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# Integrated HNAS Network Model Based Lossless Compression with Data Hiding using Parity Check in Medical Images

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***Abstract***: ***A massive volume of medical data is generating through advanced medical image modalities. With advancements in telecommunications, Telemedicine, and Teleradiologyy have become the most common and viable methods for effective health care delivery around the globe. For sufficient storage, medical images should be compressed using lossless compression techniques. In this paper, we aim at developing a lossless compression technique to achieve a better compression ratio with reversible data hiding. The proposed work segments foreground and background area in medical images using semantic segmentation with the Hierarchical Neural Architecture Search (HNAS) Network model. After segmenting the medical image, confidential patient data is hidden in the foreground area using the parity check method. Following data hiding, lossless compression of foreground and background is done using Huffman and Lempel-Ziv-Welch methods. The performance of our proposed method has been compared with those obtained from standard lossless compression algorithms and existing reversible data hiding methods. This proposed method achieves better compression ratio and a hundred percent reversible when data extraction.***

***Keywords : Lossless Compression, Semantic segmentation, HNAS Nets, Reversible Data Hiding.***

## I. INTRODUCTION

Lossless image compression methods are commonly preferred for medical images. Lossless methods are particularly important for systems transferring and archiving medical data, since lossy compression of medical images used for diagnostic purposes is, illegal by regulations in several countries. Lossless compression can reconstruct the original image perfectly without any loss. All the medical images are having foreground and background pixels. In this paper, we separate these foreground and background pixels using semantic segmentation and then compress separately.

Segmentation is an essential task in image analysis, which divides the given image into several regions.

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Its basic idea is recognizing the image at the pixel level. It is the process of assigning a class label for each pixel. It can be applied to any task that involves segmentation of visual information such as road segmentation, medical image segmentation, segmentation for robotic vision, etc.

Semantic segmentation can be implemented using state of the art networks like U-Net, SegNet, ResNet (Residual network), DeepLab (Deep Labelling), FCN (Fully Convolutional Networks), ENet (Efficient Neural network), LinkNet, DenseNet (Dense Convolutional Network)), MultiNet and DFN (Discriminative Feature Network).

In this semantic segmentation, Hierarchical Neural Architecture Search (HNAS) method is used to find the edges of the medical images which separate the region of interest (RoI) and Non-region of interest (NRoI) pixels.

Generally, image compression can be categorized into lossy and lossless image compression. Lossy image compression loses some data when compressing the image, whereas Lossless compression compresses the image without any loss.

The RoI and NRoI are compressed using standard lossless compression techniques like Huffman coding, Run Length coding, and Lempel-Ziv-Welch Coding. Huffman code is a specific kind of optimal prefix code, which is commonly used for lossless data compression. It uses a particular method for selecting the representation for each symbol, resulting in a prefix code [1].

Run-length encoding (RLE) is a simple method of lossless data compression in which runs of data are stored as a single data value and count, rather than as the original run.

This is most advantageous on data that comprises many such runs. Lempel–Ziv–Welch (LZW) is a popular and widely used lossless data compression algorithm. It became part of the GIF image format in 1987 and is also used in TIFF and PDF files [2].

This rest of the paper is organized as follows. In Section II, the Literature Review is discussed. In Section III, an elaborate description of the proposed lossless compression technique and reversible data hiding are presented.

The performance of the proposed method is analyzed and compared with the other existing standard methods in Section IV, and the conclusion is presented in Section V.

## II. LITERATURE REVIEW

### A. Semantic Segmentation

Ronneberger, O et al. [3] proposed U-Net architecture; they validate the application of the u-net in different segmentation tasks like segmentation of neuron structures in electron microscopic recordings and cell segmentation tasks in light microscopic images.

Badrinarayanan V et al.

[4] presented SegNet in which they have developed a deep convolutional network architecture for semantic segmentation. The primary purpose behind SegNet was the requirement to design a well- organized architecture for road and indoor scene understanding, which is efficient in terms of computational time and memory as well.

Kaiming He et al. [5] proposed ResNet architecture where 34-layer and 18-layer residual nets (ResNet) are evaluated. Their method has excellent simplification performance on other recognition tasks.

Evan Shelhamer et al. [6] presented fully Convolutional Networks, a rich class of models that perform many pixel-wise tasks. FCNs for semantic segmentation intensely get better accuracy by transferring pre-trained classifier weights, fusing different layer representations, and learning from the beginning to end on whole images. End-to-end, a pixel-to-pixel operation at the same time make easier and speeds up learning and inference.

Chen et al. [7] proposed semantic segmentation with deep learning and made three main contributions that are performed convolution with upsampled filters, and Atrous Spatial Pyramid Pooling (ASPP) to robust segment images at multiple scales and improve the localization of image boundaries by combining methods from DCNNs and probabilistic graphical models.

Adam paszke et al. [8] developed a neural network (ENet) architecture designed from the ground up particularly for semantic segmentation. Their objective is to make able use of scarce resources accessible on embedded platforms, compared to qualified deep learning workstations.

Huang et al. [9] proposed new convolutional network architecture. It is a Dense Convolutional Network (DenseNet) that presents direct connections among any two layers with the same feature-map size. They demonstrated that DenseNets scale absolutely to hundreds of layers while revealing no optimization difficulties.

Chaurasia et al. [10] proposed LinkNet, a Pixel-wise semantic segmentation for the visual view, but it is also capable of realizing that no application is available in real-time use.

Liu et al. [11] present the Neural Architecture Search as well as image classification for dense image prediction problems. Rather than fixating on the cell level, they recognize the significance of spatial resolution changes and hold the architectural variations by combining the network level into the search space.

### B. Data hiding

Chan et al. [15] proposed a data hiding method by simple LSB substitution with an Optimal Pixel Adjustment Process (OPAP). It is used to improve the visual quality of the stego image after embedding in LSB planes. This method performs well at high embedding rates (4 bpp) compared to standard LSB embedding. The image quality of the stego-image can be greatly improved with low extra computational complexity.

Kuo et al. [16] developed a signed digit data hiding scheme. It uses the Modified Signed Digit (MSD) and Exploiting Modification Direction (EMD) to embed secret data. It maintains a minimum embedding capacity of 1 bpp and also performs well against visual bit plane analysis.

A novel steganographic method based on four pixel differencing and modified LSB substitution is proposed by Liao et al. [17].In every pixel the secret data is hidden using k-bit modified LSB substitution method, where k is decided by the average difference value of a four-pixel block. Modification has been carried out to retrieve the hidden data perfectly and to minimize the perceptual distortion.

Lu et al. [18] proposed a dual imaging-based reversible hiding technique using LSB matching. This method supports a capacity of 1 bpp and achieved image quality better than Chan et al. (2004) method.

## III. PROPOSED METHOD

This proposed method uses semantic segmentation through which the foreground and background regions of the medical image are identified and separated. Then the positions of first and last non zero value of each row of the segmented image are saved. RoI region is converted into a set of vectors corresponding to each row using the coordinate points. These vectors are compressed using Huffman coding and LZW separately. Finally, the secret data are hidden in the compressed bits. The proposed method is implemented in the following three phases

***Phase I :*** Segment the foreground and background pixels of the medical image using the HNAS Network model-based semantic image segmentation.

***Phase II :*** Compress the foreground pixel values using Huffman and LZW

***Phase III :*** Secret data hidden in the compressed bits

The output of semantic segmentation yields two regions: RoI and NRoI regions. NRoI region is the background which mostly contains zeros. Hence the proposed methods compress only the RoI region using LZW and Huffman encoding, respectively.

### A. HNAS Network model-based semantic segmentation

In this semantic segmentation, Hierarchical Neural Architecture Search (HNAS) method is used to find the edges of the medical images which separate the RoI and NRoI.

Hierarchical Neural Architecture Search model has a two-level hierarchical architecture search space that is outer network level and inner cell level. In Network level search space, once a cell architecture was found, the whole network is built using a pre-built pattern. Then the network level was not exists in the architecture search; hence forth, its search space has never been proposed nor designed. In Cell level search space, it tends to define a cell to be a short, fully convolutional module, indeed repetitive multiple times to form the whole neural network. Several normal cells are separated equally by inserting reduction cells.

### B. Lossless semantic segmentation

As medical images contain vital information for disease diagnosis, they are generally compressed using lossless compression techniques. In lossless compression, Huffman coding and LZW coding are given a good Compression Ratio and Saving Percentage.

When compared with other lossless compression techniques. Hence in the proposed method, lossless compression techniques like Huffman coding and Lempel Ziv Welch (LZW) coding are used for compressing the foreground and background image. After segmentation, the following steps are followed for compression

- The first and last non zero values of each row are found out, and their coordinate points are saved in a separate matrix.
- Using the co-ordinate points, the RoI region is converted into a set of vectors and NRoI into another vector.
- These vectors are compressed using Huffman coding and LZW separately.

### C. Reversible Data Hiding (RDH) using Parity Check

A novel technique of secret data hiding into the compressed medical image is presented in this section. This technique is perfectly matched for hiding patient information and also generates a stego image. Both the host image and secret patient information are recovered at the receiver side without any loss, which is very essential for medical analysis.

Least Significant Bit (LSB) embedding technique is an easier method in steganography. Like all steganographic methods, it hides the secret data into the host image so that it cannot be recognized by a casual observer.

The overall architecture of the proposed method is pictorially represented in Fig. 1.

Parity Check Method embeds the hidden data at the Least Significant Bits. In this method, the parity of the pixel value is checked for odd or even, and data is embedded as per the conditions given in Table I.

**Table - I. Embedding Process of Parity Check**

| Parity | Hidden Data Message Bit | Modification |
|---|---|---|
| Even | 0 | No Change Occurs |
| | 1 | Reverse the LSB |
| Odd | 0 | Reverse the LSB |
| | 1 | No Change Occurs |

Secret data and the cover image data is easily recoverable during the extraction process. Table II shows the conditions for extracting the secret and cover image data.

**Table - II. Embedding Process of Parity Check**

| Parity | Hidden Data | LSB of Stego Image Data | Host Image Data |
|---|---|---|---|
| Even | 0 | 0 | No Change Occurs |
| | | 1 | Reverse the LSB |
| Odd | 1 | 0 | Reverse the LSB |
| | | 1 | No Change Occurs |

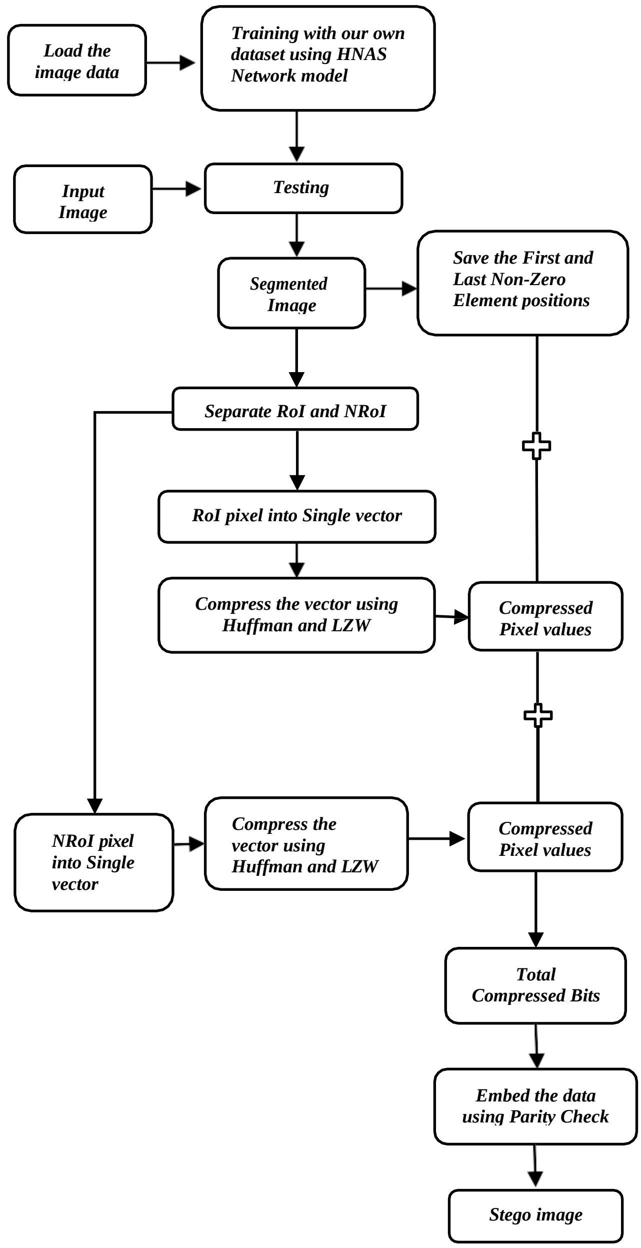


**Fig. 1.Overall Architecture of the Proposed Method**

## IV. RESULTS AND DISCUSSION

The paper presents a novel method that blends deep learning based segmentation, lossless compression, and RDH using parity check. The proposed method is tested using medical images of size 512 x 512 with 256 gray levels. The medical image dataset is divided into two parts as training and validation, respectively. In the first section, image segments are created from labeled images and gathered all images into a single folder named as train.

The training was done with these segmented images. In the second part, segmented and non-segmented labeled images are trained using a neural network. In this step, the neural network automatically learns to segment images.

This step validates how to segment labeled images. In the third step, testing was performed on the collected sample of images. The performance of the proposed method is validated using the following metrics.

Space efficiency is the most crucial factor for determining the performance of a compression algorithm.

The compression efficiency of the algorithm is measured objectively using the Compression Ratio and Saving Percentage, which are calculated as follows.

***Compression Ratio:*** It is the ratio between the size ofthe compressed file and the original file, as given in Equation (1).

$$Compression\,Ratio = \frac{Original\ file\,size}{Compressed\ file\,size} \qquad (1)$$

***Saving Percentage:*** This is the percentage of the size reduction of the file after the compression, which is calculated using Equation (2).

$$Saving\ Percentage = \left(1 - \left(\frac{Compressed\ file\,size)}{Uncompressed\ file\,size}\right)\right) * 100 \quad (2)$$

Semantic segmentation shows good accuracy and good segmentation results, as well. Fig. 2 shows original image and semantically segmented image.

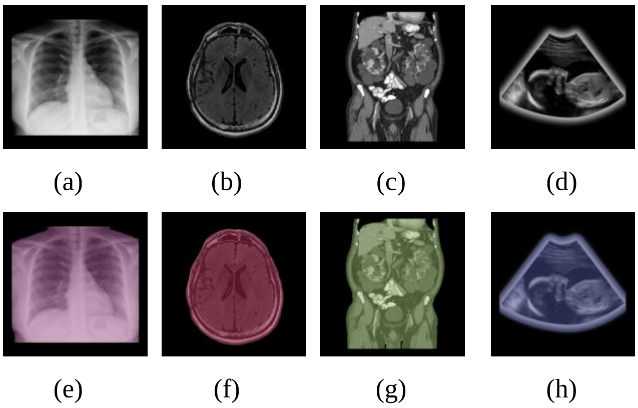


**Fig. 2.** (a) X-Ray Image (b) MR Brain Image (c) CT Abdomen (d) Fetus Ultrasound (e) Segmented X-Ray Image (f) Segmented MR Brain Image (g) Segmented CT Abdomen (h) Segmented Fetus Ultrasound

**Table - III. Performance Analysis of HNAS with LZW Method**

| Image | Original Image Size (in bits) | Sem.Seg + Huffman Compressed Size (in bits) | Compression Ratio | Saving Percentage |
|---|---|---|---|---|
| **Chest X-Ray** | 2097152 | 870224 | 2.41 | 58.50 |
| **MR Brain** | 2097152 | 866700 | 2.42 | 58.67 |
| **CT Abdomen** | 2097152 | **784657** | **2.67** | **62.58** |
| **Fetus Ultrasound** | 2097152 | 899024 | 2.33 | 57.13 |

Table III demonstrates that the proposed HNAS with the LZW method produces a better saving percentage and a good compression ratio. It is evident from Table III that the maximum compression ratio achieved by the proposed method is higher than that of the standard lossless compression. Table III also reveals that the proposed method achieves a compression ratio ranging between 1.99 – 2.41 and the saving percentage between 49.75 - 58.48 as well.

**Table - IV. Performance Analysis of HNAS with Huffman Method**

| Image | Original Image Size (in bits) | Sem.Seg + LZW Compressed Size (in bits) | Compression Ratio | Saving Percentage |
|---|---|---|---|---|
| **Chest X-Ray** | 2097152 | 940808 | 2.23 | 55.14 |
| **MR Brain** | 2097152 | **870658** | **2.41** | **58.48** |
| **CT Abdomen** | 2097152 | 1053793 | 1.99 | 49.75 |
| **Fetus Ultrasound** | 2097152 | 910776 | 2.30 | 56.57 |

Table IV demonstrates that the proposed HNAS with the Huffman compression produces a better saving percentage and a good compression ratio. It is also evident from Table IV that the maximum compression ratio of the proposed method is higher than that of the standard lossless compression. Table IV reveals that the compression ratio ranges between 2.33 and 2.67 and the saving percentage range is 57.13 - 62.58.

The comparison analysis of these methods are presented in Table V.

**Table - V. Comparative Analysis of Proposed Methods**

| | | Chest X-Ray | MR Brain | CT Abdomen | Fetus Ultrasound |
|---|---|---|---|---|---|
| **Original Image** | **Original Image Size (in bits)** | 2097152 | 2097152 | 2097152 | 2097152 |
| **LZW** | **Compressed size (in bits)** | 1274554 | 1730468 | 1331357 | 1607506 |
| | **Compression Ratio** | 1.65 | 1.21 | 1.58 | 1.30 |
| | **Saving Percentage** | 39.22 | 17.48 | 36.52 | 23.35 |
| **Huffman** | **Compressed size (in bits)** | 1239452 | 1600025 | 1095119 | 1436209 |
| | **Compression Ratio** | 1.69 | 1.31 | 1.91 | 1.46 |
| | **Saving Percentage** | 40.90 | 23.70 | 47.78 | 31.52 |
| **Sem. Seg + LZW** | **Compressed size (in bits)** | 940808 | 870658 | 1053793 | 910776 |
| | **Compression Ratio** | 2.23 | 2.41 | 1.99 | 2.30 |
| | **Saving Percentage** | 55.14 | 58.48 | 49.75 | 56.57 |
| **Sem. Seg + Huffman** | **Compressed size (in bits)** | 870224 | 866700 | **784657** | 899024 |
| | **Compression Ratio** | 2.41 | 2.42 | **2.67** | 2.33 |
| | **Saving Percentage** | 58.50 | 58.67 | **62.58** | 57.13 |

The salient feature is that the proposed methods have demonstrated its excellent performance in terms of high compression ratio in the range of 1.99 - 2.67. The proposed methods also perform better than existing standard lossless compression in terms of compression ratio.

Experimental comparison results are graphically represented in Fig. 3 – 5.

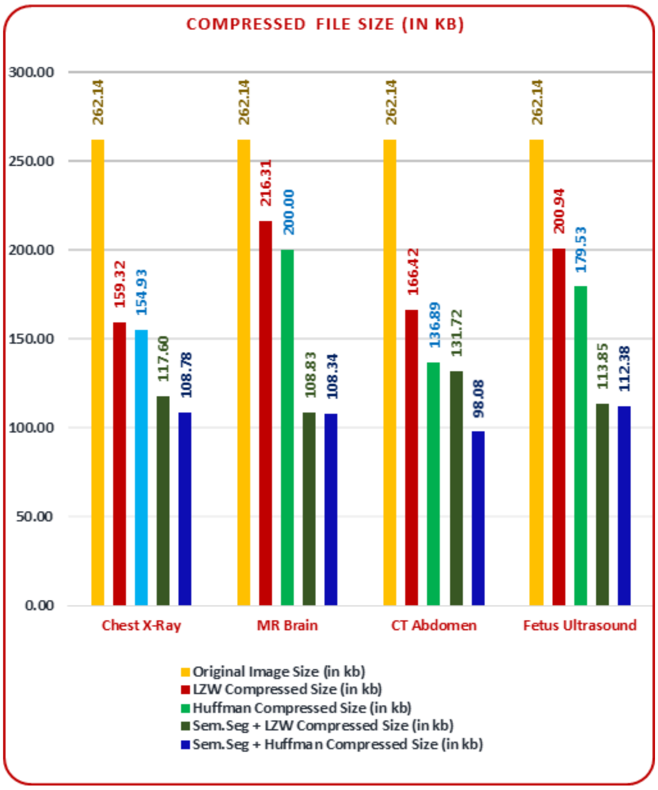


**Fig. 3. Comparative Analysis of Compressed File Size**

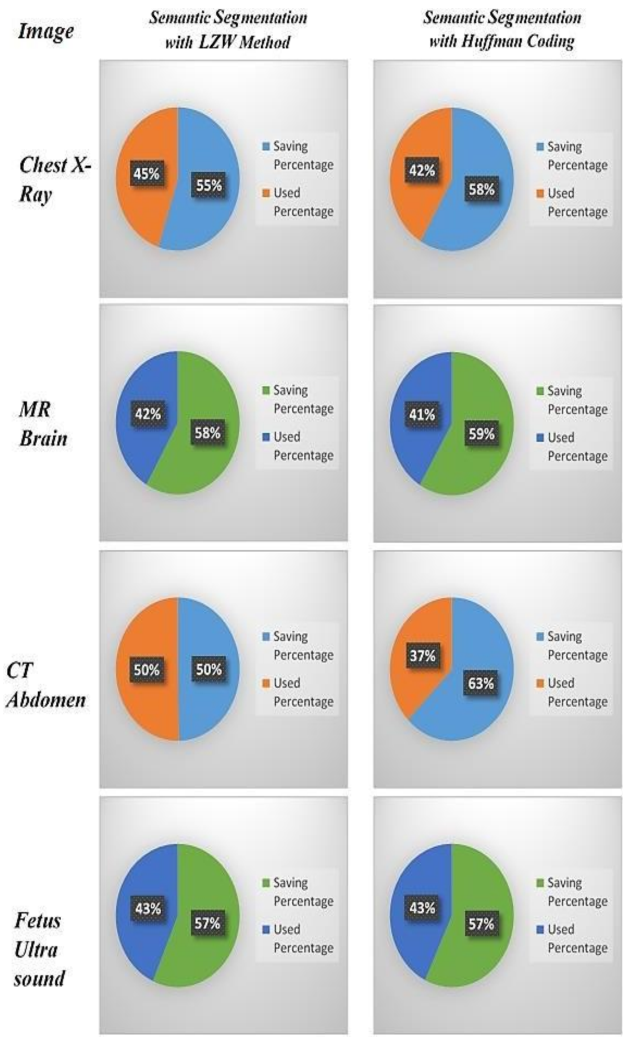


**Fig. 4. Comparative Analysis of Proposed Methods based on Saving Percentage**

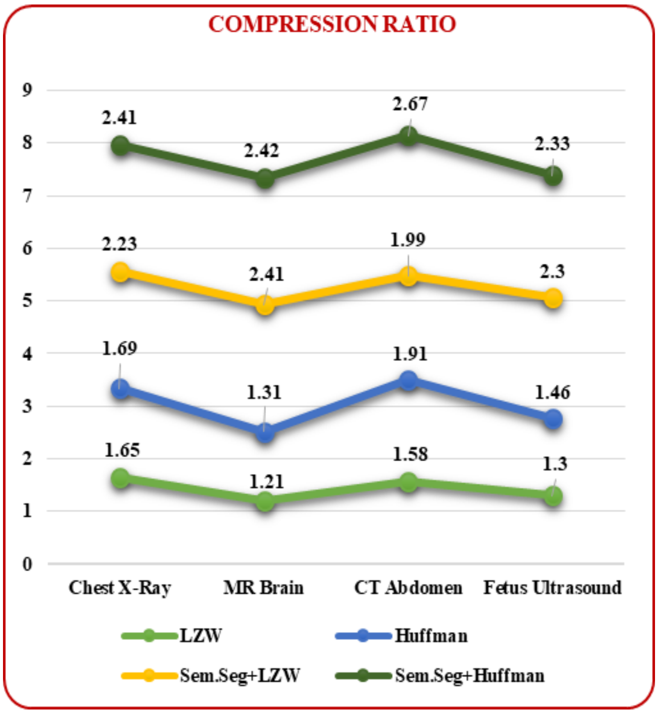


**Fig. 5. Comparative Analysis of Compression Ratio**

Following compression, RDH is performed on the LZW and Huffman Encoded values. The parity check method is one kind of RDH method. This method only performed on encoded values, but other LSB techniques are performed on whole images, so it does not compare with other LSB techniques.

**Table - VI. Performance Analysis of RDH Methods**

| | Images | MSE | PSNR | Embedding Capacity | BPP |
|---|---|---|---|---|---|
| **Sem.Seg + LZW+ Parity Check** | **Chest X-Ray** | 0.4999 | 51.14 | 235201 | 0.90 |
| | **MR Brain** | 0.5003 | 51.14 | 217663 | 0.83 |
| | **CT Abdomen** | 0.4996 | 51.14 | **263448** | **1.01** |
| | **Fetus Ultrasound** | 0.4999 | 51.14 | 227693 | 0.87 |
| **Sem.Seg + Huffman + Parity Check** | **Chest X-Ray** | 0.5013 | 51.13 | 217555 | 0.83 |
| | **MR Brain** | 0.5006 | 51.14 | 216674 | 0.83 |
| | **CT Abdomen** | 0.5017 | 51.13 | 196164 | 0.75 |
| | **Fetus Ultrasound** | 0.4991 | 51.15 | **224755** | **0.86** |

From the observation in Table VI, it is clear that same PSNR level is displayed by all the test images when embedding the secret data in LZW encoded values. Moreover, BPP is high in CT Abdomen image when compared to other images.

Table VI reveals that the proposed method achieves BPP in the range 0.75 – 0.86 with good PSNR values between

51.13 – 51.15db even after embedding the secret data in Huffman encoded values.

The performance analysis of these methods is graphically presented in Fig 6 and 7.

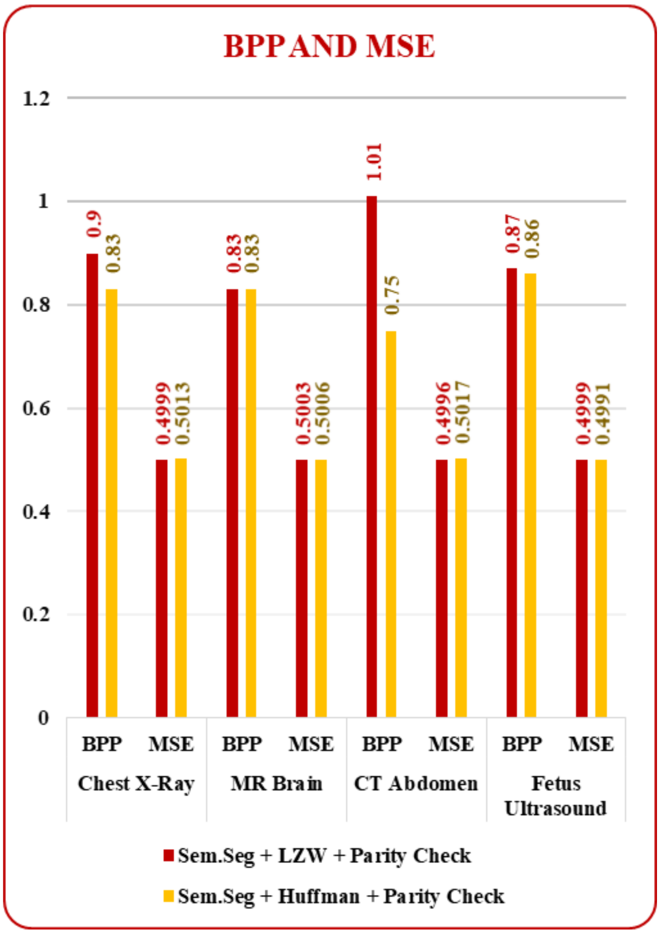


**Fig. 6. Performance Analysis of BPP and MSE**

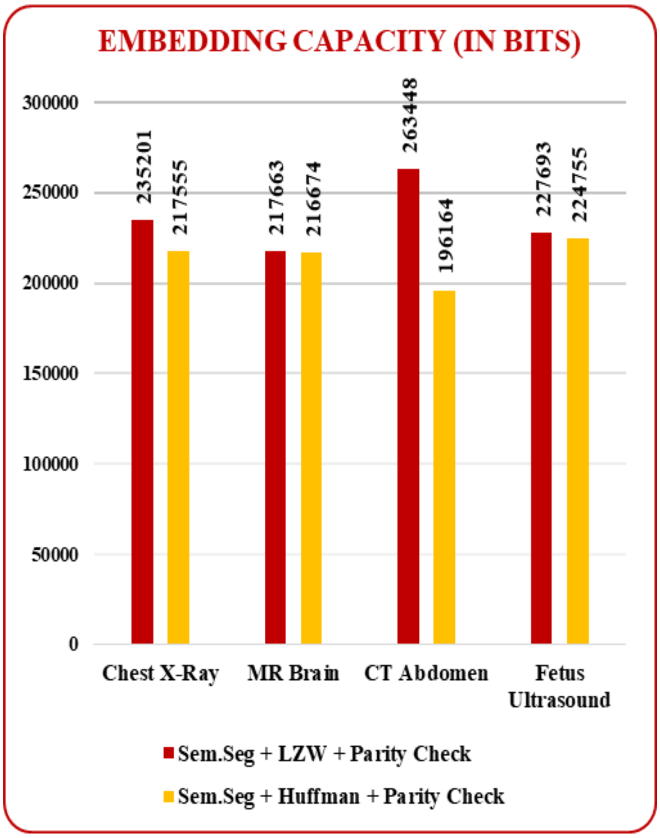


**Fig. 7. Performance Analysis of Embedding Capacity**

## V.CONCLUSION

This paper proposes a new approach that couples semantic segmentation and compression with reversible data hiding in medical images. Medical images are having more sensitive binary data, so in this proposed method RDH is used. Experiments prove the superior performance of the proposed method with good accuracy and a high compression ratio for medical images. Semantic segmentation is used for segmenting the foreground and background of the medical image. Huffman coding and LZW lossless compression methods are used for compression. This paper also presented a technique of embedding patient information inside encoded values. The experimental results reveal that the proposed method yields high-quality images even after hiding data, making the medical image visually agreeable for good medical diagnosis. Moreover, the method extracts both hidden data and cover image accurately without any loss. The theoretical significance proposed method is RDH is applied to the RoI of medical image. This amalgamated method can effectively prevent attacks that come from perceptual coding. In our proposed method, grayscale images used for testing, and our future work would be to extend to color images as well.

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