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Comparative Analysis of Lempel-Ziv-Welch and Embedded Zero Tree Compression Algorithms on Kidney Images

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Abstract

Image compression refers to the reduction of digital image data to store or transmit images with less rate of distortion. It is the reduction of the quantity of graphical data required to represent a digital image. Medical images play an important role in providing detailed information about patient injuries, fractures and other critical issues related to different disease and discomfort. Transmission of a reduced size of image data will help reduce computational burden as well as storage cost. Several compression algorithms have been adopted for use by numerous research on different types images, of which embedded zero tree (EZT) and Lempel-Ziv-Wetch (LZW) compression algorithms are most commonly used amongst others. The choice of a suitable compression algorithm for compression task on specific images has been an open issue, which this research seeks to look into. In this research, the compression capability of embedded zero tree (EZT) and Lempel-Ziv-Wetch (LZW) compression algorithms on Kidney images was compared. The performance of these algorithms was evaluated using peak signal noise ratio (PSNR), and compression ratio (CR). Effective compression implies that the resultant stream of image will be smaller than the original image size, without loss of vital content. Empirical results obtained shows that the LZW, having PSNR and CR of 97.28 and 2.85 respectively outperforms EZT with PSNR of 89.17 and CR of 1.82 when the same sets of images were subjected under the two compression algorithms. The results from this research suggest the usability of LZW for compression task involving kidney images. Similarly, lossless compression is recommended because loss of vital information content of medical images could lead to wrong diagnosis.

Keywords: compression ratio, peak signal noise ratio, algorithms, medical images

1.0 Introduction

An image is an object that records the information about visual perception of the human being such as two- or three-dimensional images. Image processing involves analyzing and visualizing an input image to obtain an output which summarizes the characteristics of the image. However, these images face major challenges due to their size during transmission and storage. To minimize redundancies in digital images as well as efficient transmission and archiving, compression is requisite (Sreenivasulu, Rajan and Thenappan, 2019). Image compression is the technique which is used to compress images, resulting in a reduction of the storage space and in cost while retaining necessary information (Awwal, Gholamreza and Hassan, 2014). Medical imaging has become an integral tool in clinical practice. Due to the enormous sizes of medical image data, there is need for an efficient compression to ensure effective storage and transmission without losing the salient content. Hence,

compression of digital images becomes essential in medical imaging (Liu, Hernandez-Cabronero, Sanchez, Marcellin and Bilgin, 2017).

Compression is a technique used to reduce the size of some data by lowering the number of bits used in its formation. Image compression is an application of data compression procedure that encodes the original image with few bits. The objective of image compression is to reduce the redundancy of the image and to store or transmit data in an efficient form. Image compression research aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible for transmission or storage while maintaining an acceptable image quality.

The compression of image data involves a combination of compressor and decompressor, often regarded as compressor-decompressor (CODEC). These results in two types of data compression schemes, lossy and lossless. In lossy image compression, the data which is not visible to human eye is discarded. In lossless compression, the data is decompressed to acquire it exactly as it was before, without any losses. The compression ratio for lossycompression is greater than lossless compression. JPEG compression is lossy and it is the most commonly used standard for digital images. The goal of JPEG compression is to remove redundancy from the image data and produce the reconstructed image (Sekar, Chisna, Aswathy, Gokul, Kalpana, 2017).

The main goal of medical image compression is to achieve a reduced size of the patient's medical data without degrading the perceptual quality of the image and thereby making the images robust against transmission errors. (Rajakumar and Arivoli, 2013).

A vast number of image compression algorithms have been continuously explored. Run-length coding, Huffman encoding, entropy encoding, vector quantization, fractals, discrete cosine transform, among which Lempel Ziv welch (LZW) and Embedded ZeroTree (EZT) are most common (Dharanidharan, Manoojkumaar and Senthilkumar, 2013).

LZW (Lempel Ziv Welch) algorithm is an image compression algorithm, which is lossless in nature and incorporated by the standard of the consultative committee on International telegraphy and telephony (ITT). It is a universal lossless data compression algorithm created by Abraham Lempel, Jacob Ziv, and Terry Welch. It was published by Welch in 1984 as an improved implementation of the LZ78 algorithm published by Lempel and Ziv in 1978. The algorithm is fast to implement. Lempel Ziv Welch (LZW) compression works by reading a sequence of symbols, grouping the symbols into strings, and converting the strings into codes. Because the codes take up less space than the strings they replace, compression is achieved (Sahami and Shayesteh, 2012)

Embedded Zero trees Algorithm (EZT) is a lossy image compression algorithm. It is simple, yet remarkably effective, having the property that the bits in the bit stream are generated in order of importance, yielding a fully embedded code. Using an embedded coding algorithm, an encoder can terminate the encoding at any point thereby allowing a target rate or target distortion metric to be met exactly (Rehna and Jeya, 2012).

Also, given a bit stream, the decoder can cease decoding at any point in the bit stream and still produce exactly the same image that would have been encoded at the bit rate corresponding to the truncated stream. Zerotree is a quad-tree of which all nodes are equal to or smaller than the root. The tree is coded with a single symbol and reconstructed by the decoder as a quad-tree filled with zeros. The root has to be smaller than the threshold against which the wavelet coefficients are currently being measured (Shingate, Sontakke and Talbar, 2010).

EZT is a multiple-pass algorithm, with each pass consisting of two steps: significance map encoding or dominant pass, and refinement or the subordinate pass. The algorithm is based on four key concepts; Discrete wavelet transform or hierarchical sub-band decomposition, Prediction of the absence of significant information across scales by exploiting the self-similarity inherent in images, Entropy-coded successive-approximation quantization and universal lossless data compression which is achieved via adaptive arithmetic coding (Raid, Khedr, El-dosuky and Wesam, 2014).

As enormous data is been generated on daily basis by health centers for surgery, disease diagnosis and research, there is the need to offset data volume which is achievable via compression. It is of absolute importance to

examine the suitability of a compression algorithm to be employed to achieve rapid, real time and accurate compression task without loss of valuable information. This however is an open issue which this research seeks to look into.

2.0 Related Researches

Medical imaging plays an important role in the diagnosis of diseases and surgical planning. Most modern techniques of medical imaging produce 3D data; magnetic resonance image (MRI), computed tomography (CT), ultrasound, positron emission tomography as well as 4D data; functional MRI, 3D echocardiography images. These images produce the most voluminous data, hence the need for compression before storage and / or transport through networks of telecommunication. These mega data need efficient transmission and long-term storage, thus it is pertinent to use compression algorithms in order to reduce the amount of data to be stored and transmitted (Imp and Bramah, 2015). Himani and Mishra (2018) presented a DiscreteCosine Transform (DCT) embedded with block processing. The work employed the use of DCT for transformation of the image into several parts. It proceeded to apply block processing on the transformed image, which was done with block size of 8x8. Experimental results shows that the block-based DCT outperforms the conventional DCT in terms of speed of compression of images.

Elhannachi, Ahmed, Benamrane and Abdelmalik (2017) presented an efficient reversible discrete cosine transform (RDCT) based embedded image coder for lossless ROI. This was joined with a lossless embedded zerotree wavelet coder (LEZW), while set partitioning in hierarchical trees (SPIHT) technique was used for background compression. Results of the procedure on brain MRI dataset shows that the combination of techniques compared favorably well with state-of-art still image compression methods. However in the research, it was concluded that the choice of ROI is an open issue. Shakya, Ramola, and Pandey (2017) presented a mathematical approach which applied both lossless and lossy compression on the same digital imaging and communications in medicine (DICOM) images. Some of the mathematical operations applied include matrix addition, subtraction and multiplication. The mathematical operations helps to achieve a high quality region of interest (ROI) as well as high degree of compression. The approach was able to achieve a reduced storage space and transmission time. However, the signal to noise ratio was not reported with the adoption of both lossy and lossless compression methods on the same image. Sreenivasulu, Rajan and Thenappan, (2019) presented a medical image compression which encompasses Segmentation, Image compression, and Image decompression. Segmentation was used to split the ROI from Non ROI using Modified Region Growing (MRG) algorithm. Image compression of ROI was then carried out using Discrete Cosine Transform (DCT) model and set partitioning in hierarchical trees(SPIHT) encoding method whereas compression of Non-ROI region was carried out by Discrete Wavelet Transform (DWT) and Merge-based Huffman encoding (MHE) methods. The resultant filter coefficients from both DCT and DWT techniques were further optimized using Modified Rider Optimization Algorithm (ROA). The work achieved a minimal compression ratio and high accuracy compared to the state of the art. The work however carried out decompression as the third step in the procedure by performing the reverse concept of compression process with same optimized coefficients, which may imply complexity of the whole process.

Yee, Soltaninejad, Hazarika, Mbuyi, Barnwal, and Basu (2017) presented a state-of-the-art image compression format known as Better Portable Graphics (BPG), which was based on the High Efficiency Video Coding (HEVC). In the proposed compression method, the medical images were segmented into two parts: ROI and non-ROI regions using Flood filling algorithm. Lossless BPG compression algorithm was then applied to the ROI areas, and lossy BPG was utilized for non-ROI regions. The resultant reconstructed images were combined to create a complete compressed image. The performance of the proposed method was evaluated on the brain MRI

scan dataset hosted by the University of Cyprus. The work varied the dimensions of the images for performance comparison. An improved result was obtained with lower dimension of images. However, the work did not report empirical results for PSNR and CR.

Yogita and Admuthe (2014) analyzed image compression using hybrid method of Artificial Neural Network (ANN) and Discrete Wavelet Transform (DWT). The compression ratio using this method was almost doubled. The PSNR for Lena image by the proposed method was 1 to 2 decibels more when compared to Self-organizing Feature Map (SOFM) Neural Network method. It was observed that if the block size was reduced, then PSNR and CR increases. Thus, the combination of ANN with DWT can provide higher compression ratio along with slightly higher PSNR values than SOFM Neural network-based method. Tan and Tan (2012) presents image compression technique utilizing reference points coding with threshold values. The method seeks to perform both lossy and lossless compression. A threshold value was associated the compression process, whereby different compression ratios can be achieved by varying the threshold values. Lossless compression was achieved when the threshold value was set to zero. The method allows the quality of the compressed image to be determined during the compression process. Lossy compression is achieved when the threshold value of a parameter assumes positive values. The researchers suggest further study to calculate the optimal threshold value that should be used.
Srikanth, *et.al.*, (2013) presents a technique for image compression which uses different embedded Wavelet based image coding with Huffman-encoder for further compression. The work implemented SPIHT and EZW algorithms with Huffman encoding using different wavelet families and thereafter compared the PSNRs and bit rates of the discrete wavelets. These algorithms were tested on different images, and results indicated that the algorithms exhibit good quality of PSNR and high compression ratio as compared to the existing lossless image compression techniques. The combination of algorithms however results in complexity of the overall compression procedure.

Rajkumar, *et.al.*, (2013) presents an implementation of Multi Wavelet Transform coding for lossless image compression. In the research, Integer Multiwavelet Transform (IMWT) was used for image reconstruction. The resultant effect was a lossless compression of images with magnitude set coding. The transform coefficient was coded with a magnitude set of coding & run length encoding technique. The performance of the integer multi wavelet transform for the lossless compression of images was analyzed. It was found that the IMWT can be used for the lossless image compression. The bit rate obtained using the MS-VLI (Magnitude Set-Variable Length Integer Representation) with run-length encoding (RLE) scheme is about 2.1 bpp (bits per pixel) to 3.1 bpp less than that obtained using MS-VLI without RLE scheme. Although the PSNR and CR was not reported, the major drawback of multiwavelet run-length encoding is image degradation.

Firas and Hindi (2012) proposed a novel method for image compression which was called Five Module Methods (FMM). This method converts each pixel value in 8x8 blocks into a multiple of five for each of RGB-array, and afterwards the value was divided by 5 to get new values which are bit length for each pixel and it was observed to be less in storage space than the original values which was 8 bits. The work demonstrates the potential of the FMM based image compression techniques. The advantage of this method was that it provided high PSNR (peak signal to noise ratio) although it has low CR (compression ratio). This method is appropriate for bi-level like black and white medical images where the pixel in such images is presented by one byte (8 bit). Ashutosh,Subhash, Ashiwani, Prabhanjan, Deepak and Prem(2012) presents a novel hybrid image compression technique. This technique inherits the properties of localizing the global spatial and frequency correlation from wavelets and classification and function approximation tasks from modified forward-only counter propagation neural network (MFOCPNN) for image compression. In this scheme, several tests were used to investigate the usefulness of the proposed scheme which uses MFO-CPN networks to predict wavelet coefficients for image compression. The performance of the proposed network was tested for three discrete wavelet transform functions. Evaluation of the proposed compression technique indicated that Haar wavelet results in higher compression ratio

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but the quality of the reconstructed image was not good. On the other hand, db6 with the same number of wavelet coefficients leads to higher compression ratio with good quality. Overall they found that the application of db6 wavelet in image compression out performs the other two discrete wavelet transform functions. Image degradation was a drawback of the technique.

Rengarajaswamy and Imaculate(2013) presents a novel technique in which encryption and compression of an image was done. In this method, stream cipher was used for encryption of an image after which set partitioning in hierarchical trees (SPIHT) was used for image compression. Stream cipher encryption was carried out to provide better encryption. SPIHT compression provides better compression as the size of the larger images was compressed with minimal or no loss in the original content of image. A high and confidential encryption and the best compression rate was realized to provide better security, thereby fulfilling the aim of the work.
Awwal, Gholamreza and Hassan (2014) presented a new lossy image compression technique which uses singular value decomposition (SVD) and wavelet difference reduction (WDR). These two techniques were compared and the SVD compression results in very high image quality but low compression ratio; on the other hand, WDR compression results in high compression ratio. The reviewed researches reveal that a vast amount of efforts have been made by numerous researchers to realize an appreciable reduction in data size for the purpose of achieving a conservative storage and representation that is optimal.

The reviewed work also shows that some of the compression procedures result in image degradation whereby the visual quality of the decompressed image becomes low compared to the original image. Other methods that involve combination of algorithms in a hybrid manner turn out to increase the computational complexity of the procedure, especially those involving a combination of lossy and lossless method. The choice of ROI is also an open issue while some of the works are not explicit on the PSNR and CR values obtained from the experiment. This work seeks to recommend based on the result of the experiment, a compression algorithm suitable for kidney images under the specified condition in which the experiment was carried out.

3.0 Methodology

In this research a lossy compression algorithm (EZT) and a lossless compression algorithm (LZW) were applied differently on kidney image data to determine the effect of each of the algorithms on the data. The dataset was acquired online from the University of California Irvine (UCI) machine learning dataset repository: https://archive.ics.uci.edu/ml/datasets/Chronic_Kidney_Disease. A sample kidney image from the dataset is shown in figure 1.

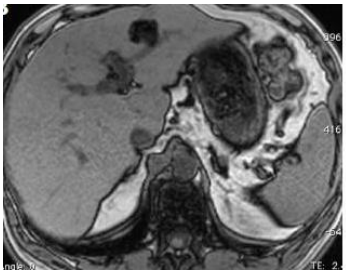


Figure 1: Sample Kidney image

3.1. Compression using EZT

The first phase of this procedure involves performing Discrete Wavelet Transform variation on the images. The wavelet filter was varied based on three arbitrary wavelet decomposition level namely; 'bior1.5', 'bior2.5' and

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'bior3.5' which represent biorthogonal wavelet settings. The biorthogonal values below 1.5 gave very low PSNR and CR values. The implementation continues by passing the images unto Discrete Wavelet Transform block which carries out the 2D DWT on the input image and outputs the 2D wavelet coefficients. This was then passed to an EZW encoder which carries out the embedded zero tree encoding and produces an output of the dominant pass and the subordinate pass. This helps in selecting the significant values and discarding the sub threshold values. This is still in the uncompressed form. Therefore, arithmetic encoding was done on the EZW reordered data. This results in a compressed bit stream that can be transmitted to the decoding system.

3.1.1. EZW Thresholding

EZW thresholding procedure involves varying a threshold value among the arbitrary biorthogonal filter values 'bior1.5', 'bior2.5' and 'bior3.5'. Threshold values were varied between 50 and 100. Threshold value of 100 was selected because at that point the wavelet filter gave the most visible encoded filter and at bior1.5.

The decoding system consists of the Arithmetic decoder, which decodes the compressed bit stream obtained from the arithmetic encoding block in the transmission end into the dominant pass and the subordinate pass form that can now be passed to the EZW decoder block, including the image size and the threshold (100) using the header file. Now this block outputs the original coefficient levels that were obtained from the 2d DWT. These coefficients are now passed to the IDWT block that performs the inverse discrete wavelet transform and gives back the reconstructed image. The EZW algorithm calculates the initial threshold, using the equation (1): Goyal (2012)

$$T_0 = 2^{log_2^{\max|C(x,y)|}} \quad (1)$$

where, T_0 is the initial threshold, *max* is the maximum coefficient value of the image $C(x, y)$. That is, the initial threshold is the largest power of two that is less than the maximum absolute value of the coefficients. Using this initial threshold, a 'dominant pass' procedure carried out on all the coefficients will identify all those features that are significant; that is, all those that are larger in absolute value than the initial threshold. After the dominant-pass procedure is completed, the current threshold is halved, and a subordinate-pass procedure is performed. It progressively encodes detailed information about the significant coefficients.

3.1.2. Compression

Furthermore, after the Discrete Wavelength transform and EZW encoding parameter variation has been done, compression was carried out on the images. This process (starting with a dominant-pass at the current threshold) was reiterated until some desired state is achieved. The 'desired state' is either when the threshold reaches a minimum value (usually one (1), though it is possible to continue with threshold values between zero and one) or when a predetermined function has been satisfied. Compression process here was achieved by counting the number of bits written to the compressed data stream and ending it when a specified value is reached. The choice of the value is arbitrarily chosen in this experiment. Since the input bit count was known based on the size of the image, and the number of output bits is controlled, this process guaranteed exact compression ratios.

For each of the image, the performance was measured by peak signal noise ratio which computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and a compressed image. Bit per pixel (BPP) is an absolute measure and represents the average number of bits needed to encode each image's pixel information. Compression ratio is defined as the amount of bits in the original image divided by the amount of bits in the compressed image.

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The Compression Ratio (CR), mean square error (MSE) and peak signal noise ratio (PSNR) were computed using equations 2, 3 and 4

$$CR = \frac{size\ of\ original\ image}{size\ of\ compressed\ image} \quad (2)$$

$$MSE = \frac{1}{original\ image\ size - compressed\ image\ size} \quad (3)$$

$$psnr = 10log_{10}^{225^2/_{MSE}} \quad (4)$$

In order to select the best combined parameter values, the *threshold* as well as the *biorthogonal wavelet* are two important parameters that must be tuned in the course of experimenting with EZT compression procedure in order to achieve high PSNR as well as CR. Therefore, a test image of size 334 KB was passed onto the EZT compression algorithm. The wavelets with biorthogonal (1.5) at threshold of 100 generate the best compression output due to the fact that it has the highest PSNR and the highest CR compared to the other wavelet filter values experimented with at that threshold. This is shown in table 1. This informs the choice of threshold value 100 and 'bior1.5' as the combined values of the parameters for which the whole thirty test images were experimented on. The result of the average PSNR and CR for the thirty images tested is shown in the result section in table 2. A sample of the image after compression is shown in figure 2.



Figure 2: Image after compression with EZT

Table1: Result of a sample compressed image at threshold value 100

Wavelet filters at threshold 100	Size of Original Image (in KB)	Size of Compressed Image (in KB)	Compression Ratio (%)	Mean Square Error	Peak signal Noise Ratio (db)
'bior1.5'	334	192	1.74	0.00704	69.65
'bior2.5'	334	215	1.55	0.00840	66.89
'bior3.5'	334	241	1.39	0.01075	63.82

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3.2. Compression using LZW

The images were passed onto LZW compression algorithm. The images are read as sequence of symbols; symbols are grouped into strings and converted into a code which takes up less space than the original strings, resulting into compression. The procedure requires that a dictionary keeps a correspondence between the longest encountered string and a list of code values. The strings are replaced by their corresponding codes and so the input image is compressed. The LZW compression procedure is simple and does not require setting of parameter values as is the case with EZT. The resultant image at the end of the compression is shown in figure 3. The process flow of the experiment with the two compression algorithm is shown in figure 4.

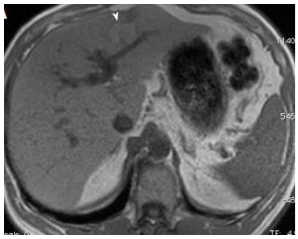


Figure 3: image after compression with LZW

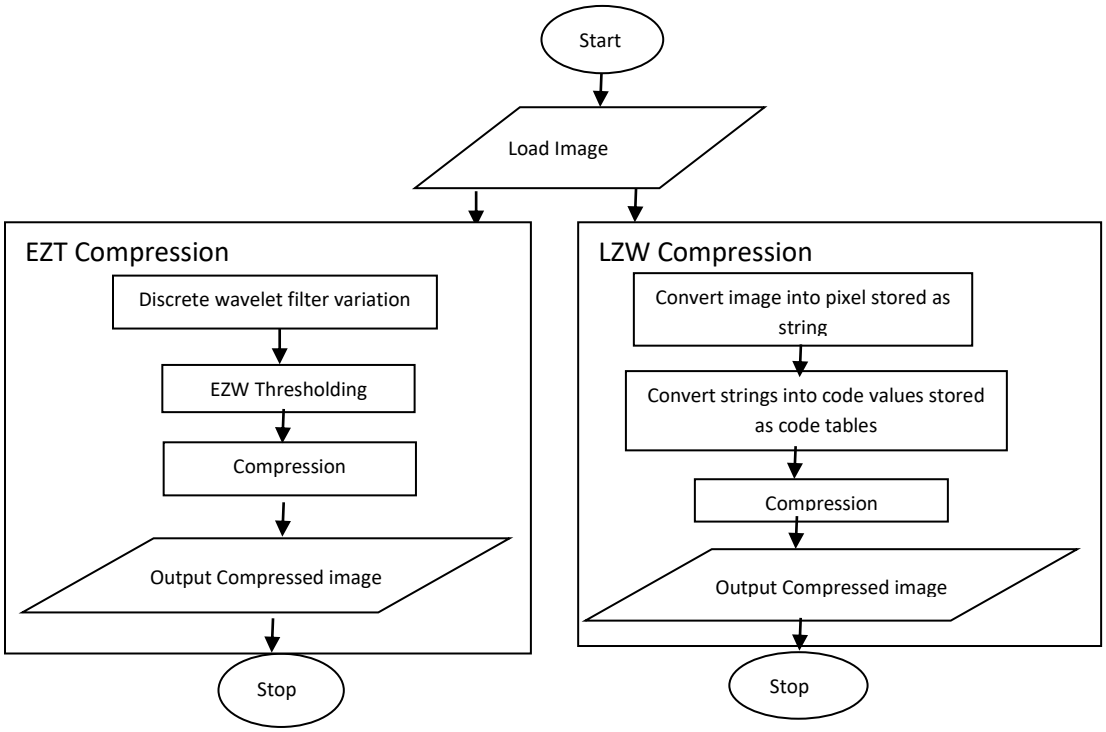


Figure 4: Process Flow of the proposed system

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4.0 Result and Discussion

The system was tested over thirty (30) samples of kidney images obtained from UCI machine learning dataset repository as earlier stated. The metrics for performance evaluation of the algorithms include; the **bit rate** which shows the bit per pixel rate, measuring the average number of bits needed to encode the image pixel information. The **mean square error** represents the cumulative squared error between the compressed and original image. The **peak signal noise ratio** (PSNR) computes the peak signal-to-noise ratio between the image before compression and after compression. It measures the peak error, however, the lower the MSE value, the lower the error. The signal in this case is the original data, and the noise is the error introduced by compression. The average of the PSNR obtained for the 30 tested samples was 89.17 and the average for the compression ratio (CR) for all the tested sample was 1.82.

The result obtained for the PSNR and CR for all the tested images using the LZW algorithm on the average was 97.28 and 2.85. This result indicates that the LZW outperforms EZT in terms of PSNR and CR when the same set of images was subjected under the two compression algorithms. Table 2 gives a summary of the result of the comparison for the two algorithms.

Table 2: Average Compression result for the LZW and EZT compression algorithms on the 30 images.

	Compression Ratio	**Peak signal Noise Ratio(db)**
LZW	2.85	97.28
EZT	1.82	89.17

5. Conclusion and Further work

Compression is an image processing activity that helps reduce image dimension, size, and features as well so as to prepare images for further necessary processing. Evidently, from this work, for EZT compression algorithm, the efficiency of the compression is largely dependent on the biorthogonal value as well as the threshold settings. Additionally, the higher the compression ratio, the faster the computational time and reduced storage space for the images. Also, the PSNR in LZW is slightly higher, having value 97.28 than EZT, having value 89.17, indicating that the information content in the original image is highly retained even after compression, making it a suitable algorithm for adoption on kidney images based on this research. Furthermore, the CR in LZW (2.85) being slightly higher than EZT (1.82) indicates that reduced storage space can be achieved with LZW. Further intention of this research, is to experiment these compression algorithms on other medical image datasets such as liver, lungs, electrocardiogram amongst others in a bid to further investigate the suitability of the algorithms for compression purposes.

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