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The Comprehensive Review of Neural Network: An Intelligent Medical Image Compression for Data Sharing

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Abstract: In the healthcare environment, digital images are the most commonly shared information. It has become a vital resource in health care services that facilitates decision-making and treatment procedures. The medical image requires large volumes of storage and the storage scale continues to grow because of the advancement of medical image technology. To enhance the interaction and coordination between healthcare institutions, the efficient exchange of medical information is necessary. Therefore, the sharing of the medical image with zero loss of information and efficiency needs to be guaranteed exactly. Image compression helps ensure that the purpose of sharing this data from a medical image must be as intelligent as possible to contain valuable information while at the same time minimizing unnecessary diagnostic information. Artificial Neural Network has been used to solve many issues in the processing of images. It has proved its dominance in the handling of noisy or incomplete image compression applications over traditional methods. It contributes to the resulting image by a high compression ratio and noise reduction. This paper reviews previous studies on the compression of intelligent medical images with the neural network approach to data sharing.

Keywords: Medical Image Compression, Intelligent Medical Image Compression, Neural Network, Data Sharing.

1. Introduction

The medical images contain much information that is required by doctors and specialists for the correct diagnosis. The visual image plays crucial roles in supporting the work of the medical practitioner. It is also the main asset of the health system that medical practitioners widely used to identify, diagnose, treat and study various types of diseases in electronic form. It is also the best practice to monitor a person's health, which is popularly utilised today.

Everyone knows in general that the medical image consumes a vast amount of memory. There are several modalities such as X-Ray, Magnetic Resonance Imaging (MRI), Single-photon Computed Tomography (SPECT), Computed Tomography (CT), Positron Emission Tomography (PET) and ultrasound imaging. Each mode that consumes a considerable size requires a massive amount of storage space of memory. The hospital information system administrator must ensure that the storage space is sufficient to accommodate the process flow needs. This storage occupies more space to store images for a long time, as numerous patients need to be recorded [1], [2].

Medical practitioners also need to share data, especially medical images, to share opinions, idea, and knowledge to diagnose and analyse the disease. They need to transfer the medical image files over the network, which requires very

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high bandwidth. The distribution of the medical image needs to deliver accurately, precisely, and safely [3]. Hence, the medical image must be compressed and sent securely through the network in the system.

Medical imaging in the modern world has become a useful and necessary method for effective and proper treatment of a human's health-related problems. Medical imaging is the technique and procedure of producing visual representations of a body's interior for clinical diagnosis and medical procedure. While medical evaluation may be required before many conditions are treated, the use of medical imaging services is essential for the identification, proper assessment and monitoring of conditions of many diseases, as well as for the assessment of clinical responses. Through improved health care programs and increased availability of medical equipment, there is a substantial increase in the number of international imaging-based procedures. Medical images are of great significance for surgery, diagnosis, treatment and study, which serve as the vital component of digital patient records. For many medical decisions, efficient, and high-quality imaging is critical and can reduce unnecessary procedures. It has resulted in a significant increase in the use of medical images in recent times [1], [4].

The effect of increasing medical image file size leads to more substantial resources requirement. Therefore, additional storage, bandwidth and time costs are required. Besides, when transferring data, comprehensive data are also exposed to security vulnerabilities and threats. Medical data is a patient's privacy right. In addition to healthcare professionals, patients are also demanding that the privacy of their data be secured and protected. [5]. Thus, we may see the need to ensure that medical data distributed accurately and efficiently.

Consequently, compression has attained much attention in medical images. Medical image compression is utilised in applications to promote faster transmission speed and reliable data and reduce storage costs and increase transmission speed [6]. Compression of medical images is essential since the efficient storage and transmission of data via high bandwidth digital communication networks is crucial. Image compression will enable Picture Archiving and Communication System (PACS) in Hospital Information System to reduce file size while retaining relevant diagnostic information in their storage requirements. Here the compression requirement is realised [7], [8]. PACS can overcome at least in part of the processing and communication problems. Still, it is also necessary to take into account the ever-growing quantity of data that needs to be managed [9]. This communication is generally based on an on-demand database using Internet technology. In contrast, most new hospitals have been used by the PACS archiving and correspondence network to archive, monitor, transfer and process medical information [10].

In recent years, researchers have investigated smart image compression concerning low loss and higher compression rates for its high performance. Though auto-encoders are challenging to automate, sub-pixel architecture neural networks display consistent results [11]. The solutions to intelligent data processing using Artificial Neural Networks (ANN) look very impressive, mainly because of their architectures, which provide parallel calculations and the use of the learning process in order to make the network more adaptable mainly because of their structures, providing possibilities for parallel calculations and the use of the [12].

The purpose of this paper is to investigate the intelligent compression techniques used over the last several years in the neural network. The paper structured as follows: the paper's first section will briefly present the entire idea of the article. Section 2 specifically addresses the technique of image compression. Here is a brief explanation of the image compression classification and performance metrics. The sources and practices of the corresponding intelligent medical image compression study using neural network techniques will also be studied in Section 3. The discussion on summarising findings from previous studies will be present in Section 4. Finally, section 5 gives the final remarks of the paper.

2. The Medical Image Compression

Medical images contain a great deal of information that is necessary for diagnosis by doctors and medical professionals. It is a process of reducing image data irrelevance and redundancy so that data can practically be stored or transmitted. It minimises the size of a representation document in bytes without degrading the image's nature. Image compression includes a forward process referred to as encoding and a reverse process referred to as decoding. The compression proses start once the encoder received the image as the input. The encoder converted the image input into an array of bit-stream binary data. Then the decoder gets the encrypted bit-stream, also known as the resulting image, and decodes it to produce the decoded image. Figure 1 shows the basic flow of image compression [13].

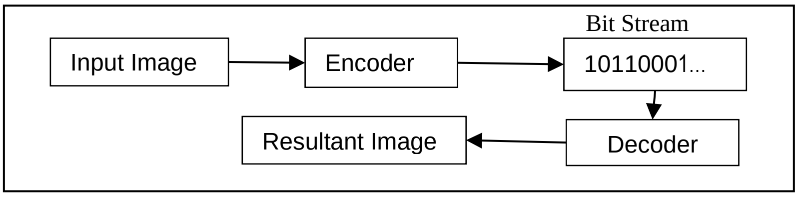

Fig.1: Basic Flow of Image Compression [13]

The image compression techniques used and can be divided into two main categories: Lossless Image compression (or reversible) and Lossy Image Compression (or irreversible). In lossless compression, the recovered data matches the original, however in the case of lossy compression, the recovered data is a tight copy of the first with insignificant information impairment [14], [15].

In the lossless image compression technique, reconstructed data from compressed data is similar to original input data. Data loss is very slight in the lossless data compression technique compared to lossy compression. Therefore, this algorithm is used in domains where reliability and data protection are vital. For ethical and ethics considerations, lossless compression methods (or reversible ones) are preferred because the original image can be replicated correctly. The output of this technique contains precisely the same data as the input data. This technique reaches 1:1 compression and a small compression ratio. It is suitable for applications in which data loss is not permitted, taking backup of information and archiving of records. Thus, lossless compression is typically used for medical image compression [16]–[19].

Lossy Image algorithms are used when the human observer is not able to perceive the loss of image data, or the loss of information is acceptable [19]. Lossy compression algorithms acquire a loss of information. There is a missing of information, and the original image is not recovered exactly as it was before it was compressed. Since part of the information contained in an image can be lost during a compression algorithm with loss, it allows higher data compression and can reduce the image size to minimal dimensions. Furthermore, the compression ratio of these algorithms is extensive Lossy techniques are intended to achieve total compression ratios that permit sufficient image degradation. It uses complex algorithms to reduce input to low output data with a much-reduced amount of information. It is suitable for applications where bandwidth or storage management is vital through compromising on data quality. Examples of loss compression algorithms include MP3, JPEG and MP4 videos [16].

Though in medical imaging, compression schemes are not used with the lossy compression algorithm due to the possible loss of clinical information, and operations such as the enhancement may lead to further impairments in lossy compression. The doctor was not willing to implement lossy compression since any loss of information or errors caused by the compression process could affect clinical diagnosis decisions and could pose a legal challenge [15], [20].

The performance of a compression technique or tool may be described with several parameters. The implementation of specific codecs for the compression ratio, encoding costs and decoding costs has been reported in three measurement steps [14], [21]. Many different parameters can be used to describe and compare the performance of a compression technique such as mean square error (MSE), peak signal to noise ratio (PSNR), compression ratio (CR), Bit per pixel, Structural Similarity Index Measurement (SSIM) and time-consuming to compress the image [14], [21], [22]. The compression ratio indicates the efficiency of the compression algorithm. When comparing compression ratios, the higher the compression ratio, the more efficient the compression algorithm is in the image [13]. The following equation can calculate the compression ratio:

$$Compression\ ratio\ = \frac{OriginalImageSize}{CompressImageSize} \quad (1)$$

Besides, the execution time is also crucial in determining the successfulness of a medical image compression algorithm. Encoding and decoding costs are characterised as the total amount of time required to compress or decompress input information separated by file volume. This value reflects the time needed for encoding or decoding that megabyte of information in milliseconds.

The MSE and PSNR is the way to measure the quality of the appropriate image. The MSE defined as the square of the pixel value differences between the two images corresponding pixels. The MSE of $M * N$ size image is given by:

$$MSE = \sum M, N\, [I_1(m,n) - I_2(m,n)]^2 (M * N) \quad (2)$$

m & *n* – number of rows and columns in the input images

While the PSNR is the parameter calculates the total difference between the compressed image and the original image. To calculate PSNR first, MSE is calculated. MSE is the aggregate contrast between the picture condensed and the original frame. A higher MSE value improves the quality of the image and eliminates the error. The greater the PSNR value, the higher the image quality [13]. The PSNR value is determined with the following equation:

$$PSNR = 10\ log_{10}\,(\frac{R^2}{MSE}) \quad (3)$$

R is the maximum fluctuation in the input image data type

Bit per pixel or BPP gives the significant number of bits that are essential for storing one pixel of the image. It is given by:

$$BPP = \frac{CompressImageSize}{TotalNumberofPixel} \quad (4)$$

The Structural Similarity Index Measurement (SSIM) is a measure based on the computation of the overall index with the luminance term, the contract term and the initial term gives quality assessment index**.**

3. Intelligent Medical Image Compression

In the era of the industrial revolution 4.0, all areas were geared toward the internet of things where intelligent elements and network communication were crucial factors in every innovation. So is medical technology. All the equipment and image production are becoming more sophisticated, detailed and complex. The medical practitioner was demanding medical image compression technique income that smart and optimised to ensure accurate data transmission, efficient and less data loss during sharing of data communication between the healthcare system. Image researchers have begun to incorporate artificial intelligence into the field of image processing. Artificial Neural Network (ANN) has been applied to many problems in image processing and has demonstrated their superiority over classical methods when dealing with noisy or incomplete data for image compression applications

Neural Network is now a valuable tool that emerges, which can be very useful, especially for the processing of images. This functions as the brain and works parallel to ANN like biological nervous systems. The ANN will be used to recognise the patterns, classify data, compress and decompress images through the training and learning process. In this network, different layers of processing components, known as neurons, are simulated (input, hidden and output) to establish the target. Each connected neuron is the strength of these connections.

Neural networks are suitable for medical image compression because they are capable of producing simpler patterns with fewer components before processing input patterns. This compressed (hidden-layered) information preserves the complete information obtained from an outside environment. The compressed functions can then leave the network in its original uncompressed form and go into the external environment. There are different type of ANN techniques such as the backpropagation algorithm, convolutional neural network, feed-forward algorithm and Kohonen's algorithm [23].

T.M.P. Rajkumar and Mrityunjaya V.Latte propose the medical Image Compression technique based on Region-of-interest of the image. The medical image was initially separated into blocks with a particular size. This is then used for improving the image before encoding with the Discrete Wavelet Transform (DWT). The suggested optimisation process involves the conversion of the block wavelet, threshold value calculations and The Feed Forward Back Propagation Neural Network (FFBNN) to conduct the training and testing process. The following split the object into the K-means algorithm based on clustering. The image coding is carried out using Listless SPECK (LSK) modified Wavelet Transform for the regions of interest. The algorithm is tested using MATLAB (Matlab 7.12) using knee MRI, Brain MRI and Lungs CT images as test images used in the test. PSNR with 39.82 dB and 4.88 CR of the quality of the reconstructed images was measured [24].

Perumal Balasubramani and Pallikonda Rajasekaran Murugan suggested a compression dependent Hybrid Discrete Wavelet Transform with Neural Network Back-Propagation Approach (DWT-BP) of medical image. This research use brain image, CT, MRI and PET as their sample. For BPNN technology, they hybridise the DWT approaches to boost compression. The input picture of size 256 x 256 is given where these algorithms provide the compressed frame. They concluded that the practical hybrid DWT-BP tests of 0.72 of CR, 64.88db of PSNR, 8.01 of BPP: and 1.67 of MSE had been obtained [25].

GV Maha Lakshmi uses fractal image compression and neural networks to accomplish medical image compression. For his invention, he used the brain image MRI as a dataset. It utilises encoding time, PSNR, and CR to evaluate the innovation with the result of 502.35 seconds, 12.7 CR and 35.16 PSNR. Due to the addition of information, the encoding time has been reduced to almost a third. The CR is not changed, and the PSNR values for some MRI images are lowered while the values for others have been comparable to higher [26].

Emir Turajlić from the University of Sarajevo has recommended that Kohonen self-organising maps for segmentation of feature space and the use of several finely tuned multi-level to improve compression efficiency, perceptrons. Kohonen's Self Organizational Maps (SOM) is an artificial feeding neural with a single computational layer which adopts an unregulated competitive learning process to generate an input space for low-dimensional depiction. The tests were performed on an ELAP server subset containing 20 CT pulmonary imagery. Objective image quality metrics, that is 13.59 mean square error, and 37.17 dB peak signal-to-noise ratio, suggest image reconstruction quality [27].

Mohamed Uvaze Ahamed Ayoobkhan and his colleagues suggested Feed-Forward Neural Network-Based Predictive Image Coding for Medical Image Compression. The method of image encoding is proposed to maintain the quality of medical images even after compression in the area of interest. This way, a graph-based segmentation process for an object is first separated into two parts, which is Region-of-Interest and non-Region-of-Interest. The prediction is carried out via the compression and decompression phases with two different feed-forwards neural networks (FF-NNs). The suggested approach is evaluated by CLEF med 2009, a database containing more than 15 K of the images in Intel Core i7-4770 CPU@ 3.40GHz, 16 GB of RAM, x64-based processor, using a MATLAB 2010. The research findings show that the suggested approach is designed to compact medical pictures with limited image quality degradation. The suggested solution was found to take 67 s, with an average 8.85 of compression ratio and 41.47 dB of PSNR [28].

M. A. P. Manimekalai and N. A. Vasanthi offer fully automatic skin lesion segmentation technique by through using 19-layer deep convolutional neural networks (CNNs). It is qualified end-to-end and is not based on prior acquittal. Large networks separate the preprocessed image with a gap from Jaccard into a region of interest and a non-region of interest.

During ROI segmentation, the ROI edge is stripped and encoded with the Freeman chain coding. The ROI element is comprised at this stage by hybrid Lempel–Ziv–Welch and clipped histogram equalisation (CHE). The optimal threshold value is chosen in CHE to improve the conservation of brightness using particle swarm optimisation techniques. The non-ROI component is being condensed with the Zero Tree wavelet (EZW) improved. The results are assessed utilising a 94% compression ratio, a 56% peak signal-noise ratio and a 10% mean square error [29].

Asif Shahriyar Sushmit and his crew present method of compression of X-ray images based on the Convolutional Recurrent Neural Networks (RNN-Conv). During deployment, the proposed architecture can produce varying compressive rates, while each network requires training only once for a specific aspect of X-ray images. The model uses a multi-level grouping method that learns contextualised compression features. On the national Chest X-ray8 Health Institute (NIH), they conducted their image compression tests to equate the architectural quality with state of the art RNN technical and JPEG 2000 techniques. The reconstructed images have been shown physically distinct from the original images. They have deficient noise levels that are necessary for the medium-sized processing and distribution of high-quality pictures. The results show that the method of the proposed 0.9509 of Structural Similarity Index (SSIM) and 34.8701 dB of PSNR, which improve compressive performance [11].

Laxmi Prasnna Rani M, Sasibhushana Rao G and Prahakara Rao B have the clinical image compressed using backpropagation neural network with LM training algorithm (BPNNLM) throughout their laboratory analysis. These techniques have been used on CT, brain and chest ray images, as well as on MRI. The performance of these techniques is evaluated based on Peak Signal to Noise Ratio (PSNR), Mean Squared Error and Structural Similarity Index Measurement with 36.6254 of PSNR, 10.6372 of MSE, 0.9675 of SSIM. [30].

4. Discussion

Medical image is a crucial asset for the medical practitioner. The transfer of image data to printed or optical media has become insufficient for current needs. Furthermore, the widespread dissemination and accessibility of image data make sense for an efficient medical ecosystem and exchange between health organisations. While archiving and accessing medical image data is a rather tricky technical problem. Such as the volume of the image, time constraint and privacy regulations to generate public confidence in centralised storage of confidential data, healthcare organisations increasingly depend on their hybrid cloud environments. It is crucial to ensure that all hospital information system transactions and communications are carried out accurately and without loss of data.

The compression of images is a compression method of data, encoding a unique image with fewer bits. The goal of image compression is to reduce the image size from the original image, and the compressed image must be similar to the original image. Here we can develop an idea of the different types of redundancies that need to manage while compressing an image, following different compression techniques and their approach to compressing an image. Each method has the goal of achieving a clear objective. In the success of any medical image compression technique, selecting the type of compression plays an essential role.

Neural Network (NN) is one of the architectures most widely used to compact data processing. NN seems to be well suited for medical image compression, as they can preprocess input patterns with fewer components. Laura et al. proved that NN predominates over traditional methods of handling noisy or incomplete implementations of imagery. The resultant image should provide a high compression ratio and reduce the noise to the compression [31].

New and innovative technologies have been established as image medical technology has evolved. This innovation results in more detailed image characteristics that increase the storage of the image. Nonetheless, higher capacity will reduce transaction performance and take more resources for data sharing purposes. Therefore, for a smart approach that embraces and adapts to current demands, an imaging clinical sharing system is essential. Several experiments to establish intelligent clinical image compression are carried out to satisfy this need. Review of eight previous studies was done to write this article. This research was performed with a neural network approach to intelligent medical image compression. Table 1 shows the summarised of the techniques that have been using by the previous studies.

Table 1 - Summarised of the Previous studies

References	Dataset	Methodology
[24]	knee MRI, Brain MRI and Lungs CT images	Hybrid Discrete Wavelet transform with The Feed Forward Back Propagation Neural Network (FFBNN)
[25]	brain MRI, CT, MRI and PET	hybrid the DWT techniques with BPNN
[26]	MRI of brain image	Fractal Image Compression and Neural Networks
[27]	CT images of lungs	Kohonen's Self Organizing Maps (SOM) parallel to a feed-forward artificial neural
[28]	CT, MRI, X-Ray, Mammogram	Feed-Forward Neural Network-Based Predictive Image Coding for Medical Image Compression.
[29]	MRI-brain, MRI-neuro, MRI-skull full and MRI-tumor images	segmentation technique by leveraging 19-layer deep convolutional neural networks (CNNs),
[11]	Chest X-Ray	Convolutional Recurrent Neural Networks (RNN-Conv)
[30]	CT, MRI of brain image and chest x-ray images	backpropagation neural network with LM training algorithm (BPNNLM)

The method of determining the technique of the appropriate algorithm implementation approach plays an essential role in the overall process of algorithm development for medical image compression. Developers need to be aware of the goals and objectives of the compression implemented. This is because each technique has its advantages and disadvantages. If not adequately considered at the time of design, this can lead to severe failure on compressed image results such as poor quality of output, poor performance, long compression time and wasted storage [32]. The findings of the technique analyses have shown that two approaches can be used in compressing the medical image to incorporate the neural network approach. The first approach is to use the neural network before performing compression during the segmentation process. The second method is the direct use of the neural network when the medical image is compressed. The method taken by each researcher was compiled in Table 2.

Table 2 - Summarised of the Method Selection

References	Approach 1 (Segmentation)	Approach 2 (Compression)
[24]		√
[25]		√
[26]		√
[27]	√	
[28]	√	
[29]	√	
[11]		√
[30]		√

The first method was used by researchers [27]–[29]. Fig.2 is a flow chart for this process implementation. Segmentation is the separation into small pieces of the medical image. The segmentation process involves the neural network method here. The medical image will only be compressed then.

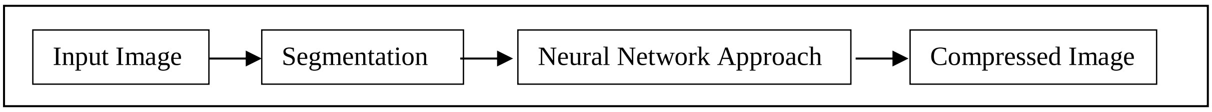

Fig. 2 - Basic Flow of the first approach

Writer [24], [25], [26], [11] and [30] employed the second method. The neural network approach is applied to the medical picture directly. For the application, Fig.3 presents a flow chart of this method.

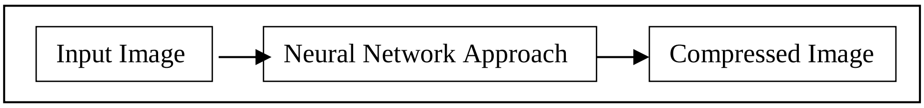

Fig. 3 - Basic Flow of the second approach

We found that the selection of the evaluation technique must be in line with the objective of the studies to get the optimum result of the survey is essential [33]. The CR is used to evaluate the ratio of compression that the proposed technique. The higher the compression ratio, the more effective the compression algorithm will be in the image. MSE and PSNR are used to evaluate the quality of the image. MSE is referring to the noise in the image. At the same time, the PSNR indicates the quality of the compression image compared to the original image [22]. Table 3 summarised the performance analysis of the previous studies. Most researchers prefer to use PSNR as the primary evaluation techniques and compression ratio support. Fig. 4 shows the trend result of the PSNR for neural network approaches intelligent medical image compression by previous studies.

Table 3 - Summarised of the Performance Analysis

References	CR	PSNR	MSE	BPP	SSIM	Time(s)
[24]	4.88	39.82	-	-	-	-
[25]	0.72	64.88	1.67	8.01	-	-
[26]	12.7	35.16	-	-	-	502.35
[27]	-	37.17	13.59	-	-	
[28]	8.85	41.46	-	-	-	67
[29]	0.94	0.56	0.1	-	-	-
[11]	-	34.8701	-	-	0.9509	-
[30]	-	36.6254	10.6372	-	0.9675	-

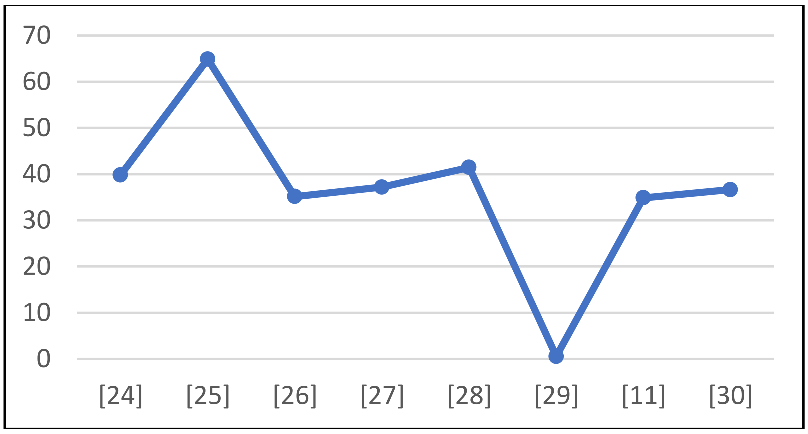

Fig. 4 - The PSNR of the Compression Image Trends by the Previous Studies

The researcher realises the compression algorithm by executing and evaluate using MATLAB. MATLAB widely used by the image processing and computer vision community. MATLAB and the Image Processing Toolbox provides functions and interactive tools for improved and analysing digital images and developing image processing algorithms. The latest version is MATLAB R2020a [34].

Medical science evolution is a gap between medical science and available technologies to support it with a purpose. It is imperative to restore the efficiency of resolution and quality of perception when performing compression in medical images. The massive data with minimal channel capacity for transmission purposes leads to a loss of vital information. Therefore, compression of the medical image performs as an essential research topic about the degree of compression and maintenance of the relevant information [35].

5. Conclusion

The medical image is an essential digital resource in the hospital information system. There are different types of modalities for medical images, such as CT, X-ray, MRI, PET, and SPEC. It was commonly known that the medical image consumes a high volume of size. The medical practitioner demand to share the image to diagnose and analyse the disease with an accurate, secure and fast transition. Therefore, the most challenging issue with sharing medical image is on data storage and network performance. This idea inspired the image processor practitioner to ensure accuracy, protection and quick medical image sharing in compressing the medical image.

This paper focus on This paper discusses the review on intelligent medical image compression algorithms with a neural network approach. Compression is useful as a result of it helps to cut back resource consumption such as disk space and also the bandwidth of network transmission. This paper summarises the comparison of the algorithm and performance. The reconstruct medical image using this technique helps to reduce the size of the image while not degrading the quality of the medical data.

This review paper offers a transparent idea concerning essential compression algorithm. The choice of the analysis technique is additionally essential to confirm that the algorithm achieves optimum performance. The project objective engages the practical demand of compression of medical image procedures and therefore, the evaluation techniques. For this purpose, we manage to make sure that the evaluation techniques got to be in line with the target of the studies. The NN seems to be nicely suited for compression of medical images, as they can preprocess incomplete input pattern and work well with noise. The resulting image should provide a high compression ratio and reduce noise to compression. We conclude that there is two technique to implement a neural network approach in medical image compression, which is in segmentation preprocess and direct in the compression methodology. The selection of performances analysis has to inline with the objective of the studies.

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