ISSN: 0975-3583, 0976-2833 VOL12, ISSUE 02, 2021

Dimensionality Reduction on MRI and CT medical images using Deep Autoencoder

Saravanan.S, Sujitha Juliet.D
Department of Computer science and engineering Karunya Institute of Technology and Sciences, Coimbatore
Saranrulz671@gmail.com, Sujitha.juliet@gmail.com

Abstract :
Medical images play a significant role in diagnosis and experimentation. For years, many experimentation and analysis have been made on medical images with a broad scope of achieving the desired results. Medical modalities like MRI, CT, PET, X-Ray, Ultrasound, etc. are popular in representing internal organ pictures of human bodies. Such volumetric images are stored and accessed with a huge demand in storage space. Compressing the images solves the problem of storage and transmission and also become beneficial for the telemedicine application. Since Medical images depict the human body's detailed and vital information, it needs to be compressed without distorting the details present over it. The lossless image compression approach works efficiently in representing the information present on the medical images without distorting the details. Deep learning neural networks proved to be efficient in analyzing the medical images in recent years. Deep Autoencoder attains to be achieving a higher level in dimensionality reduction with retaining the original quality of the input data. Pretraining of the architecture with the Deep Boltzmann Machines makes the algorithm more efficient to achieve a higher compression ratio with a high PSNR value. Analyzing the Deep autoencoder's performance with the other state of the art architecture proves to be efficient with low computational time.

Keyword: Deep Autoencoder, Medical images, Deep Boltzmann Machine

Introduction:

Deep learning methodology brings a state of art accuracy over the Machine learning method on facilitating identification or any diagnosis application. Due to the advancement of deep learning algorithms, research has identified that deep learning-based algorithms will be implemented on all the state of day-to-day activities over the next few years. On medical image analysis, deep neural networks prove to be efficient in achieving the desired results. An autoencoder is a set of neural networks, which is trained to attempt to copy its input data to the output. Hinton et al [1] proposed the method of dimensionality reduction on data using the deep neural network. PCA [2] (Principal Component Analysis) has been identified to achieve a higher impact on the dimensionality reduction. Restricted Boltzmann Machines used as a pre training architecture proved to be highly efficient in dimensionality reduction than PCA [3]. Linear and non-linear dimensionality reduction detailed in Figure 1 as a comparison of PCA and autoencoder.

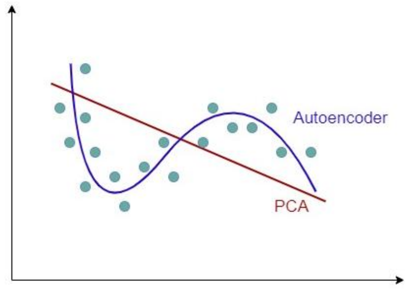

Figure 1. Methodology of PCA and Autoencoder

Autoencoder works on the principle of obtaining the input data values to the output without any huge loss. Figure 2 depicts the sample input data and reconstructed input data obtained from the MNIST dataset. Most of the deep learning analysis research article are examined using the MNIST dataset which is comprised of text data. Autoencoder is a neural network that is trained to copy the input data to its output. It works on internal component such a hidden layer (h) also represented as code. Encoder function (f) represented as h= f(x), where x denotes input data. Decoder function (g) is represented by r=g(h), where r denotes reconstructed data.

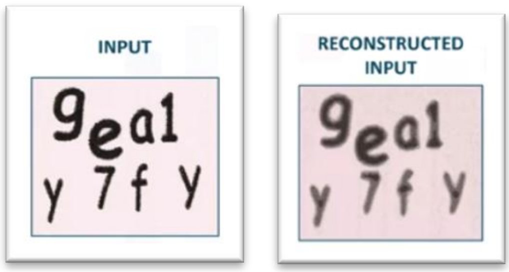

Figure 2. Sample input and Output data using Autoencoder from MNIST dataset

Autoencoder are generally categories as undercomplete and overcomplete autoencoders. Undercomplete is defined as when the number of inputs has a higher dimension than that of the code. And overcomplete is defined as when the input has a less dimension than the code. General structure of the autoencoder is depicted in Figure 3. X denotes the input layer, h denotes the hidden layer and r denotes as reconstructed layer. Autoencoders can learn non-linear continuous, non-intersecting surfaces. Autoencoders are mostly trained in a single hidden layer, multiple hidden layers can be added depends on the type of application. When more than a single layer is implicated it is said as deep autoencoder also called as stacked autoencoder.

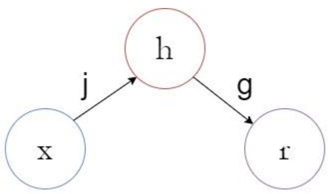

Figure 3. Structure of an Autoencoder

ISSN: 0975-3583, 0976-2833 VOL12, ISSUE 02, 2021

Literature survey:

In different medical imaging modalities, CT and MRI images are highly used in healthcare center. Since several number of algorithms are already proposed for the purpose of medical image compression, retaining the important features on the medical image remains challenging. Transform based image compression methods are widely popular to achieve lossless compression on medical images. DCT [4], DWT [5], JPEG [6] are well known algorithms implemented in the domain of image analysis. Hybrid methods on transforms are also implemented to attain the high efficiency on image compression[7],[8]. Optimization Techniques are involved in the process of threshold variation among images in machine learning algorithms[9],[10]. In Deep learning methodology, Image data are analysed and reconstructed using various neural network architectures. [11] achieves a deep learning-based image compression using learning of transforms with its quantisation method. Multiple transforms are learned on different distortion rate in quantisation to control the loss of data is achieved in this deep learning autoencoder article. In [12], deep autoencoder are used on x-ray images with a pretraining architecture of Deep Boltzmann machine and the resultant output proved to be lossless.

Convolutional Neural network (CNN) are widely used neural network on deep learning architecture. It had played an efficient role in image reconstruction as well with various pre training architectures with an average of 49 dB as a PSNR value[13]. Dense autoencoder are used on low bit rate images, which brings efficient output compared to JPEG and JPEG 2000 [14]. Kai-jian xia et al [15] proposed a Deep convolutional neural network architecture for image fusion methodology which has the image reconstruction processing as well. On evaluating with different data set, DCNN with Stacked autoencoder achieves an efficient image fusion with less computational time. Chuxi yang et al [16] proposed a deep image compression method using discrete wavelet transform for decomposing the high level and low sub-bands. Prediction model is used with the high-level sub bands to attain redundancy. Result outperforms JPEG, JEPG2000 and BPG in terms of MS-SSIM and PSNR. An article proposed with Recurrent convolutional neural network [17] concentrates on X-ray chest images from NIH dataset proved to be efficient on image compression. High PSNR and High SSIM are achieved in comparing with the state-of-the-art other neural network architectures. [18] proposed a convolutional neural network based medical image reconstruction process and achieves a low reconstruction error and low CT.

As an outcome of the literature survey, Convolutional neural network and autoencoders are efficient in the deep learning architecture. On considering the medical images, which needs to be compressed to achieve a low storage space at the same time retaining the diagnostic quality present in the image is also important. Autoencoders and its categories are found to be efficient from the survey for implementing in the lossless compression. Pre-training of the network with a Deep Boltzmann architecture, Restricted Boltzmann architecture and Back propagation architecture is to be determined for implementation with the medical dataset.

Methodology and Experimentation:

MRI and CT Images are collected from Harvard Medical image dataset (http://www.med.harvard.edu/AANLIB/home.html). Sample images considered for experimentation is illustrated in Figure 4. Stacked autoencoder or deep autoencoder basic architecture is depicted in Figure 5.

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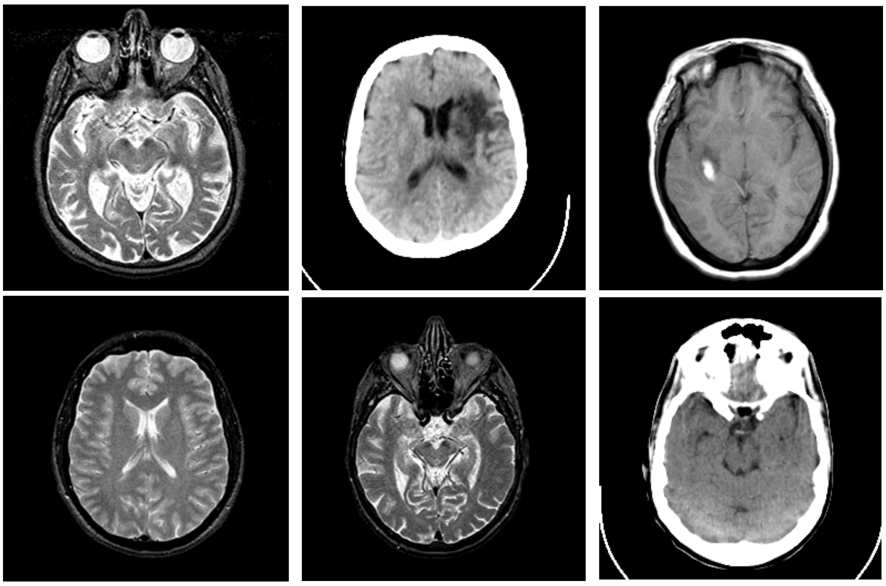

Figure 4. Sample MRI/CT images obtained from Harvard Medical dataset

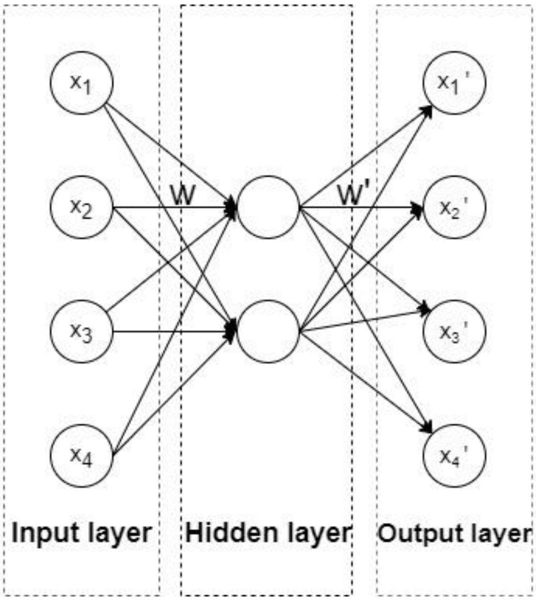

Figure 5. Simple Autoencoder architecture

A simple autoencoder architecture which has a single hidden layer is illustrated in Figure 5. Three major components such as Input layer, hidden layer and output layer comprises to make an autoencoder. Set of Input layer and Hidden layer are called as Encoder and Hidden layer with output layer is named as Decoder. Equation 1 and 2 denotes the process of hidden layer and reconstructed layer.

$$h=f(x) \quad (1)$$

$$r=g(h) \quad (2)$$

To attain the learning process, in order to make the architecture more efficient among the data, the

ISSN: 0975-3583, 0976-2833 VOL12, ISSUE 02, 2021

function is defined in Equation 3.

$$g(f(x))=r \tag{3}$$

Learning process is described by $L(x,g(f(x)))$,as a equation, where L represents the loss function $g(f(x))$ for being divergent from x, represented as Mean Square Error. When multiple hidden layers in autoencoder are added in the architecture, which results in advantage of coding to represent multiple complex and non-linear relations with low computational time. Stacked or Deep autoencoder architecture is depicted in Figure 6. As multiple hidden layer are employed in the architecture with a 2500 neurons to the next hidden layer of 1500 neurons and achieves a code space of 30 neurons. As a resultant decoder part comprises from 30 neurons to the 2500 neurons to retain the input data without any loss.

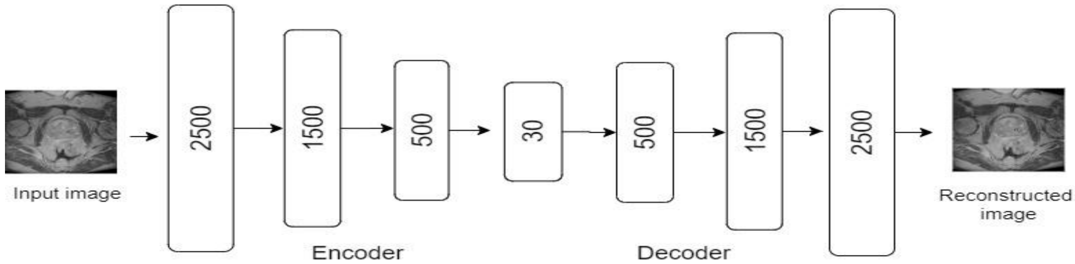

Figure 6. Symmetric view of Deep autoencoder

As a pre-training phase, MRI and CT medical image dataset is trained using the Deep Boltzmann Machine (DBM). DBM is an undirected graphical model with several layers of latent variable /code space. As compared with Restricted Boltzmann machine, the DBM has multiple layers of latent variables / codes. Each of it are mutually independent on the variables with its neighboring layers. And the main advantage of using the DBM contain only binary units, which achieves simplicity of our presentation in the architecture. Equation 4 represents the Joint probability of visible layer (v) with different hidden layers (h1, h2 and h3).

$$P\left(\boldsymbol{v},\boldsymbol{h}^{(1)},\boldsymbol{h}^{(2)},\boldsymbol{h}^{(3)}\right)=\frac{1}{Z(\boldsymbol{\theta})}\exp\left(-E(\boldsymbol{v},\boldsymbol{h}^{(1)},\boldsymbol{h}^{(2)},\boldsymbol{h}^{(3)};\boldsymbol{\theta})\right) \tag{4}$$

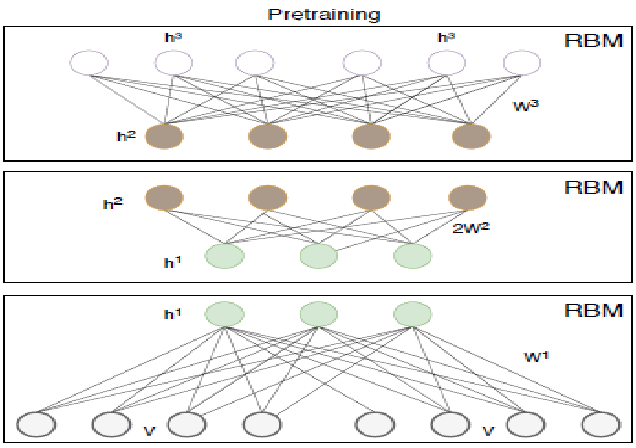

Figure 7. Pre-training of DPM using stacked RBM

ISSN: 0975-3583, 0976-2833 VOL12, ISSUE 02, 2021

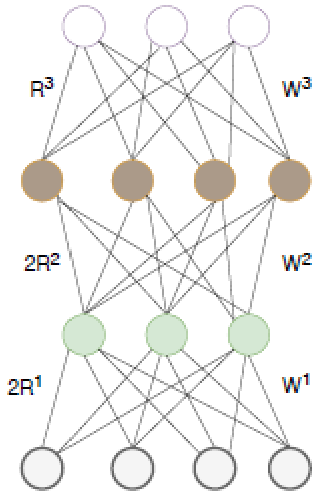

Figure 8. DPM architecture

On experimentation, the proposed Deep autoencoder architecture is tested with 100 epochs and pre-trained using the deep Boltzmann machine. And the method is compared with the Recurrent Neural Network, Deep Belief Network and Convolutional Neural network for obtaining the performances. Performances of the proposed method is compared with the state-of-the-art existing algorithms. Subjective and objective analysis of the experimentation is obtained to find the efficiency of the proposed method. Experimentation results are depicted as graph and tables in the performance analysis section.

Performance analysis:

To analyse the efficiency of the algorithm, compressed images are compared with the input images through performance metrics such as Peak Signal Noise Ratio, Mean Square Error, Compression Ratio, Computational Time and Structured Similarity Index. Compared with MSE, MS-SSIM is the quality evaluation metric that reflects the image quality observed by human eyes, as an output. Multiscale SSIM is the measurement of distortion in training and testing process generally occurs with multi-frame components. Equations for evaluating the different performance metrics are depicts follow.

$$\text{PSNR} = 10 * log_{10}\left({255^2}/{\sqrt{MSE}}\right) \quad (5)$$

$$MSE = \frac{1}{N} \times \sum_i \sum_j \left(f(x,y) - F(x,y)\right)^2 \quad (6)$$

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\delta_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\delta_x^2 + \delta_y^2 + C_2)} \quad (7)$$

$$Compression\ ratio = \frac{Size\ of\ the\ Original\ Image}{Size\ of\ the\ compressed\ image} \quad (8)$$

From the Harvard medical image dataset, the performance is calculated with the different metrics and the values are depicted in table 1. Figure 9 and Figure 10 depicts the comparison of Bits per pixel with PSNR values and Multiscale SSIM.

Rate (BPP)	Deep Autoencoder (proposed)	Recurrent Neural Network	Convolutional Neural network	Deep belief network
0	39.4	36.9	37.1	38.2
0.05	40.2	39.1	36.4	40.2
0.08	40.1	35.0	36.8	39.9
0.1	40.2	35.2	38.3	37.5
0.3	41.3	38.3	40.6	40.2
0.6	41.0	40.7	40.4	39.1
0.8	41.6	35.1	38.2	37.5

Table 1. PSNR value Comparison of existing methods with the Proposed method in BPP

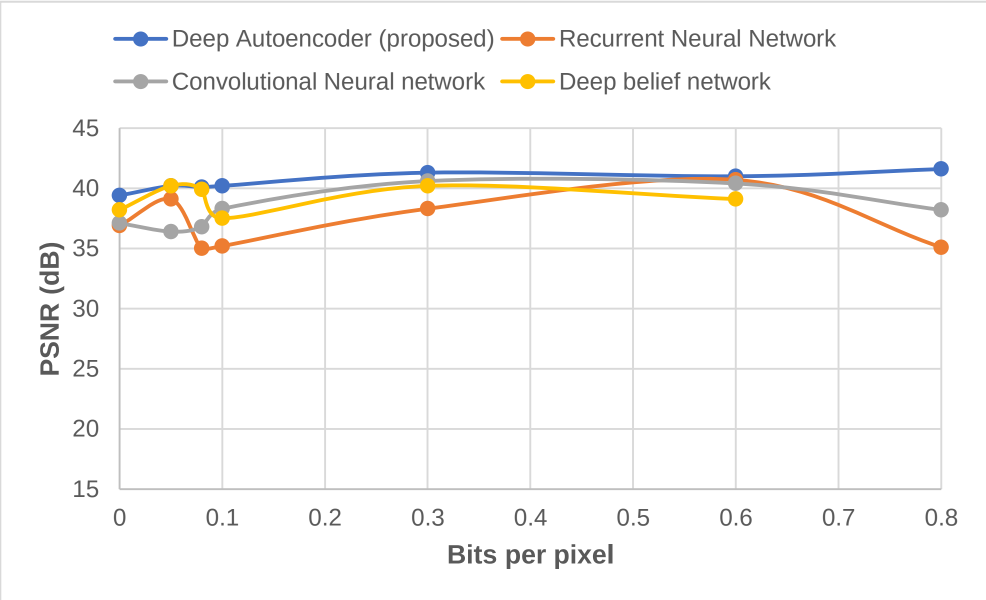

Figure 9. PSNR with BPP – Distortion curve with other methods

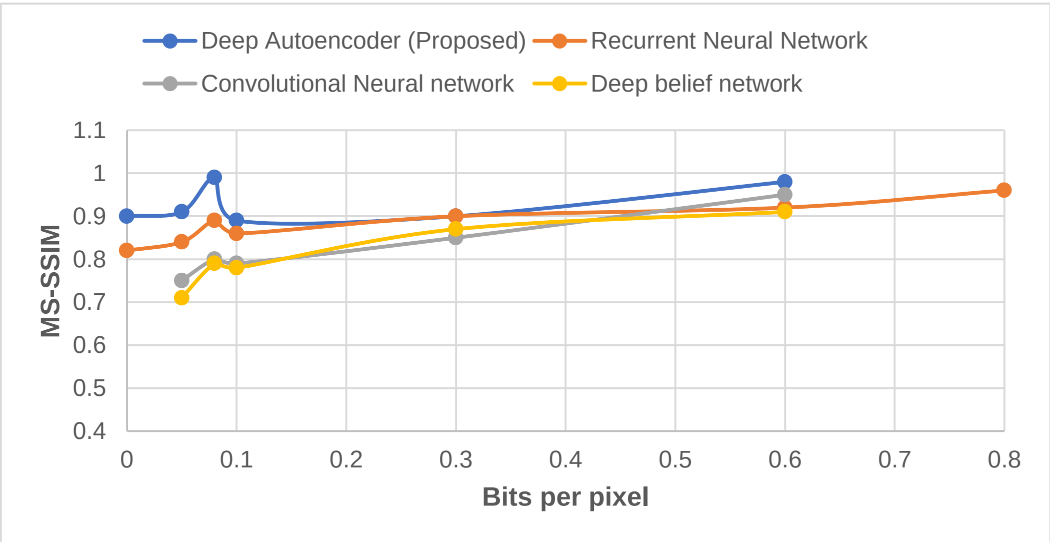

Figure 10. BPP with SSIM – Distortion curve with other methods

Figure 9 and Figure 10 depicts the distortion curve attained with the proposed method in comparing with the other state of the art existing architectures. At a 0.6 BPP, the proposed method achieves a 0.98 SSIM value with a quality less medical image data. Also, the PSNR value of 40dB average is achieved with a lossless compressed data.

Conclusion:

Results obtained from the different performance metrics proves that the proposed method is found to be efficient in achieving lossless compression. From the experimentation and its results, Deep autoencoders or stacked autoencoders achieves a high PSNR rate and High compression ratio without a quality loss. In addition of pre-training with Deep Boltzmann Machines proves to beneficial in training a huge set of medical CT and MRI images. DBM found to be efficient in retaining the structural quality of the medical images. Though the computational time is little high as compared with the transform-based image compression algorithms, compressed medical image quality proves that the proposed Deep autoencoder trained with the DBM are efficient in achieving the lossless image data. As a future a scope, path-based methods with the hybrid transforms can be implemented in order to attain a low computation complexity.

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