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A comparative analysis of wavelet families and their various wavelet forms for the compression of medical images

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Abstract:

Since computer images possess a great deal of data, they require a large amount of storage space. As a result, it can take a long time to send an image between the devices. Techniques for image compression may eliminate through additional data from images, preserving transmission time and storage space. The study is about key aspects of the wavelet transform used in image compression. The wavelet transform is a rapidly evolving tool that offers effective compression performance for images, in terms of both signal-to-noise ratio and visual quality. Wavelet transformation offers information about an image in both the spatial and frequency domains. In this study, the optimal wavelet function for a specific grayscale image compression is chosen. The work examines wavelets for compression: Biorthogonal, Symlet, Coiflets, reverse biorthogonal and Daubechie. In order to compress images using the Huffman coding technique, this analysis compared wavelet families in all of their variants. All of the primordial wavelets are studied in relation to the image compression scheme, and the wavelets that produce the best compression are provided as the output. When all parameters are taken into account, it was determined that Db4 wavelets significantly preserve useful data in corrupted images.

Keywords — **Compression, Huffman code, Wavelet, Haar, Daubechies, Symlet, Biorthogonal, Coiflets, reverse biorthogonal.**

I. INTRODUCTION

The primary goal of image compression is to preserve acceptable image quality while representing an image with the fewest number of bits possible. By eliminating statistical redundancy and exploiting perceptual irrelevancy, all image compression algorithms seek to minimize the amount of data. Lossless compression and Lossy compression are the two categories that best describe image compression techniques. The images are kept in the form of files due to information technology. However, the size of these image files makes it impossible to store them in medical records in tandem with printed information. Image compression is one way to lower the file size. By eliminating data duplication in the image, image compression seeks to minimize the amount of memory needed to represent digital images, requiring less memory than the original image. One of the advantages of reducing images is a decrease in the data transmission time over the information transfer route. Sending images from fax or video conference calls, mobile devices, the online world transferring information from satellites, including medical data. use fewer bytes of memory while maintaining the data than the uncompressed image [1].

Reconstructing information from compressed data may yield a copy that is similar but not exactly the original. Lossy compression methods use compression to boost efficiency, despite the quality loss [2].

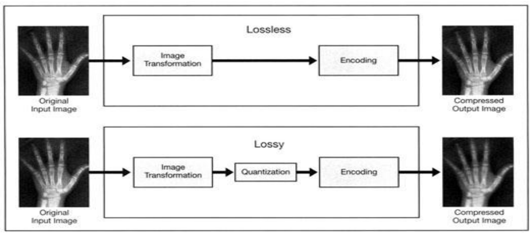


Fig 1. Image compression techniques, both lossless and lossy.

Although the compression ratio is lower, the reconstructed image is identical to the original. As we can see in the medical field, where we can't make compromises with any information of an image because bit of information is more important in medical application to diagnose a patient, this method or scheme can be used for the application where no loss of any information is compromised [3]. Error-free compression is required for a variety of applications, such as radiography services, satellite imagery, and image compression for medical evaluation. where a small image gap will have unexpected consequences. such as adaptive based on a dictionary (LZW), Run Length Encoding (RLE), and Huffman-style entropy encoding and Arithmetic coding.

This article is organized as follows: In Section 1, image compression is introduced, the various wavelet families are described, and the Wavelet Transform is used for image compression. In Section 2 a brief overview of the related work on image compression is given. in Section 3 a concise summary of the mathematical aspects of compression using wavelet technology and different parameters to assess the quality of compressed images is given. In Section 4 the methodology, including a flow chart and key steps of the suggested methodology, is presented. explains the methods and instruments used for compression. In Section 5 the experimental results of several compressions using grayscale images using various wavelet families are shown. Research work is concluded in Section 6.

1.1 Wavelet Transforms:

A wave motion whose amplitude begins at zero, increases, decreases, and returns to zero is called a wavelet. Images can be compressed using wavelets. Voice de-noising, signal compression, object recognition, fingerprint compression, image removal, heart disease assessment, and voice recognition are just a few of the computer science applications that use wavelets. The wavelet transforms, also known as the mother wavelet or wavelet model, is a form of mathematics that evaluates or produces a certain signal in the time domain by employing different forms of an inflated, assigned, and culminated framework function.

1.2 Characteristics of the wavelet function [6]:

Wavelets are the fundamental units of functions: In general, functions and signals are depicted by wavelets. The mean of an infinite series of wavelets in the wavelet space represents a function.
Space-frequency localization: the majority of their vitality is contained within a limited range, and the frequencies within the transform are from a specific frequency range.
Embrace both rapid and effective transform algorithms: Because the wavelet transforms require O(n) operations, the number of additions and multiplications corresponds to the signal's size. This is a straight speculation of the transform's rigidity property.
Multiresolution ability: Representation of a function or signal at multiple levels, derived from the original one.
Yield inferior coefficients from superior coefficients: Using Filter Banks, a structured chain of filters resembling a tree, one can produce inferior coefficients from superior coefficients.
Symmetry: Significant values resulted on by negative edges triggered by repetition can be evaded via symmetric filters, which are best at reducing impact of edges in the wavelet depiction of a function.
Filters' dimensions: The wavelet or wavelet file transform takes more time to compute when using lengthy filters.

Wavelets are categorised into two categories [6]:
Discrete Wavelet Transform (DWT): A discrete collection of wavelet increases and interpretations that adhere to certain predefined standards are used

in the DWT, an implementation of the wavelet transform.

Continuous Wavelet Transform (CWT): The wavelet transform is performed using precisely random wavelets and random scales in CWT. The wavelets used in this transform are not identical, and the resulting data are extremely similar. We employ this transform for the discrete time series, subject to the requirement that the smallest wavelet translations match the sampling of the data.

Wavelet Families:

- SYMLET (Sym)
- BIORTHOGONAL (Bio)
- REVERSE BIORTHOGONAL (Rbio)
- COIFLITS (Coif)
- DAUBECHIES (Daub)
- HAAR (haar)

Symlet: These are referred to as symmetric wavelets because they are predicated on the greatest number of dissolved moments and the least amount of asymmetry [5]. It isn't perfectly symmetrical, though. Almost symmetric, orthogonal, and biorthogonal are the characteristics of Symlets Wavelets. Plotting symlets wavelets allows one to display they have the highest count and a great deal of symmetry Timeless moments that disappear [6].

Biorthogonal: They are referred to as bior wavelets, or biorthogonal if they are frequently used in place of orthogonal ones. Accordingly, two different wavelet functions are used in the pair and evaluation rather than a single scaling and wavelet function, which could result in different multi-resolution evaluations [5].

Reverse Biorthogonal: Reconstruction and decomposition of scaling filters serve as its foundation. For analysis and reconstruction of synthesis, this wavelet has moments that disappear on decomposition and disappearing moments on reconstruction [5].

Coiflets: Daubechies and Symlets are similar to Coiflets, but Coiflets have a different shape. as well as the scaling function's greatest number of disappearing moments that make the 2N-1 moment equal to 0. It is a general wavelet function with 2N moments equal to 0. SixN-1 length is supported by the two functions [3].

Daubechies: DAUDECHIES is used to model orthogonal wavelets with reassigned smoothness that are efficiently supported. The wavelet functions and scaling are calculated using the inverse product of the coefficients and the four data values. For every iteration, Wavelet calculates the values of the scaling function and the wavelet function. It is the most significant member of the wavelet family [8].

Haar: The most basic wavelet family for image compression is the HAAR wavelet transform. It has a step function-like appearance and is not continuous. There is more computational performance with this wavelet. It computes the difference and sum for each image in each column of the final matrix [8].

II. Related Work

[9] In 2007, Yogendra Kumar Jain, et al shows evaluating and contrasting wavelet families used for image compression while considering PSNR and the visual quality of the image as quality metrics. On test images, the impact of the Biorthogonal, Reverse Biorthogonal, Daubechie, Coiflet, and Symlet wavelet families has been assessed. Each family's CR, PSNR, and visual quality for the wavelet function are also shown. The RBIO_1.3 offers superior compression efficiency for all tested images, according to an analysis of the results for a broad variety of wavelet families. With regard to image quality, the test images' wavelet RBIO_1.3 at compression ratio 100 and decomposition level 5 produced a result with an adequate visual impact. In conclusion, the choice of wavelet for image compression is reliant upon the dimensions, composition, and quality of the image.

[10] In 2013, Amrut N. Patel, et al compared various wavelet families for image compression and

assessed the results in terms of compressed visual quality and mean square error. used a range of test images to analyze and contrast different wavelet families, including Haar, Daubechies, Symlets, Coiflets, Biorthogonal, and Reverse Biorthogonal. MSE, CR, and PSNR are used to quantify the results as interpretive metrics. The optimal wavelet selection for image compression is reliant upon the intended visual impact and content.

[2] In 2024 Ankara Yıldırım, et al evaluates the effectiveness of different wavelet families in image compression by carefully contrasting and assessing them. According to the findings, all test images can have an average compression ratio of about 75% and a PSNR value of 38 dB. Utilizing the proposed NWI wavelet, the test-2 image produced the best results, with a compression efficiency of 3312.08. The study assesses 8 wavelet families and illustrates the image. While maintaining the same encoding algorithm for all computations of image processing instances, compression relies on the type of image as well as the chosen wavelet family. Novel wavelet families, like the NWI, can be integrated into image compression to increase efficiency and yield better results.

[4] In 2015, Neeraj Saini, et al presents Wavelet transform is used in the frequency domain to implement the implied image compression technique. Using Haar, Symlet, Coiflets, reverse biorthogonal, biorthogonal, and Daubechies wavelets, the compression is assessed in this work. Each of these mother wavelets is discussed in connection with a mechanism for image compression. The obtained wavelets that yield high-quality compression are then provided. It is acceptable to use rbior5.5 or bior5.5 wavelets if MSE is a significant factor; sym30, rbio5.5, or bior5.5 wavelets if Quality Index is a crucial factor; and sym3 wavelets if structural content and compression ratio are crucial.

[3] In 2021, Rohima, et al Measuring the compression ratio, the peak signal-to-noise ratio, and the mean square error can be used to assess whether the compression is acceptable. In our experiment using the 'Lena' image, the developers found that while the coif1 wavelet produced the lowest compression ratio, the results based on all wavelets were nearly identical. When it comes to accuracy, coif5 produces the best outcomes. Several coiflet wavelets used for image compression produce various outcomes. Coif1 has the lowest compression ratio (75.531%) and Coif4 has the highest (75.551%), despite the fact that the compression ratios from all wavelets produce results that are basically the same. Out of all wavelets, coif5 provides the highest accuracy arise (56.9861 dB).

[11] In 2015, R. Devi, et al. The paper explores into the efficiency evaluation of wavelet families and includes an outline of digital watermarking as well. investigates four wavelets—HAAR, DAUBECHIES, SYMLET, and BIORTHOGONAL—in comparison. Standards of the results include compression ratio, BPP, MSE, and PSNR. The BIORTHOGONAL wavelet provides a minimal compression ratio of 1.62 based on the empirical findings. The least MSE of 10.85 is even generated by the HAAR wavelet, but its compression ratio is significantly greater. Therefore, in comparison to other wavelets, the BIORTHOGONAL wavelet is superior.

[14] In 2023, Imen Chaabouni, et al. The technique being presented incorporates ISOM image compression with DWT decomposition. One of the main benefits of wavelet compression over other transform compression techniques is that it applies to entire images, eliminating the creation of restricting objects. Bi-orthogonal, Daubechies, Coiflet, and Symlet are the four wavelet families that are taken into evaluation. It examines three test images with distinct but low frequency events since the appropriate basis wavelet for the DWT compressor may vary depending on the test image selection. Next, they assess each test image's efficiency for each of the three wavelets families. In conclusion, they provide the comparison outcomes based on PSNR versus CR for four wavelet families, demonstrating that Bior3.3 outperforms the other Wavelets with respect to PSNR and Sym5 with respect to CR.

[13] In 2020, Owais Rashid, et al. presents a comparison of various wavelet transforms is presented in this paper. These wavelets include the following: Daubechies, Coiflets, Symlets, Discrete Meyer, Biorthogonal, Fejer-korovkin, and Reverse Biorthogonal wavelets. There are six wavelet decomposition levels for every wavelet. Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE) are used to compare the efficiency of the restored images with the initial images. Several wavelet families are compared in this paper using a constant filter length for all wavelets.

III. ESTIMATING STANDARDS

In order to evaluate the performance, essential criteria are used: Mean Square Error (MSE), Peak Signal Noise Ratio (PSNR), Compression Ratio (CR), Bit per pixel (Bpp) and Structural Similarity Index Measure (SSIM).

CR: A numerical representation of the proportion of elements in the compressed image compared to the original image's number is known as the compression ratio (CR). This ratio is used to calculate the compression percentage that a compression algorithm achieves [3].

$$CR = \frac{\text{Size of original image}}{\text{Size of compressed image}} \quad (1)$$

PSNR: is the ratio that determines the quality of a signal's representation by comparing its maximum possible significance to the amount of distorting noise, which is defined by [5]:

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \quad (2)$$

BPP: It is described as the quantity of bits needed to compress every pixel. It needs to be minimal in order to minimize the need for storage [5].

$$\text{bpp} = \text{Scomp} / \text{NPixels} \quad (3)$$

The compressed data size is denoted by Scomp, while the number of pixels is represented by NPixels.

MSE: The mean square error, or MSE, can be used to calculate the average energy loss during lossy compression of the original image. If the MSE value is very low, the image is very similar to the original [12].

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[y(i,j) - x(i,j)]^2 \quad (4)$$

SSIM: The SSIM value establishes how similar two images are to each other and can be utilized to evaluate how well one image is related to the other when it is used as an instance of reference.

$$\text{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (5)$$

IV. EXPERIMENTAL METHOD

This study compares and contrasts the effects of image compression based on the multiple wavelet family using MATLAB software. The study was completed by computing the Peak Signal Noise Ratio (PSNR) and Mean Square Error (MSE) and Structural Similarity Index Measure (SSIM) between the compressed image and the original image.

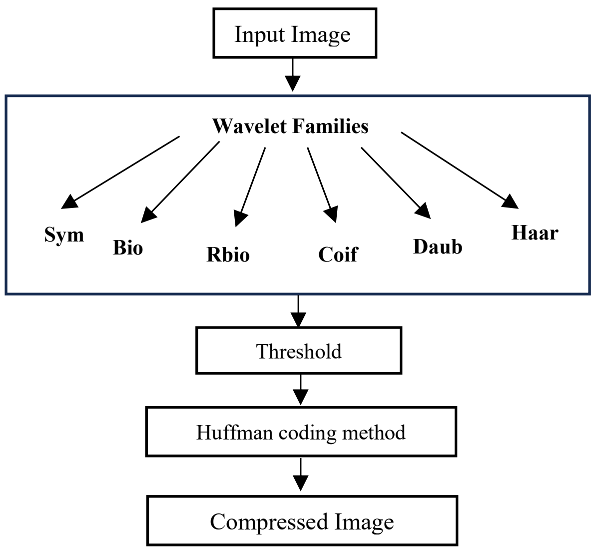


Fig 2. General work flow of proposed method

The fundamental phases of the recommended technique are as follows:

1. Take input image.
2. Use a tool that employs different wavelets to compress it.
3. compute threshold value (helps to reduce less significant or noisy information, leading to compression).
4. Apply Huffman coding method to create a compressed file.
5. Evaluate each image's quality using a range of quality metrics.

5. Experimental Outcome:

Carried out the experiments and examined various wavelets. For the assessment of the test images, six wavelets Haar, Daub, Sym, Coif, Bio and Rboi, are selected from the various wavelet families. Table-1 shows the effects of various wavelet families on medical images. It is possible to determine which wavelet provides a higher compression ratio by examining this table. Table-2 shows the test CT image (512x512) and displays the wavelet family attributes for the test image. For the test images, the empirical results for every member of the six-wavelet family have been examined. Figure3 displays the results, which are expressed in terms of CR, PSNR, BPP, MSE and SSIM and illustrating how various wavelets affect a medical image. Using this, one can determine which wavelet offers a greater compression ratio. The figure.4 represents the SSIM value for all the 6 wavelet families. Using Haar, Symlet, Coiflets, reverse biorthogonal, biorthogonal, and Daubechies wavelets, the compression is examined in this work. Here, wavelet families in all their variations were compared for image compression using the Huffman coding technique. In addition to producing nearly identical results for the compression ratio from all wavelets, the results offer an abstract notion of how to use the appropriate wavelet depending on different parameters. The wavelet with the highest accuracy results in terms of PSNR is db4. Use Db4 wavelets if MSE is a significant factor, and Coif1 wavelets if Quality Index is a significant factor. Here, we demonstrate that the Haar compression method offers the worst performance.

TABLE 1. A TABLE SHOWS THE IMPACT OF VARIOUS WAVELET FAMILIES ON MEDICAL IMAGES

Wavelets	bior1.3	sym4	coif1	rbio1.5	Db4	Haar
BPP	8.83	7.43	7.80	7.48	7.72	8.63
PSNR	36.42	37.93	37.60	36.20	37.95	33.27
MSE	14.94	10.56	11.39	15.74	10.51	30.85
SSIM	0.84	0.93	0.93	0.85	0.92	0.67

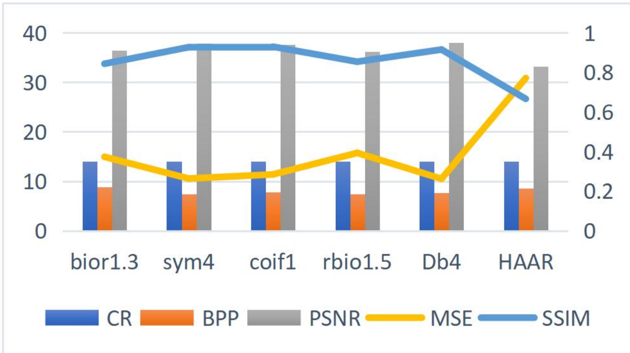


Fig 3. Resultant graph for wavelet families in terms of CR, PSNR, SSIM, Bpp, MSE.

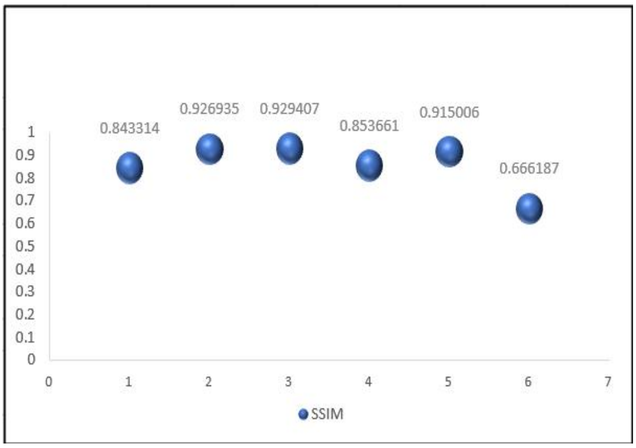
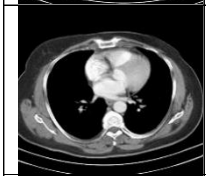


Fig 4. Shows the resultant graph for wavelet families with SSIM values.

TABLE 2. A TABLE WITH SAMPLE DATASET IMAGES SHOWING HOW VARIOUS WAVELETS AFFECT A MEDICAL IMAGE IS SHOWN BELOW. THIS CAN BE USED TO FIND WHICH WAVELET PROVIDES A HIGHER COMPRESSION RATIO.

Original Image	Bior1.3	Sym4	Coif1	Rbio1.5	Db4	Haar

	BPP=8.830901 PSNR=36.421148 MSE=14.940498 SSIM=0.843314	BPP=7.432618 PSNR=37.927990 MSE=10.560413 SSIM=0.926935	BPP=7.800858 PSNR=37.599135 MSE=11.391121 SSIM=0.929407	BPP=7.480687 PSNR=36.196000 MSE=15.735477 SSIM=0.853661	BPP=7.715880 PSNR=37.949432 MSE=10.508404 SSIM=0.915006	BPP=8.629185 PSNR=33.272588 MSE=30.847584 SSIM=0.666187
	BPP=9.304336 PSNR=35.802469 MSE=17.227928 SSIM=0.812188	BPP=7.836294 PSNR=37.747277 MSE=11.009109 SSIM=0.922227	BPP=8.141737 PSNR=37.063830 MSE=12.885372 SSIM=0.926631	BPP=7.915312 PSNR=35.411678 MSE=18.850033 SSIM=0.814719	BPP=8.111972 PSNR=37.766564 MSE=10.960327 SSIM=0.912313	BPP=9.171812 PSNR=32.135677 MSE=40.078568 SSIM=0.583405
	BPP=7.977315 PSNR=34.352534 MSE=24.056171 SSIM=0.745071	BPP=6.796128 PSNR=35.483671 MSE=18.540131 SSIM=0.859609	BPP=7.094423 PSNR=35.172683 MSE=19.916435 SSIM=0.862859	BPP=6.820899 PSNR=34.104876 MSE=25.467854 SSIM=0.745438	BPP=7.016199 PSNR=35.493785 MSE=18.497005 SSIM=0.848936	BPP=7.692318 PSNR=31.381668 MSE=47.677467 SSIM=0.479921
	CR=11.611109 BPP=9.304336 PSNR=35.802469 MSE=17.227928 SSIM=0.812188	CR=11.611109 BPP=7.836294 PSNR=37.747277 MSE=11.009109 SSIM=0.922227	CR=11.611109 BPP=8.141737 PSNR=37.063830 MSE=12.885372 SSIM=0.926631	CR=11.611109 BPP=7.915312 PSNR=35.411678 MSE=18.850033 SSIM=0.814719	CR=11.611109 BPP=8.111972 PSNR=37.766564 MSE=10.960327 SSIM=0.912313	CR=11.611109 BPP=9.171812 PSNR=32.135677 MSE=40.078568 SSIM=0.583405

V. CONCLUSION

This analysis presented and comparison of wavelet families with their various forms for image compression using Huffman coding technique. Image compression measuring parameters are computed using MATLAB code such as BPP, CR, PSNR, MSE and SSIM for each algorithm used. In this paper, the compression is analyzed using Haar, Symlet, Coiflets, reverse biorthogonal, biorthogonal, and Daubechies wavelets. In order to compress images using the Huffman coding technique, this analysis compared wavelet families in all of their variants. The results of table 1 provide an abstract idea of how to use the appropriate wavelet based on various parameters, while the compression ratio from all wavelets yields nearly identical results. out of all the wavelets, Db4 produces the highest accuracy result in terms of PSNR. If MSE is important factor than Db4 wavelet should be used, if Quality Index is important then Coif1 wavelets should be used. Here we show the Haar gives the lowest performance for image compression.

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