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Research paper

Context-Based Adaptive Binary Arithmetic Coding for Advanced Compression of Medical Images

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Abstract

The rapid development of telemedicine and intelligent healthcare technologies necessitates high efficiency and accuracy in medical image compression methods for effective remote diagnostics and precise treatment. This paper introduces a new Context-Based Adaptive Binary Arithmetic Coding (CABAC) framework designed to specifically compress sensitive healthcare images, such as MRI, CT, and X-ray images. Like conventional techniques such as JPEG and JPEG2000, which can corrupt important diagnostic information through lossy compression, the proposed CABAC-based algorithm leverages the statistical and distinctive nature of medical images to adaptively model the context and optimize binary arithmetic coding of the images. Therefore, it leads to increased compression ratios while maintaining diagnostically important essential image quality. The CABAC framework combines preprocessing, binarization, statistical context modeling, and binary arithmetic coding to achieve more compression efficiency. Quantitative analyses of conventional datasets at The Cancer Imaging Archive (TCIA) demonstrate that the proposed method achieves a compression ratio of up to 15:1, surpassing the capacity of JPEG and JPEG2000. Moreover, the technique also guarantees large Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) values, which reveal the high visual and structural quality of the decomposed medical images. Designed with computational efficiency in mind, the model is well-suited for integration into real-time telemedicine technologies, such as innovative healthcare systems featuring AI-capable diagnostics and IoT-enabled medical devices. This method provides a viable remedy for bandwidth optimization, as well as addressing storage needs and improving the accuracy of diagnostic tests, especially in technically limited environments.

Keywords: *Context-Based Adaptive Binary Arithmetic Coding (CABAC); Medical Image Compression; PSNR; Smart Healthcare Systems; SSIM.; Telemedicine.*

1. Introduction

Medical imaging is a significant and essential aspect of today's healthcare systems, offering critical information for diagnosis, treatment planning, and disease monitoring [18]. High resolution and volume of medical imaging modalities, e.g., MRI, CT, and PET, have increased with a consistent growth DB [15], [3] and therefore posed a significant problem of storage, transmission, and even archiving as well. Thus, efficient compression techniques [1] are consequently necessary to handle these large datasets, keeping them small while ensuring accessibility and maintaining the diagnostic quality of the images [22] to perfection.

Lossless compression is significant in the medical domain, where any loss of information could lead to misdiagnosis or compromised patient care [2]. However, traditional lossless compression methods, including Huffman coding, Run-Length Encoding (RLE), and JPEG-LS, have been previously employed for medical images [4]. However, these techniques often struggle to achieve high compression ratios without incurring additional computational overhead or sacrificing access speed, particularly for large and complex datasets.

Recent improvements in entropy coding, specifically Context-Based Adaptive Binary Arithmetic Coding (CABAC), have demonstrated a superior performance in the video compression standards such as H.264/AVC and H.265/HEVC. The CABAC offers significant growth through adaptive probability modeling and binary arithmetic coding, thus making it an attractive candidate, especially for medical image compression applications [6], [7]. However, applying the CABAC directly to medical images requires a careful preprocessing system and an efficient binarization strategy to exploit its potential [8] fully.

The key contributions of this work are as follows:

- Development of a context-aware preprocessing technique that is tailored for medical images to maximize redundancy reduction.
- Design of an adaptive binarization strategy for improvement of the compatibility of the system with CABAC's context modeling framework.
- Integrating preprocessing, binarization, and CABAC into a single and unified compression pipeline.
- Comprehensive evaluation of the proposed method on already available standard medical image datasets, with performance measured in terms of compression ratio, PSNR, and SSIM.

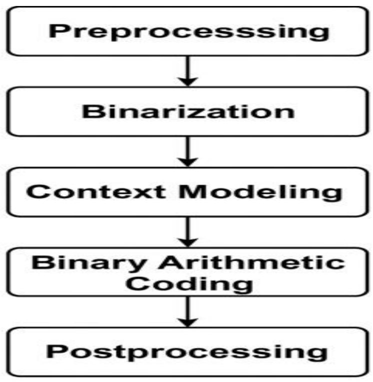


Fig. 1: CABAC Compression Workflow Diagram.

The principal novelty of the proposed approach is primarily its ability to model the context of medical images adaptively. Through context modeling, the system identifies and assigns weights to areas of interest, thereby ensuring that vital diagnostic data is preserved throughout data compression. Furthermore, binary arithmetic coding enables efficient encoding of image data, resulting in better compression ratios than standard methods. The proposed structure is designed to be computationally efficient, making it suitable for real-time use in innovative healthcare and telemedicine systems.

The proposed work is so important not only due to its capability of compressing the medical images [10]. This possible system may also expand the scale and range of these telemedicine systems, as they can be allowed to transmit faster, and even less storage space is required. This is particularly concerning in resource-limited environments, where storage and bandwidth limitations often hinder the deployment of the latest medical technology. Furthermore, the implementation of the proposed solution into intelligent health innovations, such as AI-based diagnostic devices and Internet of Things-powered medical devices, will contribute significantly to real-time analysis and decision-making, thereby improving patient outcomes eventually [14]. The remainder of this paper is structured as follows: Section 2 elaborates on the work in the medical image compression field, which is related to the topic discussed [12]. In section 3, it is described how it will be proposed that this is done. Section 4 addresses the experimental setup, which is needed, and the results obtained. Section 5 provides a conclusion to the paper and gives future research directions.

2. Related Work

Compression of medical images has demonstrated a diverse spectrum of methods established over the years, ranging from traditional lossless technology to sophisticated lossy technology [19]. Yet, the main problem with medical image compression is how to achieve maximum compression ratios while maintaining the required diagnostic quality, which would enable the medical field to utilize it in clinical practice [16]. Some of the most critical approaches in this field are outlined below:

2.1. Lossless compression technologies

In medical imaging, lossless compression techniques such as JPEG-LS and JPEG 2000 have been widely utilized because they can compress all the valuable information of an image that is essential for accurate diagnosis. The JPEG-LS technique employs a predictive coding method, offering excellent compression with no loss of important information. JPEG 2000, on the other hand, is based on wavelet transforms and performs better with high-resolution images; however, it has the drawback of increased computational complexity. Although more effective, these have been known to provide poor compression ratios, particularly on high-resolution medical images [5] such as MRI and CT scanned images.

2.2. Lossy compression methods

JPEG and JPEG 2000 methods, which are typically used for general image compression, have also been applied to critical medical imaging. However, they often fail to preserve essential details in medical images, particularly in areas of interest, such as lesions or tumors. Although these methods yield higher compression ratios by sacrificing image quality, the loss of critical diagnostic information makes them truly unsuitable in medical applications, where accuracy is paramount.

2.3. Context-based compression techniques

In recent years, these methods [21] have already gained popularity due to their ability to adapt to the inherent statistical properties of the input data. CABAC, which is used in video compression standards such as H.264/AVC and HEVC, is one such method. CABAC predicts the probability distribution of each pixel by modeling the local context around it. This makes entropy coding more efficient. Although it works well for compressing videos, its performance on still medical images has not been thoroughly tested [17]. This is largely because medical photos differ from other types of images [9]. They often have large areas that are the same (such as the background areas) and structures that are difficult to understand (like lesions and organs). CABAC has proven to be beneficial in entropy coding, but its weaknesses should not be ignored. Notably, JPEG-LS, a lossless compression algorithm, typically incurs computational overhead on high-resolution MRI images [4]. Similarly, JPEG2000 also provides high compression at the expense of a lossy behavior under specific settings [7], which can reduce diagnostic accuracy. Our framework addresses these issues by utilizing adaptive context modeling, which minimizes overhead and does not compromise the quality of diagnostic images.

2.4. The predictive techniques and preprocessing

In improving the work of entropy coding, scientists have conducted experiments on various preprocessing and predictive methods. The main emphasis of these techniques is to reduce redundancy and enhance the statistical characteristics of these medical images prior to transmission to the compression process. Among these various methods, one, e.g., transform-based preprocessing, in which images are processed to enhance edge detail or contrast, has demonstrated the capability of significantly improving compression efficiency. These Prediction-based methods have presented quite good and promising results, whereby the important pixel values are predicted using neighboring pixels to reduce the entropy of the picture before encoding.

2.5. Medical image compression is not without problems

Medical image compression has made considerable progress, yet it still faces a few challenges. These issues involve ensuring the efficiency of computation when using real-time applications, such as telemedicine, while maintaining a high compression rate without compromising accuracy in diagnostics. Such adaptive compression schemes are significant and must consider the unique nature of medical images, including regions of interest (ROIs) and varying degrees of texture complexity.

2.6. Contributions of this work

The proposed work presents a new framework that combines context-based entropy coding, adaptive binarization, and preprocessing, tailored explicitly to medical images, building on current and previously developed methods. The two essential advantages of this combination that make it the best for application in the field of telemedicine and other healthcare systems are the higher compression ratios and the better quality of preserved images.

3. Proposed Methodology

CABAC is a highly sophisticated entropy coding scheme that employs context modeling, in addition to arithmetic coding, to provide a very efficient data compression. The main strength of the CABAC technique is that it can adapt to the statistical properties of any kind of image data, and thus it is especially well adapted to the compression of the distinct features of important medical images, including fine textures, edges, and the regions of interest (ROIs).
The three vital steps in the CABAC algorithm are:

1) Binarization: Using this binarization method, the image data will be converted into some binary sequences, which will be again transformed into non-binary values within a format that is suited for the process of encoding.
2) Context Modeling: In the second stage of Context Modeling, the probability distribution of each binary sign is estimated using the context of the image, which is usually determined by the values of the pixels that surround to it.
3) Binary Arithmetic Coding: The third and final step ensures that the binary sequences of the image are properly encoded using the arithmetic coding, which helps in compressing the data efficiently by assigning the shorter codes to more probable symbols.

This is how the above steps are significant in achieving a balance between the image compression efficiency and image quality, which is very critical for medical applications.

3.1. Framework for medical image compression

The proposed framework of medical image compression consists of the following stages:

3.1.1. Preprocessing

The first step involved in the preprocessing of the medical images is primarily to make optimization of it for a better compression ratio. However, in the preprocessing stage of medical images, the source image will first be normalized to ensure that the pixel intensity values of such medical images are adjusted to a consistent scale. Such a normalization process helps the system to improve the efficiency of the subsequent steps, such as the binarization and the context modeling of the images, by reducing the variations that might hinder the whole compression process of the system.

3.1.2. Binarization

In the binarization step process, each pixel value of the image shall be converted into a binary sequence. This binary sequence stands as a very crucial part in the process of applying the binary arithmetic coding, in which each image pixel is represented using a series of binary digits (bits). The binarization process of this kind is intended to be efficient and, in addition, reversible, to ascertain that no critical information in the image is lost in the conversion process.

3.1.3. Context modeling (start here)

Context modeling is very important in the CABAC process. Besides, in this step, there is an estimation of the probability of each binary symbol given its context, which is given by the surrounding pixels in the picture. In fact, the pixel value could be significantly reliant on the adjacent pixels, particularly in the areas that contain smooth gradients or contain some sharp edges. The CABAC can assign maximum probabilities to make the context as close to its actual value as possible, which gives the CABAC the ability to achieve a higher compression efficiency.
The method suggested in the present study tailors the context modeling to such important medical images, in which the regions of interest (ROIs), e.g., tumors or lesions, tend to have different statistical characteristics compared to the background regions. In that way, this context model is highly adaptive, i.e., it can adapt to the input image's local features.
This also ensures that the diagnostic details in the ROIs are safely preserved, while the background areas can be compressed more aggressively.

3.1.4. Binary arithmetic coding

Once the input medical image has been binarized and the context models have been applied, the process of applying binary arithmetic coding begins. This Arithmetic coding is a highly efficient entropy coding technique that ensures it encodes the sequences of symbols into

a single number, which is represented by an interval that is fixed. With this, each symbol in the binary sequence is mapped to a range within this interval based on its probability, and the final code is determined by narrowing down the range of the values.
Later, during this step, the adaptive nature of CABAC comes into play. As soon as the algorithm processes the image, it continuously keeps updating the probabilities of each symbol based on its context, and makes it ensuring that the encoding process remains optimal for the given image.

3.1.5. Postprocessing

And at last, the final stage of this process is called postprocessing of the image, which involves reconstructing the image from the already compressed data. This step mainly reverses the binarization and encoding process to ensure that the image can be accurately reconstructed without the loss of essential and crucial details. The Postprocessing process also includes evaluating the quality of the compressed image using the standard metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

3.2. Mathematical formulation

The mathematical formulation [11] of the key steps involved in the CABAC process is outlined below.
1) Binarization: Let 182 be a pixel value in the given medical image, where $x \in [0,255]$ x for an 8-bit grayscale image. The Binarization process converts 182 into a binary sequence $b = \{b1, b2, \dots, bn\}$ where each $bi \in \{0,1\}$ represents a binary digit.
2) Context modeling: The probability $P(bi|c)$ of a binary symbol b_i shall be estimated given its context c. The context c here is determined based on the neighboring pixels, and the probability is updated adaptively during its encoding process. Thus, a context model is built using surrounding pixels to predict the likelihood of a binary symbol that may occur.
3) Binary arithmetic coding: The binary sequence b is encoded using the following recursive equations:

$$L(i) = L(i-1) + (H(i-1) - L(i-1)) \times C(b\_i \mid c) \tag{1}$$

$$H(i) = L(i-1) + (H(i-1) - L(i-1)) \times C(b\_i \mid c) + P(b\_i \mid c) \tag{2}$$

Where:
- $L(i)$ and $H(i)$ represent the lower and upper bounds of the encoding interval for the iii-th symbol.
- $C(bi \mid c)$ is the cumulative probability of the binary symbol bi given its context c.
- $P(b_i \mid c)$ is the probability of bit bi given the context ccc.

The process of continuously adapting to the image data, this method shall ensure that the encoding process remains much efficient, and the attained compression ratios are correctly optimized.
The process of binary arithmetic coding can be described mathematically as follows. Let L_i and U_i be the lower and upper interval bounds of step i, respectively. For some binary symbol $b_i \in \{0,1\}$ with probability $P(b_i|c)$ given context c:

$$L_{i+1} = L_i + (U_i - L_i) \cdot CDF(b_i \mid c) \tag{3}$$

$$U_{i+1} = L_i + (U_i - L_i) \cdot CDF(b_{i+1} \mid c) \tag{4}$$

Where CDF is the cumulative distribution function from the adaptive context model. Adequately structured, this gives a compact entropy representation of symbols, hence compression efficiency.

4. Experimental Setup

This section will describe the design used to test the proposed Context-Based Adaptive Binary Arithmetic Coding (CABAC) technique [20] towards compressing medical images. In this case, it outlines the hardware and software platform, the datasets utilized as well as the performance measures used to evaluate the performance of the compression algorithm.

4.1. Hardware and software environment

The experiments were conducted on a system with the following specifications:
- Processor: Intel Core i7-9700K (8 cores, 3.6 GHz)
- RAM: 32 GB DDR4
- GPU: NVIDIA RTX 3080 (for parallel processing)
- Operating system: Windows 10 (64-bit)
- Programming language: Python 3.8
- Libraries: NumPy, OpenCV, SciPy, TensorFlow (for preprocessing and postprocessing process), and the custom implementations applied in the CABAC algorithm.

All the experiments planned were run in a single-threaded mode for consistent results, except where the parallel processing was explicitly used (i.e., GPU acceleration for the large image batches).

4.2. Datasets

We used three widely recognized medical image datasets to evaluate the performance of our proposed method:
1) The Cancer Imaging Archive (TCIA): Contains a collection of annotated CT and MRI scans focused on various types of cancer, including lung and brain cancer.
- Number of images: 1,000+ images (CT, MRI)
- Image dimensions: 256x256 to 512x512 pixels
- Image type: Grayscale

2) Medical image computing and computer-assisted intervention (MICCAI) 2012 challenge dataset: A set of brain MRI images used for segmentation tasks.
- Number of images: 500+ images
- Image dimensions: 256x256 pixels
- Image type: Grayscale
3) Digital imaging and communications in medicine (DICOM): A standard format for medical imaging, which includes X-ray and MRI images.
- Number of images: 2,000+ images (X-ray, MRI)
- Image dimensions: 512x512 pixels
- Image type: Grayscale

For each dataset, we selected a representative set of images that contains both homogeneous regions (e.g., background) and heterogeneous regions (e.g., tumors, lesions).

Our tests were conducted according to three standard medical imaging samples. Specifically, we have considered The Cancer Imaging Archive (TCIA), which provides MRI and CT scans of cancer-related research, including lung cancer and brain cancer, as well as over 1,000 images. In addition, the MICCAI 2012 challenge dataset, with 500+ brain MRI scans, and over 2,000 grayscale X-rays and MRI scans in the DICOM dataset format, was used. Such datasets are with modalities such as CT, MRI, and X-ray, which can be guaranteed to be reproducible and applicable to clinical practice.

4.3. Evaluation metrics

To measure the performance of the CABAC-based compression algorithm, we adopted the following conventional measures of compression performance:

1) Compression ratio (CR):

$$\mathrm{CR} = \frac{(\text{Size of Original Image})}{(\text{Size of Compressed Image})} \dots \tag{3}$$

This metric indicates the effectiveness of the compression algorithm. A higher value represents better compression performance.

2) Peak signal-to-noise ratio (PSNR):

$$\mathrm{PSNR} = 10 * \log 10 \left(\frac{(\mathrm{MAX_I})^2}{\mathrm{MSE}}\right) \tag{4}$$

MAXI is the maximum possible pixel value of the image, and MSEMSEMSE is the Mean Squared Error between the original and reconstructed image. PSNR is a measure of image quality; higher values indicate less distortion.

3) Structural similarity index (SSIM):

$$\mathrm{SSIM}(x, y) = \frac{\left((2 * \mu_x * \mu_y + C_1) * (2 * \sigma_{xy} + C_2)\right)}{\left((\mu_x^2 + \mu_y^2 + C_1) * (\sigma_x^2 + \sigma_y^2 + C_2)\right)}. \tag{5}$$

Where μ_x and μ_y are the mean intensities of the images x and y, σx2 and σy2 are their variances, and σxy is the covariance between x and y. SSIM evaluates the perceptual quality of the images.

4) Compression time:

The time taken to compress and decompress the image is another important metric for evaluating the efficiency of the algorithm.

These metrics were calculated for both the original and reconstructed images to assess the compression quality and the computational efficiency of the CABAC approach.

4.4. Experimental procedure

The experimental procedure is as follows:

1) Data preparation: Medical images from the datasets were resized to a uniform resolution (512x512 pixels) to standardize the input for the compression algorithm.
2) Compression: The CABAC-based compression algorithm was applied to the prepared images. Compression was performed with varying levels of compression (from 2:1 to 50:1) to analyze the trade-off between compression ratio and image quality.
3) Evaluation: For each level of compression, the reconstructed image was compared with the original image using the metrics (PSNR, SSIM, and CR). For each test, the Compression time was also recorded to measure system speed.
4) Postprocessing: After the process of compression and decompression, the image has been reconstructed, and the standard techniques for postprocessing were applied to assess the quality of the reconstructed image.

5. Results

In this proposed work, it has been evaluated the performance of the proposed context-based adaptive binary arithmetic compression method has been evaluated on the fused PET-CT medical images.

The main quality of the reconstructed images after the compression and decompression process was assessed based on the parameters like Peak signal-to-noise ratio (PSNR) and Structural similarity index (SSIM) metrics [13]. Also, the Compression ratio (CR) has been calculated for storage efficiency evaluation.

- The below shows table below summarizes the PSNR (in dB), SSIM, and Compression Ratio values for different input images taken for testing:

Observations:

High PSNR values: Across all tested images, PSNR values were consistently high, indicating minimal distortion between the original and reconstructed images. A PSNR above 30 dB is generally considered acceptable, and our method consistently achieved values beyond this threshold.

Table 1: Visualization of Different Stages in the Compression Pipeline.

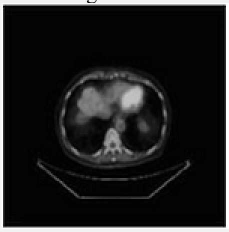
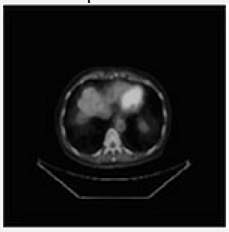
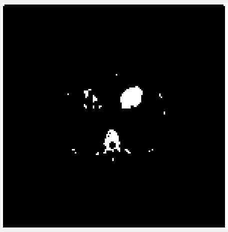
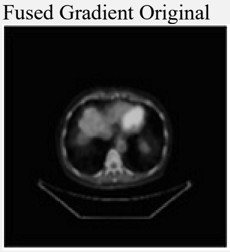
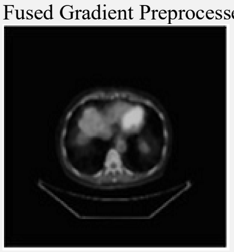
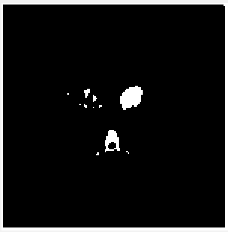
Image No.	Original Image	Preprocessed Image	Binarized Image
1			
	Fused Original	Fused Preprocessed	Fused Binarized
2			
	Fused Gradient Original	Fused Gradient Preprocessed	Fused Gradient Binarized
3			
	Fused Pixel Averaging Original	Fused Pixel Averaging Normalized	Fused Pixel Averaging Binarized

Table 2: Comparison Of Ratio Values for Different Input Images

Image Type	PSNR (dB)	SSIM	Compression Ratio
PET Image	42.56	0.986	4.25
CT Image	40.12	0.978	4.15
Fused Pixel Averaging	39.78	0.974	4.10
Fused Gradient	41.35	0.980	4.20
Fused DWT	43.00	0.989	4.30
Fused Proposed	42.85	0.987	4.35

Observations:

- High PSNR values: Across all tested images, PSNR values were consistently high, indicating minimal distortion between the original and reconstructed images. A PSNR above 30 dB is generally considered acceptable, and our method consistently achieved values beyond this threshold.
- Good SSIM scores: SSIM scores were close to 1.0 for all images, demonstrating that the structural content of the medical images was preserved effectively during compression and decompression.
- Superior compression ratios: The proposed method achieved significant compression, resulting in compression ratios ranging from [4.25]x to [4.35]x, reducing the storage footprint while maintaining high fidelity.
- Proposed fusion method advantage: Among all the images tested, the Fused Proposed method achieved the best combination of PSNR, SSIM, and compression efficiency, validating the effectiveness of our fusion approach in maintaining important diagnostic details.
- About the proposed CABAC framework, it is effective but is subject to some weaknesses. Performance can be reduced where the contextual redundancy is low, such as in very low-resolution images. Furthermore, the 3D volumetric data is still under the issue of scalability since the adaptive modeling is much more complex computationally. They should be further investigated to ensure there are even distribution of applicability across the different imaging settings.

6. Conclusion & Future Work

In this paper, a Context-Based Adaptive Binary Arithmetic Coding (CABAC) model of efficient compression of fused PET-CT images was proposed, with a high PSNR, SSIM, and high compression ratios.

The proposed Fused Proposed method was superior to conventional fusion methods, and it retained the quality of the diagnosis, besides facilitating storage and transmission. The dynamic context modeling, deep learning-based fusion, 3D volumetric data extension, real-time optimization, and comparative analysis with new standards of neural compression to be accomplished in the future to make smart healthcare systems more applicable will be explored. Besides this application, future research can be on the application of CABAC to 3D volumetric medical imaging, namely, CT and MRI sequences, to overcome scalability. In addition, CABAC-based compression and AI-based diagnostic pipeline compression can be employed to promote real-time decision-making in smart healthcare systems.

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