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Composite Lempel - Ziv - Welch and Huffman Coding for Medical Image Compression

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Abstract:

Imaging in medicine plays vital role in the medicine by supporting diagnosis and treatment of a disease. DICOM images files occupy high storage space due to high resolution and quality. Medical image sharing is crucial in the healthcare sector for disease diagnosis and subsequent therapy. At present the medical imaging becomes increasingly digital and image files increase in size and require substantial storage that is accessible, resilient and easy to backup with healthcare industry standards. When image size is reduced, it makes it possible to store more images in the available memory space. To resolve this problem, it is required to reduce the size of image file by means of compressing. Various compress methods help to compress the medical image. Compressing DICOM MRI brain images without mutating the features of the reconstructed resultant images is the main goal of this research project. The former research use technique clipped histogram equalization to compress the image. Present method produces the higher Compression Ratio and Peak Signal Noise Ratio than former method. The present research method DICOM Magnetic Resonance imaging are enhanced by Ant Colony Optimization Technique (ACO). The U-Net convolutional neural network design divided the improved image into two region such as region that important portion brain part and another part background of the MRI brain image (non-ROI). Consequent to the segmentation, the Region of interest part compacted by means of hybrid Lempel Ziv Welch (LZW) with Huffman encoding. In LZW dictionary size is controlled by fire fly optimization method to decrease the memory space. NonROI part compressed by Embedded Zero Tree Wavelet (EZTW). At last reconstruct the image by decompression. The experimentation proves that present method with high compression ratio than the prior method.

Keywords: diagnosis, Consequent, substantial.

1 Introduction

Medical imaging technology produce high resolution and quality images for analysis of diagnose the disease. The DICOM standard layout used to accumulate the MRI Medical imageries in health industries. DICOM format file created by Medical imaging machines, these file holds a huge amount of data that is difficult to be stored. Image condensing necessary to distribute, packing, and administration of digital medical image collection due to the growing use of medical imaging in clinical practice and the expanding sizes of data volumes produced by different medical imaging modalities. Image can be processed in two ways while compressing image are lossless compression and lossy compression. Lossless compression always compresses the images with original quality that means of without change in pixel value of image. The techniques usually used in lossless compression are lossless transform coding, predictive coding and entropy encoding. Lossy compression reduces file size by always eliminating the actual data. Lossy method can produce much smaller compressed file than any loss less methods.

Lossy Compression discards some information when the image is compressed. Some of the methods or techniques used in lossy compression are discrete cosine transform, Wavelet transform and Quantization based methods. In DCT, higher compression achieved with losing of few data [1]. Then the memory size of the MRI brain will be decreased by using this technique and quantization is applied during encoding process due to this process may chance to discard the important information. Using DWT method, during the compression need to round off coefficients by vector quantization due to this some less important information removed to achieve the higher compression to occupy less storage space. Because of the medical images in health care industries requires the huge storage for a greater number of patient's history [2].

Recent days, there will be a greater demand in higher compression with high quality of medical image. To address this issue, Region of Interest (ROI) techniques have emerged in recent years. It joins both lossless method and lossy methods to acquire greater compression. Various methods are available for lossless compression, some methods are Huffman Coding, and Dictionary based methods, entropy coding and run Length Coding. ROI image part condensed through of Lossless compressing methods and NROI part compressed by lossy methods.

In the motive of acquiring the outstanding Compression Ratio hybridization of LZW and Huffman utilized with optimization technique. In this paper, the image transformed using Lempel -Ziv – Welch (LZW) the dictionary size controlled by means of firefly optimization and then the Huffman coding applied with help of Huffman tree. This process performed on region of interest and Non region of interest image part compressed with the EZZTW. Greater ratio of compression and PSNR achieved with present method.

2 Related Work

Gupta, Akshu, and Kanika (2012). Introduced this technique to increase the pixel count along the edges. Increasing the edges' total intensity has also been beneficial. ACO for picture enhancement also requires reduced computation time [17].

Trupti N. Baraskar and Vijay R. Mankar (2019). The retrieved detail coefficients initially encoded by RLE after two dimensional discrete wavelet transform and multi-level decomposing used to the medical data set in this embedded work. Second, the Huffman encoder used to encode the encoded detailed coefficients and the extracted approximate coefficient. For higher decomposition levels (N = 4), DWT provides improved compression size, compression ratio, and compression gain; however, image quality metrics such as PSNR and MSE are deteriorated [18].

Bindu Puthentharayil Vikraman, Jabeena Afthab (2024) MRI image data gathered from BRATS data set. Gathered data filtered to remove the noise by using ALSHE. ROI part of the image compressed by means of DCT with Zero Wavelet. Non-ROI part compressed through lossy compression method. It gives better performance than the existing method [11].

Srikanth & Ramakrishnan (2005) The medical images compressed by using the spatial transformation and content-based entropy encoding based on energy contexts, product contexts and texture contexts [7].

Retinex is a technique that Dalvir Kaur and Kamaljit Kaur (2013). There are three stages to it. Huffman coding initially used to compress images. In stage 2, all Huffman codeword's are connected. LZW coding and decoding used to compress the data. The Retinex algorithm applied to the compressed image in stage 3. It used to update the image's complexity and to improve the overall image quality. The proposed method used in MATLAB software to compute CR, PSNR, and MSE [9].

R. Monika, Samiappan Dhanalakshmi, for compressing various medical photos with a high compression ratio, use Coefficient Mixed Thresholding ABCS (CMT-ABCS). The Adaptive Block Compressed Sensing (ABCS) method, which based on coefficient mixed thresholding, introduced to compress a variety of medical images in order to reach a high compression ratio. When compressing the data, the photos divided into small parts, and a sample selection is produced utilizing these regions. The frequency distribution equalized by coefficient mixing, which facilitates seamless image reconstruction.

M. A. P Manimekalai, N. A. Vasanthi, Initially clipped histogram equalization done to increase the contrast of an image based on the threshold value define by means of Particle Swarm Optimization (PSW) algorithm and LZW dictionary based Lossless technique used to compressing the MRI image would increase the compression ratio [10].

3 Proposed Methodology

Proposed method segment the MRI DICOM image into two portions as Foreground as (ROI) and background as NROI by U-NET convolutional neural network architecture with dice loss function. Consequent to the segmentation, the foreground portion condensed by applying the hybrid lempel ziv welch- huffman coding with firefly optimization algorithm and NROI part of the image condensed by Embedded Zero Tree Wavelet (EZTW). The figure 1 shows system flow of proposed method.

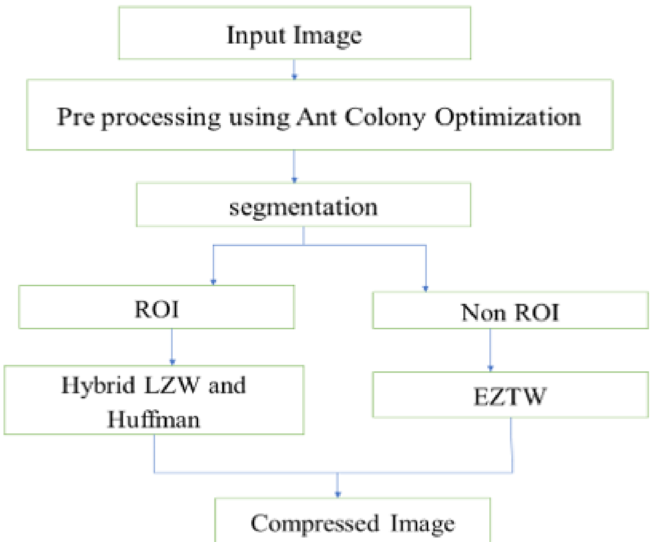

Figure 1: Proposed system flow Diagram

3.1 Enhancement with ACO

Ant Colony Optimization (ACO) technique on the basis of mimicking seeking behaviour of ants. When combined with eigenvalues and diffusion for image pre-processing. Adjusting diffusion coefficients based on the pheromone trails, ensuring that diffusion more restrained across edges and boundaries identified by the ants. Depends on the quality of solution found by the ant leads to update the pheromone trails. Ants deposit pheromones on pixels where the denoising process was successful. Monitor convergence criteria determines to stop the algorithm, such as a fix number of iterations or a threshold value used for improvement. The algorithm repeat the process until ending benchmark met, such as a finite number of iterations or convergence to an optimal or near-optimal solution.

3.2 Segmentation

MRI images have intensity values that carry diagnostic information. The histogram equalization might distort these values leads to the loss of information [10]. Main goal of present method to resolve this problem, the present method segment the image by using U-Net Model with Dice Loss function. The proposed system fragmented into foreground as (ROI) and background as (non-ROI).

The proposed system segmenting the relevant region of interest and reducing the data size. Input layer accepts the input image and Encoder extracts the spatial and contextual information from image via convolutional layers and pooling. Bottleneck part of U-Net retain critical information for reconstruction.

In decoder part, up sampling the extracted features to reconstruct the original resolution. For output, layer present method utilized the sigmoid function as activation function. Convolution layers utilizes the ReLU as activation function. The ReLU applied after each convolutional layer.

$$x=w\cdot I+b$$

- w: Weight matrix of the convolutional filter.
- I: Input feature map.
- b: Bias term.

The result of the convolutional layer is feature maps and calculated as

F(m,n,p)=x,y ∑ I(m+x,n+y)·W(x,y,p)+bp Where:

F(m,n,p)F(m, n, p)F(m,n,p) is Value of the feature map at position (m,n)(m,n)(m,n) for filter p. I(m+x,n+y)I(m+x, n+y) I(m+x,n+y) is Input image value or previous layer's output. And the cost of the computation in convolutional layers represented Cost=Hout × Wout × Cout × (Kh × Kw× Cin) where Hout, Wout is spatial dimensionality of the output feature map. Cout represents total output channels (filters). Cin represent the input channels. Kh, Kw are Kernel (filter) height and width.3

Loss Function

The presented method uses Dice loss function that depends on the Dice similarity coefficient (DSC) which assess the similarity among segment anticipated and binary image of original. The Dice Loss Function defined as

$$\text{Dice Loss} = 1 - \frac{2 \cdot \sum_{i=1}^{N} p_i g_i}{\sum_{i=1}^{N} p_i^2 + \sum_{i=1}^{N} g_i^2}$$

.

Where, pi is anticipated probabilistic value for intensity i belongs to brain part of the image. Gi represent binary image value of intensity i (1 for foreground, 0 as background). N represents total intensity in the image. The adam optimizing method used to update the network weight to minimize the dice loss. It formulated as

$$m_t = \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot \nabla_\theta L(\theta)$$

$$v_t = \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot (\nabla_\theta L(\theta))^2$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

Where, mt and vt are the exponentially decayed averages of the gradient and its square. The hyperparameters β1 and β2 regulate the rates of decay. A little constant called ϵ keeps division by zero from happening. α is the rate of learning.

3.3 Region of Interest Part Compressing (Hybrid Lempel Ziv Welch with Huffman Coding)

In proposed system, foreground part of the MRI image (ROI) compressed through LZW. A well-known Lossless Lempel Ziv Welch (LZW) and (HF) compressing methods combined in the HFLZW algorithm. The LZW method serves as both the transformation and the reverse transformation in the encoding and decoding operations with suggested situation. The system is encoding and decoding operations managed by the Huffman encoding method.

The method that uses LZW to build a dictionary that stores the brightness of the pixels in an image using a hash function (modulo operation). Following dictionary construction, the symbols (values) encoded using Huffman coding and arranged using a min-heap binary tree.

Hash function

During the compression process, the Lempel-Ziv-Welch (LZW) hash function effectively manages the dictionary. A dictionary created to record patterns found throughout the compression procedure. The formula for hash function applied to construct the dictionary is,

$$\text{hash}(S) = \left(\sum_{i=1}^{n} s_i \cdot 31^{n-i} \right) \bmod N$$

Input S is a sequence of symbols (e.g., characters or pixel intensity values in the case of DICOM images). Prime Multiplier (31) is the value 31 is a commonly used prime multiplier that minimizes collisions for small sequences. Modulo N is the size of the hash table (usually a prime number larger than the expected number of dictionary entries). Weighted Sum means, the symbols in the sequence weighted by their position, providing uniqueness even for similar sequences.

Firefly optimization algorithm

The Firefly Algorithm guarantees that optimal balance between dictionary size, compression efficiency, precision, and computational overhead. Minimizes processing overhead by choosing the smallest dictionary size that maintains superior compression performance. Initialize the population of fireflies and maximum size of the dictionary. This function typically depends on the distance between fireflies and their brightness (objective function value). Update the position of fireflies based on their attractiveness. The position of firefly i is updated based on its movement towards a brighter firefly j. The general update equation is:

$$x_i = x_i + \beta e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha \cdot \text{rand}$$

Distance (rij)

$$r_{ij} = \sqrt{\sum_{k=1}^{n}(x_i^k - x_j^k)^2}$$

Attraction Term ($\beta e^{-\gamma r_{ij}^2}$):

Evaluate the objective function fort each iteration of fireflies. Fitness function calculated by using formula

$$\text{Fitness} = w_1 \cdot \frac{\text{Original Size}}{\text{Compressed Size}} - w_2 \cdot \frac{D_{\max}}{D_{\text{limit}}}$$

Update the dictionary probabilistically by replacing less useful sequences with hopeful new ones, directed by brighter fireflies. Replace less-used sequences based on the sequences accessed less frequently or contributing less to compression. The dictionary entries pruned by Least Recently Used (LRU) strategy. Evaluate the current dictionary by means of the objective function. Create new dictionary configurations by applying firefly-inspired attraction and randomness. Update the dictionary with the best configurations while enforcing size constraints. Continue iterating until the maximum iterations met.

Pseudo code for Firefly Algorithm

Initialize parameters

Size of the population (n), Max value of generations (MaxGen), Light absorb coefficient (γ), Attract coefficient base (β_0), Randomization parameter (α), Maximum dictionary size (D_max),

Objective function F(D)

Initialize a value for fireflies population

Estimate the brightness of each firefly

Compute brightness using the objective function F(D)

For each generation (t = 1 to Max)

For each firefly j (1 to m)

For each firefly k (1 to m)

If firefly k is brighter than firefly j

Movement of firefly j towards firefly k

Update dictionary D_i

Prune dictionaries to maintain size constraint

Evaluate the brightness of updated dictionaries

Track the best dictionary

Repeat steps until Max reached

Huffman encoding

Apply Huffman coding to compress the symbols produced by lzw method. LZW compression replaces the repetitive sequences in the pixel data with unique symbols. The Huffman tree constructed using a min-heap. Each node in the tree represents either a symbol (leaf node) or a combination of symbols (internal node).

Min heap is comfortable data structure build by using binary tree. In min heap, the value of the parent node is smaller than that of its offspring. Until the min heap property met, swap out the new element. The following formula can be used to get a node's parent index at index i: ⌋parent(i)=⌊2i−1⌋ The following formulas can be used to get a node's left and right child indices at index I: RightChild(i)=2i+2 LeftChild(i)=2i+1. To give each symbol a distinct binary code, traverse the Huffman tree.

3. 4 Non- ROI part Compression

Applying improved Embedded Zerotree Wavelet (EZW) compression method to compress NROI part of image for preserving critical brain structure. The EZW technique Trans form the NROI part of image by applying the haar wavelet transform. In this transformation, image divided into sub-bands to represent frequencies such as low frequencies and high frequencies. The result of the wavelet transformation Low–Low (LL), Low-High (LH), High-Low (HL), High-High (HH)**.** Then apply threshold value to the high frequency value sub band to remove all small co-efficient.

Max Coefficient Value Thresholding

Fix the threshold value that must equal to maximum absolute value of coefficient.

$$\text{Threshold}_{max} = \max\left(|C_{LH}|, |C_{HL}|, |C_{HH}|\right)$$

The $|C_{LH}|$ represents the lowest frequency coefficients maximum. $|C_{HL}|$ represents the highest- lowest frequency sub bands co - efficient maximum value. $|C_{HH}|$ represents highest frequency sub band coefficients maximum absolute value. It used to remove insignificant ones. Construct the zero tree for wavelet coefficients. Zero tree encoded when the coefficient is lower than threshold value.

EZW algorithm

Initialize the threshold factor, max absolute value

Apply wavelet transform

Split into sub bands (LL, HH, LH, HL)

Filter the coefficients that smaller than the threshold value

Each coefficient c in the wavelet transform compared with a threshold T.

If the absolute value of c is smaller than T, then the coefficient considered "insignificant" and is set to zero.

$$|c_{i,j}| < T \quad \Rightarrow \quad \textbf{Coefficient } c_{i,j} \textbf{ is marked as part of a zero tree}$$

For a given coefficient, say ci, jc{i,j}ci, j, we check its associated child coefficients.

If ci, jc{i,j}ci,j is below the threshold TTT, then it is part of a **zero tree**.

Its child coefficients (if they exist) are also likely to be zero, and this relationship forms the "tree" structure.

Encode the significant coefficients and zero tree for each sub band

Add the value to the bit stream for encoding

Encrypting the all symbols with binary code

4. Experimental Result

MatLab used to evaluate the suggested and current system approaches. The Matlab environment used for the implementation. Additionally, the present system experimental output compared to those of the current or existing system. The findings compared using performance metrics such execution time, space saving, CR, and PSNR.

The hypothetical comparison prove that present method gives high compression ratio without affecting quality of image than the existing one. MRI DICOM brain images taken from standard dataset to test the present algorithm. Figure 1 shows the input image of brain.

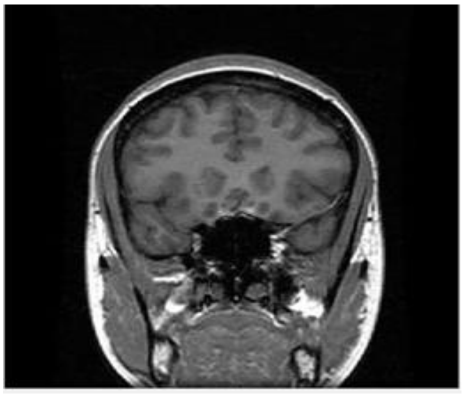

Fig 1: Input Image

The input image pre-processed by applying Ant Colony Optimization (ACO) shown in figure2.

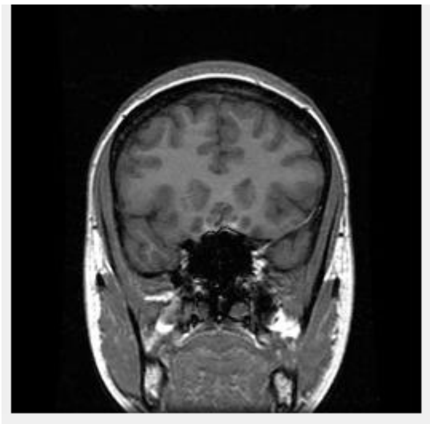

Figure 2: Pre-Processed Image

The enhanced image segmented into ROI and Non –ROI part. Figure 3 displays the segmented part of image would be used for compression.

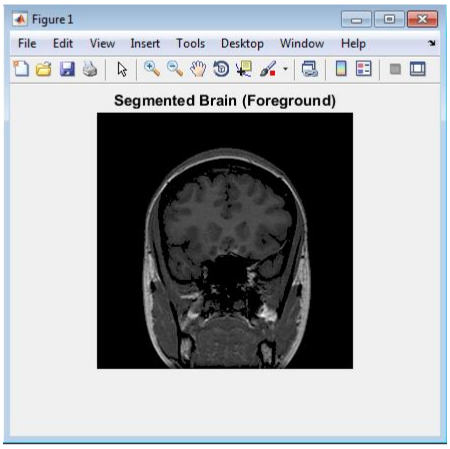

Figure 3: Segmented ROI part of Image

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Figure 4 displays the outcome of the proposed the algorithm after compression has been complete. The compressed image can stored to minimize the storage whenever we need the image that can reconstructed like its original.

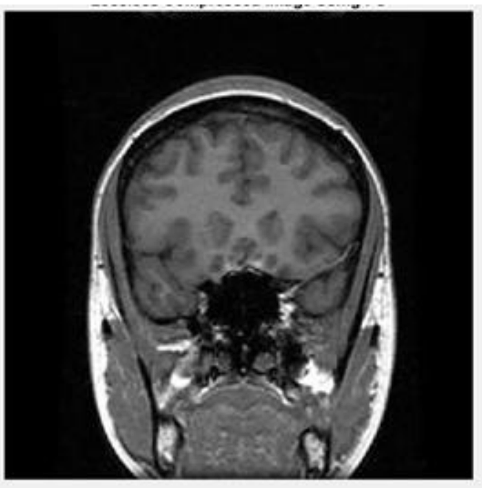


Figure 4: Compressed Image

Performance Factors

The effectiveness of the presented method and existing assessed by various performance metrics and existing algorithms. The performance variables are Execution Time, Space-Saving, CR (compression ratio), and PSNR (peak signal noise ratio).

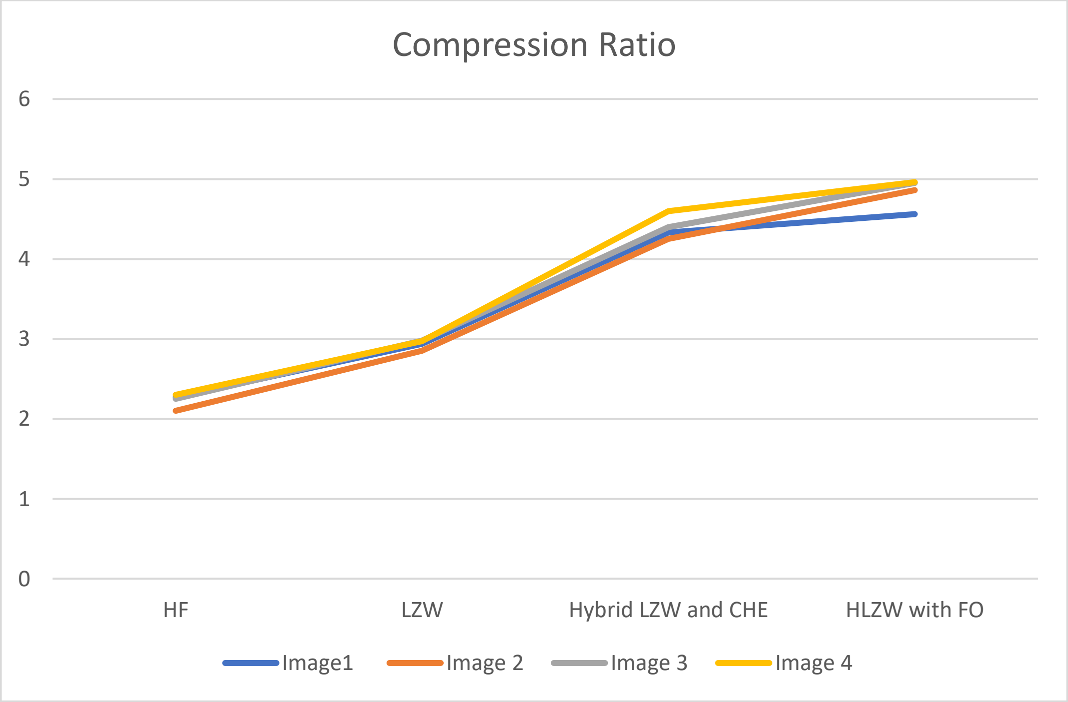
Compression Ratio (CR)

The ratio between uncompressed image file size and the compressed image file size referred as the Compression Ratio (CR). . It evaluated by formula,

$$CR = \frac{Original\ Uncompressed\ Image\ Size}{Compressed\ Image\ Size}$$

The estimation chart if compression ratio performance for LZW – HF with Firefly optimization algorithm shown in the Fig: 4. In this proposed method optimal parameter is identified by the Firefly optimization algorithm. It increases the compression ratio. Table 1 shows the compression ratio vs the images.

Image/ Compression Algorithm	HF	LZW	Hybrid LZW and CHE	HLZW with FO
Image1	2.27	2.94	4.33	4.56
Image 2	2.10	2.85	4.25	4.86
Image 3	2.25	2.98	4.40	4.95
Image 4	2.30	2.97	4.60	4.96



Peak Signal Noise Ratio (PSNR)

PSNR defines the quality of the reconstructed image. The original and compressed MRI picture quality compared using the Peak Signal Noise Ratio (PSNR). Table 2 shows the PSNR vs MRI pictures. The PSNR as determined by

$$PSNR = 10.log_{10}\frac{MAX}{\sqrt{MSE}}$$

$$MSE = \sum_{MN}\frac{[I1(m,n)-I2(m,n)]^2}{M*N}$$

Table 4: PSNR Comparison

IMAGE/ COMPRESSION ALGORITHM	HF	LZW	Hybrid LZW and CHE	HLZW with FO
Image1	30.51	31.06	41	**42.81**
Image 2	30.4	30.98	42	44.89
Image 3	30.46	31.35	43	45.23
Image 4	31.23	31.85	40	45.45

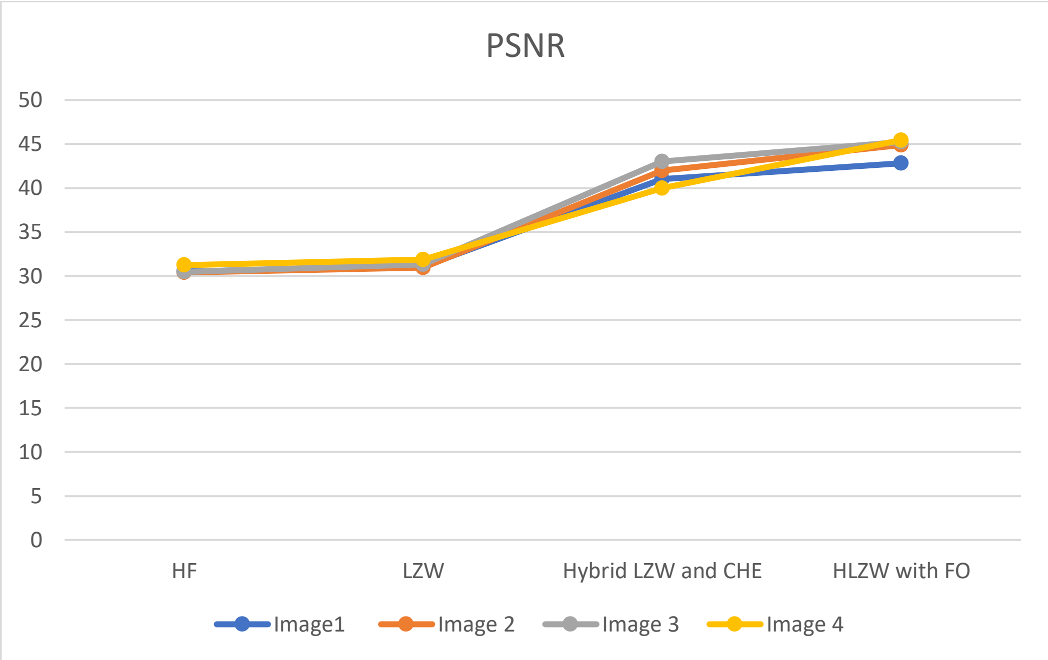


Fig: 5 PSNR Comparison

Space Saving (SS)

Space Savings (SS) is the term used to describe how compression methods lower the amount of memory used by a computer system. The definition of the SS is

$$SS = Original\ Uncompressed\ Image\ Size\ - Compressed\ Image\ Size$$

Execution Time

The amount of time needed to compress the MRI pictures is measured.

Table 3: Execution Time Comparison

Image/ Compression Algorithm	**HF**	**LZW**	**Hybrid LZW and CHE**	**HLZW with FO**
Image1	1386	1081	638	600
Image 2	1212	1098	559	516
Image 3	1200	998	524	500
Image 4	1180	900	500	480

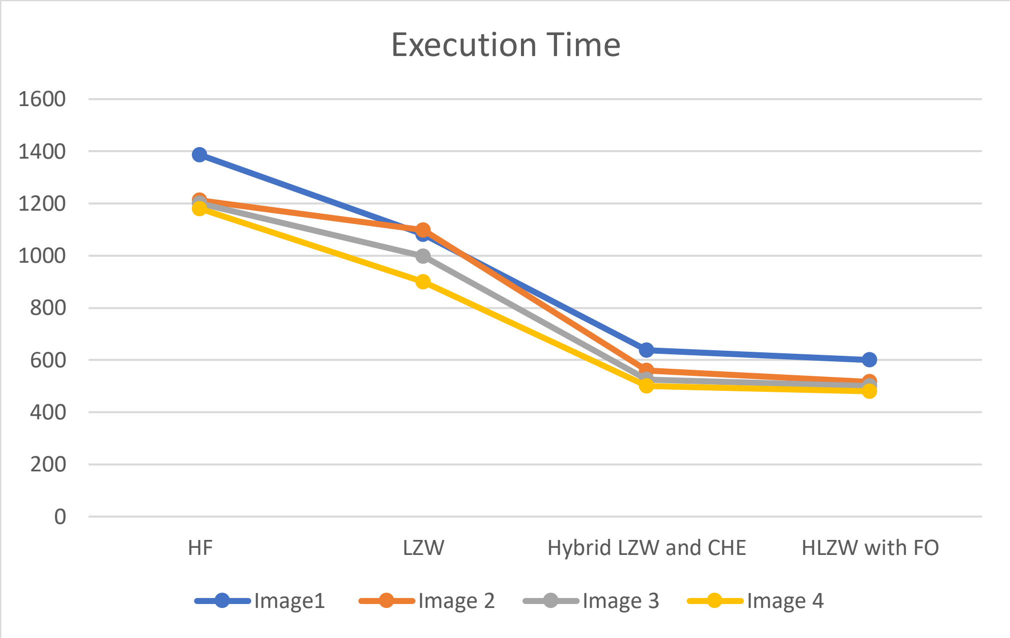


Fig 6: Execution Time Comparison

5 CONCLUSION

Utilizing lossless compression algorithm based on optimization to compress the DICOM MRI brain dataset with high compression and not affecting quality is the main goal of this research. In this context, a novel Firefly Optimization (FO)-based lossless compression technique introduced. This method results a greatest compression ratio without sacrificing the quality of rebuilt images. The suggested algorithm's performance in comparison to popular current techniques. The pre-processing step performed using Ant Colony Optimization (ACO) in this method. The experiments conducted using the outcomes of the pre-processing phase. The processed image then compressed using a hybrid LZW-Huffman and Firefly Optimization algorithm. Various pperformance parameters assessed after compression (Execution Time, Space Efficiency, Compression Ratio, and Peak Signal-to-Noise Ratio).

The proposed method achieved greater compression ratio when compared with existing techniques. The analysis of experiment output indicates that the suggested FO algorithm operates more efficiently than current lossless algorithms.

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