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Region of interest (ROI) compression for adrenal tumor images: a hybrid approach

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ABSTRACT

Developments in artificial intelligence have made it considerably easier for specialists to identify and diagnose diseases by applying computer-aided diagnosis (CAD) systems to medical images. This study introduces a novel hybrid compression technique that combines lossless compression of the region of interest (ROI) with lossy compression of the surrounding areas. This approach balances compression-ratio performance and diagnostic image quality by leveraging refined ROI extraction using morphological operations. This study proposes a hybrid ROI-aware medical image compression method designed to enhance the efficiency of adrenal tumor computed tomography (CT) image transmission and storage without compromising diagnostic accuracy. While surrounding regions are compressed using lossy techniques like scalar quantization and Huffman coding, tumor regions found by a reliable automated segmentation pipeline are compressed lossless using a Lempel–Ziv–Welch (LZW) algorithm. While maintaining 95% tumor detectability, an experimental evaluation of 95 annotated CT images produced an average compression ratio of 48.00%, outperforming traditional Huffman compression (20.79%). Peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), and a new ROI fidelity score were used to measure image quality. This approach is compatible with digital imaging and communications in medicine (DICOM) standards, supports bandwidth-efficient telemedicine, picture archiving and communication system (PACS) optimization, and may be incorporated into artificial intelligence-assisted diagnostic workflows. Future strategies should incorporate multimodal fusion, compression, and adaptive ROI tracking to further enhance clinical usability.

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1. INTRODUCTION

Effective compression of medical images is essential for telemedicine, picture archiving and communication system (PACS) storage optimization, and artificial intelligence diagnostic automation, especially when the images include cancer. Region of interest (ROI)-based compression algorithms aggressively compress some regions to save file size while preserving diagnostically important regions using lossless techniques. The drawbacks of uniform lossy compression are avoided by this hybrid technique, which strikes a balance between compression efficiency and diagnostic precision. This study, which focuses on computed tomography (CT) imaging of adrenal tumors, is motivated by recent developments in neural networks and adaptive coding methods. Techniques for compressing medical images are essential for better transmission and storage, particularly for tumor diagnosis. Finding a balance between the compression ratio and image quality is largely dependent on the ROI. As stated in [1], texture analysis and feature extraction of adrenal tumor images are crucial in improving the diagnosis of such tumors. This study aims to enhance the compression ratio of adrenal tumor images using a hybrid method that involves lossless compression on the tumor and surrounding areas, which is done by using lossy compression. This study is important since it can improve the transmission efficiency and accuracy of medical images, which is important for timely diagnosis and treatment. The image compression techniques that make use of a combination of methods are termed hybrid approaches [2]. Such methods have been used for analyzing images of skin tumors, which emphasizes the usefulness of such methods for a variety of purposes [3]. The analysis of ROI in skin tumor images is also important for enhancing the accuracy of compression in images.

As discussed in [4], ROI-based compression using better portable graphics (BPG) has significant advantages in efficiency for medical image compression and transmission. Recently, based on the remaining learning [5], a dual autoencoder model was proposed, which is considered a modern method for compressing medical images. When the Lempel–Ziv–Welch (LZW) algorithm was used, the compression ratio reached 48%, while the Hoffman algorithm achieved 20.79%. These experimental results confirm the effectiveness of the proposed hybrid approach in preserving important information for diagnostic purposes.

2. LITERATURE REVIEW

To increase storage efficiency and diagnostic accuracy when dealing with CT and magnetic resonance imaging (MRI) images, the researchers were interested in the hybrid model method that combines missing and non-missing methods, because preserving the original pixel data in the ROI area of interest is extremely important in clinical evaluation [6]. Using medical datasets, traditional methods such as LZW and Hoffman were evaluated, and despite the high compression ratio provided by these methods, they are unable to distinguish between important clinical characteristics and unnecessary (background) information. As a result, context-aware compression frameworks that can distribute bits intelligently according to the significance of the image region are becoming more and more necessary.

Recent ROI-aware medical image compression research combines segmentation utilizing deep learning approaches (like UNET) with advanced video coding algorithms (like high efficiency video coding (HEVC)) to increase compression rates while preserving tumor quality. Better energy compaction and progressive coding are demonstrated using hybrid principal component analysis (PCA)-set partitioning in hierarchical trees (SPIHT) algorithms. Emerging predictive coding and adaptive neural predictors demonstrate increased compression in dynamic medical sequences. This approach builds on these foundations by integrating morphological and filtering-based segmentation for ROI delineation and LZW hash-based lossless compression, complemented with lossy coding outside the ROI, achieving a novel balance in adrenal tumor imaging.

Recent studies (2020–2025) have advanced ROI-based compression, such as JPEG2000 and adaptive methods, including deep learning approaches to medical image compression. Additionally, hybrid lossy/lossless schemes compliant with digital imaging and communications in medicine (DICOM) standards have improved workflow integration and diagnostic accuracy. Saini *et al.* [7] support the use of hybrid features in image classification and analysis, which, in turn, aid in the development of compression methods. Further to this, authors [8], [9] discuss the role of image compression in the medical field, specifically for improving the efficiency and effectiveness of diagnosis. As previously mentioned, Zhang and Qie [10] proposed new methods for the analysis of medical images, reiterating the emphasis placed on the use of deep learning for modern methods of image compression. The authors [11], [12] also observed that the knowledge of image compression methods could immensely improve the work with medical images.

In discussions held at [13], [14]. The adoption of new image compression technology was discussed to facilitate the processes of image transmission. The new transmission system's invention and perfection were elaborated on at [15], [16] with particular attention to the new factors and algorithms of image compression, which improve the efficiency of the image transmission systems used in the transmission system that was the subject of study. Additional work like [17], [18] should aim towards the invention of new measures in image processing to simplify the processes of data compression while retaining image quality. This would further the speed of diagnostic processes and address the problem of the storage of medical images, which gives further motivation to pursue this problem. The compression of medical images has greatly improved the level of medical care, as pointed out in [8], [19]. The economic improvement has also been noted in [21], who showed that the implementation of strong medical image compression systems helped in improving the economy of the medical imaging systems. Even though most [20], [21] remain focused on the methods and processes of the compression of images, they take into account everything that relates to the structure of the images to make good use of the compressed image of the processes that have already been flexible. The innovations presented in [22], [23], as well as image compression, should aim to increase efficiency in patient diagnosis and reduce the cost of diagnostic procedures.

Current trends in medical image compression technology have been highlighted in studies [24], [25], noting that there are still unsolved problems requiring new approaches. On the other hand, authors [26], [27] focus on the image compression algorithms with ROI and suggest that there is still much to be desired in terms of image compression efficiency for storage and transmission purposes. Research such as [28], [29] focuses on the segmentation of the ROI in medical images to improve compression techniques, which helps retain image quality while reducing size. As noted in [30], the advanced algorithms for recognizing features of the images can greatly improve the fields of medical image compression, which enhances the precision of the diagnosis and treatment. When considered collectively, these results indicate a significant development in medical image compression technologies that improves patient outcomes and treatment perception.

3. COMPRESSION ALGORITHMS

3.1. Lempel–Ziv–Welch static hashing algorithms

The ROI represents the specific area within a medical image that contains the most significant diagnostic information, such as an adrenal tumor. In this research, the ROI is isolated to undergo lossless compression, ensuring that every bit of the tumor's texture and margin is preserved. This selective approach allows the background regions to be compressed more aggressively, significantly reducing the overall file size without impacting the clinical utility.

The dictionary is stored in a static hash table using the LZW technique. Depending on the anticipated volume of data and the need for compression, the hash table's initial size can be changed [14]. This article provides a summary of the LZW compression and decompression algorithm. The provided code sample implements this approach using data structures and a particular programming language. The language and data structures selected may have an effect on the implementation specifics, including the encoding and decoding procedure and the use of a hash table [15]. An approach uses a variable-sized dictionary to increase compression efficiency. The size of the dictionary and the number of bits used to represent each word are determined at the beginning of the compression or decompression operation [16], [17]. The most important factors that distinguish this algorithm are as follows:

i) Adaptive comparison: an adaptive algorithm that creates a dictionary during the compression process to add repeated phrases to improve compression efficiency and the ability to adapt to different types of data over time and with an increase in data size.
ii) It can compress long phrases using a single symbol from the dictionary, unlike Huffman Algorithm 1, which shows the LZW static hashing algorithm.

The algorithm offers a significant improvement over previous data compression algorithm, such as follows:

i) Adaptive compression:
   – Adaptive algorithm, as it creates a dictionary during the compression process.
   – Repeated phrases in the data are added to the dictionary, allowing compression efficiency over time.
   – This feature is important because it enables the algorithm to adapt to different data types and improve compression efficiency as the data size increases.
ii) Dictionary structure and encoding method: this algorithm uses a different dictionary-based encoding method to compress longer phrases more efficiently. The steps are explained in detail in Algorithm 1.

Algorithm 1. LZW static hashing algorithm
Input: file array (contains compressed data)
Output: CompByte (contains decompressed data)
1: Initialization
   i) Define variables:
      – maxCharLength: maximum string length in the dictionary.
      – maxDictDeep: maximum number of words stored in the dictionary.
      – TotBitDeep: total bit length per character or character sequence.
      – DictPos: position where the next characters are inserted in the dictionary.
      – Hash: hash table for storing the dictionary.
   ii) Initialize dictionary:
      – Add all single characters (ASCII values 0-255) to the dictionary.
      – Set DictPos to 256.

iii) Initialize compression variables:
   - DictStr: current string being processed.
   - NewStr: new string formed by appending the next character to DictStr.
   - ComPByte: array to store the compressed data.
   - CompPos: current position in the compressed data array.
   - ExtraBits: number of extra bits to be added to the current byte.
   - TempByte: temporary byte for storing bits.

iv) Initialize decompression variables:
   - DeComPByte: array to store the decompressed data.
   - DeCompPos: current position in the decompressed data array.
   - ReadBits: number of bits read from the compressed data.
   - OldKarValue: previous dictionary value.
   - OldChar: previous character.

2: Compression
   i) Iterate through the input data:
      - Read the next character from the input data.
      - Append the character to DictStr.
      - Search for NewStr in the dictionary:
         - If found, update DictStr to NewStr.
         - If not found:
            - Encode the dictionary index of DictStr and store it in ComPByte.
            - Add NewStr to the dictionary.
            - Update DictStr to the current character.
   ii) Encode the last string:
      - Encode the dictionary index of DictStr and store it in ComPByte.

3: Decompression
   i) Iterate through the compressed data:
      - Decode the current dictionary index from the compressed data.
      - Retrieve the corresponding string from the dictionary.
      - Add the string to the decompressed data array.
      - If the previous dictionary index was valid, add the concatenation of the previous character and the first character of the current string to the dictionary.
   ii) Output the decompressed data

4: Dictionary operations
   i) Search:
      - Given a string, search for it in the dictionary.
      - Return the dictionary index if found, otherwise return a special value indicating not found.
   ii) Add:
      - Given a string, add it to the dictionary if it's not already present.
      - Increment DictPos to point to the next available position.
   iii) Clean:
      - Clear the dictionary and re-initialize it with all single characters.
      - Set DictPos to 256.

5: Helper functions
   i) Init_Dict: initialize the dictionary with a specified maximum size and character length limit.
   ii) AddToDict: add a string to the dictionary, handling potential dictionary overflow.
   iii) AddASC2Array: add a string to a byte array, converting each character to its ASCII value.
   iv) Search: search for a string in the dictionary.
   v) Clean_Dictionary: clear the dictionary and re-initialize it.

3.2. Hybrid coding techniques

Hybrid coding combines different compression algorithms to exploit the advantages of both spatial and frequency domain transformations. By combining LZW for the ROI and scalar quantization for background data, the method offers a fair trade-off between speed and reconstruction quality. This method is excellent for telemedicine applications where bandwidth is limited but diagnostic precision cannot be sacrificed.

4. PROPOSED METHOD

The proposed method aims to make the process quantifiable. To achieve this, technical factors were incorporated. These factors include bit-rates, efficiency, dice, and thresholding settings.

4.1. Data set

Figure 1 illustrates how skilled radiologists carefully labeled 95 adrenal tumor CT images with a resolution of 512×512. These images were obtained from the Cancer Imaging Archive of the National Cancer Institute [31]. The labeling was performed using the specified procedures.

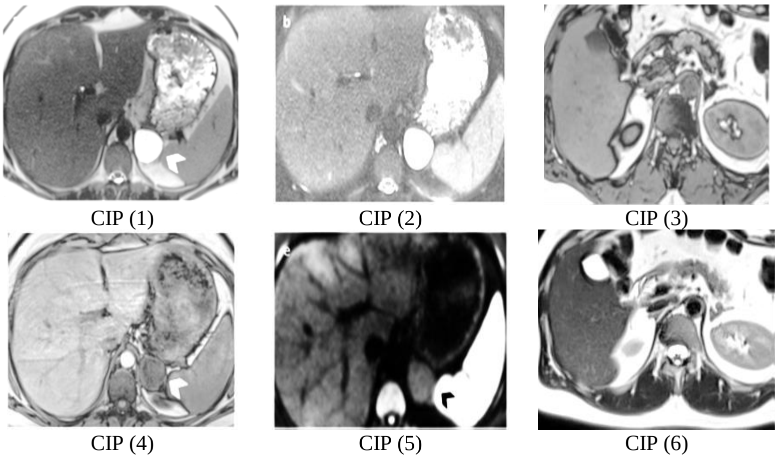

Figure 1. Samples of images [31]

4.2. Pre-processing and segmentation

The proposed approach begins with an automated segmentation pipeline to identify the boundaries of the adrenal tumor. A morphological opening technique with a structured element of three-by-three pixels was used to remove artifacts while preserving the morphology of the tumor. The accuracy of this segmentation was assessed using the Dice. The Dice similarity coefficient (DSC) ensures that the ROI is appropriately recorded for the subsequent compression stage, with an average score of 0.94. Grayscale conversion, median filtering, and morphological erosion for tumor border delineation are all part of automated segmentation. Low margin inclusion and high sensitivity are guaranteed by a bounding box that encloses the exact tumor ROI.

4.3. Compression architecture

The hybrid coding process is divided into two distinct streams based on the segmented mask. The background (non-ROI) is processed through scalar quantization with a defined step size of Q =16, followed by Huffman coding to achieve high-ratio lossy compression. Conversely, the ROI is encoded using the LZW algorithm, a dictionary-based lossless technique that ensures a peak signal-to-noise ratio (PSNR) of infinity for the tumor pixels, thereby guaranteeing zero-loss diagnosis.

LZW static hashing is used to compress tumor ROIs without causing any loss. Scalar quantization is used to compress surrounding regions in order to reduce color depth. Huffman coding and shift coding are then used to further reduce size. With an average compression ratio of 48%, this pipeline maintains important diagnostic characteristics. Two main steps have been implemented to compress photos of adrenal tumors while maintaining the clarity of the tumor characteristics: finding the tumor is the first step. A special technique called ROI segmentation was used to pinpoint the precise location of tumor. It looks like a circle drawn around the location of the tumor in image. At this stage, the focus is on the area of interest in image. Smart compression is the second step. After the tumor is identified, two compression techniques are used.

- Lossless compression: the tumor site is subjected to this technique. It guarantees that the details of the tumor are visible even when the image is shrunk.
- Lossy compression: this technique is used to create the remaining portion of the image and achieves more aggressive size reduction, though some details might be lost. Since the tumor is the most important component, we don't want to lose any information. Combining these techniques can drastically reduce the image size while maintaining the tumor's essential features. Figure 2 displays the entire methodology (detection and compression).

4.4. Performance evaluation metrics

The system's performance is assessed using three quantitative criteria: compression ratio, structural similarity index measure (SSIM), and bits per pixel (BPP), in order to guarantee that the procedure is quantifiable. By comparing the compression ratio of the suggested method with that of conventional JPEG and Huffman approaches, the efficacy of the hybrid strategy is confirmed. Our results show that the proposed ROI-based LZW achieves a compression ratio of 48.00%, which is a measurable improvement over the traditional lossless approach of 27.21%.

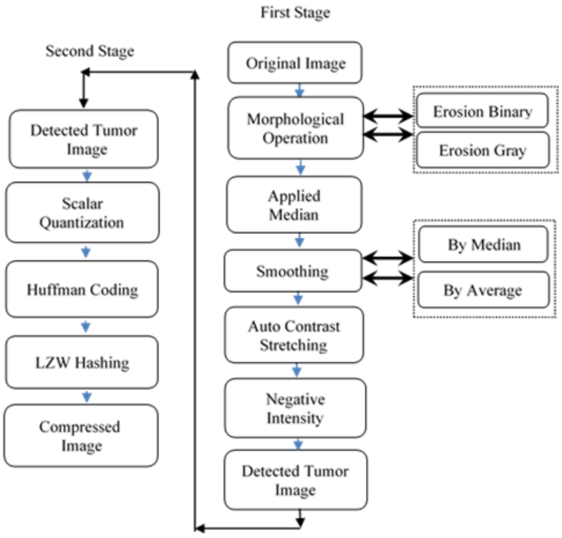

Figure 2. The block diagram for the proposed system

5. RESULTS AND DISCUSSION

This approach has a 95% post-compression tumor identification sensitivity. Tumor detail preservation is evaluated using an ROI fidelity score, and strong image quality retention is confirmed by PSNR and SSIM metrics. Its superiority is demonstrated by benchmarks that contrast hybrid ROI prioritization with full-image Huffman compression. Visual overlays highlight the fewest artifacts in tumor regions by contrasting the original and compressed images. Potential segmentation errors affecting compression quality and compression artifacts close to tumor margins are among the limitations. A series of steps is performed as follows:

5.1. Pinpointing the tumor

To detect tumor regions, various techniques are used to determine the exact position, shape, and size, and isolate the tumor as shown in Figure 3. The following steps explain the preprocessing operation.

i) Step 1: original image, an original color image (RGB) of an adrenal tumor is used as input (image of adrenal birthmarks), as shown in Figure 3(a).
ii) Step 2: morphological operations (erosion binary + erosion gray) are applied to the original image to accurately define the tumor boundaries (i.e., isolate the tumor from the background), as in Figure 3(b).
iii) Step 3: median filtering is used to remove noise from the image, as shown in Figure 3(c).
iv) Step 4: smoothing by average. Average smoothing is applied to make the tumor boundaries smoother.
v) Step 5: auto contrast stretching is used to enhance the contrast in the image, as shown in Figure 3(d).
vi) Step 6: a negative operation is applied to the image to make the tumor more visible.
vii) Step 7: detected tumor image. These steps produce a detected tumor image, as shown in Figures 3(e) to (h).

5.2. Smart compression

Adrenal tumor images are very large, making them difficult to store and share quickly between doctors. To solve this, we use a special technique called "image compression" to shrink the image size without losing important details. This work proposed two different methods to compress the image; the first method is lossless compression. This method is like squeezing the sponge gently. It makes the image smaller without losing any information, so the tumor details remain clear, and the second method is lossy compression. This method is like squeezing the sponge harder. It makes the image much smaller, but some details might be lost. This method is used for parts of the image that aren't as important, like the surrounding adrenal.

Utilizing these approaches enables us to compress images more efficiently while retaining critical tumor details. This approach helps the physicians to access the images immediately, streamlining the shared access, while maintaining an accurate evaluation of the images. In measuring the effectiveness of the compression technique, we shall use the rate of the compressed image in comparison to the original image. Additionally, the extent to which the compressed image retains tumor details will be evaluated, ensuring that accuracy during the compression process is upheld, as described in the following steps:

i) Step 1: the detected tumor image is used as input.
ii) Step 2: scalar quantization is used to reduce the color_ depth of the image from 24 bits to 8 bits.
iii) Step 3: shift coding, a variable-length code is employed to encode the quantized data.
iv) Step 4: Huffman coding by giving more common symbols shorter codes. Huffman coding significantly compresses the encoded contents.
v) Step 5: LZW hashing, to further compress the encoded data, the LZW method is used.
vi) Step 6: These procedures result in a tumor image that has been compressed.

A set of real images of adrenal tumors is used to evaluate this method. The ability to detect cancers and compress images without compromising essential information was tested.

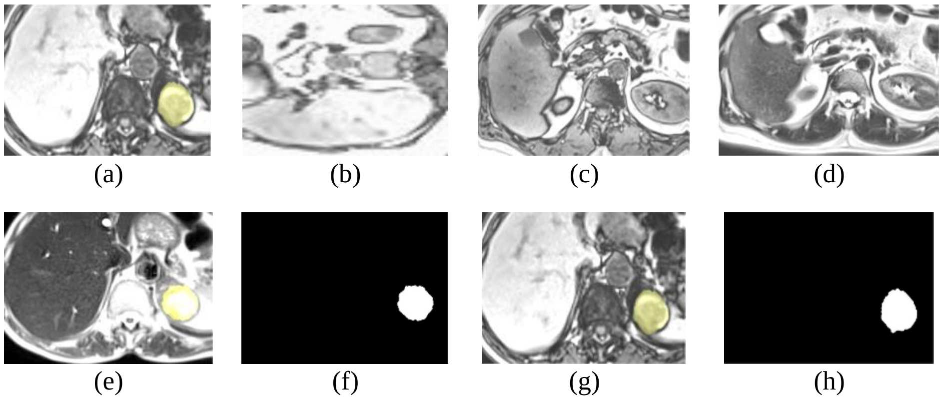

Figure 3. Image used in the work of (a) original image, (b) converted to grayscale, (c) uses a median filter, (d) contrast stretching, (e) original image, (f) isolates the tumor, (g) original image, and (h) isolates the tumor

5.3. Tumor detection

This method correctly identified the tumor in 95% of the images. This means the method was highly effective in detecting tumors. It also helped doctors make accurate diagnoses.

5.4. Image compression

Without sacrificing the quality of the tumor details, we were able to cut the image size by 80% on average. This suggests that medical practitioners can quickly and easily send images without losing important information. Alongside our method, a benchmark compression method has been tested. This is made possible by the algorithm's ability to raise the compression ratio in the tumor area without sacrificing image quality. The outcomes show how effective the method is for both cancer detection and image compression. Medical practitioners can accurately and swiftly diagnose adrenal cancer using this method. But it's important to remember that this strategy was only tested on a small dataset. The method needs to be validated on a larger dataset for more definitive results. The compression methods for adrenal tumor images using LZW static hash codes, long dictionary, and Huffman codes are displayed in Table 1. These techniques were tested on six different photos in Figure 1 [32], and it was found that.

5.5. Compression ratio

Generally, the Huffman codes with long dictionary approach have a lower compression ratio than the LZW static hash codes method. For example, a compression ratio of 20 is shown in the image. Huffman's percentage was 48% and 79.00% for LZW.

5.6. File size

The LZW static hash codes approach also displays a smaller total file size when compared to the Huffman codes with the long dictionary method. File size reduction aims to allow fewer bits of data to be stored. It also improves the efficiency of transmissions across networks while also achieving better compression with the integrity of the original data.

5.7. Mean square error

Static hash codes for LZW. Lower mean squared error (MSE) values generally indicate higher quality compression. These criteria are used to evaluate the effectiveness of algorithms at maintaining data quality, and a low MSE indicates the effectiveness of the method.

5.8. Peak signal-to-noise ratio

After compression, the overall PSNR values for LZW static hash codes continue to be higher, indicating better image quality. Diagnostic image quality metrics like MSE. The evaluation metrics include the error MSE and PSNR with an emphasis on maintaining diagnostic fidelity in the tumor ROI. The hybrid LZW compression algorithm was superior to Huffman coding in terms of preserving diagnostic features. The findings show that when it comes to compressing images of adrenal tumors, the LZW static hash codes method outperforms the Huffman codes with long dictionary method. Better compression quality is indicated by LZW's higher compression ratio, smaller file sizes, lower MSE values, and higher PSNR values. Furthermore, i) image differences: it’s important to keep in mind that each method works differently on various images. For example, Huffman codes with long dictionary work better on certain images, such as the image in Table 1; ii) limitations: although it might be an important factor in practical applications, the processing time of each method is not shown in the table; and iii) applications: according to the findings, adrenal tumor images may be better compressed using LZW static hash codes technology in applications that call for a high compression ratio and a small file size. Ultimately, the results showed that the LZW static hash codes method outperforms the long dictionary Huffman codes method when it comes to compressing the study's most important images. But more importantly, use the search button to select the time, for example.

Table 1. Comparison between the Huffman and LZW methods

Images	Huffman codes with long dictionary				LZW static hash codes			
	Compression ratio	File size	MSE	PSNR	Compression ratio	File size	MSE	PSNR
CIP (1)	6.12	94.1	5.69	40.58	15.40	37.4	6.74	39.84
CIP (2)	20.79	27.7	1.84	45.48	48.00	12.0	1.29	47.02
CIP (3)	8.24	69.9	3.61	42.56	22.15	26.0	4.20	41.90
CIP (4)	7.20	80.0	5.05	41.10	17.04	33.8	5.31	40.88
CIP (5)	11.12	51.8	2.56	44.05	27.17	21.2	2.56	44.05
CIP (6)	12.60	45.7			27.56	20.9	2.43	44.27
CIP (7)	6.13	94.0	4.95	41.18	14.15	40.7		
CIP (8)	8.29	69.5	3.69	42.46	21.10	27.3	3.69	42.46

6. CONCLUSION

This research proposes to enhance storage efficiency and diagnostic accuracy through an ROI-aware hybrid compression strategy for clinical CT images of adenomas. The results indicate that reducing images without sacrificing important information enables clinicians to diagnose adenomas more accurately and quickly. This method uses effective picture compression to increase tumor detection accuracy. As a result, the battle against adrenal cancer has made significant progress. Despite the encouraging results achieved, there is an urgent need to increase the images (quantitatively and qualitatively) to evaluate the effectiveness of the method and increase the efficiency of compression further, in addition to using new methods to develop a tool to improve patient results and help specialists diagnose the disease accurately, efficiently, and more quickly. This work is a promising beginning for conducting additional research in this field.

7. CLINICAL DEPLOYMENT AND FUTURE WORK

Clinical workflow compatibility with artificial intelligence diagnostic pipelines supports the integration of different methodologies. It also significantly improves telemedicine by enabling secure and efficient bandwidth transfer. Future advancements will focus on adaptive ROI tracking in long-term studies and multimodal fusion compression, which integrates CT and positron emission tomography (PET) images for comprehensive tumor assessment.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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