JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

LOSSLESS ROI IMAGE COMPRESSION USING SHEARLET TRANSFORM AND SPIHT ENCODING

Dr P. Sreenivasulu[1] ,Sk. Asreen[2],T. Sireesha[3], P. Madhavi[4], S. Michael[5]
Professor[1] , Student[2,3,4,5]
Electronics and Communications Engineering
Audisankara College of Engineering &Technology, Gudur, Tirupati, A.P, India.

Abstract:

Large volumes of medical images data are being collected, communicated and archived in the modern medical imaging era, making the development of effective image compression techniques for both 2D and 3D pictures necessary. To facilitate remote healthcare services, the compression of medical pictures is a crucial technique. More precise information from a picture is needed for medical diagnoses provided by these services. As any type of compression method has the feature that the compression rate and image quality are inversely related , one of those attributes (quality or compression rate) must be sacrificed. Region of Interest (ROI) codec are developing in this environment to lower this proportionality, resulting in an increased compression rate without sacrificing quality.

***Keywords*: Lossless image, Compression rate, ROI, SPIHT technique, Biological image.**

I. INTRODUCTION

The current decade dwells in a visually captivating universe that explores a wide range of elements like colours, textures, motions, and so forth. Any of these characteristics can be easily accommodated by the human visual system, which also has the ability to distinguish between and understand such things. These ideas are being transferred to a mechanical point of view via image processing techniques. As a result, image processing programmes have become a crucial aspect of daily life since they allow for the compact representation of a vast amount of information in an image. The significant increase in image use across a range of industries, including satellite imaging, bioimaging, multimedia services, and various web-based applications, has an amplified influence. Also, medical images play a crucial part in our day-to-day lives. Image processing is important to our daily lives in any way given that we live in the digital age. Image compression is a potent tool for representing images in a little space. It results in cheap transmission costs by lowering the actual number of bits required to hold the images. The term "lossless" refers to the reversible compression because there is no account of data loss after decoding. In contrast, lossy compression, also known as irreversible compression, resulted in data loss. A significant amount of medically related data and images are processed in the medical civilization. The use of both 2D and 3D medical images in the diagnosis process has increased as a result of improvements in medical imaging techniques. The accuracy and viability of a diagnosis are directly connected to the quality of the medical image. While near-lossy compression provides acceptable reconstruction quality with higher compression performance, lossless compression methods produce great reconstruction quality with low compression efficiency. With these issues in mind, a number of 2D and 3D medical image compression techniques were presented. Image compression is necessary for a number of applications, including multimedia, documents and medical imaging, which call for a significant amount of data to be stored, transmitted, and retrieved. For uncompressed photos, a sizable amount of storage space and transmission bandwidth are required. Reducing the redundancy of image data can achieve the goal of image compression, which is to represent images as compact data.

II. LITERATURE SURVEY

For an image compression system, different researchers have suggested many approaches. Among them , a handful of significant studies are presented in this section. An efficient lossless ROI image compression using wavelet-based modified region growing algorithm (P.Sreenivasulu and S.Varadarajan ,2018 [1]). In this approach, the wavelet transform and encoding approach are used in this ROI to accomplish lossless picture compression. The segmentation in this case is carried out using the MRG algorithm, ROI compression is accomplished using the DWT with SPIHT encoding technique, and non-ROI compression is accomplished using the DCT with MHE methodology. The results show that, when compared to the current method, the suggested method has a high PSNR and high compression ratio.Only a small portion of the medical photos may be diagnostically helpful. In that study, Dr.P.Sreenivasulu and Dr.S.Varadarajan, 2019 [2] suggested a method to compress the image without a lossless version using the Shearlet coefficient and ROI (region of interest) detection in order to improve the ratio of image compression. It shows the suggested image compression framework based on shearlet has outperformed by having a superior average PSNR value of 67.3 dB and better average compression ratio of 8.36 when compared to current methods. As the property of inverse proportionality between the compression rate and quality of the image takes place in any kind of compression method, there is a need to sacrifice any one of those credentials (Quality or Compression Rate). With this context, Region of Interest (ROI) codecs are emerging and reduces this proportionality that yields more compression rate without compromising the quality. In that study,Dankan Gowda V, Avinash Sharma , Rajesh L , Mirzanur Rahman , Ghazaala Yasmin, Parismita Sarma, A. AzhaguJaisudhanPazhani , 2022 [3]proposed an ROI based near lossless image compression method that incorporates the Set Partitioning in Hierarchical Trees (SPIHT) and Vector Quantization coding for medical images.A new improvised steering angle and gear-based ROA (ISG-ROA), a modification of the Rider Optimisation Algorithm (ROA), is proposed for this purpose by Dr.P.Sreenivasulu and Dr.S.Varadarajan, 2019 [4] and this research work uses the optimisation concept for the optimal selection of filter coefficients from DWT and DCT approaches. The filter coefficient is adapted to finalise the result with reduced compression ratio.Medical Image Compression by Optimal Filter Coefficients Aided Transforms using Modified Rider Optimization Algorithm proposed by Dr.P.Sreenivasulu and Dr.S.Varadarajan, S. Thenappan ,2019 [5].This employs clever strategies to provide a novel medical image compression model. Segmentation, image compression, and image decompression are the three main components of the medical image compression that has been accepted. By applying the segmentation technique and the Modified Region Growing (MRG) algorithm, the region of interest (ROI) and non-ROI parts of the picture are first separated.Algorithmic Analysis on Medical Image Compression Using Improved Rider Optimization Algorithmproposed by Dr.P.Sreenivasulu and Dr.S.Varadarajan, 2020 [6]that is three-stage medical image compression method using the ROI-discrete cosine transform (DCT) and SPHIT encoding methods, the non-ROI-discrete wavelet transform (DWT), and merge-based Huffman encoding (MHE) for segmentation and picture compression, respectively. On the other hand, directional transforms can efficiently adapt and sparsely represent such geometric structures; the classical DWT, on the other hand, is limited to efficiently representing point singularities and is unable to sparsely capture more complex, higher-order discontinuities such as lines and curves proposed by C.L.Chang and A.Munteanu, 2007 [7-8].Medical imaging typically uses lossless compression to prevent any detrimental effects of lossy compression on image quality and diagnostic capabilities. A significant number of technical advancements in lossless compression of 3D medical images have been reported in the literature. Most of these methods take advantage of correlations between slices within the data volume to improve the compression performance by either using a 3D discrete wavelet transform (3D-DWT) or a 2D wavelet transform (2D-DWT) propose by X.Wu and T Qiu , 2005 [9] and Image compression using the 2D wavelet transform in 1992 [10]. Ming-Ming Li et al ,2011 [11] propose that, we use an improved set partitioning in hierarchical trees (SPIHT) coding pipeline with a lossy Bayer image compression pipeline to reduce the memory requirements of the video application. The next technology encrypts and decrypts images made available by the CFA arrangement. A demosaicking phase that creates a full-colour image is typically carried out after the image coding phase is finished. For medical colon CT images are compressed using a hybrid model that uses lossless compression in the ROI and high-rate, motion-compensated, lossy compression in other areas.A series of 3-D morphological image processing techniques are used to segment the colon wall. An initial approximation for ROI areas is provided by the motion-compensated coding output this was proposed by S.B.Gokturk, 2001 [12].It may be possible to build medical image compression techniques that concentrate on the areas that are crucial for diagnostic purposes by encoding arbitrarily formed portions inside an image at various quality levels. The entire image is typically changed during area of interest (ROI) coding, and the coefficients related to the ROI are typically coded with higher accuracy (up to lossless) than the background. A specific compression bit rate of the entire image can be attained either after the image has been manually or automatically segmented into significant regions, and only ROI-related coefficients can then be coded and this was proposed by A.Jarvi , J.Lehtinen and O.Nevalainen , 1999 [13].The adaptive predictor to increase the prediction precision of encoded image blocks. A local mean predictor and one of the seven JPEG lossless mode predictors adaptively predict each block first this was proposed by Zuo-Dian-Chen ,Ruey-Feng Chang and Wen-Jia Kuo, 1999 [14].

III. PROPOSED METHOD

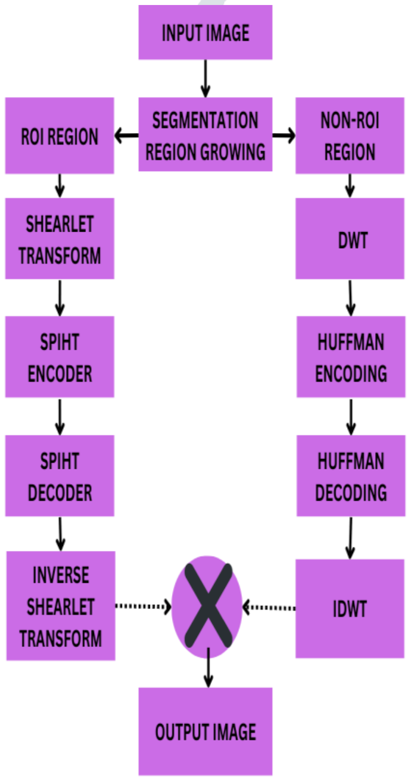

Fig. 1. Block diagram of proposed method.

The block diagram of our proposed method is depicted in Fig. 1 and the step-by-step methodology of our proposed method is explained through the following steps.

There are mainly three steps in our proposed method and they are

Step 1: Segmentation

Step 2: Compression

Step 3: Decompression

In step-1 for segmentation we are using RG (Region Growing) algorithm this separates the input image into two parts they are ROI (Region Of Interest) Region and Non-ROI Region.

In step-2 the compression of the image in ROI Region is done by the shearlet transform and SPIHT encoder. As the compression in Non-ROI Region is done by the DWT (Discrete Wavelet Transform) and Huffman encoding.

In step-3 the decompression of the image for ROI Region is done by SPIHT decoder and Inverse shearlet transform. As the decompression in the Non-ROI Region is done by the Huffman decoding and IDWT.

SEGMENTATION :

The most important component of a medical image is the ROI. It contains the most important information in the medical image and shouldn't be changed. A medical image may contain a number of disconnected ROIs, and there are several ways to describe a ROI in a medical image. In this case, the ROI is found using a segmentation method from the input image. One of the most crucial stages in the processing of images is segmentation, which plays a crucial role in object detection.In this study, we use the region-growing method to separate the ROI from the input image. Think about the 256 x 256-pixel input image. We start by extracting the ROI from the input image. The input image is divided using the projected region growing approach according to a seed point. The main goal of the region-growing segmentation is to control the initial seed spots. A seed point is where area growth begins, and the segmentation strategy heavily depends on the choice of this point. The advantages of the Region growing segmentation are region growing methods can correctly separate the regions that have the same properties we define and other advantage is Region growing methods can provide good segmentation results if the original image have clear edges. The procedure of the projected region growing-based image segmentation is explained below:

Step 1: Take, for instance, the input image I (a, b), which measures 256 x 256 pixels. First, we divide the image into several blocks (A^i, in this case). There are a few neighbourhood pixels and one centre pixel for each block.

Step 2: The intensity threshold is then set, (V^{IN}).

Step 3: Continue with the subsequent processes in Step 7 for each block A^i until the total number of blocks for an image is reached.

Step 3 (a): Determine the histogram H for each A^ipixel.

Step 3(b): Set theA^{ith} block's most frequent histogram to F^H and regulate it.

Step 3 (c): In accordance with F^H, select any pixel and designate that pixel as the seed point with the intensity IN_s.

Step 3 (d): Select the pixel that is adjacent and has the intensity IN_i.

Step 3(e): Track down the force contrast of those pixels s and i.

$$z_{IN}=\|IN_s-IN_i\|.$$

Step 3(f): If ,$z_{IN} \leq V_{IN}$ then the region grows when the consistent pixel is added to it; if not, proceed to step 3(h).
Step 3(g): Check whether all pixels are added to the locale. If this is the case, proceed to step 2, then step 3 (h).
Step 3(h): Reestimate the area, locate the new seed points, and carry out the steps in step 3(a).

Step 4: Stop the entire process.

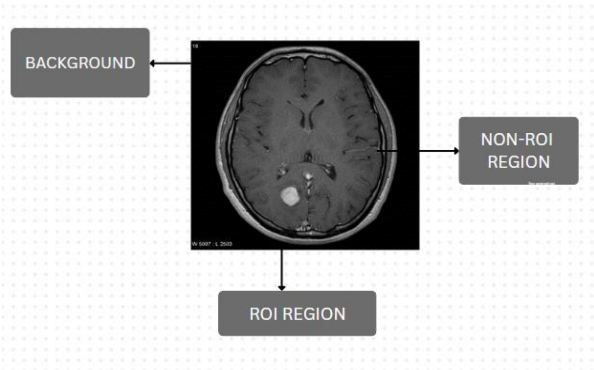

Fig 2: Illustration of regions in the medical images

COMPRESSION IN ROI REGION:
SHEARLET TRANSFORM :

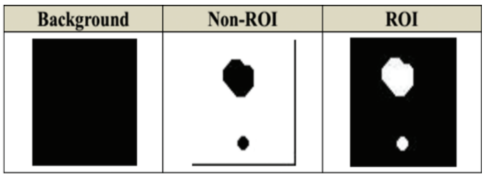

Fig 3: Segmented regions such as background, Non-ROI, ROI.

The ROI region's use of the Shearlet transform:

1. Getting the ROI:
The original image should be referred to as I (x,y), and the ROI should be referred to as R (x,y). The following equation makes it possible for us to extract the ROI from the original image:

R(x,y) = I(x,y) * M(x,y), where M(x,y) is a binary mask that is equal to 1 within the ROI and 0 outside of it. * denotes element-wise multiplication.

2. The Shearlet Transformation:
The following equation can be used to apply the Shearlet transform to the ROI: Let S(I) be the shearlet transform of the original image I, and S(R) be the ROI R.

S(R) = F(-1) [W(-1) * S(I) * W], where W is the matrix of the Shearlet transform, F(-1) is the inverse of the Fourier transform, and W(-1) is its inverse.

3. Integrating the Picture:

Whenever we have dissected the coefficients created by the Shearlet change in the return for money invested district, we can utilise them to combine another picture that underlines the significant highlights. This should be possible utilising the accompanying condition:
I'(x,y) = F(-1) [W * S'(I) * W(-1)], where S'(I) are the thresholded or filtered modified Shearlet transform coefficients that highlight the relevant ROI features.
In total, we are able to use these equations to extract a region of interest from an image, perform a Shearlet transform analysis on its features, and create a new image that emphasises the relevant features within the ROI.
For ROI region we are using shearlet transform. In order to compress images, the DCT and DWT were crucial. The introduction of DWT coefficients to image compression was made possible by the visual quality issue that occurred in the DCT transform. However, the main issue with DWT is that it performs poorly when dealing with multivariable functions and pinpointing the locations of edges when numerous edges are contiguous or cross one another. Additionally, the wavelets' capacity to handle directional information is somewhat limited. When addressing edges, the shearlet offers directionality and computational effectiveness. Our adaptive system uses the discrete shearlet transform to compress data, and as a result, it performs much better than the wavelet transform in our work. The shearlet is made up of a variety of locally well-localised waveforms at different sizes, angles, and positions. The Discrete Shearlet Transform is a strong contender for picture compression applications due to its great capacity to capture directional features and effective localization.
In this study, we evaluate the discrete shearlet transform's capability for picture compression. Directional filtering and the Laplacian pyramid method are used to perform the shearlet transform. Concider, for an image $D_{m,}$ the shearlet transform is a mapping .

$$D_m \rightarrow \delta H_\psi D_m(p,q,r)$$

It depends on the scale p>0, the orientation q∈Z and the location r. This provides a directional scale-space decomposition of D_m and the shearlet transform can be expressed as:

$$\delta H_\psi D_m(p,q,r) \equiv \langle D_m * \psi_{pqr} \rangle, \quad p>0,\ q\in Z,\ r\in Z^2$$

Where;

$$\psi_{pqr}(y) = \left| \det I_{Pq} \right|^{-1/2} \psi\left(I_{Pq}^{-1}(y-r) \right)$$

$$I_{Pq} = \begin{pmatrix} p & q \\ 0 & \sqrt{p} \end{pmatrix}$$

Observe that I_{Pq} can be factorized as $J_q\ K_p$, which are shear matrix and dilation matrix is given by:

$$J_q = \begin{pmatrix} 1 & -q \\ 0 & 1 \end{pmatrix},\ K_p = \begin{pmatrix} p & 0 \\ 0 & \sqrt{p} \end{pmatrix}$$

Where, p, q are in Z and r is in Z^2

With this definition, shearlets will have good spatial and frequency localization. The shearlet ψ_{pqr} is made up of a variety of locally well-localised waveforms at different scales, directions, and places. The discrete shearlet transform is a strong contender for picture compression applications due to its great capacity to capture directional characteristics and good localization (each of the shearlet frame elements is well-adapted in both the space and frequency domains). The quantization process is carried out by the quantization matrix after the shearlet transform has been applied to the input image. Higher perceptible frequency components are supposed to receive higher resolution from the quantization matrix than lower perceptible frequency components, which can be encoded most effectively.

SPIHT ENCODER :For ROI region we are using SPIHT encoder.The SPIHT technique is a more effective way to implement EZW (embedded zero wavelet). The SPIHT algorithm divides the decomposed wavelet into significant and insignificant partitions based on the following function after applying the wavelet transform to an image:

$$S_n(T) = \begin{cases} 1, \max\limits_{[a,b]\in T}\{C_{a,b}\} \geq 2^n \\ 0, elsewhere \end{cases}$$

In this case, C(a,b) is the coefficient value at coordinate (a,b), and Sn(T) is a significant set of coordinates. The sorting pass and the refinement pass are the two passes in the algorithm. The LIP (list of insignificant pixels), which consists of individual coefficients with magnitudes below thresholds; the LIS (list of insignificant sets), which consists of the set of wavelet coefficients determined by tree structures and determined to have magnitudes below threshold; and the LSP (list of significant pixels), which is a list of pixels determined to have magnitudes above threshold (significant), are all used in the SPIHT encoding process. The maximum number of bits needed to present the largest coefficient in the spatial orientation tree is found and represented by $n_{\max}$:

$$n_{\max} = \left\lfloor \log_2\left(\max_{a,b}\{|c\ (a,b)|\}\right\rfloor.$$

COMPRESSION IN NON-ROI REGION:

DWT: The image is transformed from its spatial domain to its frequency domain using DWT. Wavelets are signals that are local in scale and typically have an atypical shape in time. A wavelet is a waveform with an average value of zero and an effectively determined duration. Since it integrates to zero and oscillates up and down across the axis, the term "wavelet" is derived from this property. A property suited for compact signal representation is also shown by numerous wavelets. A signal can be broken down into a variety of scaled and shifted copies of the original mother wavelet. A wavelet transform can be used to break down a signal into component wavelets. The images are broken down into low-low (LL), low-high (LH), high-low (HL), and high-high (HH) elements, where LL denotes an approximation and the other three denote detailed coefficients. Once this has occurred, it is possible to ignore some of the subtleties by decimating the wavelet coefficients. A wavelet function has two main properties:

$$\int_{-\infty}^{0} \psi(t)\, dt = 0$$

That is, the function is oscillatory or has a wavy appearance :

$$\int_{-\infty}^{0} |\Psi(t)|^2\, dt < \infty$$

For a better understanding of the 2D Haar-DWT of an image, let's look at an example. The pixel-by-pixel representation of a 4 x 4 image is shown in Figure 4. The 2D Haar-DWT's output is depicted in Figure 5.

7	5	8	6
2	1	7	8
6	8	3	5
1	9	4	1

Fig 4: Pixel by pixel representation of a 4x4 Image

A)

7+5	8+6	7-5	8-6
2+1	7+8	2-1	7-8
6+8	3+5	6-8	3-5
1+9	4+1	1-9	4-1

12	14	2	-2
3	15	1	-1
14	8	-2	-2
10	5	-8	3

Horizontal operations

B)

12+3	14+15	2+1	-2+1
14+10	8+5	-2-8	-2+3
12-3	14-15	2-1	-2+1
14-10	8-5	-2+8	-2-3

15	25	3	-1
24	13	-10	1
9	-1	1	-1
2	-3	6	-5

Vertical operations

Fig 5: Example of 2D-Haar DWT of an Image

HUFFMAN ENCODING :The Huffman coding method is a compression approach that targets both data and pictures. Usually, it involves two stages. In the first step, a comprehensive statistical model is acquired; in the second phase, the picture data are encoded using the statistical model's output from the first phase. These codes, which use an essential number of bits, have different code lengths. Because of this idea, the average code length is reduced, and

$$Compression\ ratio = \frac{size\ of\ original\ image}{size\ of\ compressed\ bit\ stream}$$

than it was before.

Step 1: Read the image in Matlab's workspace as the first step.

Step 2: The second step is to convert the colour image to a grayscale image.

Step 3: The images' probabilities are arranged in decreasing order, with lower probabilities being combined. This process continues until only two probabilities are left, at which point codes are eliminated by choosing the most improbable plausible image to have a shorter length code.

Step 4: Advance Huffman encoding is carried out, producing packed data by mapping the code words to the compared images.

Compression ratio is given as:

$$Compression\ ratio = \frac{size\ of\ original\ image}{size\ of\ compressed\ bit\ stream}$$

$$I^{Com}[x,y] = \frac{[ROI]c + [non-ROI]c}{2}$$

DECOMPRESSION IN ROI AND NON-ROI REGION:

The compression and decompression processes are exact mirror images of one another. The ROI mask code's bit stream is first decoded using the SPIHT decoding decompression algorithm, and the non-ROI code's bit stream is decoded using the matching modified Huffman decoding technique. The important phases in the proposed picture decompression stage are as follows:

Input: compressed bit stream $I^{Com}[x,y]$.

Output: compressed image $I^{Dec}[x,y]$.

Step 1: Calculating [non-ROI] Decompression

The [non-ROI]dc is computed from the compressed picture [non-ROI]c using the modified Huffman decoding and inverse DWT. To obtain non-ROI dc, the reverse operation of merging DWT and Huffman coding is carried out.

Step 2:[ROI]dc calculation

Through the reverse operation of the DCT and SPIHT decoders, the decompressed ROI image [ROI]Dec is here calculated from the compressed image [ROI]c. In the end, [ROI]Dec is obtained using the SPIHT decoder and inverse DCT.

Step 3: Calculate decompressed image $\boldsymbol{I^{Dec}[x,y]}$ using OR operation

We combine the two decompressed sections as in steps 1 and 2 to calculate the decompressed **image** $\boldsymbol{I^{Dec}[x,y]}$. Finally, using a logical OR operation, the final decompressed **image** $\boldsymbol{I^{Dec}[x,y]}$ is obtained.

$$I^{Dec}[x,y] = [ROI]^{Dec} \| [non\text{-}ROI]^{Dec},$$

where [ROI] Decompression is the decompressed ROI, [non-ROI] Decompression is the decompressed non-ROI, and $\boldsymbol{I^{Dec}[x,y]}$ is the decompressed output image.

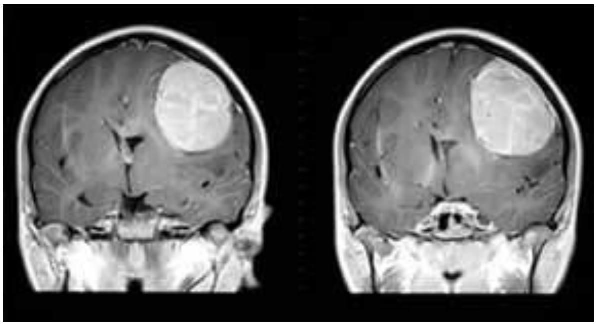

Fig 6: Compressed and Decompressed images

IV. CONCLUSION :

A significant factor in cutting broadcast and capacity costs is image reduction. The majority of picture compression frameworks are helpful in their respective domains, and new compression frameworks that increase the retrieved compression ratio are emerging daily. The suggested approach might be used as a starting point for research. This study implements ROI lossless picture compression with wavelet transform and encoding. Here, the ROI is compressed using the Shearlet transform with SPIHT encoding method, and the non-ROI is compressed using the DWT with Huffman encoding. The segmentation is carried out based on the Region Growing algorithm. As SPIHT is an embedded coder, our technique also inherited the embedded coding property. As a result, the decoder can be shortened at any time when it reaches the required visual quality, which improves the diagnostic process' accuracy. Sensitivity, specificity, and accuracy metrics were used to evaluate how well the segmentation step performed.

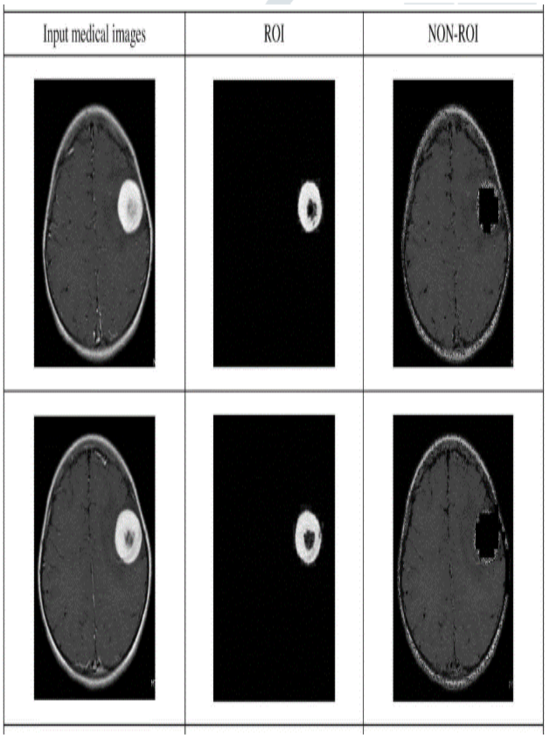

Fig 7: Input medical images with ROI and Non-ROI

Images	Compression Ratio		PSNR	
	Proposed	DCT	Proposed	DCT
Image1	4.01	3.8	40.25	38.01
Image2	3.85	3.5	39.56	35.25

V. REFERENCES :

1)P.Sreenivasulu and S.Varadarajan, An efficient lossless ROI image compression using wavelet-based modified region growing algorithm, (2018), https://doi.org/10.1515/jisys-2018-0180.

2)Dr.P.Sreenivasulu and Dr.S.Varadarajan, Hybrid Image Compression Using Shearlet Coefficients and Region of Interest Detection, Vol. 6, 506–517, 2019.

3)Dankan Gowda, Avinash Sharma, ,Rajesh L, Mirzanur Rahman, Ghazaala Yasmin , Parismita Sarma , A. AzhaguJaisudhanPazhani , A novel method of data compression using ROI for biomedical 2D images, Vol. 24, December 2022, 100439.

4)Dr.P.Sreenivasulu and Dr.S.Varadarajan,Medical Image Compression Using DCT based MRG Algorithem,Second International Conference on Smart Systems and Inventive Technology (ICSSIT 2019) IEEE Xplore Part Number: CFP19P17-ART; ISBN:978-1-7281-2119-2.

5)Dr.P.Sreenivasulu, Dr.S.Varadarajanand S. Thenappan, Medical Image Compression by Optimal Filter Coefficients Aided Transforms using Modified Rider Optimization Algorithm, International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958, Volume-9 Issue-2, December, 2019.

6)Dr.P.Sreenivasulu and Dr.S.Varadarajan, Algorithmic Analysis on Medical Image Compression Using Improved Rider Optimization Algorithm, Springer Nature Singapore Pte Ltd. 2020 H. S. Saini et al. (eds.).

7)C.-L. Chang, B. Girod, Direction-Adaptive discrete wavelet transform for image compression, IEEE Trans. Image Process. 16 (2007) 1289–1302.

8)A. Munteanu, O.M. Surdu, J. Cornelis, P. Schelkens, Segmentation driven direction-adaptive discrete wavelet transform, in: IEEE International Conference in Image Processing, vol. 1, 2007, pp. 437–440.

9) X. Wu and T Qiu, "Wavelet coding of volumetric medical images for high throughput and operability," IEEE Trans. on Medical Imaging, vol. 24, no. 6, pp. 719-727, June 2005.

10)Image compression using the 2-D Wavelet transform, IEEE Trans. Image Processing, vol. 1,pp.244-250, Apr. 1992.

11) Ming-Ming Li," Lossy compression of Bayer image with SPIHT",6th IEEE conference on industrial electronics & applications, (2011),(2244-2248).

12) S.B. Gokturk, C. Tomasi, B. Girod, and C. Beaulieu, "Medical image compression based on region of interest, with application to colon CT images," in Proc. 23rd Ann. Int. Conf. IEEE EMBS, Istanbul, p. 2453, 2001.

13)A. J¨arvi, J. Lehtinen, and O. Nevalainen, “Varible quality image compression system based on SPIHT,” Signal Process.: Image Comm. vol. 14, pp. 683-696, July 1999.

14)Zuo-Dian Chen, Ruey-Feng Chang,* and Wen-Jia Kuo, Adaptive Predictive Multiplicative Autoregressive Model for Medical Image Compression, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 18, NO. 2, FEBRUARY 1999.