2024 5th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI) | 979-8-3503-9523-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICMCSI61536.2024.00078

Reconstruction of Medical Images from Sparse Data: A Deep Learning Approach

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***Abstract*— For diagnosis, medical imaging technology plays a significant role in today's scenario. Accordingly, enormous amounts of medical data are generated daily on research centers and hospitals. Storing the medical images needs a lot of space where in 3D (Three dimensional) medical data acquires a huge space over it. All the medical image details need to be stored digitally for efficient diagnosis. The Digital Imaging and Communications in Medicine (DICOM) standard was established as the global norm for digitally storing patient images from diverse medical imaging modalities. Efficient compression over medical images is required to maintain efficacy in storage space. Compression over images like JPEG, PNG, etc. may not be efficient in bringing an effective lossless image compression in all the types of imaging modalities. Hence, an efficient methodology of Image compression over medical images are required in today's scenario. This research study compares the performance of different methods of compression standard for medical images with the proposed method called DL Based Compressive sensing on Medical Image compression. The primary aim of Compressive Sensing (CS) is to achieve compression of a sparse signal at a sampling rate below the Nyquist rate. Results are analyzed using performance metrics like PSNR, MSE, BPP and CR. And it proves that the proposed algorithm achieves a higher PSNR value and states that it is efficient in bringing a lossless medical image compression.**

Keywords*— *Image Compression, Compressive Sensing, Medical Imaging, Deep Learning

I. INTRODUCTION

Medical image compression is a critical component of data storage and communication, particularly given the substantial volume of medical data generated. Specifically, compression refers to the method of reducing the number of bits needed to represent an image. The main objectives of the compression are to eliminate redundancy, growing need of compression and to minimize the data storage as well as the cost, Minimized bandwidth and efficient data transmission. Direct digital image acquisition is becoming more common in medical imaging. Many modalities now deliver images directly in digital form, including DSA (digital subtraction angiography), Positron Emission Tomography - PET, Single Photon Emission Computed Tomography - SPECT, Magnetic Resonance Imaging -MRI, and Computed Tomography - CT. The growing trend in medical imaging proves digital imaging will eventually trade telemedicine and conventional film imaging in medicine. Therefore, when it comes to digital medical imaging procedures, medical picture compression is essential.

Based upon the human visual perception, approximation over high quality of original image towards the reconstructed image is through image transmission with minimal number of samples. The primary objective of picture compression is to obtain the optimal bit rate, or compression rate (CR). The scalability of image compression systems relates to the quality reduction achieved by bit stream file manipulation. Scalability is mostly used in the sector of image preview. Region of interest coding is also an important property in image compression. It deals with selection of parts over an image, and it's encoded with higher quality apart from other parts of the image. Compressed data contains information's about the image which can be used for searching, categorizing, or browsing images. Colour and texture data, thumbnail images, and information on the author or copyright of the image—another crucial attribute known as meta information—are all included. Other important property of image compression includes processing power. Processing power requirements for encoding and decoding a compression technique vary. A lot of processing power is needed for certain high compression methods. Peak signal-to-noise ratio (PSNR) is a common metric used to assess the quality of a compression technique. A digital image or series of photos frequently contains redundant or useless data. The common characteristics carried in most images are, neighbouring pixels that correlate and therefore contain redundant information. The Traditional image compression algorithms are generally classified into lossy compression and lossless compression techniques. Figure 1 and 2 describes the flowchart of lossy and lossless compression technique.

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DOI 10.1109/ICMCSI61536.2024.00078

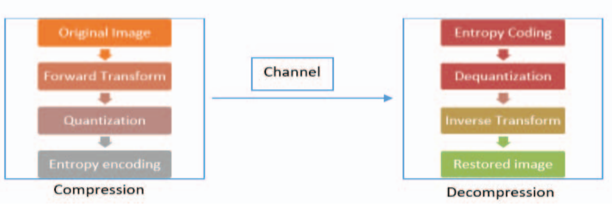

Figure 1. Flowchart of Lossy Compression technique

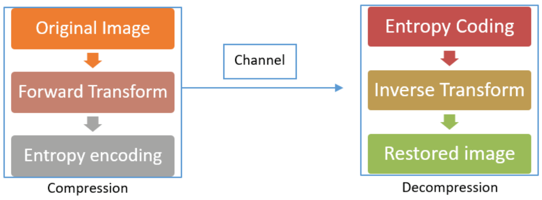

Figure 2. Flowchart of Lossless Compression technique

Reconstructed data from compressed data in a lossless method is comparable to the original input data. In contrast, the reconstructed data in a lossy method differs from the original input data. There is some data or information loss. The suggested method, called compressive sensing (CS), aims to achieve lossless medical image compression by compressing sparse signals at a rate lower than the Nyquist sampling rate.

II. LITERATURE SURVEY

There are countless compression algorithms available, and each has special qualities of its own. A person by the name of Huffman invented the entropy-based Huffman coding [1], [2], which is also present in many hybrid compression models. Run Length Coding (RLE) uses a pair (L, V) to switch data, where L represents the total number of repeated values and V indicates the values that are repeated [3]. Arithmetic coding uses a finite interval between 0 and 1 to represent a message through the probabilistic occurrence of symbols[4]. The predicted error based on the pixels that surround the current pixel under investigation is what drives the predictive coding[5]

Dictionary coding, also known as LZW coding, is suitable for text encoding. Depending on the application, the LZW coding may be static or dynamic[6]. The GIF and TIFF formats employ the LZW compression algorithm. According to Mohammed et al.'s [7] proposal, the Discrete Cosine Transform (DCT), which finds applications in signal and image processing, plays a significant role in frequency domain transformation. The DCT transform is the foundation of the conventional JPEG compression.

JPEG 2000 employs the Discrete Wavelet Transform (DWT), which replaced the DCT blocking technique[8]. Barnsley pioneered fractal image compression [9] wherein contractive transforms and functions were used to represent the compressed image. It is applicable for reconstructing damaged images and is based on the Collage theorem. To compress medical images, Vector Quantization's primary idea depends on the creation of a codebook and modifications to classical VQ [10]. Figure 3 provides specifics regarding the categorization of compression methods.

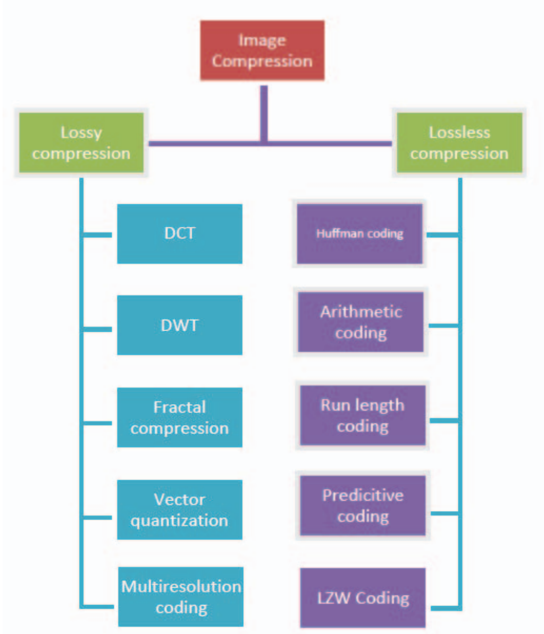

Figure 3. Classification of Compression techniques

The coarser version of an input image can be efficiently represented in Wavelet transforms [8] by using a wavelet base; however, the high-frequency components of the image representation are affected by discontinuities across a simple curve. An appropriate technique for approximating the set of vectors also referred to as an orthonormal linear transformation is the well-known optimal transform KLT [11]. However, because the KLT produces a floating-point number that must be rounded off, the output is not reversible and leads to lossy compression. The region-based analysis model attains to be an efficient method for compression with low computational time.

ROI and Non- ROI selection on a medical image [12] enables to attain the lossless compression for a considered region of the image. However, selecting the regional area over the image is still a challenging task. Metaheuristic algorithms are also adapted in order to achieve an image without a quality loss but appear to be high in computational time. Deep Neural networks [13], methodology implements with different iteration over architecture to train and test the set of huge volumetric medical images and found to be efficient in achieving a high PSNR and CR. Compared to other encoders. Set Partitioning in Hierarchical Trees (SPIHT) is a well-liked encoder [14] that offers notable features like improved visual quality, intensive progressive capability, and low computational complexity.

In recent years, deep learning neural networks [15] have shown to be effective in the analysis of medical images. Using various algorithms, deep learning-based medical image compression reaches a remarkable extent. A compression algorithm that analyses the non-linear transform using a uniform quantizer was proposed by Balle et al. A non-linear transform is used to implement a convolutional neural network (CNN). In terms of the Mean Square Error (MSE) between the original input and the reconstructed output, distortion is parametrized. The suggested approach is fully optimised, yielding distinct operational points for a given value (λ). This method's drawback is that it needs a different model and new training for every value of (λ).

TABLE 1. ANALYSIS OVER COMPRESSION TECHNIQUES

Coding techniques	Type of compression	Advantages	Applications
RLE	Lossless	Fast Process in implementation	Image /text compression
Huffman	Lossless	Efficient and Overall acceptable	JPEG,MPEG
LZW	Lossless	Accepted with all type of data	Image compression
VQ	Lossless	Less complex	Data Compression
Fractal	Lossy	Data with texture information	Image compression
Arithmetic	Lossy / Lossless	Adapted with all kinds of data	Multimedia data compression

III. PROPOSED METHOD

This research presents a novel approach that integrates Deep Learning with Compressive Sensing to improve the efficiency and accuracy of medical image reconstruction. The proposed method leverages the strengths of both techniques to address the challenges associated with acquiring, storing, and transmitting large volumes of medical imaging data. By fusing Compressive Sensing's ability to capture sparse information efficiently with Deep Learning's capacity to learn complex patterns, The aim is to accelerate image acquisition and enhance diagnostic accuracy. Flowchart of the compressive sensing model is depicted in Figure 4. Sample images from the database considered for training is shown in Figure 5.

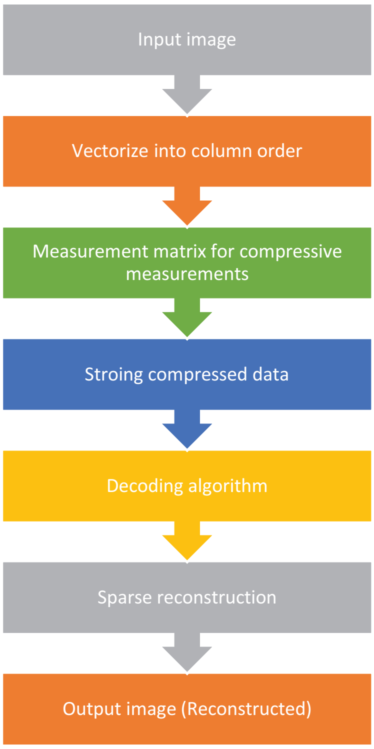

Figure 4. Flowchart of Compressive Sensing Model

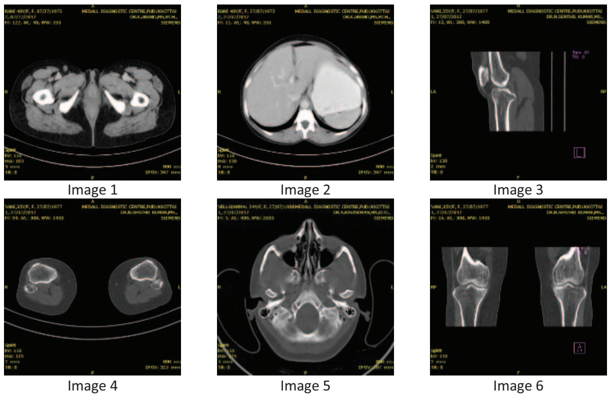

Figure 5. Sample images from database considered for testing

In the proposed method, a diverse dataset of medical images, including various modalities such as X-rays, MRIs, and CT scanswere included with corresponding ground truth images for reference. It is alowed to work with the Compressive Sensing (CS) framework. This framework captures compressed measurements of the medical images efficiently. And involves creating a sensing matrix and generating compressed data from the acquired images. Resultant Matrix values are analysed with a Deep learning model. By developing and training a Deep Learning (DL) model, with a Convolutional Neural Network (CNN), compressed measurements as input focuses on the reconstruction of high-quality medical images from them. By training the DL model with the acquired dataset and associated ground truth images, resultant output with desired lossless data. Validating the model's performance using a separate validation dataset, adjusting hyperparameters as necessary to optimize reconstruction quality and speed.

Using the evaluation perameters of the DL-enhanced CS approach using various metrics. Common evaluation metrics include Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and clinical metrics relevant to the specific medical imaging application. By comparing the performance of this approach with traditional methods, this DL based CS combination proves to be efficient in achieving a better quallity output image which can be opted for quality and quanltitative analysis. Comparision table of PSNR obtained with other traditional algorithms are shown in Table 2.

Steps involved in the proposed method are

Step 1: Selection of Medical image database
Step 2 : Pre-procesing the images to remove artifacts
Step 3: Compressive Sensing Framework - sensing matrix for compressing the images and Capture compressed measurements of the medical images.
Step 4: Deep Learning Model - Design and implement a deep learning model, often a convolutional neural network (CNN). And Set up the architecture, including the number of layers, activation functions, and loss functions.
Step 5: Training and Validation

Step 6: Split the dataset into a training set and a validation set.
Step 7: Train the deep learning model using the training set and backpropagation.
Step 8: Use the validation set to tune hyperparameters and monitor the model's performance.
Step 9: Image Reconstruction - Resultant reconstructed output image with parameters

This algorithm outlines the systematic approach for implementing the method, starting from data acquisition and ending with the evaluation of the deep learning-enhanced compressive sensing method's performance.

IV. PERFORMANCE EVALUATION

Performance metrics helps to objectively assess the quality of image reconstruction. PSNR, MSE, BPP, CR and CT are evaluated and compared with the existing traditional algorithm to determine the efficiency of the proposed algorithm.

Peak Signal-to-Noise Ratio (PSNR):

PSNR measures the quality of the reconstructed image by comparing it to the original image. Higher values indicate better image quality.

$$\text{PSNR} = 10 * log_{10}\left(255^2/\sqrt{MSE}\right) \quad - (1)$$

Mean Squared Error (MSE):

MSE quantifies the average squared difference between the pixels in the original and reconstructed images. Smaller values indicate better reconstruction.

$$\text{MSE} = \frac{1}{N} \times \sum_i \sum_j \left(f(x,y) - F(x,y)\right)^2 \quad - (2)$$

CR denotes Compression ratio, CT stands for Computational time and BPP denotes Bits per pixel.

$$\text{Compression Ratio (CR)} = \frac{Size\ of\ the\ Original\ Image}{Size\ of\ the\ compressed\ image} \quad - (3)$$

TABLE 2. COMPARISON OF DL-CS WITH OTHER TRADITIONAL ALGORITHMS

Algorithm	PSNR	MSE	BPP	CR	CT
Radon	49.74	0.8575	1.1862	14.847	0.73037
DCT	44.35	2.155	1.2687	15.885	0.6026
Haar	49.10	0.96	0.7462	9.325	0.46475
CS	50.4	0.98	1.21	10.4	0.41
DL-CS	**51.3**	**0.99**	**1.18**	**10**	**0.37**

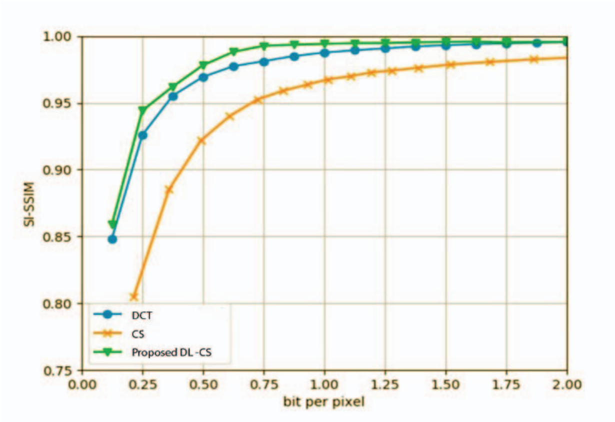

Figure 6. Rate distortion curve on structural similarity using SI -SSIM index

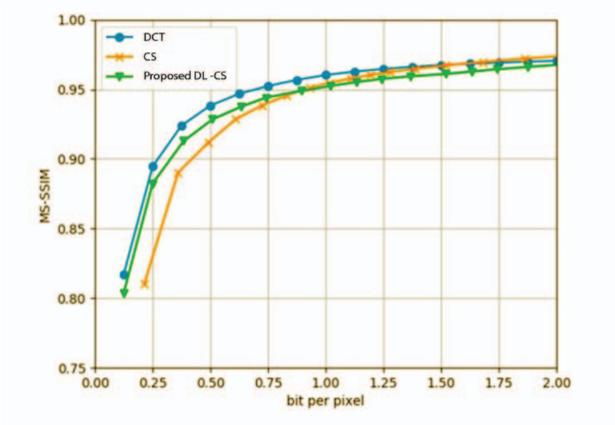

Figure 7. Rate distortion curve on structural similarity using MS -SSIM index

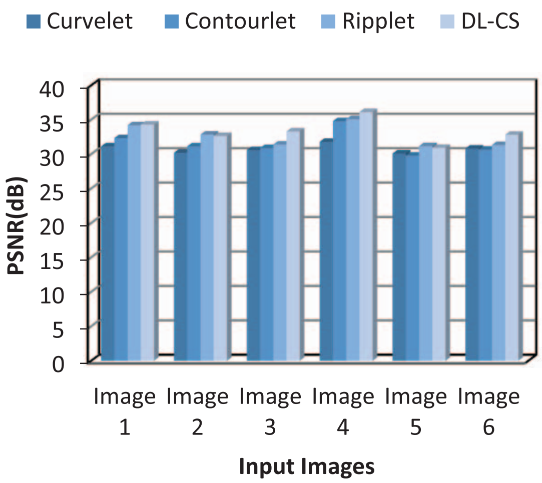

Figure 8. Comparison of input images on PSNR with other algorithms

Figure 8 denotes the comparison of Peak signal noise ratio with other exsiting compression algorithms such as Curvelet, Contourlet, Ripplet transform based algorithms.

In this study, It is explored that the integration of Deep Learning (DL) with Compressive Sensing (CS) to enhance the quality and efficiency of medical image reconstruction. This research aimed to address the challenges associated with acquiring and processing large volumes of medical imaging data.

V. CONCLUSION

This methodology proves that the process of using Deep Learning in conjunction with Compressive Sensing to enhance the reconstruction of medical images. This research aimed to address the challenges associated with acquiring and processing large volumes of medical imaging data. By combining the sparsity-driven principles of CS with the pattern-learning capabilities of DL, this has made several significant observations and contributions. It addresses the challenges associated with efficient data acquisition and reconstruction, ultimately aiming to improve the quality and speed of medical image processing. The improved reconstruction quality translates to enhanced diagnostic accuracy, which is of paramount importance in healthcare. Additionally, the reduction in data acquisition requirements and the expedited reconstruction process can lead to significant resource and cost savings in medical imaging, making it more accessible to a broader population. Also, when compared with the traditional algorithms, DL-CS Method proves to be efficient in attaining a reversible reconstructed medical image without data loss.

REFERENCES

[1] R. C. Gonzalez, R. E. Woods, and B. R. Masters, “Digital Image Processing, Third Edition,” *J. Biomed. Opt.*, vol. 14, no. 2, p. 029901, 2009, doi: 10.1117/1.3115362.

[2] H. Kaur, R. Kaur, and N. Kumar, “Lossless compression of DICOM images using genetic algorithm,” *Proc. 2015 1st Int. Conf. Next Gener. Comput. Technol. NGCT 2015*, no. September, pp. 985–989, 2016, doi: 10.1109/NGCT.2015.7375268.

[3] M. M. S. Rani, “A Hybrid Medical Image Coding Method based on Haar Wavelet Transform and Particle Swarm Optimization Technique,” *Int. J. pure Appl. Math.*, vol. 118, no. 18, pp. 3059–3067, 2018.

[4] M. Li, W. Zuo, S. Gu, J. You, and D. Zhang, “Learning Content-Weighted Deep Image Compression,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 8828, no. c, pp. 1–1, 2020, doi: 10.1109/tpami.2020.2983926.

[5] A. J. Hussain, D. Al-Jumeily, N. Radi, and P. Lisboa, “Hybrid Neural Network Predictive-Wavelet Image Compression System,” *Neurocomputing*, vol. 151, no. P3, pp. 975–984, 2015, doi: 10.1016/j.neucom.2014.02.078.

[6] L. Jacques, L. Duval, C. Chaux, and G. Peyré, “A panorama on multiscale geometric representations, intertwining spatial, directional and frequency selectivity,” *Signal Processing*, vol. 91, no. 12, pp. 2699–2730, 2011, doi: 10.1016/j.sigpro.2011.04.025.

[7] A. A. Mohammed and J. A. Hussein, “Hybrid transform coding scheme for medical image application,” *2010 IEEE Int. Symp. Signal Process. Inf. Technol. ISSPIT 2010*, pp. 237–240, 2010, doi: 10.1109/ISSPIT.2010.5711785.

[8] M. E. Emara, R. F. Abdel-Kader, and M. S. Yasein, “Image compression using advanced optimization algorithms,” *J. Commun.*, vol. 12, no. 5, pp. 271–278, 2017, doi: 10.12720/jcm.12.5.271-278.

[9] M. Omari and S. Yaichi, “Image compression based on genetic algorithm optimization,” *2015 2nd World Symp. Web Appl. Networking, WSWAN 2015*, pp. 1–5, 2015, doi: 10.1109/WSWAN.2015.7210304.

[10] K. Chiranjeevi, U. R. Jena, and B. M. Krishna, “Computational Intelligence in Data Mining,” vol. 711, pp. 373–382, 2019, doi: 10.1007/978-981-10-8055-5.

[11] S. S. Bhairannawar and S. Sarkar, “ORIGINAL RESEARCH PAPER FPGA Implementation of Optimized Karhunen – Loeve Transform for Image Processing Applications,” *J. Real-Time Image Process.*, vol. 17, no. 2, pp. 357–370, 2020, doi: 10.1007/s11554-018-0776-x.

[12] C. S. Vincent and J. Janet, “An Enhanced N-Pattern Hybrid Technique for Medical Images in Telemedicine,” *Procedia Comput. Sci.*, vol. 79, pp. 305–313, 2016, doi: 10.1016/j.procs.2016.03.040.

[13] M. A. P. Manimekalai and N. A. Vasanthi, “Hybrid Lempel–Ziv–Welch and clipped histogram equalization based medical image compression,” *Cluster Comput.*, vol. 22, no. s5, pp. 12805–12816, 2019, doi: 10.1007/s10586-018-1761-7.

[14] B. Anjana and R. Shreeja, “Image compression using artificial neural network,” *IET Conf. Publ.*, vol. 2012, no. CP652, pp. 288–290, 2012, doi: 10.1049/cp.2012.2551.

[15] Johannes Ball’e and Valero Laparra and Eero P., “END-TO-END OPTIMIZED IMAGE COMPRESSION,” *ArXiv*, vol. abs/1611.0, 2017.