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AN IMPLEMENTATION OF DENOISING AUTO-ENCODER BASED DEEP LEARNING APPROACH ON MAGNETIC RESONANCE IMAGING

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Abstract

Now a day's medical images, especially images of internal organs taken by the aid of X-rays, CT scans and MRI need large space for storing and the compression technique need to be introduced to diminish the storage space consumed by cloud. The vital information of the medical images needs to be compressed without distorting details. Also the ubiquitous noise has to be reduced with less computation from the medical images for further processing. Manual reading of a medical report lacks the accuracy of finding exact illness. Various Deep Learning techniques like Convolutional Neural Network, Recurrent Neural Network, Autoencoders and Generative Adversarial Network architectures made the diagnosis easily and accurately. The experiment conducted on denoising on brain tumor dataset using auto encoder is presented in this paper and which can be further used for applications of medical imaging. A tensor flow based frame work is proposed to denoise Magnetic Resonance Image with minimum loss of information.

Keywords: Auto encoder, Generative model, CNN, medical image synthesis, neural network, noise reduction, MRI, Image reconstruction

1. INTRODUCTION

In order to prescribe apt medicine, doctor need exact diagnosis of the illness which is still an extensive area of medical research. MRI scan is mainly used to find out the abnormalities present as it can captures multi planar images and is less costly and low radiation emitting scan than the CT scan. Denoising algorithms such as Total Variation Regularization Algorithm, Non-Local Mean Algorithm, Convolution Denoising Auto Encoders those are focused on neural network are mainly found in the literature. The auto encoder approach seems to be used in denoising medical images. There are so many Deep learning techniques in which work has been done by researchers especially CNN (Convolutional Neural Network), DNN (Deep Neural Network), and RNN (Recurrent Neural Network) as well as two generative models namely Generative Adversarial Networks (GANs) and Variational Auto Encoders (VAEs), that piqued the interest of academics for their smart designs [1,4].

The encoder of the auto encoder framework compresses the input and stored in the latent space of the hidden layer which then decodes to the original. Since it is a lossy compression technique, output does not have the exact representation as the input. The lossy compression can be carried out by the process of mapping, coding, entropy coding and quantization [1-2].

Generative variational auto encoder models are very well suited for reconstructing images similar to the input images and can be used for training the model efficiently. Auto encoder follows self-learning mechanism and analyzes hyper parameters to determine the efficiency and it requires only minimum training data. The loss function of the variational auto encoder consists of a rebuilding component and a regularization parameter. The higher compression rate in such algorithms results in loss of high frequency information and ultimately affects the quality of the restored image [3].

The disadvantages of GAN discovered are nonconvergence, mode collapse, and uncertainty in small dataset and complication in medical picture mode [7]. The alternative generative model, auto encoder plays a tremendous role on image compression than the conventional lossy algorithms both in quantitative as well as qualitative aspects [5]. Iterative optimization process is done out in auto encoder technique where data had been fed in the architecture and compare the output with initial data and then back propogate the error to update the weights of the network. As the latent space is well organized in the training phase, we can take any point and the decoder acts as a generator to get a new content. The continuity and completeness property ensures the regularity of the latent space especially covariance matrix and the distribution mean and intern makes generative process easily [6].

Image synthesis tasks such as reconstruction of images, augmenting data and modality transfer, the systematic analysis or manipulating certain properties of the input data is required as it a key tool for the synthesis. Traditional methods of identifying brain tumors, the significant growth of brain cells, are via Computed Tomography (CT) and depending on professional doctors. It is time-consuming and difficult since the location and size of the tumor vary in different individuals. Therefore, a system that could automatically classify brain tumors based on CT images is necessary to be built. However, the quality of these images could be unsatisfactory because of noises, which could lead to decrease of the accuracy of further medical image analysis, including tumor identification [7-8].

1.1 Types of Auto encoders

Auto encoder can be of two types namely Regularized auto encoder as well as Variational auto encoder. Regularized auto encoders can be further divided into three types such as Sparse auto encoder, Denoising auto encoder and Contractive auto encoder and is represented in figure1 [7-8].

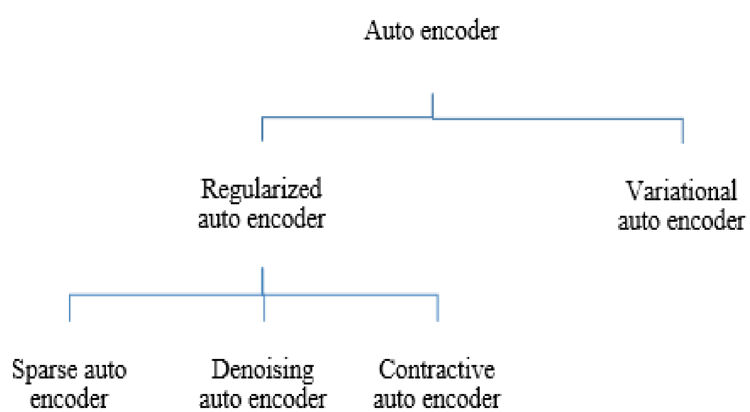

Figure 1: Types of auto encoders

Since it is difficult to build a neural network with a variable number of nodes in its hidden layers, sparse autoencoders penalise the activation of some neurons in those levels. The loss function is penalised in a direct proportion to the number of neurons engaged. The sparsity function prohibits extra neurons from being triggered as a way of regularising the neural network.

Using a denoising autoencoder, we feed a noisy notion into our network and allow it to map the concept onto a lower-dimensional manifold, where noise filtering is much easier to achieve. The bottleneck consists of the encoded information of input image that use to learn the image representation and further it is being decoded in Contractive auto encoder. Auto encoders can be used for image inpainting, information retrieval, anomaly detection and clean up noisy images or audio files.

Classical auto encoders aim to minimize the reconstruction error and are purely deterministic whereas variational auto encoders follows a probabilistic distribution instead of a single value representation. Regularization of encoding distribution is done in the latent space of the VAE to ensure the quality of properties which in turn used for generating new data [9-10].

2. LITERATURE REVIEW

K. Zheng et. al. presented a Vatiational Auto Encoder for conditional image synthesis without a discriminator experimented on MNIST and Fashion-MNIST data sets and quality of image was measured using inception score [11].

Furthermore, image synthesis for MR image has been carried out by Zhou et al. suggested based on a hybrid-fusion GAN model (Hi-Net). Features of each modality has been found out separately and then combines as a generator by taking hierarchical features from each modality thereby perform multi-modal segmentation [12].

Cao and Bing extracts region-wise as well as voxel-wise information using an adversarial confidence learning framework. They did it by converting the encoder into the pixel sensitive discriminator so that it can be used for the reconstruction as well as discrimination purpose [13].

Yurt et. al. proposed a mustGan, a shared feature map with multi-stream approach from many-to-one stream also from multiple one-to-one streams on medical images [14].

Dalmaz et. al. [15] worked on multimodal image synthesis in medical images, a transformer-based generator named ResViT (residual vision transformers) using conditional deep adversarial network on MRI and MRI-CT datasets preserving local and contextual sensitivity.

Ozbey et. al. [16] experimented on image synthesize problem with the help of conditional adversarial diffusion model and tries to learn correlation of the image distribution.

Thomas et. al. created a denoising convolutional autoencoder, the unsupervised artificial neural network-based technique for the reconstruction of low noisy fetal movement signals of 75 images. They used two convolutional layers for both encoder and decoder using Tensor flow libraries with 30 epochs [17].

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Bodapati et. al. [18] presented an end-to –end trainable CNN with Xception network to recognize tumor using MRI dataset. They used Sparse Convolutional Denoising Auto encoder for dimensionality reduction on three types of datasets such as brain tumor dataset, Br35H and dataset from Figshare repository.

3. METHODOLOGY

A denoising auto encoder methodology that focuses on reducing noise through identity mapping is applied in this experiment which has two important parts namely encoder and decoder. An auto encoder's fundamental principle is that high-dimensional data has been encoded into a latent vector space of low-dimension and then reconstruct the input data as accurately as possible. Input volume x has been mapped by the encoder to a compressed latent space and further reconstruction process has been carried out with minimum noise through decoder. Encoder part consists four convolutional layers with number of filters as 32, 64, 128 and 128 respectively. Except for the final transpose convolutional layer, which utilizes sigmoid activation function and all other convolutional layers uses Rectified Linear Units (ReLus) and it is analyzed using Tensor flow libraries. Figure 2 shows the pictorial representation of the architecture of the proposed denoising auto encoder. The MaxPooling layer used in the encoder and the UpSampling2D is of window size 2 x 2 and all the kernals are of size 3 x 3.

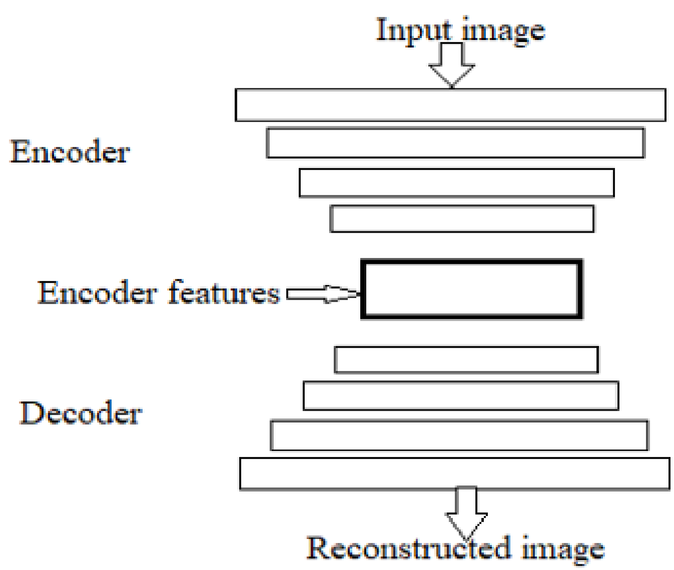

Figure 2: Architecture of denoising auto encoder

In this paper, the back propagation algorithm employed is RMSprop, and the loss function is mean squared error. MaxPooling 2D is used in encoder part and UpSampling2D in decoder section. 80% of the data is used for training and the remaining 20% for testing. Table 1 shows the parameters employed, types of the layers used in the proposed model and the output shape got after each layer.

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Table 1: Layer types, output shape obtained and parameters trained for the proposed model

Layer Type	Output Shape	Param
Input Layer	(None,224,224,3)	0
Convolutional Layer	(None, 224,224,32)	896
Maxpooling Layer	(None, 112,112,32)	0
Convolutional Layer	(None, 112,112,64)	18496
Maxpooling Layer	(None,56,56,64)	0
Convolutional Layer	(None,56,56,128)	73856
Maxpooling Layer	(None,28,28,128)	0
Convolutional Layer	(None,28,28,128)	147584
Convolutional Layer	(None,28,28,128)	147584
UpSampling2D	(None,56,56,128)	0
Convolutional Layer	(None,56,56,128)	147584
UpSampling2D	(None, 112,112,128)	0
Convolutional Layer	(None, 112,112,64)	73792
UpSampling2D	(None, 224,224,64)	0
Convolutional Layer	(None,224,224,3)	1731

The brain tumor dataset consists of 253 color images and initially resized it of size 224x224. The experiment was carried out on 200 epochs. The training and validation loss is depicted in the figure3. Figure4 represents sample test image and Figure5 shows the reconstruction of test image.

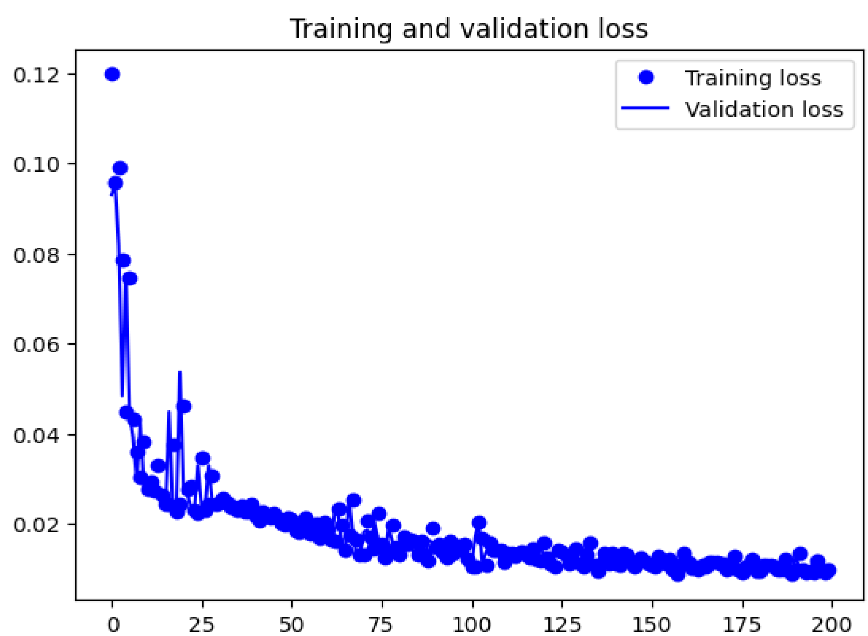

Figure 3: Training and validation loss obtained after 200 epochs

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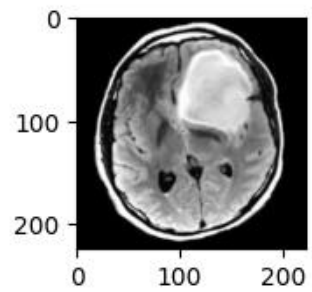

Figure 4: Sample Test Image

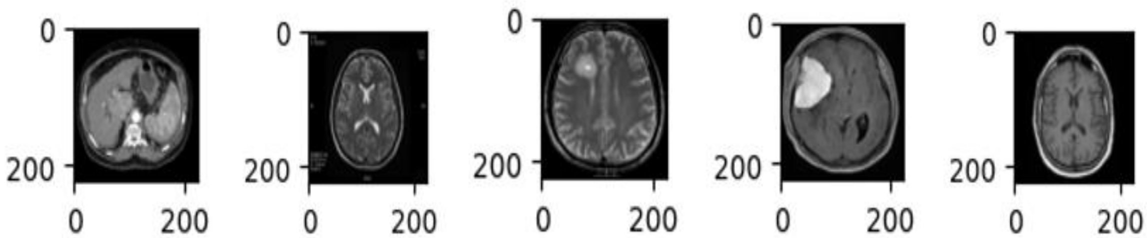

Figure 5: Reconstructon of test image

4. CONCLUSION

Image denoising is an important part in the case of medical images. Autoencoder (AE) is an end-to-end learning system that combines an encoder and a decoder to compactly represent and accurately replicate the original input signal. AE's objective is to improve the semantically effective and adequate encoded representation to have the decoder of the input signal reproduce it. The corruption and reconstruction processes used by denoising autoencoders (DAEs) enable to produce clear and reliable samples from noisy inputs. After pre-processing of denoising images, it can be further used for classification. Appropriate metrics for conditional synthesis still remain to be studied.

References

1) Selvi, C. Thirumarai, J. Amudha, and R. Sudhakar. "Medical image encryption and compression by adaptive sigma filterized synorr certificateless signcryptive Levenshtein entropy-coding-based deep neural learning." Multimedia Systems (2021): 1-16.

2) Jeromel, Aljaž, and Borut Žalik. "An efficient lossy cartoon image compression method." Multimedia Tools and Applications 79.1-2 (2020): 433-451.

3) Khalid, Beenish, et al. "EEG compression using motion compensated temporal filtering and wavelet based subband coding." IEEE Access 8 (2020): 102502-102511.

4) Pareek, Piyush Kumar, et al. "IntOPMICM: intelligent medical image size reduction model." Journal of Healthcare Engineering 2022 (2022).

5) Tina, S. K. Dubey and A. K. Bhatt, "Implementation of Autoencoder for Super Resolution of 3D MRI Imaging using Convolution Neural Network," *2022 12th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, Noida, India, 2022, pp. 398-404, doi: 10.1109/Confluence52989.2022.9734118.

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6) K. Palanisamy, "Wavelet based Convolutional Autoencoder for Medical Image Compression," *2023 International Conference on Intelligent Systems for Communication, IoT and Security (ICISCoIS)*, Coimbatore, India, 2023, pp. 83-88, doi: 10.1109/ICISCoIS56541.2023.10100599.

7) Diamantis, Dimitrios E., Panagiota Gatoula, and Dimitris K. Iakovidis. "EndoVAE: Generating Endoscopic Images with a Variational Autoencoder." 2022 IEEE 14th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP). IEEE, 2022.

8) Nasrin, Shamima, et al. "Medical image denoising with recurrent residual u-net (r2u-net) base auto-encoder." 2019 IEEE National Aerospace and Electronics Conference (NAECON). IEEE, 2019.

9) Jifara, Worku, et al. "Medical image denoising using convolutional neural network: a residual learning approach." The Journal of Supercomputing 75 (2019): 704-718.

10) Nawarathne, Thoshara, et al. "Comprehensive Study on Denoising of Medical Images Utilizing Neural Network-Based Autoencoder." Advanced Computational Paradigms and Hybrid Intelligent Computing: Proceedings of ICACCP 2021. Springer Singapore, 2022.

11) K. Zheng, Y. Cheng, X. Kang, H. Yao and T. Tian, "Conditional Introspective Variational Autoencoder for Image Synthesis," in *IEEE Access*, vol. 8, pp. 153905-153913, 2020, doi: 10.1109/ACCESS.2020.3018228.

12) Zhou, Tao, et al. "Hi-net: hybrid-fusion network for multi-modal MR image synthesis." IEEE transactions on medical imaging 39.9 (2020): 2772-2781.

13) Cao, Bing, et al. "Auto Encoder-Driven Multimodal Collaborative Learning for Medical Image Synthesis." International Journal of Computer Vision (2023): 1-20.

14) Yurt, Mahmut, et al. "mustGAN: multi-stream generative adversarial networks for MR image synthesis." Medical image analysis 70 (2021): 101944.

15) Dalmaz, Onat, Mahmut Yurt, and Tolga Çukur. "ResViT: Residual vision transformers for multimodal medical image synthesis." IEEE Transactions on Medical Imaging 41.10 (2022): 2598-2614.

16) Özbey, Muzaffer, et al. "Unsupervised medical image translation with adversarial diffusion models." IEEE Transactions on Medical Imaging (2023).

17) Thomas, Jintu Merin. "Bio-medical Image Denoising using Autoencoders." 2022 Second International Conference on Next Generation Intelligent Systems (ICNGIS). IEEE, 2022.

18) Bodapati, Jyostna Devi, and Bharadwaj Bagepalli Balaji. "TumorAwareNet: Deep representation learning with attention based sparse convolutional denoising autoencoder for brain tumor recognition." Multimedia Tools and Applications (2023): 1-19.