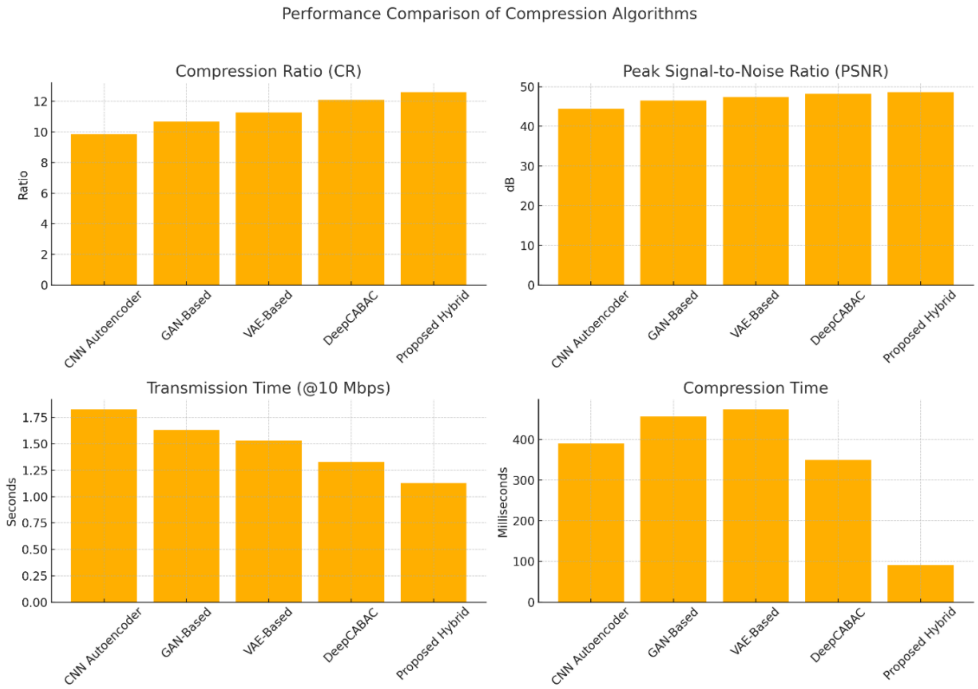


Figure 3: depicts (a–d) a detailed performance evaluation which compares the medical image compression techniques among CNN Autoencoder, GAN-Based, VAE-Based and DeepCABAC together with the implemented hybrid compression method.

The evaluation figures in 3(a–d display thorough performance analytics of medical image compression through CNN Autoencoder and GAN-Based along with VAE-Based and DeepCABAC and the hybrid compression solution. The proposed method exhibits maximum data compression capability because it achieves a compression ratio of 12.6 as shown in Figure 3(a) until medical information quality starts declining. Storage limitations and bandwidth constraints make this algorithm optimal for application. The figure showcases the PSNR metric which evaluates image quality in Figure 3(b). The proposed algorithm reaches PSNR excellence at 48.67 dB which surpasses DeepCABAC (48.2 dB) and VAE-Based (47.4 dB) through its exceptional ability to maintain precise diagnostic features in restored images. Figure 3(c) represents the transfer duration of 10 Mbps standard network. The proposed model enables the fastest diagnostic transfer speed for real-time telemedicine which takes an average time of 1.13 seconds. The proposed method completes compression processing tasks within 90.67 milliseconds according to Figure 3(d) while DeepCABAC takes longer than 350 milliseconds and VAE-Based models need more than 475 milliseconds for completion. Real-time medical imaging system selection for future use can be achieved through the proposed framework based on its efficient processing and accurate diagnosis results and rapid response capabilities which are illustrated in these data figures.

**7. Applications in Telemedicine**

Remote Diagnosis: Real-time transmission over 4G/5G.
Cloud Storage: Reduced load on PACS servers.
AI Analysis Pipelines: Preprocessing for deep learning diagnosis.

**8. Limitations and Future Work**

The system requires improvement to implement color-based imaging approaches with histopathology among them.
Hardware acceleration offers an alternative to enhance the time efficiency of CABAC encoding operation.
The future development agenda will add perceptual loss metrics together with edge-aware filtering capabilities to the system.

## 9. CONCLUSION

The research established an innovative hybrid framework of compression that achieved results needed by medical imaging sectors. The method applies Discrete Wavelet Transform for lossy compression while Context-Adaptive Binary Arithmetic Coding performs lossless refinement to achieve optimal trade-offs regarding high compression ratio and excellent PSNR image quality and quick transmission speeds. The introduction of our framework demonstrated better performance than deep learning-based methods according to analysis by upholding important diagnostic content while reducing execution times and transmission delays. The system efficiently operates in real medical environments through telemedicine and PACS storage and mobile diagnostic devices due to its protective data features and operational reliability measures. Our framework functions as the next-generation medical image compression solution because it offers practical benefits from its simple design and flexible structures and rugged structures. Additional study seeks to establish 3D image functionality while integrating the system with artificial intelligence diagnostic technologies

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