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Evaluation of Deep Learning in Medical Image Processing – A Methodical Review

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ABSTRACT

State of the art in medical image fusions are extensively deliberated and spatial resolutions are still a biggest challenge as it has constraints including time taken for acquiring images, insufficient irradiation dose and limitations of hardware. This review focuses on advancements in technologies used for acquiring images from various modalities and Management strategies on medical data in big data analytics using AI. Then it covers the emerging techniques used in classifications and segmentation for diseases and organs or tissues respectively using AI and Deep Learning (DL) frameworks. Now days, DL becomes a successful technology and it is mandatory to cover the current trends in DL especially in super resolution of medical imaging. This work provides the introduction of DL methodologies followed by notable DL techniques for solving problems like super resolutions. Then it provides the DL applications in medical imaging for solving high resolution problems and its challenges are presented.

KEYWORDS: Deep Learning, Medical Image, Data Analytics, Image Fusion, Modality

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1. HIGH MEDICAL IMAGE RESOLUTIONS

Super resolution in medical images refers the techniques used to increase the spatial resolutions of numerical or digital images. Generally, Super Resolution Techniques (SRT) are categorized based on the process of input and output images[1]. Here, SIHR (Single Image High Resolution) technique which recovers super resolution medical image from low-resolution medical images. Imposture problems and optimizing techniques used to solve these problems are proposed with the help of machine learning techniques like Deep learning as well as Dictionary Learning[2].

Deep Learning Techniques (DLT) are emerging nowadays in medical image processing era. Reconstructing images, HD resolution, Segmentation, De-noising etc. are the notable fields which achieves tremendous progress in DLT[3]. DLTs are proposed to solve challenges to attain HD Resolution from natural source image data sets. From then, n number of DLTs were proposed and investigated widely in medical image processing[4]. HD resolution medical images requires additional significant data than natural source images comparatively. Preserving significant information of an image and enhancing the features of structures are considered as the main challenges. Medical image datasets are small and it's tough to collect for low as well as high resolution medical images[5].

The main agenda of this article is to concentrate DLTs for HDR (High Definition Resolution) problems in Medical Image Processing (MIP)[6]. The various techniques and approaches in DL for HDR medical images on natural source images are concentrated followed by the applications of DLT in MIP. At the end of this article, how data scarcity and integration of priors are resolved and discussed.

2. DL-A SHORT NOTE

In MIP like de-noising, classification and segmentation, DLTs are promising solutions and parallel calculations and ability to represent powerful are considered as important features than other techniques[7]. In parallel calculations, the end user has benefited without having knowledge of low level GPU programming and architecture. DLTs performance are based on the quantity of data. We can get the high efficient result in a huge amount of data[8].

2.1 Deep Learning Network (DLN)

DLN is a multilayers based neuron network. Input and output layers are considered as first and layer and in between first and last layers are considered as hidden layers. Each neuron consists of point activation functions based on point-wise preceded with linear transformation. In linear transformation, each neuron is connected with all the neuron along with its weight and index[9].

Whereas in activation functions, it is necessary for the network as it produce nonlinear factors. This function resolves values of negative as well as non-negative along with various degrees.

2.4 Convolutional Neural Network (CNN)

This one consents network to discover the identical feature in image with various regions. Single layer in CNN discovers the native image features and multilayer rises the perception area and produces features extracted from the preceding layers[10]. In this network, it reduces the weight as it shares between neurons and leads to minimal requirements of memory.

2.4 Network Optimizations (NO)

The parameters like weights are optimized through minimizing loss function which varies with its types of task. Over-fitting or inject priors limitations are reduced by integrating regularization with loss function. The forward propagation is used to compute the loss function value. Similarly, the back propagation used to detect the loss function gradients based on parameters. Stochastic gradient-descent is a technique which increases back propagation by handling small amount of dataset. The optimized parameters are obtained by progressive pass and recessive pass[11]. The network capacity is denoted by 'bias' which equalizes the risk on training dataset. The 'variance' computes the generalization capacity on test dataset. The bias should be directly proportional to the variance size in the large network size.

2.4 Regularization Methods (RM)

DNN (Deep Neural Network) computes from the relationship between I/O and the capacity of the architecture model. The overfitting issues are overcome by the regularizing the network capacity and capacity reduction is possible by modifying its architecture. While training process, some neurons can be called off randomly[12]. Dropout is considered as average equally or shared weight in many models. The inner covariate-shift is reduced by normalizing batch layers which is used widely for High Definition Resolution models. Loss function is the another technique to reduce the network volume[13].

2.5 Generative-Adversarial networks (GAN)

GANs are based on producer and discriminator network. The n number of GAN methods are proposed to meet the outcome of old-fashioned CNN. The producer produces forged images to spot the discriminator during the output generated from the real data. The Wasserteingan (WGAN) technique is proposed based on the distance and weight extraction[14]. Gradient extraction and spectral neutralization are the other techniques have been proposed for GAN.

3. DL IN HD RESOLUTION

3.1 Single Image Vs Multiple Image HDR

High Definition methods can be classified as single and multiple image. The main goal is to create a High definition image from either single or multiple natural source images. Multiple Image HDR is defined based on the image fusion. In multiple image techniques, the geometric regions are utilized for reconstructing accurate HDR medical images[15]. DLTs improves the performances of single image HDR method and considered as evolutionary techniques.

3.2 Assessment Metrics and Loss Functions

The reconstruction assessment metrics are used for loss function and the PSNR is the widely used parameter for measuring the quality of a medical image[16].

The PSNR is calculated as $PSNR = 10.log10\left(\frac{p^2}{\frac{1}{m}\sum_{i=1}^{m}(T(i)-\hat{R}(i))^2}\right)$ →(1)

Where, p is maximum value of pixel, m is the number of pixels and R is the source image and $\hat{R}$ is the reconstruction[17]. The peak signal to noise ratio is computationally related to the MSE (Mean Square Error) and produces the data about the variance at the pixel level. These losses lead to poor performance which represents the inaccurate quality reconstruction in target images. The SSI (Structural Similarity-Index) is the another parameter to evaluate the quality of medical image which represents the humanoid visual system. This SSI is based on Structures, Contrast and luminance[18].

3.3 Up-Sampling Function

There are n number of ways in order to upscale images. The bicubic technique is proposed to interpolate low definition images in convolutional layer. The parameters are fixed in this layer. The up-scaling function is determined with a convolution layer where the metrics are updated during network optimization[19]. Transpose convolution technique is flexible for upscaling low definition resolution medical images. The network efficiency may reduce if the up-scaling low definition resolution images at the starting layer of the network.

3.4 Resnet Merging New Up-Sampling

The EDSR (Enhanced Deep Residual Networks) is proposed to utilize the residual block to enrich the structural details at low-resolution definition scale. In this technique, the batch normalization is removed and constant scaling layer is introduced. The elimination of batch normalization decreases memory usage and retains the regions flexibility[20]. Deep Laplacian Pyramid-Network is an another technique used for high definition resolution problems. It has two partitions. One is for extracting features and another partitions for reconstruction[21]. In order to learn the residual features, the bilinear kernel is proposed in deconvolution layers in the reconstruction part. Low frequency information is responsible for reconstruction part and feature extraction part enhances the significant details and provides high definition resolution frequency data to the reconstruction part.

Table No. 1: "Comparison of PSNR parameter with various techniques for natural dataset Set 3 and Set 12"

Methods	Set 3	Set 12
DRRN	32.15	29.34
DRCN	33.12	28.45
SRCNN	31.72	29.61
FSRCNN	32.58	26.78
LAPSRN	31.79	27.91
SRGAN	28.74	31.24
VDSN	30.33	30.02
EDSR	32.25	29.69
RDN	33.32	28.73
ESPCN	30.34	29.68

The Table No. 1 depicts the comparison of various techniques and the parameter is PSNR for natural dataset Set 3 and Set 12. Here, the low definition resolution images are produced with BI poverty technique. The up-scaling factor is considered as 3. The above table results are gathered from correspondent publications.

4. DISCUSSION

DLTs are massive field in MIP like registration, classification, segmentation etc. In the development process of DLTs for High Definition Resolution, researchers especially in MIP have given new architectures and models for betterment of performances. High eminence references and image constraints are the two bottlenecks issues in DLTs. The choices of appropriate pre-processing are also essential for some specific modality. Data augmentation is a utilized in order to increase the dataset. Augmented Convolutional Data comprises changing brightness, flipping, translation, modifying colors, rotation, gamma transformation, adding additive-noises and etc. This augmented data is a dominant tool for small dataset and it has consistent medical applications. Both source image datasets and medical images set need pre-processing to improve the performance of high definition resolution technique.

5. CONCLUSION

From the above, the state of the art of DLTs for High Definition Resolution Images are presented along with its applications and development process for medical images. The data paucity and pre-processing are the main challenges focused here. DLTs shows highest potentials to resolve High Definition Resolution medical images and becomes proves its promising functionalities.

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