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A Review: Compression on Medical Images

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***Abstract*— Digital image processing is plays a critical role for digital world; the medical field is also not untouched. A lot of work has been done for medical images with the help of digital image processing whether it is their enhancement work or, it can be the work of automatic disease detection or storage-related work. Medical images are the crucial part of the medical field that every medical organization and hospital has to maintain it, to help the patients for their future references. Storage of medical images requires an ample amount of space and transferring those medical images requires high bandwidth. The whole concern of this paper is to pay attention related to the storage problem of medical images and the problem of their transmission. The term image compression is the only solution to these all issues. Image compression is a basic step of digital image processing through which reduces the size of an image in bytes without devaluing the standard and quality of the image to an acceptable extent. So that medical images will take less space in memory to store image sequences and can also be transferred in less time. Numerous image compression techniques are available in medical imaging used in MRI, CT scan, radiography, Mammography, Fluoroscopy, Ultrasound medical images. The primary goal of this article is to discuss comprehensive knowledge of image compression methods for medical images.**

Keywords*— Image Compression; Mammography; Fluoroscopy; PACS; DICOM; ROI; Lossless; Lossy;

I. INTRODUCTION

In this modern digital world, we are all witnessing how digital images performs tremendous role in several applications in the field of medical science. It is the responsibility of digital image processing to give its important support in the field of medical through which the images used in the medical area like MRI, CT scan, X-Ray, etc helps to improve suitable and efficient treatment like cancer, heart-disease, bone disease by enhancing images[**17**][**18**]. Compressing these images is very necessary for storing easily those medical images and relocate images from one location to another. We need to keep record of medical images to improve clinical ability, proper diagnosis, and improvement in treatment. Medical organization has a big responsibility to manage P.A.C.S. i.e. Picture Archiving and Communication Systems. That allows for the display, collection, communication, and preservation of medical images and data **[9]** without P.A.C.S. it is an impossible to maintain it always a large space in the disk for storage of medical image sequences and also manage high bandwidth to transfer the medical image in their actual form. Generally MRI images requires 131 KB, CT-Scan requires 524 KB, Digital radiology requires 18 MB, Digital mammography requires 27 MB. That is why new technologies are working to increase storage capacity and faster transmission. Image compression technique has proved to be a feasible solution for this problem which will be applicable to both the major issues.

Digital image is collection of pixels and represented as matrix of pixels, each pixel contain some gray scale value and mostly these gray scale values in images are repeated several times which is called pixel redundancy. Image compression reduces the number of bits that are required for image representation by reducing these redundancies to an acceptable limit which is also called coding and reverse of this process called decompression or decoding which brings the compressed image back to the original form.

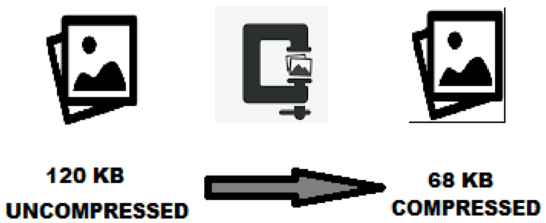

Fig.1. Simple Compression technique.

II. COMPRESSION TECHNIQUE

In the area of digital image processing, the compression technique of an image is a necessary thing when we doing any processing on a large size image. The process of encoding or transforming an image file so that it takes up less space than the original image is known as image compression without affecting or degrading its quality to a greater extent. The compression technique's sole purpose is to reduce the image's irrelevance and redundancy in order to store or transmit data more efficiently. It's all about reducing the amount of bits needed to display an image **[11]**. Compression technique deals with these types of redundancies that follow.

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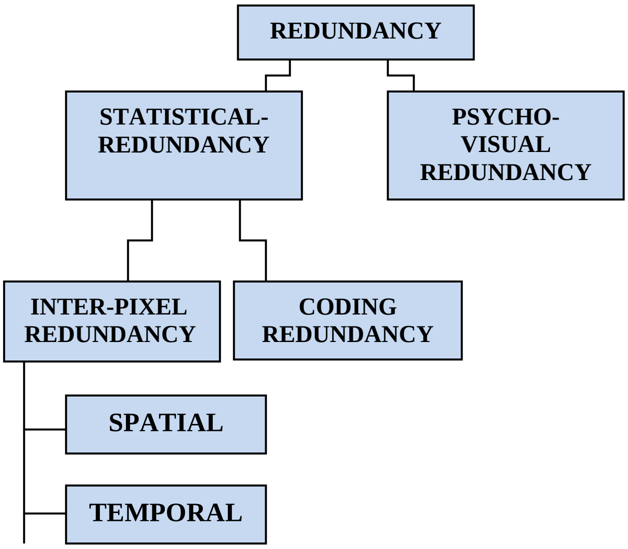

Fig.2. Types of Redundancies.

1. Psychovisual Redundancy

Since human vision does not require quantitative analysis of each pixel or luminance quantity in the picture, psycho visual redundancies exist. So destroying some less relative critical data in our visual preparation might be satisfactory.

2. Coding Redundancy

If a picture's grey levels are coded in such a way that more code images are used to answer each grey level than could possibly be required, the following image is said to have coding redundancy.

3. Inter_pixel Redundancy

The statistical association between adjacent pixels in an image causes inter_pixel redundancy.

3.1 Inter_pixel Spatial Redundancy

The grey value of a random pixel can be predicted by looking at the grey values of its neighbours, assuming they are closely related.

The amount of information transmitted by a single pixel is usually small. The contrast between adjacent pixels can be used to address an image to reduce inter pixel redundancy..

3.2 Inter_pixel Temporal Redundancy

The statistical association between pixels from subsequent frames in a video sequence is known as inter_pixel temporal redundancy.

Inter_frame redundancy is another name for temporal redundancy. Motion-compensated predictive coding can be used to take advantage of temporal redundancy.

Compression technique classified majorly in two ways lossless technique and lossy technique.

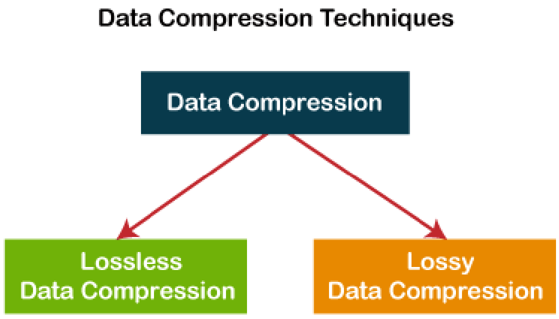

Fig.3. Compression Techniques

1. Lossless Technique

The Lossless technique reconstructed image is an exact replica of the original image [**2**]. This reproduces the original image without any quality loss. This is reversible Lossless techniques are most suitable for medical images processing, where a small loss of data may lead to very serious effect on human lives. Run-length encoding, LZW coding, Huffman encoding, Area coding are few examples [**2**].

2. Lossy Technique

In Lossy Compression technique, the reconstructed image will not be the exact copy of the original input image instead the rebuilt image contains some loss of data or degradation from the original input image [**2**] therefore; it is less used in medical imaging.

III. MEDICAL IMAGE FORMATS

Medical Image file formats standardize the way information about how a computer file contains the image. The image file format describes how image data is organized inside the file and how software can view pixel data for proper stacking and projection. [**19**]. Medical image file format separated mainly in two categories first one is standardized as diagnostic modalities i.e. Dicom [**20**] and the second one is as aspire to make post-processing analysis easier and more efficient i.e. Minc [**23**], Analyze [**21**], Nifti [**22**].

1. Dicom

The Dicom standard was developed jointly by the American. College of Radiology. and the National Electric Manufacturers. Association. The Dicom standard is now used by all medical imaging departments. Dicom was the first file format to recognize that pixel information could not be separated from the definition of the drug that led to the image's development. Image compression is supported by Dicom. Dicom offers run_length encoding (RLE), JPEG, JPEG_2000, JPEG_LS, MPEG_2, and MPEG_4 compression techniques. [**19**] [**22**].

2. Minc

Starting in 1992, the Montreal Neurological. Institute (MNI) created the Minc file format to have a file type for diagnostic imaging that is versatile. Minc_1 the original version was based on the standard of Net_CDF. As a result, Minc's production team opted to upgrade from Net_CDF to HDF_5 in order to solve the constraint of assisting with big data documents while also including major improvements (HDF_5). Minc_2, the most recent version, was incompatible with the prior one. [**19**] [**23**].

3. Analyze.

Analyze_7.5 was established first at Mayo. Clinic's in Rochester, Minnesota in the late 1980s as a format for the commercial program Analyze. The standard was the "de facto" format for post_processing medical images. for more than a decade. The Analyze format had a major breakthrough in that it was created for multidimensional data (volume). An Analyze_7.5 version is made up of 2 binary-files: a voxel raw data image file with the extension ".img" and header doc of metadata having extension ".hdr." [**19**] [**21**].

4. Nifti

Nifti seems to be a file extension developed by a National Institute of Health committee in early 2000s with the aim of creating a format for neuro imaging that retains the advantages of the Analyze standard while eliminating its flaws. Nifti has support for data types that Analyze does not, such as unsigned- 16_bit. Despite the fact that the header and pixel data must be stored in separate files, Most image are stored as an unique ".nii" file that contains both header and pixel information.

[**19**] [**22**].

Table 1. An Overview of the medical image formats [19].

Formats	Header	Extending	Data_types
Dicom	Variable Length Binary Format	".dcm".	Signed. & Un_signed. Integer. 8 Bit. 32 Bit allows only for radiotherapy but float data type assisted not.
Minc	Extensible Binary Format	".mnc."	Signed. & Un_signed Integer. 8 to 32 Bit float 32 to 64 Bit and in complex 32 to 64 Bit
Analyze	Fixed. Length. 348 Byte. Binary. Format.	".img." & ".hdr."	Un_signed Integer 8 Bit, Signed Iinteger 16 to 32 Bit, float 32 to 64 Bit and in complex 64 Bit.
Nifti	Fixed. Length. 352 Byte. Binary. Format and 348 in case data saved in ".img." and ".hdr." Format."	".nii."	Signed. & Un_signed. Integer 8 to 64 Bit, float. 32 Bit to 128 Bit and complex. 64 Bit to 256 Bit.

IV. RELATED WORK

Several studies in the field of compression of medical image and to address concerns related to compression of medical image have been performed in the last decade. The researcher's approach is determined by the type of application required and the problem on which he wishes to work.

Recently Prasantha et al. [1proposed a novel image compression technique based on modified Singular Value Decomposition. The lossy method is used in the proposed solution for compression of medical images because it has the best compression ratio. It is also concerned about computation complexity, so they preprocessed the SVD, resulting in a modified SVD.

Magar et al. [9] using the oscillation theory, a groundbreaking approach to biomedical image compression has been developed. They repeatedly extracted the principal component from medical images and obtained more compression ratios than the others medical image Due to which the compression results were better than other works. It gives the end user the freedom to use any principle variable that meets his or her needs and applications. For each iteration, the number of theory components increases, resulting in a higher compression ratio.

Kundlik et al. [6] show another novel approach of compression i.e. Oscillation and DCT based biomedical image compression. The proposed method is quite similar to the previous one but with the extension of the DCT. Here Discrete Cosine Transform (DCT) converted image signal into elementary frequency component which is wildly used in medical image compression and having the advantage to hold number of information in less number of pixel. With Oscillation and DCT concept proposed approach provides a high compression ratio with fine compressed image.

Perumal et al. [3] proposed an approach i.e. Medical Images Compression and Decompression Using Neural

Networks. Where it uses Support Vector Machine Neural Network approach to compress medical images. The main drawback of this paper is this approach become very complex due to Neural Network methodology used and high amount of data loss from the medical image during compression. Where best part of this paper is that its compare its approach with several performance parameters like Mean Square Error (MSE), Bits per Pixel (BPP), Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR).

Yee et al. [7] presents a technique to compress the medical image with Region of Interest (ROI) using Better Portable Graphics (BPG). In this approach firstly medical image is segmented in two part, ROI region and Non-ROI region which makes technique to more focused on only interested area of image then on ROI region Lossless BPG applied because they don't want any risk with information of ROI region and in Non-ROI part Lossy BPG applied and at the end resultant images are combine to create final compressed medical image. Presented approach experimented by DICOM MRI brain-scan image **[16**] which represents good compressed ratio.

Li et al. **[8**] provided a novel method, lossy and lossless encoding of 16_bit depth images of medical using an optimized JPEG_XT_based algorithm, where the optimized JPEG_XT_based algorithm (OPT. JPEG_XT) with amplify DCT coefficient is used for medical image compression while we use it for satellite infrared images. The tiny integer information a digital component of medical images is kept by amplification of DCT coefficients, which helps to improve compression efficiency. The method begins by spitting a 16_bit depth image into two 8_bit depth sub images, then using 2D_DCT to separate the each block's largest DCT coefficients, known as coefficient of DC, from the left, known as coefficient of AC. Zig_Zag scanning is used instead of the conventional baseline JPEG process. The method entails amplifying the iteratation of DC and AC coefficient for N term and by a certain NDP's to hold all of the data from the AC coefficient, with the last rounded DC and AC coefficients being contained in compressed data.

Anandan et al. [4] Using the Discrete Curvelet Transform and the wrapping technique, they proposed a method for compressing various PET and CT scan images. The curvelet coefficients are quantized using vector quantization, and the coefficients are then encoded using the arithmetic coding technique. Finally, using the inverted curvelet transform as well as the proposed method, restored images are obtained. output is measured using PSNR and CR. In contrast to Wavelet Transform and DCT algorithms, it was discovered that Curvelet_Transform performed for up gradation of PSNR & CR **[10]**.

Nasifoglu et al. **[5]** In Pelvis Radiography images, Multi-Regional Adaptive Image Compression (AIC) for Hip Fractures was presented. According to the radiologist's manual contouring, through the JPEG_method, the proposed method detects and compress 3 ROIs and the context image as Non ROI. The first order ROI is the most important region in the picture, which includes the presence of the fracture. The importance of second and third order ROIs is less than that of the first order sector, but it provide significant fracture details for the radiologist. According to ROI Priority, the first third is compressed using lossless compression, while the second third is compressed using lossy compression. As per the study, findings, 6.01 C R, 2.79 bPP, 37.61 dB PSNR, and 31.06 dB SNR seem to be the average values of compressed images, maintaining enough data diagnosis without losing any valuable data from ROI. **[10]**.

Agarwal et al. **[12]** introduce Medical Imaging Technology Employing Multiple Image Compression with the Discrete Wavelet Transform (DWT) for Faster Transmission and Storage The main goal of this technique is to allow large-scale transmission of medical images through various devices for early diagnosis and improved health-care services. In this case, the DWT Sub band Analysis was applied three times, each time level by level, to display multiple image compression techniques. In level one, DWT Sub band Analysis Level 1 is used, followed by DWT Sub band Analysis Level 2, to obtain a bit stream of the input medical image. This bit stream is then used as the input image for the third level of compression, where Dequantization and Decoding are used, followed by DWT Sub band Synthesis Level-2 and DWT Sub band Synthesis Level-1 to reconstruct the image.

Sran et al. [15] present a hybrid technique that performs the process in two steps: first, using a saliency-based Fuzzy C-Means clustering algorithm to extract the ROI from a medical image, then using the SPIHT algorithm to compress the ROI with high bit rates on ROI and low bit rates on non-ROI regions. The proposed solution is also concerned with increasing computational complexity. All of the experiments were conducted on the BRATS dataset [13], which is a widely used dataset. This method produced accurate ROI shape image detection with a high compression ratio and good visual quality compression.

V. MEDICAL IMAMGE PERFORMANCE PARAMETTERS

The different parameters are measured as shown below to evaluate the quality of the compressed medical images as result.

1. Bits_per_Pixel (BPP)

Bpp is an exact figure that reflects the average no of Bits used to encrypt each pixel of image (e.g. color).

The bpp is calculated by averaging the following values.

$$\text{Bpp} = \frac{S_{Com}}{N_{Pixel}}$$

Where S_{Com} is size of compressed image and N_{Pixel} total number of pixels.

2. Compression Ratio (CR)

For a high-quality picture, the CR should be lower. The following equation is used to measure it.

$$\text{CR}= \frac{S_{Uncom}}{S_{Com}}$$

3. Mean_Square_ Erroror(MSE)

The issue with mean-squared error is that it is highly dependent on image intensity scaling.

The following equation is used to measure it [14].

$$\text{MSE}= \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(x(i,j)-y(i,j)\right)^2$$

4. Peak_Signal to Noise_ Ratio (PSNR)

The PSNR measures the difference between the actual and compressed image's peak error. By scaling the MSE, the Peak Signal-to-Noise Ratio (PSNR) avoids the issue of mean-squared error.
The following equation is used to measure it.

$$\text{PSNR}= 20 \times log_{10}\left(\frac{255}{sqrt(MSE)}\right)$$

5. Signal to Noise ratio (SNR)

It depicts the correspondence between the actual and estimated images. This ratio shows how much noise distorted the original picture.

The following equation is used to measure it

$$\text{SNR}= 20 \times log_{10}(S/N)$$

VI. COMPARATIVE ANALYSIS

Several outstanding works in the area of image compression for different forms of medical images have been done. Each researcher proposes a method based on the work's purpose and requirements. Some related works have been compared in order to determine which proposal method produces the best results and to what degree the proposed method is superior to the other. This table of comparative research contains the methodologies used by literature reviewed work, as well as quantitative accuracy.

TABLE 2 COMPARITIVE ANALYSIS OF THE PRIVIOUS WORK

PUBLICATION	YEAR	TITLE	METHODOLOGY	PERFORMANCE PARAMETER
[8]	2020	AN. OPTIMIZED. JPEG_XT_BASED ALGORITHM FOR. THE LOSSY & LOSSLESS COMPRESSION. OF 16_BIT DEPTH. MEDICAL. IMAGE.	Optimized JPEG_XT + Zig_Zag Scanning + Running Length Encoding + Huffman Encoding	MSE 0.08 SSR 90% PSNR 60%
[15]	2020	SEGMENTATION BASED IMAGE COMPRESSION OF BRAIN MAGNETIC RESONANCE IMAGES USING VISUAL SALIENCY	Saliency_Based Fuzzy C_Means Clustering Algorithm + ROI SPIHT Algorithm	BPP 0.5000 PSNR 60.9827 VIF 60.98273 CR 25.5202 MSE 7.1599
[3]	2020	MEDICAL IMAGES COMPRESSION AND DECOMPRESSION USING NEURAL NETWORKS	Neural Network + Support vector machine (SVM)	CR 1.64 PSNR 38.88 MSE 38.88 SNR 33.17
[1]	2020	NOVEL APPROACH FOR IMAGE COMPRESSION USING MODIFIED SVD	Singular Value Decomposition (SVD)	CR 5.8098 MSE 9.2556 PSNR 38 4667
[12]	2019	MULTIPLE. IMAGE. COMPRESSION. IN MEDICAL. IMAGING. TECHNIQUES. USING. WAVELETS FOR SPEEDY. TRANSMISSION. & OPTIMAL. STORAGE.	Discrete. Wavelet Transform _(DWT) + Sub.band Coding _(SBC)	BPP 7.4144 PSNR 52.11 CR 92.68% MSE 0.4
[6]	2018	OSCILLATION AND DCT BASED BIOMEDICAL IMAGE COMPRESSION	Principle Components Analysis (PCA) + Discrete Cosine Transform + Oscillation Algorithm	CR 40.70

[5]	**2017**	**MULTI-REGIONAL. ADAPTIVE. IMAGE. COMPRESSION. FOR HIP FRACTURES. IN PELVIS. RADIOGRAPHY.**	JPEG algorithm + Region Interest (ROI)	**CR 6.01** **BPP 2.79** **PSNR 37.61 dB** **SNR 31.06 dB**
[7]	**2017**	**MEDICAL IMAGE COMPRESSION BASED ON REGION OF INTEREST USING BETTER PORTABLE GRAPHICS (BPG)**	Better Portable Graphics (BGP) + Region of Interest (ROI)	**CR 38.18**
[9]	**2016**	**INNOVATIVE APPROACH TO BIOMEDICAL IMAGE COMPRESSION USING OSCILLATION CONCEPT**	Oscillation Algorithm + Principle components Analysis (PCA)	**CR 00.4070**
[4]	**2016**	**MEDICAL. IMAGE. COMPRESSION. USING. WRAPPING. BASED FAST DISCRETE_CURVELET TRANSFORM & ARITHMETIC CODING.**	Wrapping _Based Fast Discrete Curvelet Transform + Vector_ Quantization + Arithmetic_Coding	**PSNR 40.32** **CR 74.3**

VII. CONCLUSION

We covered a lot of research work related to medical image compression in this paper, which has been helpful in improving medical issues and improving clinical capabilities. Some of the proposed work used a single method for medical image compression, while others used hybrid methodologies to boost compression ratio while maintaining efficiency. All of their efforts are commendable, and they have advanced the medical field. Despite the fact that we have done a lot of testing, there are still a lot of issues in this field that we need to address. Additionally, previous research has shown that the majority of the work was based on 2D medical images. As a result, successful compression algorithms for 3D medical images are needed.

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