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Review on Medical Image Compression

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Abstract: *In today's digital era, the demand for digital medical images is rapidly increasing. Hospitals are transitioning to filmless imaging systems, emphasizing the need for efficient storage and seamless transmission of medical images. To meet these requirements, medical image compression becomes essential. However, medical image compression typically necessitates lossless compression techniques to preserve the diagnostic quality and integrity of the images. There are several challenges associated with medical image compression and management. Firstly, medical image management and image data mining involve organizing and accessing large volumes of medical images efficiently for clinical and research purposes. Secondly, bioimaging, which encompasses various imaging modalities like microscopy and molecular imaging, presents specific requirements and challenges for compression algorithms. Thirdly, virtual reality technologies are increasingly utilized in medical visualizations, demanding efficient compression methods to handle the high resolution and immersive nature of VR medical imaging data. Lastly, neuro imaging deals with complex brain imaging data, requiring specialized compression techniques tailored to the unique characteristics of these images. As the amount of medical image data continues to grow, image processing and visualization algorithms have to be adapted to handle the increased workload. Researchers and developers have been working on various compression algorithms to address these challenges and optimize medical image compression. This review paper compares different compression algorithms that would provide valuable insights into the strengths, limitations, and performance metrics of various techniques. It would assist researchers, clinicians, and imaging professionals in selecting the most suitable compression algorithm for their specific needs, considering factors such as compression ratio, computational complexity, and image quality preservation. By comprehensively comparing compression algorithms, this review paper contributes to advancing the field of medical image compression, facilitating efficient image storage, transmission, and analysis in healthcare settings.*

Keywords: Medical image compression, lossy compression, lossless compression, hybrid compression, ROI

I. INTRODUCTION

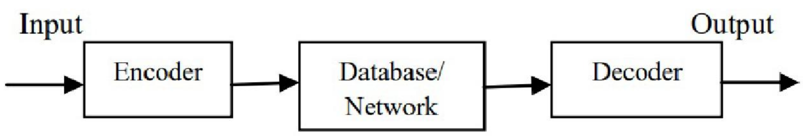

Figure 1: Basic compression techniques[21]

In earlier years, a large volume of medical image data was collected in hospitals and medical institutions through a variety of methods, including magnetic resonance imaging (MRI), X-ray imaging, Ultrasound (US) Imaging, Computed Tomography Imaging (CT), Positron Emission Tomography Imaging (PET), and Digital Fluorography Imaging (DF) [1] M. F. Ukritet.al.,[2] D. Ravichandran et.al.,[3] G. Al-Khafaji. [4] Shivaputra et.al The essential element of information and communication technology is the integrity of the transmitted medical images . Redundancy can be removed bycompressing the data. Different redundancies are 1) redundancy of coding;2) redundancy of inter pixels; 3) psycho-visual redundancy(based on information neglected by human vision) D.J. A. Pabi et.al.[5], S. Kazeminiet.al.[6],M. M. S. Rani et.al [7], M. Vaishnav et.al [8]. The compression of medical images is essential so that

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the images can be transmitted quickly via a lower band width and with high efficiency in remote areas R. Sharma et.al[9]. Compression can be defined as a coding process which reduces the total number of bits to represent certain data Data is converted into a coded format by an encoder. Encoded data is transmitted through the network. Original data is retrieved by a decoder.

II. TYPES OF COMPRESSION

This section explains the recent literature survey on medical image compression.

2.1. Lossy Compression Techniques

Bruylants et. al. [10] presented a novel Wavelet based framework that supports JPEG 2000 with its volumetric extension. The presented approach enhances the performance of the JPEG2000 for volumetric medical image compression. In their research, they extensively evaluated the effectiveness of a wide range of compression settings for volumetric compression in three essential medical modalities: CT scans, MRI images, and ultrasound. During this study, they specifically focused on examining the impact of a generic codec framework, directional wavelet transforms, and a generic intra-band prediction mode. Their aim was to determine the efficiency of proposed approach by analysing the performance of these components across various compression scenarios. By considering the intricate interplay between these technologies, they gained valuable insights into their effectiveness and potential to enhance the compression process. Through rigorous testing and analysis, they examined how the generic codec framework, directional wavelet transforms, and generic intra-band prediction mode contribute to optimizing volumetric compression. Their goal was to quantify the improvements they bring to the compression process, ultimately resulting in more efficient and reliable outcomes. By carefully assessing the performance of these techniques, we can confidently present a comprehensive evaluation of our proposed approach's efficiency. This research opens up new possibilities for improving the compression of volumetric data, benefiting medical professionals in their daily practice. Their findings had shed light on the advantages and limitations of these technologies, providing valuable knowledge for the future development of enhanced compression methods in the medical field. Ayoobkhan et. al.[11] presented a novel compression method PE-VQ for the lossy compression of medical images. To construct codebook the artificial bee colony and genetic algorithms are used. To compute the optimal results and prediction error, vector quantization concepts are involved for the effective compression of the images. It is observed that the proposed technique is able to achieve higher PSNR for a given compression ratio in comparison to the other algorithms. Rufai et. al.[12] described a novel lossy compression technique for the medical image compression. The reported approach comprised of singular value decomposition (SVD) and Huffman coding. It is seen from the simulation results that; the reported approach is able to provide better quantitative and visual results in comparison to the other conventional techniques like Huffman coding and JPEG2000. Selvi and Nadarajan [13] proposed a 2-D lossy compression technique for the compression of the MRI and CT images. With the wavelet-based contourlet transform (WBCT) at its core, their approach leverages the power of this transformative technique to efficiently process and analyse data. By harnessing the unique capabilities of WBCT, they unlocked the potential for enhanced detail preservation, improved feature extraction, and optimized data representation. In addition, they employ the binary array technique (BAT) to further augment the efficiency of their approach. By leveraging the principles of binary array manipulation, they unlock new avenues for data compression, encoding, and decoding. This technique not only streamlines the process but also ensures data integrity and minimizes storage requirements. Together, the wavelet-based contourlet transform (WBCT) and the binary array technique (BAT) form a formidable duo that propels the proposed approach to new heights. By seamlessly integrating these techniques, they enable advanced data processing, efficient storage utilization, and improved computational performance. It is concluded that the proposed approach requires less processing time and generate precise output results in comparison to the existing wavelet-based set partitioning in hierarchical and embedded block coders. Sriraam and Shyamsunder [14] introduced a 3D wavelet encoder approach to compress the 3D medical images. Here, the reported approach work is two stages, firstly the encoding can be done with four wavelet transforms named as, Daubechies 4, Daubechies 6, Cohen-Daubechies-Feauveau 9/7 and Cohen-Daubechies-Feauveau 5/3 and at later stage 3-D SPHIT, 3-D SPECK and 3-D BISK. Hosseini and Naghsh-Nilchi [15] described contextual vector quantization for the medical image compression. The medical modality ultrasound is used to simulate the experiment and conclude the results.

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Higher compression ratio and PSNR in comparison to the other conventional algorithms (JPEG, JPEG2K, and SPHIT) can be achieved using this method. Bairagi et. al. [16] reported a text based approach to compress the medical images effectively. It deals with the visual quality rather than the pixel wise fidelity. Prabhu et. al.[17] suggested an effective method for the compression of MRI images which is a groundbreaking solution, the 3-D Warped Discrete Cosine Transformation (WDCT), specifically designed to address the unique challenges of compressing MRI images with unparalleled effectiveness. By employing advanced techniques and innovative algorithms, they have developed a state-of-the-art approach that surpasses traditional methods.The 3-D WDCT technique enables to achieve exceptional compression results while preserving the essential details and quality of MRI images.Through meticulous research and rigorous testing, they have demonstrated the power of WDCT in efficiently compressing MRI data. This transformative approach not only minimizes storage requirements but also ensures the accurate representation of vital medical information within the images.3-D WDCT algorithm introduces a new level of precision and adaptability by warping the discrete cosine transformation to suit the specific characteristics of MRI images. This tailored approach enhances the compression process, resulting in improved visual clarity and reduced file sizes. By harnessing the potential of the 3-D WDCT technique, they empower healthcare professionals to effectively manage and transmit MRI images without compromising the integrity of the diagnostic information. This breakthrough technology has the potential to revolutionize medical imaging by streamlining workflows, optimizing storage capacity, and facilitating faster image transfer. Experience the future of MRI image compression with pioneering 3-D Warped Discrete Cosine Transformation (WDCT). Embrace the enhanced efficiency, unparalleled quality, and transformative capabilities as we redefine the boundaries of medical imaging.

2.2. Lossless Compression Techniques

M. Purushotham Reddy et.al.[19] explains the lossless image compression using delimiter-based compression for telemedicine images. In encoding process, the image matrix is converted into binary row vector and evaluated row vector which contains continuous unique elements with number of repetitions. It contains a smaller number of values and applying entropy encoding. The proposed method is an efficient image compression method. Lossless medical image compression techniques are lossless JPEG, JPEG-LS, JPEG 2000, PNG and CALIC. Lose less described the predictive image compression algorithm with Huffman or arithmetic entropy coder [22] JPEG-LS described low complexity image compression algorithm with entropy coding and the algorithm used is LOCO-I[23] JPEG 2000 described the algorithm based on wavelet transform image decomposition and arithmetic coding[24] PNG described predictive image compression algorithm. A universal algorithm for sequential data compression is presented. Its performance is investigated with respect to a non-probabilistic model of constrained sources. Universal code developed consistently achieves compression ratios that come very close to the smallest possible ratios achieved by specialized coding techniques called block-to-variable codes and variable-to-block codes. These specialized codes are specifically designed to work with specific types of data. In simpler terms, universal code is highly efficient in compressing data. It can significantly reduce the size of the data while maintaining its quality. The compression ratios it achieves are comparable to the best possible ratios achieved by other specialized coding techniques that are designed for specific types of data. as explained by J. Ziv et.al [25] CALIC is an algorithm that utilizes Arithmetic Entropy codes, which are known for their high compression ratio. Among the various algorithms compared, JPEG-LS stands out for having the best combination of Compression Speed (CS) and Compression Ratio (CR). When it comes to speed, JPEG 2000, PNG, and CALIC show similar performance, with CALIC slightly outperforming JPEG 2000 and PNG in terms of speed. However, when comparing compression ratios, both JPEG-LS and CALIC surpass JPEG 2000. JPEG 2000, on the other hand, outperforms PNG and Lossless JPEG in terms of compression ratio. Considering both compression speed and compression ratio, JPEG-LS emerges as the best algorithm for lossless compression of medical images. It strikes a balance between efficient compression and high-quality preservation of medical image data, making it the optimal choice for medical image compression[26]

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Lossless JPEG		JPEG-LS		JPEG 2000		PNG		CALIC	
CS	CR	CS	CR	CS	CR	CS	CR	CS	CR
11.9	3.04	19.6	4.21	4.0	3.79	3.6	3.35	4.5	4.11

Figure 2: Compression Speed and Compression Rate for different algorithms[21]

2.3. Hybrid Compression Techniques

Matthew J. Zukoski et.al[20] proposed ROI-based compression strategy with unequal bit stream protection comprises three key components, each playing a crucial role in achieving superior results:

- Region of Interest (ROI) Extraction: The first component focuses on accurately identifying and extracting the regions of interest within the medical images. These regions are carefully determined by radiologists, ensuring that the critical and diagnostically significant areas receive special attention during the compression process.
- ROI-based Coding: The second component involves a specialized coding technique that is specifically tailored to the regions of interest. This targeted approach allows for optimal compression of the important regions, maximizing the preservation of vital diagnostic information and maintaining the highest possible image quality.
- Unequal Protection of ROI Bit Stream: The third component enables an unequal protection scheme for the bit stream of the regions of interest. This means that extra care and resources are allocated to ensure the integrity and fidelity of the compressed data within the clinically relevant areas, further enhancing the accuracy and reliability of the diagnostic information.

By combining these three components, our model-based compression technique offers a comprehensive and efficient solution for medical image compression. It leverages the expertise of radiologists to prioritize the regions of clinical significance, utilizing lossless compression to preserve the utmost accuracy and quality within these areas. Meanwhile, lossy compression is applied to the non-critical regions, achieving higher compression ratios without compromising the overall diagnostic value of the image. Extracting the Regions of Interest (ROI) through a hierarchical segmentation process. This segmentation method combines Marker-based watershed with active contours using level set techniques. This meticulous approach ensures accurate delineation of the clinically significant regions within the medical images. Once the ROIs are identified, they undergo selective encoding using a specialized 3D coder based on a shape adaptive discrete wavelet transform known as 3D-BISK. This coding method takes into account the shape and characteristics of each ROI, enabling efficient compression tailored to the specific diagnostic relevance of each region. The compression ratio applied to each ROI varies based on its importance in diagnosis, ensuring that critical information is preserved with high fidelity.

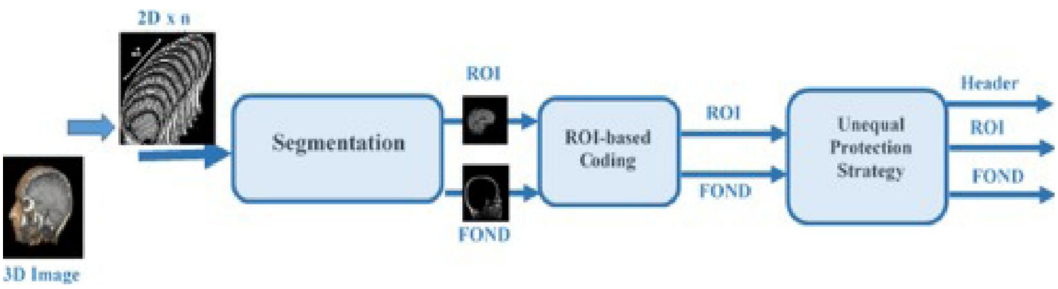

Figure 3: ROI-based compression strategy[27]

To protect the integrity of the obtained ROIs, an error-correcting code of Reed-Solomon type is employed. This code utilizes an unequal protection strategy, meaning that the code rate varies according to the relevance of each region. In this way, regions that are more diagnostically significant receive stronger error-correction protection, ensuring the highest possible data integrity during transmission or storage. By combining these advanced techniques, our model-based compression approach offers a comprehensive solution for medical image compression. The hierarchical

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segmentation, selective encoding, and unequal protection strategy optimize the compression process to preserve critical diagnostic information while achieving efficient storage and transmission as explained by D. Dhouib.et.al[27]

R. Monika et.al [28]proposes Coefficient Mixed Thresholding based ABCS (CMT-ABCS), a cutting-edge compression technique designed to achieve high compression ratios for various types of medical images. Through extensive experimentation, our method has demonstrated remarkable performance metrics, surpassing other state-of-the-art approaches in the field. The experimental outcomes have revealed significant improvements in the performance of proposed method when compared to existing techniques. Notably, there has been a substantial increase in Peak Signal-to-Noise Ratio (PSNR) by 5 – 10 dB, indicating enhanced image quality. Additionally, Structural Similarity Index (SSIM) values have improved by 0.1 – 0.2, indicating better preservation of structural details in the compressed images. Furthermore, the Normalized Cross-Correlation (NCC) values approach 1, indicating a higher degree of similarity between the original and reconstructed images. Similarly, the Normalized Absolute Error (NAE) values approach 0, suggesting minimal distortion in the reconstructed images. In particular, our method exhibits outstanding performance when dealing with low sampling rates. The reconstruction process significantly benefits from our technique, resulting in greatly enhanced image quality even with limited sampling information. By leveraging the power of Coefficient Mixed Thresholding based ABCS (CMT-ABCS), we have successfully achieved exceptional compression ratios while preserving crucial details and ensuring high-quality reconstruction.

Our method sets a new benchmark in medical image compression, outperforming state-of-the-art techniques and paving the way for more efficient storage and transmission of medical images. In medical applications, Atmost care should be taken while retaining image information in supporting different diagnosis purposes during the compression. In Wei-Yen Hsu's[29] study, presented an innovative and automatic image segmentation method specifically designed for tumor segmentation from mammogram images. Their approach utilizes an improved watershed transform technique that incorporates prior information to enhance the accuracy of segmentation. The segmented results of different regions are then subjected to lossy and lossless compression, optimizing storage efficiency without compromising the essential tumor features. The overall process consists of two main procedures: region segmentation and region compression. In the first procedure employ the Canny edge detector to detect the boundary between the background and breast regions in the mammogram images. Subsequently, an improved watershed transform, leveraging intrinsic prior information, is utilized to extract the tumor boundary. This allows for the segmentation of the mammograms into three categories: tumor, breast without tumor, and background. Moving to the second procedure, they apply Vector Quantization (VQ) in conjunction with a Competitive Hopfield Neural Network (CHNN) to compress the three segmented regions. The compression rates are adjusted based on the importance of the data within each region. This approach ensures that crucial tumor features are preserved while reducing the overall size of the mammograms for efficient storage. 2.3.1. DCT in Hybrid Compression Technique A notable reference in this field is the work presented by U.S. Mohd et al[30]. They introduce a scalable hybrid scheme that incorporates both the Wavelet and Fourier transforms. This scheme offers a flexible and efficient approach to compression, allowing for scalability and adaptability to different image types and compression requirements. By leveraging the strengths of both the Wavelet and Fourier transforms, our approach ensures effective compression by capturing both spatial and frequency information. The DWT is particularly suitable for capturing local details and eliminating redundant information within the image (intra-coding),while the DCT is effective in capturing global features and facilitating compression across multiple images (inter-coding). The hybrid scheme proposed by U.S. Mohd et al. provides a comprehensive solution that combines the advantages of both transforms. This allows for superior compression performance, enabling efficient storage and transmission of images without compromising the essential details.

In the compression process, the original data M(x, y) of size x * y is utilized. The first step is to divide the input image into blocks of size 8x8. Then, a 2-D Discrete Cosine Transform (DCT) with 8 points is applied to each block. This transformation converts the image blocks into a set of DCT coefficients. To achieve quantization, the DCT coefficients are divided by corresponding elements in an 8x8 quantization table, which follows the specifications of the JPEG standard as described by J. D. Kornblum et. al[32]. The result is rounded to the nearest integer value, thus quantizing the coefficients. This quantization process helps in reducing the amount of data required for storage and transmission. Additional compression is attained by applying an appropriate scaling factor.

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$$D_{DCT}(i,j)=\frac{1}{\sqrt{2N}}B(i)B(j)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}M(x,y)$$
$$.\cos\left[\frac{(2x+1)}{2N}i\pi\right]\cos\left[\frac{(2y+1)}{2N}j\pi\right] \quad \_(1)$$

Where

$$B(u)=\begin{cases}\frac{1}{\sqrt{2}} & if \quad u=0 \\ 1 & if \quad u>0\end{cases}$$

Figure 4: Equation of DCT [31]

This scaling factor further reduces the size of the data without significant loss of essential information. To reconstruct the compressed data, the rescaling and de-quantization steps are performed. The de-quantized matrix is obtained by multiplying the quantized matrix with the corresponding elements of the quantization matrix. Finally, the inverse-DCT is applied to the de-quantized matrix to transform it back into the original data representation

$$D_{quant}(i,j)=round\left(\frac{D_{DCT}(i,j)}{Q(i,j)}\right)$$

Figure 5: DCT quantised Equation[31]

The entire procedure is shown in Fig 5.

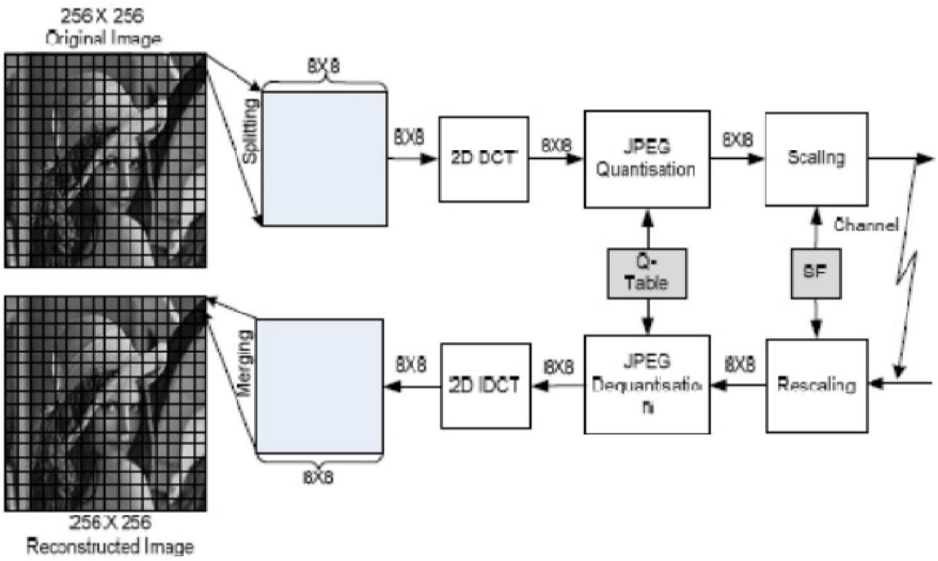

Figure 6: Block diagram of the JPEG-based DCT scheme[31]

2.3.1. DWT in Hybrid Compression Technique

The research conducted by Suchitra Shrestha et al[33] introduces a hybrid algorithm that combines the Discrete Cosine Transform (DCT) with the Discrete Wavelet Transform (DWT). This algorithm has been evaluated through simulations on various medical and endoscopic images and videos. The results demonstrate that the proposed hybrid algorithm outperforms standalone DCT and DWT algorithms in terms of Peak Signal-to-Noise Ratio (PSNR) while achieving

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higher compression ratios. The purpose of this hybrid algorithm is to serve as an image/video compressor engine in medical imaging and video applications, including telemedicine and wireless capsule endoscopy. By integrating the strengths of both DCT and DWT, the algorithm aims to optimize compression performance and quality for these specific applications. The DWT represents an image by decomposing it into wavelet functions, or wavelets, at different scales and locations. The image data is transformed into a set of high-pass (detail) and low-pass (approximate) coefficients. The algorithm divides the image into blocks of size 32x32 and applies filters to each block. The first level decomposition generates approximation and detail coefficients. The transformed matrix is obtained, and the detail and approximate coefficients are separated into LL, HL, LH, and HH coefficients. While discarding most coefficients, the LL coefficients undergo a second-level transformation. These coefficients are then scaled by a constant factor to achieve the desired compression ratio. Figure 6 illustrates this process, with x[n] representing the input signal, d[n] representing the high-frequency component, and a[n] representing the low-frequency component. For data reconstruction, the coefficients are rescaled and padded with zeros, and then passed through the wavelet filters. The algorithm utilizes Daubechies filter coefficients to facilitate this reconstruction process. The proposed hybrid algorithm provides a promising solution for image and video compression in the medical field, offering improved performance in terms of compression ratio and image quality. Its potential applications in telemedicine and wireless capsule endoscopy hold significant value for advancing these domains. By harnessing the benefits of both DCT and DWT, our hybrid algorithm empowers medical imaging and video applications with efficient compression capabilities, facilitating enhanced data transmission and storage. as explained by K. A. Wahid et.al[34]. 2.3.3. DWT - DCT Hybrid Compression Technique The method proposed by Swapna et.al[31] presents a new approach for image/frame compression. In this method, the original image/frame of size 256x256 (or any resolution that is divisible by 32) is initially divided into blocks of size N x N.

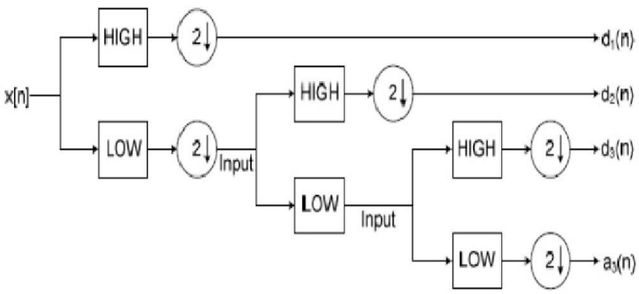

Figure 7: Block diagram of 2 level DWT Scheme[31]

Each block undergoes a 2-D Discrete Wavelet Transform (DWT) decomposition. The DWT separates the block into high-frequency coefficients (HL, LH, and HH) and low-frequency coefficients (LL). In this method, only the LL components are retained for further processing, while the high-frequency coefficients are discarded. The retained LL components then undergo another round of 2-D DWT decomposition. This additional decomposition helps capture more detailed information. Subsequently, an 8-point Discrete Cosine Transform (DCT) is applied to the DWT coefficients. To achieve higher compression, the majority of the high-frequency DCT coefficients are discarded. This reduction in high-frequency information enables significant compression. Further compression is achieved through a quantization process inspired by the JPEG standard. In this stage, many higher frequency components are rounded to zero, leading to a more compact representation of the data. The quantized coefficients are then scaled using a scalar quantity known as the scaling factor (SF). This scaling factor helps adjust the compression level according to specific requirements. Finally, the image is reconstructed by applying the inverse procedures, including the inverse DCT and inverse DWT. During the inverse DWT, zero values are padded in place of the discarded detail coefficients. This step ensures the proper reconstruction of the original image. The entire procedure is summarized in the following steps and illustrated in Figure 8 (for N=32). The sub-sampling schemes of the DWT coefficients are also shown in the figure. Figure 8a represents the fully sampled LL component, while Figure 8b depicts the quarterly sampled and half sampled LH, HL, and HH components. This method offers a systematic approach to achieve high compression while preserving important image features. By combining DWT, DCT, quantization, and scaling, the proposed method provides an efficient solution for image compression applications.

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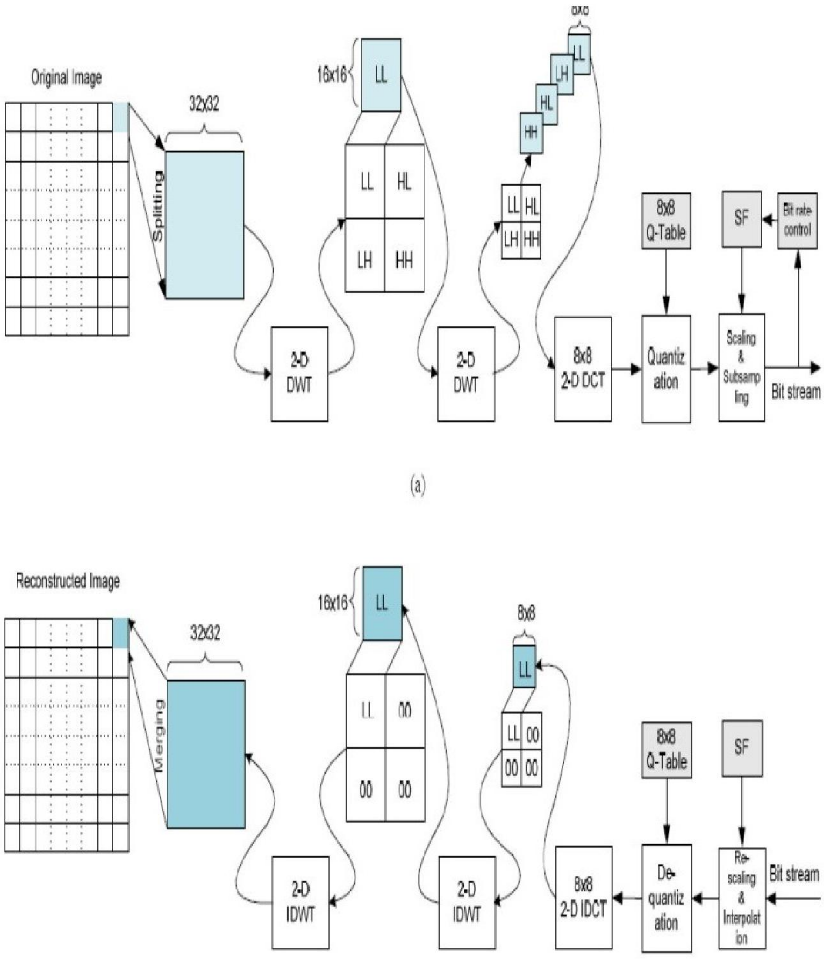

(b)

Figure 8: (a) DWT-DCT hybrid compression(b) DWT-DCT hybrid decompression[31]

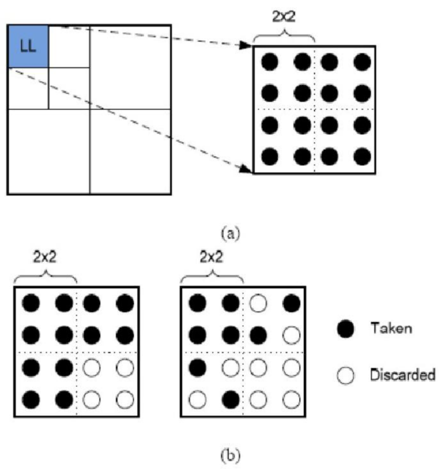

Figure 9: Sub sampling of DWT coefficients[31]

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III CONCLUSION

The demand for digital medical images is growing rapidly, emphasizing the need for effective storage and easy transmission. To address these requirements, medical image compression plays a crucial role. While lossless compression ensures exact image reconstruction, it typically offers limited compression ratios. To achieve optimal compression ratios, a promising approach involves segmenting the image into regions of interest (ROI) and non-ROI zones. By focusing on specific areas of importance, such as specific anatomical structures or pathologies, compression efficiency can be enhanced due to the reduced data scale. This segmentation allows for minimizing the computational power and time required for compression. In recent times, researchers have been exploring the development of hybrid compression algorithms. These algorithms combine different compression techniques to improve compression efficiency. By integrating the strengths of multiple approaches, hybrid algorithms can achieve better compression ratios and overall performance. One such study conducted by Iman Qays Abduljaleel et. al[18] focuses on developing such hybrid compression algorithms. When it comes to medical image transmission, bandwidth constraints become a significant consideration. Hybrid compression techniques are particularly useful in meeting these constraints. They enable efficient utilization of available bandwidth while ensuring the necessary image quality for accurate diagnosis and analysis. The security of medical images is of utmost importance. Confidentiality and authenticity measures should be implemented to safeguard patient information and ensure the integrity of the images. This includes employing secure transmission protocols, access controls, and encryption techniques to prevent unauthorized access and maintain the confidentiality of sensitive medical data. In summary, the need for medical image compression arises from the growing necessity for efficient storage and transmission. Hybrid compression algorithms offer an avenue to enhance compression efficiency by integrating different techniques. Alongside efficiency, the security of medical images should be prioritized to maintain confidentiality and authenticity while adhering to data protection regulations.

IV. FUTURE SCOPE

Medical images serve as critical digital resources within hospital information systems, enabling physicians to exchange images swiftly and reliably for accurate disease diagnosis and analysis. However, challenges arise when it comes to data storage and security in the exchange of medical files. These challenges have prompted researchers to explore various compression algorithms to address these issues effectively. While the focus of much research has been on Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), there is relatively less emphasis on other types of medical images. It is important to note that different medical imaging modalities, such as X-rays, ultrasound, mammograms, and nuclear medicine scans, present unique characteristics and challenges in terms of image size, complexity, and diagnostic requirements.

Researchers have dedicated their efforts to developing compression algorithms tailored to the specific needs of CT and MRI imaging. These algorithms aim to strike a balance between achieving efficient compression to optimize storage space and ensuring that the compressed images retain the necessary diagnostic information for accurate interpretation. However, it is equally important for researchers to expand their focus beyond CT and MRI and explore compression techniques for other medical image modalities. Each modality requires careful consideration of image characteristics, compression ratios, and diagnostic quality to ensure reliable and accurate diagnosis across different medical specialties. By addressing the challenges of data storage and security in medical image exchange and developing compression algorithms suited to various imaging modalities, researchers can contribute to a more efficient, secure, and reliable medical imaging ecosystem. This, in turn, facilitates seamless communication between healthcare providers, enhances diagnosis and treatment planning, and ultimately improves patient care..

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