A Health Care Image Compression Scheme using Discrete Wavelet Transform and Convolution Neural Network

DOI : 10.36909/jer.ICMET.17163

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ABSTRACT

Medical image processing is an important field that directly impacts the health care system. It recognizes disease and also provides information for diagnosis and surgical process. The objectives of medical image compression are to reduce the computational complexity, storage size, and transmission bandwidth. This research has proposed an image compression scheme (MIC-DWT-CNN) based on discrete wavelet transform and convolutional neural networks. Region-growing and otsu-thresholding methods have separated the interested area and non-interested area of the medical image. The DWT has compressed the region of interest, and CNN has compressed the non-interested area in the medical image. The MIC-DWT-CNN scheme has experimented on the images of the medical image dataset using the python platform. The research objective is to achieve better compression efficiency and image quality. The performance of the MIC-DWT-CNN method has been evaluated using Mean square error (MSE), Peak Signal to Noise Ratio (PSNR), and Compression Ratio (CR). The existing techniques have been used to compare with the MIC-DWT-CNN method. The MIC-DWT-CNN method has achieved a better compression performance than the existing methods. The MIC-DWT-CNN method has achieved a higher CR, i.e., 25.01, than existing methods. Also, the model has provided the required level of MSE and PSNR values.

Keywords: CNN; PSNR; CR; MSE; DWT.

INTRODUCTION

Medical image compression is essential for the health care system. The enormous medical image is used in medical science for clinical practice, academic, and research purposes to analyze image content information. Many medical images are created from X-ray, computed tomography (CT), ultrasound, and magnetic resonance images(MRI), which are always a series of 2D images. The enormous image of the healthcare system causes inaccurate processing, more storage size, and higher bandwidth requirements (Sayood K. 2018). The communication system and storage system are affected due to the large file size. Medical image compression aims to reduce bandwidth and memory requirements. It provides minimum storage requirements and is easily accessible from different sources. Medical image compression is necessary for increasing the use of biomedical images. MRI is a primary imaging technique for superb soft-tissue contrast in the health care system. It is a slow imaging technique for high-resolution and volumetric time-series images (Mardani M. et al., 2018). Day by day, the medical system is acquiring a large high-resolution image. The image management difficulty and transmission burden are due to image growth. Accurately, handling large-size images are complicated in both teleradiology and medical research. Lossy image compression reduces storage requirements and speeds up transfer (Chung K. J. et al. & Sayood K. 2018, Mukati M. U. et al., 2020). This paper reports an image compression scheme based on DWT and CNNs to achieve better performance and restore the images. This compression scheme has worked in two stages: stage1, DWT-based lossless compression compresses the important area of image, stage2, the unimportant segmented image area compresses using CNN. This research work’s main objectives are described as follows: The DWT and CNN are two compression schemes for the important and unimportant areas of the medical image. DWT-based image compression technique is used to perform the lossless scheme, and CNN-based image compression technique is used to perform the lossy operation. The important and unimportant are separated based on the region-growing and otsu-thresholding. We find the affected portions of the image using the otsu-thresholding technique. The region-growing and otsu-thresholding methods provide an actual important portation of the image for the histogram and better connectivity. The medical image compression technique compresses the image to minimize transmission bandwidth requirements and storage size. The important portion of image segmentation leads to preserving the medical image's essential details in diagnosing disease. The rest of this research article's organization is as follows: The related works present in 2. Section 3. provides the proposed model. The description of the performance evaluation is given in Section 4. Then, a conclusion presents in Section 5.

RELATED WORKS

The authors had introduced DWT and RNN-based medical image compression techniques with minimum information loss and higher CR. The region-growing and otsu-thresholding had separated the important image portion and non-important portion in the medical image. The DWT-based and RNN-based image compression techniques compressed the area of interest and area of non-important of the medical image, respectively. PSNR(dB), MSE, CR, and Space Saving (SS%) basic parameters measured the method's performance. The PSNR value was higher than the existing schemes (Sabbavarapu S. R. et al., 2020).

In 2020, Chung K. J. et al. had developed a cross-domain cascade of U-nets that was the W-net compression technique. The technique was operated over the DCT to get discarded coefficients that defined the information from adjoining blocks to suppress pixel-level compression artifacts. The authors had adopted the Automated Transform by Manifold Approximation (ATMA) technique by learning the dequantization of eight-by-eight DCT coefficient blocks for compression. Outcomes were converted to the image domain and processed by a U-net. The deep learning technique hid basic compression artifacts using high spatial frequency. The

ATMA and W-net networks were provided a higher value than JPEG decompression. W-net performed better than ATMA. Authors had leveraged DCT coefficients from adjoining blocks to improve performance (Chung K. J. et al., 2020).

In 2021, Tellez D. et al. had introduced the Neural Image Compression(NIC) method. It was a two-stage scheme to construct CNNs for large-size image analysis. The stage1 was compressing the large-size images using an artificial neural network(ANN). An unsupervised learning technique was applied to train it. ANN retained higher-order information to determine the noise of pixel-level. The stage2 was to train a CNN on compressed image presentations to prophecy image-level labels and eschew the need for fine-grained notes by a human. The authors compared many compression methods with NIC using two histopathology datasets. The authors observed that NIC successfully exploited visual indications related to image-level labels, combining global and local visual information. The authors visualized the regions of the large-size input images where CNN attended and confirmed that outcomes were superimposed with expert's comments (Tellez D. et al., 2021).

In 2020, Guo P. et al. had introduced the CNN-based compression technique using retina optical coherence tomography(OCT) images. The scheme had three steps: preprocessing, compression using CNN(ComCNN), and reconstruction using CNN(RecCNN). The first step was developed to minimize OCT noise and separate the significant area. The process of quantization is quantized to preserve the best information. ComCNN and RecCNN were trained using the segmented images from the preprocessing method as input. The authors trained the ComCNN and RecCNN sensitivity to low and high-frequency information. The authors used the adversarial discriminator to determine the high-frequency information. The distinguishable MS-SSIM technique was used to assess the low-frequency information. The scheme was trained and evaluated on OCT images with pathological details. The experimental results achieved better MS-SSIM, CR, and the reconstructed image quality. The Outcomes indicated that the compression technique was better and faster than other MS-SSIM and visualization methods, higher CR. A compression technique based on DNN for OCT images was better for image storage and teletransfer (Guo P. et al., 2020).

PROPOSED MODEL

In this compression scheme, we used two compression techniques for the important and unimportant parts of the medical image. Significant and insignificant parts of an image are compressed using DWT(suitable for lossless image compression) and CNN(useful for lossy image compression scheme). The important portion of the image is essential for the clinical diagnosis of the disease. The steps of the compression method are given as follows: (1) Input images as a medical image (2) medical image segmentation based on region growing and otsu thresholding technique, (3) lossless compression using DWT (4) lossy compression using CNN (5) reconstruct the image. Figure 1. represents the compression method's process flow. We have collected the medical images from the Medpix database(MDB), an open-access database of academic, clinical, research case studies through the twelve thousand patient cases and nine thousand topics. It has fifty-nine thousand images and has different kinds of images like X-ray, ultrasound, MRI, CT, etc., which are utilized as input to the encoding scheme.

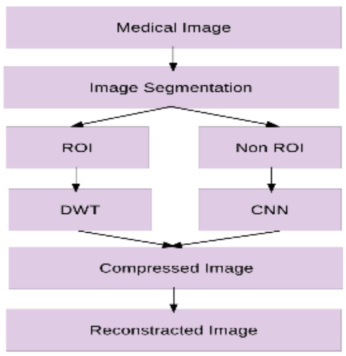


Figure 1. Process flow of proposed medical image compression model.

IMAGE SEGMENTATION

The segmentation technique divides brain images into important and unimportant parts. Here, two segmentation techniques are applied: region-growing (RG) and otsu-thresholding method(OTM). RG is utilized to separate the important and non-important portions of the medical image. Also, we have extracted the affected portions from the important part using otsu thresholding. The RG has segmented the brain images into important and unimportant areas in our method. For the brain image, the non-important image is the skull, and the important image is the remaining part. The difference between the brain's intensities and its neighboring tissues is maximized in the intensity separation process. The RG technique has been adapted using the growth threshold(GT). GT has a set of enormous threshold values. Seed point determination is based on specific criteria, likely texture, area, shape, and grayscale range in the RG. The exact location of seeds is the starting location of the region in the RG. The regions are defined based on the pixel intensity, color, grayscale, and texture from the seed to the neighbor location. RG is separated important and unimportant images using some seeds. The region's design complexity is less during segmentation (Ahilan A. et al., 2019 & Zhang Y. et al., 2020). The important and unimportant images obtained from the RG are illustrated in Figure 2. (b). The affected portion is separated from the medical image using the OTM. Here, the affected portion is considered important, and the remaining area is non-important. The OTM is mainly based on the image histogram. OTM increases the difference between the focused area and background of the medical image based on the threshold value. The important and non-important portions of an image separated using the OTM-based segmentation are illustrated in Figure 3.(b). The medical image's important and unimportant regions are separated using the OTM method and are defined as IMP and NIMP, respectively. The input of the DWT is IMP, and the input of the CNN is NIMP.

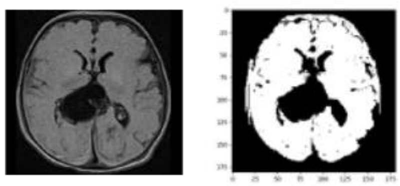


Figure 2. (a) MRI Medical Image (MDB & Sayood K. 2018), (b) region growing(RG).

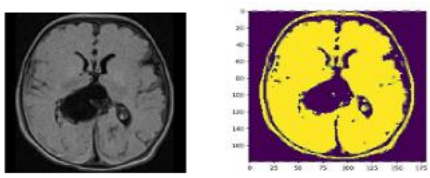


Figure 3. (a) MRI Image (MDB), (b) otsu thresholding method (OTM)

DISCRETE WAVELET TRANSFORM BASED COMPRESSION

The DWT has many applications in the image processing domain to analyze the image. The DWT is analyzed in both numerical and functional computation. It provides a temporal resolution in capturing both the frequency and location information(time). DWT compresses the important part of the medical image: the lossless compression. The DWT-based lossless technique is utilized for preserving the patient's significant information in the medical image for diagnosis. The 2D-DWT defines the scaled and translated basis functions (Gonzalez R. C. et al., 2008 & Sayood K. 2018). Equations 1 and 2 express the scaled and translated basis functions used to compute the DWT-ROI compression technique.

$$\varphi_{l,r,t}(u,v) = 2^{\frac{l}{2}}\varphi(2^l u - r, 2^l v - t) \quad (1)$$
$$\psi^k_{l,r,t}(u,v) = 2^{\frac{l}{2}}\psi(2^l u - r, 2^l v - t) \quad (2)$$

The k denotes directional wavelets are H, V, D. Equations 3 and 4 show the 2D-DWT function's [f(u,v) size PxQ] equations used to compute the DWT-ROI compression technique.

$$W_\varphi(l,r,t) = \frac{1}{\sqrt{PQ}}\sum_{u=0}^{P-1}\sum_{v=0}^{Q-1} \int(u,v)\,\varphi_{(l,r,t)}(u,v) \quad (3)$$
$$W^k_\psi(l,r,t) = \frac{1}{\sqrt{PQ}}\sum_{u=0}^{P-1}\sum_{v=0}^{Q-1} \int(u,v)\,\psi^k_{(l,r,t)}(u,v) \quad (4)$$

The image is decomposed into the LL, HL, LH, and HH sub-bands. LL sub-band provides the essential information of the image. The sub-bands are presented in Equations 5-8 to compute the DWT-ROI compression scheme (Gonzalez R. C. et al., 2008 & Sayood K. 2018).

$$LL = \varphi(u,v) \quad (5)$$
$$HL = \psi^V(u,v) \quad (6)$$
$$LH = \psi^H(u,v) \quad (7)$$
$$HH = \psi^D(u,v) \quad (8)$$
$$f(u,v) = \frac{1}{\sqrt{PQ}}\sum_{r=0}^{P-1}\sum_{t=0}^{Q-1} W_\varphi(l,r,t)\,\varphi_{(l,r,t)}(u,v) + \frac{1}{\sqrt{PQ}}\sum_{k=H,V,D}\sum_{l=l_0}^{\infty}\sum_{r=0}^{P-1}\sum_{t=0}^{Q-1} W_\varphi(l,r,t)\,\psi^k_{(l,r,t)}(u,v) \quad (9)$$

H, V, and D indicate horizontal, vertical, and diagonal directions. The u and v denote coordinates. Algorithm1 describes the ROI Compression of the medical image using DWT. The DWT decomposition process employs the low pass filter and high pass filter of an image followed by down sampling of the 1st row and columns. One part is the LL sub-band or approximation. The other parts are detailed sub-bands, namely HL, LH, and HH. Decomposing the LL sub-band is the 2nd level of DWT decomposition. Significant information in the LL sub-band at the highest-level decomposition and less significant in all other sub-bands. All images are wealthier in low-frequency information than high-frequency information. This situation indicates the energy compaction property of DWT, which is utilized to achieve lossless compression. Equation 9 shows the 2D inverse DWT equation (Gonzalez R. C. et al., 2008 & Sayood K. 2018). DWT process of brain image has been shown in Figure 4.

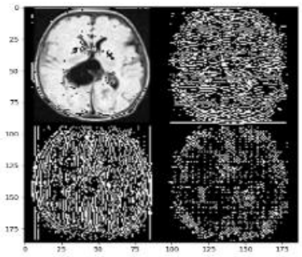


Figure 4. DWT decomposes the MRI Medical Image into four sub-bands.

Algorithm1: ROI Compression of the medical image using DWT (ROI-DWT)

Input: Original ROI medical image
Output: Compressed ROI medical image
1. Initialization:
    (a) $I_{(x,y)} = 0$, k = 0;
2. Loading the image: $I_{(x,y)} \leftarrow$ Original ROI medical image, used skimage 'io' library to load the medical image.
3. Enter decomposition level and wavelet type: mentioned the number of decomposition levels and wavelet types, like 'haar', 'db'.
    (a) No of decomposition level
    (b) Type of wavelet
4. Apply DWT: applied DWT on medical ROI image and achieved the DWT coefficients [CA, CH, CV, CD] of the image.
5. Enter the threshold: percentage of values/coefficients.
    (a) Threshold T ← X
        if cof > T then
            Stored the coefficient values
        else
            Set coefficient values = 0
6. Compressed ROI medical image $\leftarrow I^{\wedge}_{(x,y)}$

CONVOLUTION NEURAL NETWORK BASED COMPRESSION

The CNN is a neural network that employs a convolution operation in at least one of its layers. It operates on two inputs: image matrix (HxWxD) and kernel or filter matrix (F_HxF_WxD). H, W, and D denote height, width, and dimension. Convolution output matrix defines (H-F_H+ 1)x(W–F_W+1)x1. The (256x256x1) represents the grayscale image, and (256x256x3) represents the color image. The layers of CNN are shown in Figure 5. The CNN model consists of convolution layers, pooling layers or sub-sampling, and fully connected layers. We have developed CNN model for image compression and decompression. We have used a specific filter for a specific layer for image data, and in such a way, each layer has one filter as per requirement. The filter removes the unnecessary features of the image. For better performance, a small kernel size is required for the convolution operation at every image location (Zhang A. et al., 2021 & Chung K. J. et al., 2019). The kernel or filter moves to one pixel that is stride1. We shift the kernel or filters to two pixels at a time, stride2. In CNN, the padding process adds space for all sides of an image matrix. While CNN's kernel processes the image, the padding adds the number of pixels to an image as per requirement. The zero-padding process pads the image with 0s. The pooling layer is one layer in CNN that reduces the feature map's dimension but retains necessary information. The Max pooling process returns the maximum value for reducing the features map's dimension in the CNN model. We have used the ReLU (Rectified Linear Unit) activation function in CNN for a non-linear operation. ReLU activates neurons then the gradient provides all times the high value. ReLU, f(n) is defined as MAX(0,n) (Miao J. et al., 2020, Feng S. et al., 2021, Zhou Y. et al., 2019 & Rossinelli D. et al., 2020).

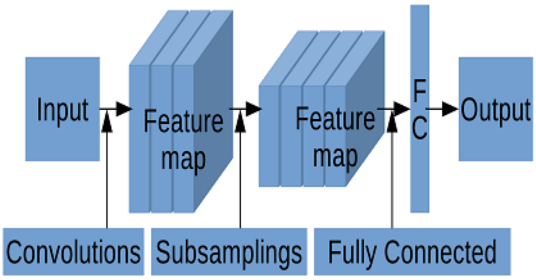


Figure 5. Basic Architecture of Convolutional Neural Network (Nousias S., et al. 2020).

Algorithm2 describes the non-ROI compression of the medical image using CNN. We have trained and tested the CNN model using input images that pass through the network layers sequence with filters or kernels. The CNN-based compression (CNN-C) scheme has 5 layers, contextual features, and input dimensions (256x256) pixels. The 1st layer performs convolution operation with 64 filters (7x7 pixels) and stride1 to construct feature maps (256x256x64), then normalization with the ReLU. This technique is a down-sampling phase. The 5th, 4th layers follow with a down-sampling rate (2x2). After CNN-C, the last contracted feature maps (32x32)xC_n (where C_n denotes the channel no.) have passed through the quantizer and the CNN-based reconstruction(CNN-ReC). The CNN-ReC is the reverse process of the CNN-C with the ReLU. The outcomes of the CNN-ReC technique are the same size as the original images. The up-sampling process enhances the resolution. Three skip connections have been added to construct the output feature maps of the 3rd, 4th, and 5th layers of the CNN-C and CNN-ReC with the quantizer. To control the compressed image size, we have used C_0, C_1, and C_3 to manage the channels of the feature maps followed by the last layer outcome of the CNN-C scheme and every skip connection. The higher CR is achieved by multiple combinations of C_0, C_1, C_2, and C_3 with better-reconstructed image quality (Huijben I. A. et al., 2020).

Algorithm2: Non-ROI Compression of the medical image using CNN (NROI-CNN)

Input: Original NROI medical Image

Output: Compressed NROI medical Image

1. Read original medical image as input

    f(x,y) ⟵ Original NROI medical Image

2. Read f(x,y) by input layer of CNN model

    A: Convolution two-dimensional layer1 & layer2 with ReLU.

    B: Max_value ⟵ Max pooling two-dimensional layer1 using padding and stride

    C: Convolution two-dimensional layer3 & layer4 with ReLU.

    D: Max_value ⟵ Max pooling two-dimensional layer2 using padding and stride

    E: Convolution two-dimensional layer5 with ReLU.

3. Output layer

Compressed NROI medical Image ← f'(x,y)

PERFORMANCE EVALUATION

We have evaluated the MIC-DWT-CNN method's performance in this section. Also, we have implemented and validated the MIC-DWT-CNN medical image compression model using the python platform. MRI brain image, chest X-ray image, non-covid, covid CT scan brain, and ultrasound breast images are considered test images for the MIC-DWT-CNN method from the Medpix database (MDB). The database has fifty-nine thousand medical images. The six medical images are used to examine the MIC-DWT-CNN compression method's performance. The performance of the MIC-DWT-CNN method, which is a hybrid model of lossless and lossy compression scheme, is evaluated using basic parameters like CR, MSE, and PSNR. Compression ratio(CR) defines the ratio between the original(n1) and compressed(n2) image (Gonzalez R. C. et al., 2008 & Zhong L. et al., 2020). Equation 10 expresses the CR used to evaluate the compression efficiency of the MIC-DWT-CNN method.

$$CompressionRatio = \frac{OriginalSize(n1)}{CompressedSize(n2)} \tag{10}$$

MSE is an error measurement matrix between the input(O) and compressed(C) image (Sayood K. 2018.). The MSE is defined in Equation 11, where M defines the number of rows and N denotes the number of columns of the medical image matrixes, i.e., O and C. MSE equation is used to compute the PSNR value of the MIC-DWT-CNN compression method.

$$MSE=\frac{1}{M*N}\sum_{I=1}^{M}\sum_{J=1}^{N}\left(O\,(p,q)-C\,(p,q)\right)^2 \tag{11}$$

The PSNR is a measurement matrix to evaluate image quality. If the image has a higher PSNR value, then the quality of the compressed or reconstructed image is better. It is expressed in Equation 12 used to evaluate the MIC-DWT-CNN compression method, where maxpixel denotes the highest possible pixel value of the image matrix (Liu H. et al., 2021).

$$PSNR = 20 * log10\left(\frac{maxpixel}{\sqrt{(MSE)}}\right) \quad (12)$$

We experimented with the MIC-DWT-CNN method on the medical images and demonstrated its improved image compression efficiency. Table 1. shows the outcomes of MSE, PSNR, and CR values of the MIC-DWT-CNN method for six medical images.

Table 1. Experimental Results of MIC-DWT-CNN method for MSE, PSNR(dB), and CR.

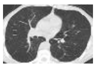
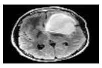
Sl No	Images	MSE	PSNR(dB)	CR
1.		22.03	34.70	27.54
2.		19.11	35.31	19.99
3.		18.24	35.52	23.87
4.		22.34	34.64	22.94
5.		16.15	36.05	26.83
6.		23.21	34.47	28.87
Average		20.18	35.11	**25.01**

Table 2. Interpretation of MIC-DWT-CNN, DWT-RNN, BWT-MTF and QFOM methods.

Sl No	Methods	MSE	PSNR(dB)	CR
1.	**QFOM (Magar S.S. et al., 2020)**	28.96	33.51	24.61
2.	**BWT-MTF (Devadosset C. P. et al., 2019)**	22.08	34.69	4.63
3.	**DWT-RNN (Sabbavarapu S. R. et al., 2020)**	20.96	35.24	23.34
4.	**MIC-DWT-CNN(Proposed)**	20.18	35.11	**25.01**

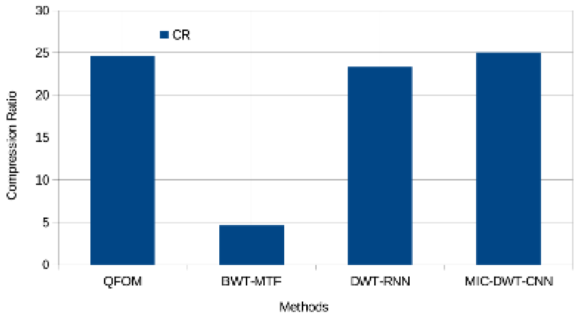


Figure 6. Comparison of different method's compression ratios (CR).

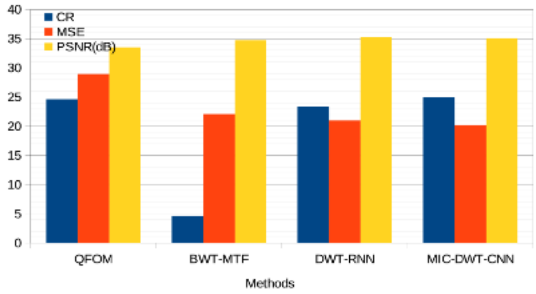


Figure 7. Performance visualization of different method's experimental outcomes.

The outcomes are compared with compression methods, namely QFOM, BWT-MTF, DWT-RRN, and MIC-DWT-CNN. Table 2. shows the MSE, PSNR, and CR values of the MIC-DWT-CNN, QFOM, BWT-MTF, and DWT-RRN compression methods. In comparison, MIC-DWT-CNN achieved a higher CR value and required level of PSNR over three existing methods. Figure 6. shows the CR values of four methods. Figure 7. shows the performance visualization of the experimental outcomes. The MIC-DWT-CNN method performs better than QFOM, BWT-MTF, and DWT-RRN compression methods in terms of CR for a particular PSNR. Thus, the MIC-DWT-CNN method will efficiently store and transmit in the medical image database.

CONCLUSION

The medical image is essential for disease diagnosis and surgical processing in the healthcare system. In this research, important and non-important portions of medical images are separated using the RG and OTM. Important and unimportant parts of the images are compressed using the DWT and CNN. The DWT-based lossless compression technique is applied on an important portion of an image to preserve the image's significant medical information at the time of compression and reconstruction. CNN is utilized for lossy compression on the non-important portion of the image. The CNN-based lossy compression technique is used to reduce the losses using weight and learning rate. The lossless and lossy scheme on the important area and non-important area of the medical images leads to the greater CR with appropriate PSNR value and minimum loss. The MIC-DWT-CNN method provides better outcomes than the existing compression schemes. The CR of the MIC-DWT-CNN method is high over the other schemes.

In the future, the technique can extend to other domains.

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