Medical Images Compression Techniques using Deep Learning: A Review

Asmaa M. Aboelmajd
Computer Science Department,
Faculty of computers and Information,
Assiut University, Egypt

E.A. Zanaty
Computer Science Department,
Faculty of Computers and Artificial Intelligence
Sohag University, Egypt

Amal Rashed
Computer Science Department,
Faculty of computers and Information,
South Valley University, Egypt

ABSTRACT
Terabytes of medical image data are everyday used in the industry of healthcare through advanced imaging modalities as Ultrasound (US), Magnetic Resonance Imaging (MRI), Computerized Tomography (CT), X-rays, and Mammograms, among others. It is difficult to detect and recover the pixels because of the highly complicated, which makes it hard to store and transmit the immense amount of data that is created. Compressing an image decrease its size, which thusly requires less storage space, allowing for the storing of more images in a given amount of space. Such photos once they have been compressed will eventually use less bandwidth for transmission and thus shorten the download time. Due to these intrinsic worth image compression is considered as a necessity for multimedia technology, so we want to design and test neural networks states like (deep neural networks, artificial neural networks, recurrent neural networks, and convolution neural networks) as one of the most thrilling deep learning techniques, which is a subset of machine learning, to track down a representation to compress images well. In order to make improvements in the performance of medical images compression. This review can be categorized into the following two subsections namely compression based on medical images, compression based on deep learning during the latest 4 years,describing each section in efficient manner then open issues to highlightin.

Keywords
Deep Learning, Convolutional Neural Networks (CNNs), medical imag, Lossless compression.

1. INTRODUCTION
The change from analog to digital systems offered more accurate, quicker and stress-free imaging growth [1]. **An image can be compressed by the removal of data redundancies** such Coding redundancies, Interpixel redundancies and Psychovisual redundancies[2].The original image is represented by F(m,n) while the compressed one by F'(m,n). The source encoder is used to remove redundancy in the input image.The channel encoder is used as overhead to combat channel noise.The job of the channel and source decoders is to basically undo the work of the source and channel encoders. In **Figure 1** below represents a sample Image Compression Model. The original image is represented by F (m,n) while the compressed one by F' (m,n). The source encoder is used for redundancy removal in the input image. The channel encoder is utilized as channel noise removal. The channel could be communication link system. The job of the channel and source decoders is to basically undo the work of the source and channel encoders.

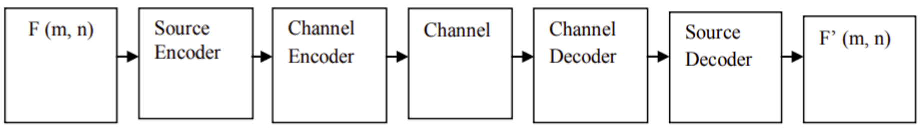

Figure 1 Image Compression Model [3]

Using deep learning patterns has the capability to be learned from the input image then convert them with less components into another pattern by changing the synapses (weights) of interconnections through layers. Digital images have their restriction not only that they take more space in memory, but also they are more critical and information loss may lead to incorrect diagnosis and can be life-threatening[4], as shown in Figure 2 that shows examples of chest X-rays from the dataset.

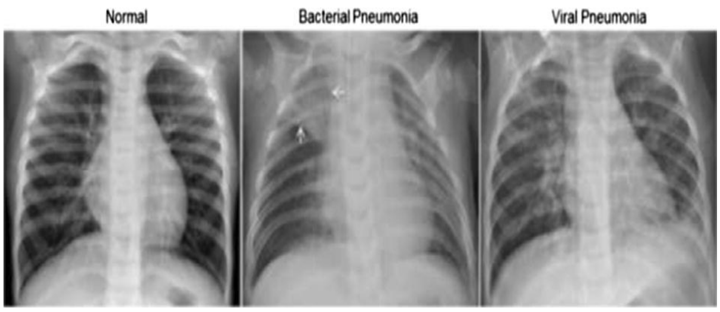

Figure 2 Data set

The normal chest X-ray (left panel) show clear lungs without any abnormal opacification areas. Bacterial pneumonia (middle), in the right upper curve (red rectangle), whereas viral pneumonia (right) appears with a more diffuse interstitial example in both lungs. A good example to outline image compression's importance is the health industry, where the challenges / issues is raised to constant scanning ,store and communicate the large volume of medical images generated by various imaging modalities [5].

The paper is organized as follows. Section 2 briefly present the image compression idea and medical image modalities followed by image compression techniques and assessment of compressed images. Section 3 reviews the deep learning with the most popular types of networks such as convolutional neural network and recurrent neural network that used in image compression. Section 4 reviews the prior studies (Related work) in image compression using deep learning and medical image compression techniques previously used. The discussion on research Challenges and some more aspects to highlight in this review summarizing findings from previous studies will be present in Section 5. Finally, the paper is ended with a conclusion in Section 6.

2. IMAGE COMPRESSION

Image compression is a process applied to a graphics file to minimize its size in bytes without degrading image quality below an acceptable threshold. It is aim to reduce memory space, less bandwidth.

2.1 Medical images modalities

Medical imaging integrates those processes that provide human body's visual data. The purpose of medical imaging is to aid radiologists and clinicians to make more efficient process of treatment and diagnostic. Medical imaging is a predominant part of diseases' diagnosis and address different imaging modalities. These include computed tomography (CT), X-ray, positron emission tomography (PET), magnetic resonance imaging (MRI), and ultrasound to give some examples as well as hybrid modalities [1][4-5]. A typology of common medical imaging modalities [6] is shown in Figure 3 is used for different body parts which are generated in radiology settings

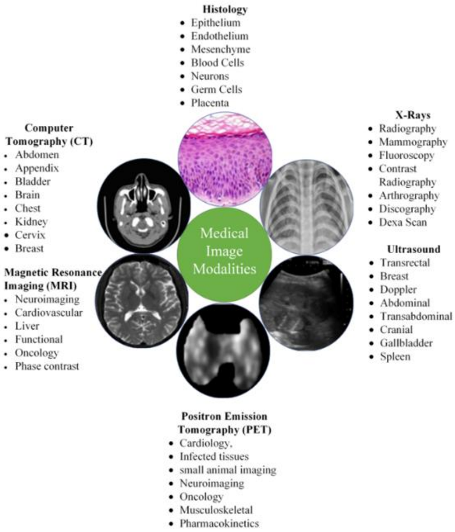

Figure 3 Medical imaging modalities' topology [6]

2.2 Image Compression Techniques

Lossy compression, some information's loss is accepted as dropping nonessential detail can save storage space and attain high compression ratio for complex images [7], it demands three stages: acquisition, quantization, and entropy coding as shown in **Figure 4(a).**

2) Lossless compression, the original digital image can be gotten back without any information's loss [8], as shown in **Figure 4 (b)**, it demands two stages, the mathematical transform to eliminate the redundancy between pixels and entropy coding technique carries out redundant coding.:

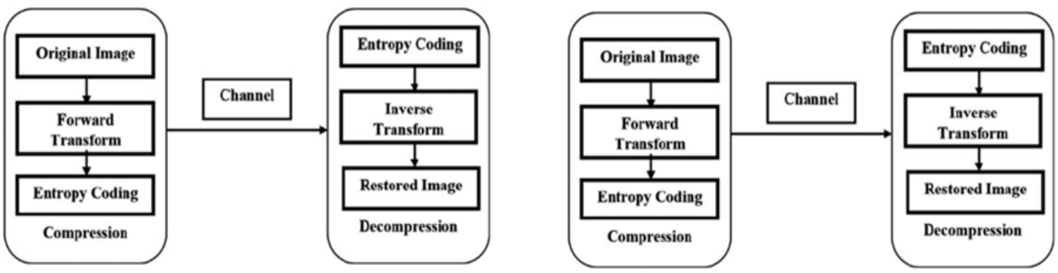

Figure 4 (a) lossy compression block diagram (b) lossless block diagram [9]

3. HYBRID COMPRESSION

It consists of two or more compression techniques whether lossy or lossless to achieve effective image compression[10].**Figure 5** indicates the various application areas of the compression techniques.

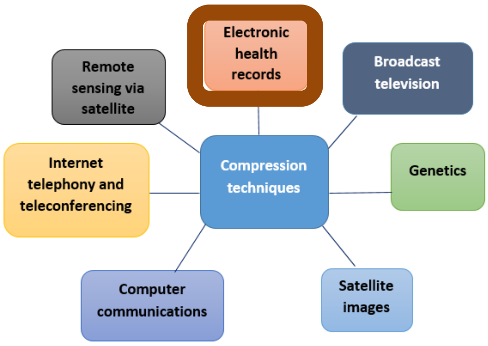

Figure 5 Various Application Areas of the Compression Techniques

3.1 Assessment of compressed images

The compression ratio is the image's compression calculation. Different factors including PSNR and MSE are mostly used because they are simple to measure [2].

Mean square error (MSE). This is calculated by the mean difference between compressed and input (original) pixel square intensities. The MSE is indicated by the following equation.

$$MSE = \frac{1}{m * n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [g'(p,q) - g(p,q)]^2$$

where MSE is Mean Square Error, and *m & n* are image rows & columns in spatial

form.**Peak signal to noise ratio (PSNR).** is the relation between the highest signal value of deforming noise, which changes its representation value and the signal value of the deforming noise. The PSNR's mathematical representation is:

$$PSNR = 10 \log 10 \left[\frac{m * n}{MSE}\right]$$

Compression ratio (CR). is the relative sum between the bits needed by the image input to the bits required by the compressed image. The following, is the compression ratio equation.

$$C_R = \frac{\text{uncompressed image size}}{\text{compressed image size}}$$

4. NEURAL NETWORKS AND DEEP LEARNING

Neural networks are simulates of the brain of the human, where each neuron is responsible for solving a small part of the problem. in **Artificial Neural Network** (ANN) each input corresponds to a pixel in the image into a feedforward ANN But, this is not perfect because the interconnections between nodes in a layer are missed. **CNN** is a special case of the ANN that overcomes this issue, it feeds patches of an image to particular nodes in the next layer of nodes (instead of all nodes), thus preserving the spatial context from which a feature was extracted like(vertical lines, edges, curves, U-shaped objects) and are known as convolutional filters (convolution kernels). and address their location on the feature map.Then the feature map is used as input for the next layer by **deep CNN**. The final features maps are then compressed from their square representations and input to a feedforward ANN[11]. **Convolutional Neural Network (CNNs)** basic construction has similar layers identified as **convolutional**, **pooling**, **rectified linear units** and **fully connected** [12] as shown in **Figure 6**, even though there are various CNN structure varieties, including deep supervised networks and fully convolution networks [13].

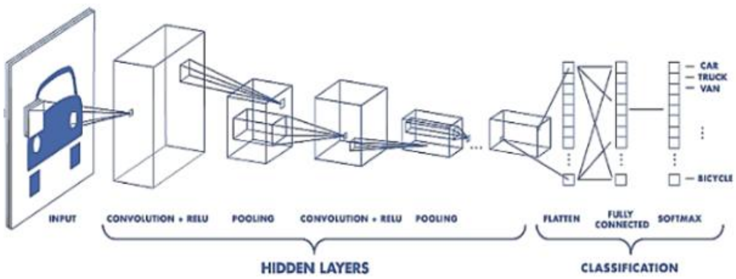

Figure 6 Architecture of CNN [14]

Recurrent Neural Network (RNN) is one of the neural networks' types which is store past-related data. RNN units have numerous connections to themselves and knowledge is convert out of the past[15].While traditional deep neural networks presume that inputs and outputs are independent of each other. **Figure 7** shows a Comparison of (a) Recurrent Neural Networks and (b) Feedforward Neural Networks

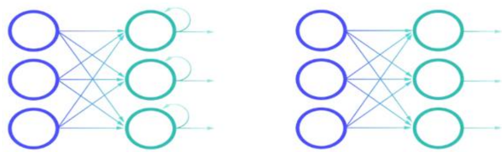

Figure 7 (a) Recurrent Neural Network (b) Feedforward Neural Network

Deep learning is pretty much resemble a large neural network, properly called a deep neural network. It's called deep learning because the deep neural networks have many hidden layers. Deep learning is a subset of machine learning that depends on artificial neural networks while machine learning relies only on algorithms[16].**Figure 8** shows a fully deep neural network architecture.

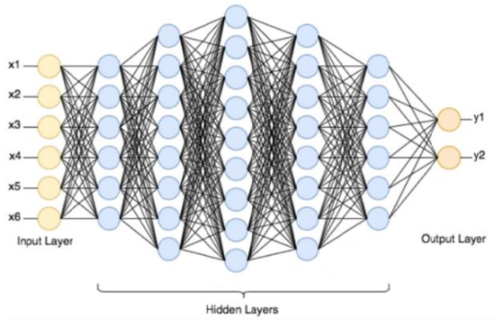

Figure 8 a fully deep neural network architecture

5. RELATED WORK

5.1 First: compression based on deep learning.

A. Krishnaraj et al.[18]. got a 79.7038% space saving with PSNR of 53.961 using Hybrid 20 CNN layer and Discrete Wavelet Transform (DWT) methodology and UWSN dataset.

H. Liu et al. [19]. got a get 92% for lossy/lossless features accuracy, 0.79 dB absolute prediction error of the model with PSNR of 35.41 and SSIM of 0.82 using Combine the CNN and JPEG coder for training and predicting Stage methodology and MCL-JCI dataset.

T. Hoang et al. [20]. got 35.31% BD-rate reduction over the HEVC-based (BPG) codec, 5% bitrate, and 24% encoding time-saving with PSNR of 33.57 and SSIM of 0.977 using Hybrid a semantic segmentation network for an upsampled image in both encoder and decoder. And the convolution neural networks to solve the semantic segment extractor methodology and ADE20K, Kodak dataset.

M. Li et al. [21]. achieved a compression ratio equivalent to the new technique and is much faster with PSNR of 31.01and SSIM of 0.978 that implemented a Deep neural networks and entropy encoding and used Kodak and Tecnica dataset.

P. Guo et al. [22]. Gained a 80% as compression ratio with SSIM of 0.985 by Training the CNNs with an adversarial objective, objective function, patch discriminator, and MSSSIM pealty.and the using of Kodak dataset.

5.2 Second: lossless compression based on medical images .

Somassoundaram, T., and N. P. Subramaniam [23]provided a 2D Bi-orthogonal multi wavelet transform and Hybrid speck-deflate algorithm applied on angiogram sequence that achieved a higher compression ratio .

Rani, M. Mary Shanthi, and P. Chitra [24]provided a Haar Wavelet Transform and Particle Swarm Optimization applied on MRI, Mammogram and X-ray that attained a higher PSNR and Better compression rate.

6. OPEN ISSUES/ RESEARCH CHALLENGES AND SOME MORE ASPECTS TO HIGHLIGHT IN THIS REVIEW

As shown in table 1, DL has become a hot topic within the field of medicine given the digital availability of information; however, many challenges still exist. Table 3. Show Open Issues/ Research Challenges in this review.

Table 1. Summarization of Open Issues/ Research Challenges in this review

Challenges with DL Models Issues/ Research Challenges	Challenges with medical images Issues/ Research Challenges	Challenges with compression techniques Issues/ Research Challenges
DL is limited by the quantity and quality of data used to train the model. EX: In medical compression, watermarking techniques are able to compress the images but not able to preserve the quality of it. It is difficult to estimate how much data are necessary to sufficiently and reliably train DL systems because it depends both on the quality of the input training data as well as the complexity of the task.[17].	Most compression techniques uses MRI and CT as their modalities but some of these techniques are only able to work on CT and MRI not on other medical modalities [15].	In Region of Interest compression, the AutoShaping is done manually by the physician i.e. chances of error should be there [15].
DL methods also suffer from the "black box" problem: input is supplied to the algorithm and an output emerges, but it is not clear enough what features were identified or how they informed the model output. [3]On the contrary, simple linear algorithms, although not always as powerful as DL, are easily interpretable. To overcome that by using deep learning, activation maps, or heatmaps, are methods that attempt to address the "black box" issue by highlighting areas of images that highlight regions of an image that "fire together" with the output classification label[29]	PSNR, CR and MSE are the parameters which are mostly considered by many researchers to compute the performance of their respective techniques and some compression techniques are able to perform on limited modalities hence there is scope of work is in this direction [15].	Some of the techniques are much efficient and effective but consumes large amount of time which is a matter of concern, so there is good scope for future work in reducing the computation time of compression techniques, also in lossy compression, the background noise removal techniques should be improved for the effective and efficient compression [15].

7. CONCLUSION

This review illustrates some of the compression techniques which are used to compress the medical images and some of the compression techniques which are used to compress the images as general using deep learning. The deep learning-based image compression methods have been examined and compared, particularly for new studies of deep-learning based image compression techniques. And about techniques applied on medical images are able to solve the storage and bandwidth limitation problems. it is concluded that performance of the compression technique totally relies over the compression ratio. Higher the compression ratio means better the technique is. Here, it is kept in mind that there should be no loss of the critical information as we deal with medical data.

8. REFERENCES

[1] Ammah, Paul Nii Tackie, and Ebenezer Owusu. "Robust medical image compression based on wavelet transform and vector quantization." *Informatics in Medicine Unlocked* 15 (2019): 100183.

[2] Sadeeq, Haval T., et al. "Image Compression Using Neural Networks: A Review." International Journal of Online & Biomedical Engineering 17.14 (2021).

[3] Zhang, Quan-shi, and Song-Chun Zhu. "Visual interpretability for deep learning: a survey." *Frontiers of Information Technology & Electronic Engineering* 19.1 (2018): 27-39.

[4] Habib, Rafi Ullah. "Optimal compression of medical images." *Int. J. Adv. Comput. Sci. Appl. IJACSA* 10.4 (2019).

[5] Boopathy, G., and S. Arockiasamy. "Implementation of vector quantization for image compression-A Survey." *Global Journal of Computer Science and Technology* (2010).

[6] Anwar, Syed Muhammad, et al. "Medical image analysis using convolutional neural networks: a review." *Journal of medical systems* 42.11 (2018): 1-13.

[7] Toderici, George, et al. "Full resolution image compression with recurrent neural networks." *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*. 2017.

[8] UmaMaheswari, S., and V. SrinivasaRaghavan. "Lossless medical image compression algorithm using tetrolet transformation." *Journal of Ambient Intelligence and Humanized Computing* 12.3 (2021): 4127-4135.

[9] Fred, A. Lenin, et al. "Bat optimization based vector quantization algorithm for medical image compression." *Nature Inspired Optimization Techniques for Image Processing Applications*. Springer, Cham, 2019. 29-54.

[10] Kumar, Pardeep, and Ashish Parmar. "Versatile approaches for medical image compression: A review." *Procedia Computer Science* 167 (2020): 1380-1389.

[11] Choi, Rene Y., et al. "Introduction to machine learning, neural networks, and deep learning." *Translational Vision Science & Technology* 9.2 (2020): 14-14.

[12] Kong, Fanzhi. "Facial expression recognition method based on deep convolutional neural network combined with improved LBP features." *Personal and Ubiquitous Computing* 23.3 (2019): 531-539.

[13] Zeebaree, D. Qader, et al. "Multi-level fusion in ultrasound for cancer detection based on uniform LBP features." *Computers, Materials & Continua* 66.3 (2021): 3363-3382.

[14] Mohammed, Soleen Basim, and Adnan Mohsin Abdulazeez. "Deep Convolution Neural Network for Facial Expression Recognition." *PalArch's Journal of Archaeology of Egypt/Egyptology* 18.4 (2021): 3578-3586.

[15] Yasin, Hajar Maseeh, and Adnan Mohsin Abdulazeez. "Image Compression Based on Deep Learning: A."

[16] Cai, Han, Ji Lin, and Song Han. "Efficient methods for deep learning." *Advanced Methods and Deep Learning in Computer Vision*. Academic Press, 2022. 159-190.

[17] Choi, Rene Y., et al. "Introduction to machine learning, neural networks, and deep learning." *Translational Vision Science & Technology* 9.2 (2020): 14-14.

[18] Krishnaraj, N., et al. "Deep learning model for real-time image compression in Internet of Underwater Things (IoUT)." Journal of Real-Time Image Processing 17.6 (2020): 2097-2111.

[19] Liu, Huanhua, et al. "Deep learning-based picture-wise just noticeable distortion prediction model for image compression." IEEE Transactions on Image Processing 29 (2019): 641-656.Jiang F, Tao W, Liu S, Ren J, Guo X, Zhao D. An end-to-end compression framework based on convolutional neural networks," IEEE Trans. Circuits Syst Video Technol. 2018;28(10):3007–3018.

[20] Hoang, Trinh Man, Jinjia Zhou, and Yibo Fan. "Image compression with encoder-decoder matched semantic segmentation." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops. 2020.

[21] Li, Mu, et al. "Efficient and effective context-based convolutional entropy modeling for image compression." IEEE Transactions on Image Processing 29 (2020): 5900-5911.

[22] Guo, Pengfei, Dawei Li, and Xingde Li. "Deep OCT image compression with convolutional neural networks." Biomedical Optics Express 11.7 (2020): 3543-3554.

[23] Somassoundaram, T., and N. P. Subramaniam. "High performance angiogram sequence compression using 2D bi-orthogonal multiwavelet and hybrid SPIHT-DEFLATE algorithm." Indian Journal of Science and Technology 8.14 (2015): 1.

[24] Rani, M. Mary Shanthi, and P. Chitra. "A hybrid medical image coding method based on haar wavelet transform and particle swarm optimization technique." International Journal of Pure and Applied Mathematics 118.8 (2018): 3056-3067.