Synthetic Vertebral Column Fracture Image Generation by Deep Convolution Generative Adversarial Networks

Sindhura D N
Department of Information and Communication Technology
Manipal Institute of Technology
Manipal Academy Of Higher Education,Manipal,India
sindhura.dn@gmail.com
https://orcid.org/0000-0001-9358-9165

Radhika M Pai
Department of Information and Communication Technology
Manipal Institute of Technology
Manipal Academy Of Higher Education,Manipal,India
radhika.pai@manipal.edu
https://orcid.org/0000-0002-0916-0495

Shyamasunder N Bhat
Department of Orthopaeadics
Kasturba Medical College
Manipal Academy Of Higher Education,Manipal,India
shyambhat.n@manipal.edu
https://orcid.org/0000-0001-9545-4838

Manohara Pai M M
Department of Information and Communication Technology
Manipal Institute of Technology
Manipal Academy Of Higher Education,Manipal,India
mmm.pai@manipal.edu
https://orcid.org/0000-0003-2164-2945

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***Abstract*— In the field of medical imaging, the challenging objective is to generate synthetic, realistic images which resembles the original images. The generated synthetic images would enhance the accuracy of the computer-assisted classification, Decision Support System, which aid the doctor in diagnosis of diseases. The Generative Adversarial Networks (GANs), is a method of data augmentation which can be used to generate synthetic realistic looking images, however low quality images are generated. For AI models, it is challenging tasks to do classification using this low quality images. In this work, generation of high quality synthetic medical image using Deep Convolutional Generative Adversarial Networks (DCGANs) is presented. Data augmentation method by DCGANs is illustrated on the limited dataset of CT (Computed Tomography) images of vertebral column fracture. A total of 340 CT scan images were taken for the study, which comprises of complete burst fracture scans of vertebral column. The evaluation of the generated images was done with Visual Turing Test.**

Keywords*— *Deep Convolutional Generative Adversarial Network, data augmentation, Image synthesis, vertebral column fracture, computed tomography, AI models, Visual Turing Test.

I. Introduction

Now a days, the AI models specially the deep learning models have made remarkable advancement in the discriminative tasks. For object detection, image segmentation, image classification task of computer vision the deep neural networks have been applied successfully[1]. The success of Convolutional Neural Networks has increased the interest in applying deep learning in the computer vision applications. To avoid overfitting, to perform well, deep convolutional neural networks require large dataset. Numerous applications such as medical image classification and analysis do not have access to large data which leads to overfitting of the model. Data augmentation is the solution for the problem of limited dataset. Data augmentation increases the size of the training dataset and hence avoid the overfitting of the deep learning models.

Deep learning applications development is a challenge in medical domain because of the limited data set availability. Collecting the large datasets is very difficult task because of the effort of collection, labelling the data, due to the rarity of patient with same type of disease, and requirement of the doctors for labelling/annotation of the data. Class imbalance is another problem in medical field. So data augmentation is needed in medical applications also. The color space augmentation, mixing images, geometric transformations, random erasing, adversarial training, Generative Adversarial Networks are different methods of image augmentation[2][3]. Medical images are high quality images which shows the clear view of internal organs such as lungs, heart, brain, kidneys, soft tissues, bones, etc. Different medical imaging modalities like magnetic resonance imaging (MRI), ultrasonography, X-Rays, computed tomography (CT), are used for image acquisition. Now a days, the augmentation that is used more for these high quality CT, ultrasound, MRI, X-Ray images is Generative Adversarial Networks.

The Generative Adversarial Networks(GANs) understand the good representations of all images for generative modelling. The GAN is a member of generative models[4]. The GAN comprises of two neural networks, generative network that takes random noise as input and returns the image that should resemble the target distribution and the discriminator network that takes generated image and real image as input and classify the generated images as real or not. Different research work has been conducted that alter the GAN architecture through evolutionary methods, loss functions, network architectures, etc. These modifications to the GAN has remarkably increased the quality, resolution of images generated by the GANs. Amongst Progressively Growing GANs (PGGANs), Deep convolutional GANs (DCGANs)[5], Wasserstein GANs (WGANs), appear to be potential methods of medical data augmentation.

Road accident, fall from height, sports causes vertebral column fracture. Use of AI models for classification of vertebral column fracture can aid the doctors in deciding the type of fracture quickly. Hence doctor can provide early treatment to the patient. But availability of such large vertebral column fracture images of same type of fracture is very difficult. So in this research work Deep Convolutional GANs are implemented for the generation of realistic fractured vertebral column images. The augmented data generated from the present work can be used for the development of deep learning model for the classification of vertebral column fractures. The DCGAN architecture uses convolutional neural networks for the generator network and discriminator network.

Thus, main aim of this work is to generate the vertebral column fracture images using DCGAN. The rest of research paper is organized as follows, literature review regarding GAN and DCGAN is given in Section II, followed by Data Collection and Architecture of DCGAN in Section III and IV respectively. Section V presents the Result and discussion, and conclusion is given in the Section VI.

II. LITERATURE REVIEW

The Generative Adversarial Networks were introduced in the year 2014 for synthesis of images[4]. Several works on GAN architecture extensions such as DCGANs[5], PGGANs[6], CycleGANs[7] were developed in the year 2015, 2017, and 2017, respectively. Using AI for the medical image classification became a popular application of Convolutional Neural Networks.

Yi et al.[8] conducted a survey of using GANs in medical imaging. In the survey, different GANs architectures used for high resolution image synthesis, texture synthesis, image translation, face synthesis were discussed. Alec Radford et. al.[5] developed DCGAN architecture which is modified CNN architecture. DCGAN can be effectively used for all type of image generation.

MaayanFrid-Adar et al.[9] developed system for classification of liver lesion using convolutional neural network. 2D CT images were used in the classification.182 CT images were taken for study in which 53 cysts, 64 metastases, 65 hemangiomas images were present. They used Deep Convolutional Generative Adversarial Networks to generate synthetic liver lesion images. This augmented data was given as input to CNN which classify the images into three Cysts, Metastases and Haemangioma classes. With traditional and GAN augmentation accuracy of the classifier was 78.5% and 85.7% respectively. So to increase the performance of classification of medical image DCGAN can be used for data augmentation.

Changhee H et. al. [10] developed a system which generates the multi sequence MRI for classification. Initially authors have used Traditional Geometric transformation to generate synthetic images. But the generated images were intrinsically almost same as the original images and hence there was no much performance improvement of the classification system. So authors have used Generative Adversarial Networks to generate multi sequence synthetic images. Brain Tumor Image Segmentation Benchmark (BRATS-220 cases) was taken as dataset. Both Deep Convolution GAN (DCGAN) and Wasserstein GAN (WGAN) were implemented for data augmentation.

ChristophBaur et. al. [11] generated synthetic skin lesions using PGGAN (Progressive Growing GAN). The dataset consists of images with benign and malignant lesions of skin. The synthetic skin lesion obtained can be used for segmentation as well as classification applications. This work exhibits that, PGGAN and DCGAN generates realistic skin lesion images, and are difficult to distinguish from the original images by the experts also. So DCGAN and PGGAN augmentation can be used for vertebral column classification also. From the literature review it is evident that the DCGAN can be effectively used to generate the medical images from different imaging modalities like CT, X-Ray, MRI, Ultrasound scan, etc.,

III. DATA COLLECTION

The anonymised CT images of vertebral column fracture were collected from Kasturba Medical College, MAHE, Manipal, India. Current study is a retrospective study. The CT scans of male and female patients in the age group 18 - 60 with vertebral column fracture between C3 - L5, who were admitted between 2017 to 2020 are considered for the study. Total of 340 CT images are taken. All the images are complete burst fracture (A4 fracture) images of vertebral column.

IV. ARCHITECTURE

The DCGANs (Deep Convolutional Generative Adversarial Networks) [5] is one of variant of Generative adversarial networks with unsupervised learning. DCGANs includes the convolutional architecture. The generator network makes use of up-convolutions with ReLu (Rectified Linear Unit) in between, and batch-normalization. Consider p_{data} be the distribution of the data **x**. Here, Generator network $G(Z, \theta_g)$ maps the input noise variable Z from the distribution P_z to data space $P_g(x)$,where (G) generator model is a neural network and θ_g are parameters of the generator. In the same way, discriminator network $D(X, \theta_d)$ is also a neural network comprising of parameter $\theta_d$which takes real data and generated synthetic data as input and gives single scalar probability value as output. The discriminator network D tries to maximize chances of predicting the correct classes and generator network tries to minimize which is called "minmax" game depicted by the equation (1).

$$\boldsymbol{G_{min} D_{max}} \ \mathbf{V(G,D)} = \boldsymbol{E_{x \sim p_{data}}}\left[\ln\left(\boldsymbol{D}(\boldsymbol{x})\right)\right] + \boldsymbol{E_{z \sim P_z}}\left[\ln\left(\mathbf{1} - \boldsymbol{D}(\boldsymbol{G}(\boldsymbol{Z}))\right)\right] \quad \mathbf{(1)}$$

Convolutional layers extract most precise, detailed features form the images and hence spatial structure of the images are preserved. So modifications to the CNN architecture was done in DCGAN which includes, i) Instead of maxpooling, use of upsampling and downsampling in the generator and discriminator networks, ii) Since the generator does not perform the classification, fully connected layers are removed from the top of convolution in the generator, iii) batch normalization is used which normalizes the input to have unit variance and zero mean, which stabilizes the training process, iv) In input layer of the discriminator and last layer of the generator batch normalization is not used to avoid model instability, v) In all the layers of generator, *ReLU* activation function is used and in the output layer of the generator the *tanh* activation is used. The symmetry of *tanh* activation function permit the model to learn quickly and to cover color space of the training distribution. In discriminator, *leaky relu* is used which is contrast to GAN [4]which used *maxout* activation, vi) Mini batch stochastic gradient is used for training the model.

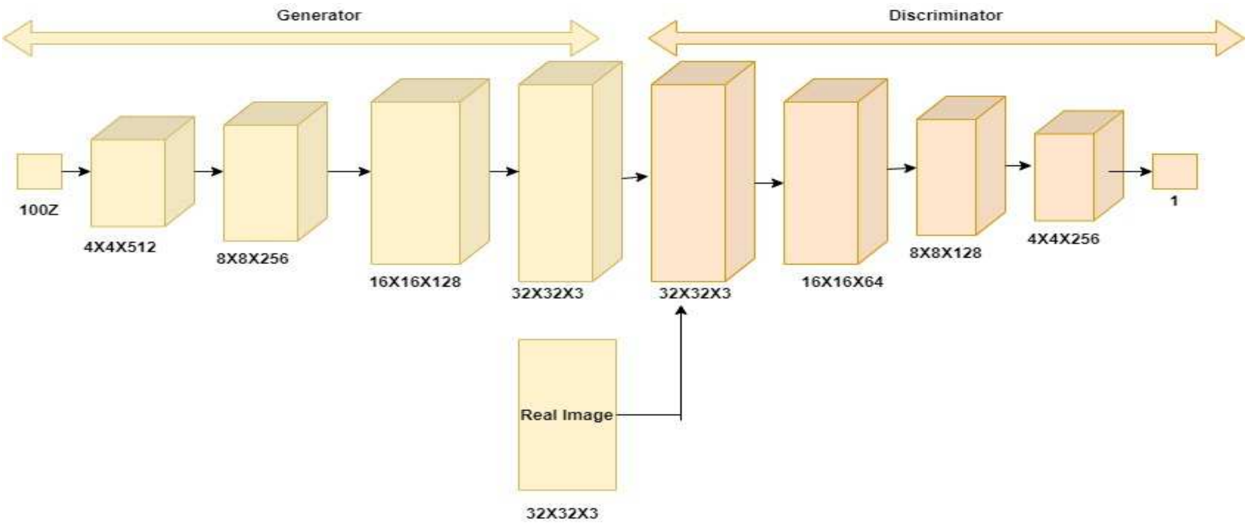

Fig. 1. Generator and Discriminator architecture of DCGAN

The architecture of generator and discriminator is as shown in the Fig 1. Implemented generator takes 100 random number vector from uniform distribution of noise as input and comprises of four convolution layers with ReLU activation for all layers, tanh activation for output layer and batch normalization. The discriminator comprises of four layers with leaky ReLU activation. The ROI is manually cropped and it is resized to 32X32 and given for training. The network is trained to generate complete burst fracture samples. Batch size of 10, learning rate of 0.0002, 1000 epochs were used for generation of samples. Adam optimizer is used. The training of the model was performed by making use of NVIDIA GeForce GTX1650 GPU.

V. RESULT AND DISCUSSIONS

Fig. 2 shows the Complete burst fracture images given as input to DCGAN and Fig. 3 shows the instances of vertebral column fracture synthetic images generated by DCGAN. The realism of generated synthetic vertebral column images was evaluated by an orthopaedician.

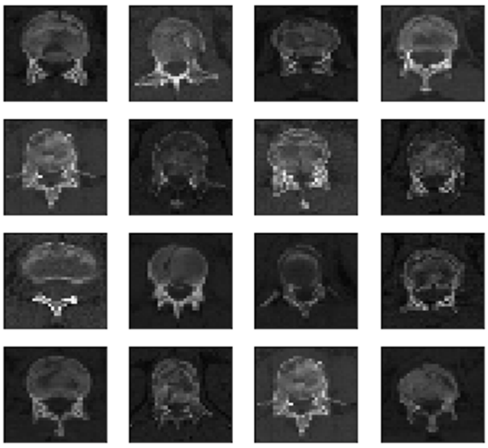

Fig. 2. Input images of Complete Burst Fracture to DCGAN

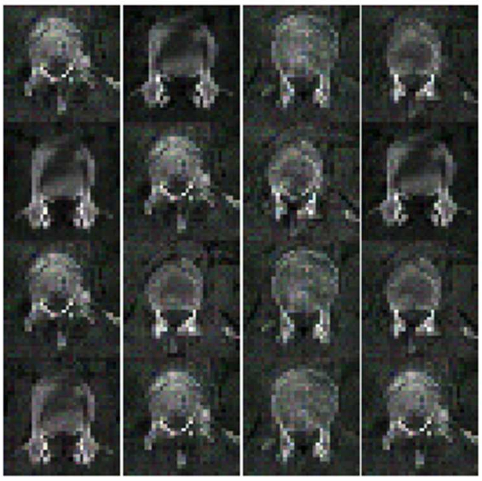

Fig. 3. DCGAN generated Complete Burst Fracture Images

To evaluate the quality of generated vertebral column fracture image, Visual Turing Test (VTT) was done. VTT is generally used to evaluate the computer vision system and GAN generated images[12] for clinical validation. Here in this work VTT was conducted with an orthopaedician. The generated CT images of A4 fracture which is also called as complete burst injury according to the AO classification of the spine was evaluated. The images do not comprise of information of the patients, type of fracture details, and background. The orthopaedician was permitted to change the view point, or zoom in – zoom out as necessary. The VTT comprises, total of 68 images in which 36 images were real and 32 images were high quality DCGAN generated CT A4 fracture images. The orthopaedician was told that images presented contain real as well as generated images. For the conducted VTT the confusion matrix is as shown in the Table 1. As we know accuracy can be calculated by the formula

$$\frac{(\text{True positive} + \text{True Negative})}{(\text{True positive} + \text{True Negative} + \text{False positive} + \text{False Negative})} \quad \textbf{(2)}$$

Accuracy value around 50% indicates superior quality fractured images are generated[10] and is even difficult and challenging for the orthopaedician in discriminating real and high quality generated images. In TABLE 1, R as R indicate Real images identified as Real, R as G indicate Real images identified as Generated, G as R indicate Generated images identified as Real and G as G indicates Generated images identified as Generated.

TABLE I. VTT RESULTS BY AN ORTHOPAEDICIAN FOR CLASSIFYING GENERATED FRACTURED IMAGES VS REAL FRACTURED

TYPE OF FRACTURE	ACCURACY	R as R	R as G	G as R	G as G
COMPLETE BURST FRACTURE IMAGES / A4 FRACTURE IMAGES	**51.47**	17	19	18	14

Results show that generative adversarial networks, particularly the DCGAN, can generate realistic computed tomography images of vertebral column fracture, that is even difficult for an expert to accurately differentiate from the real vertebral column fracture image. So DCGAN can be effectively used for medical data augmentation. This work confirms that the quality of synthetic image generated by DCGAN is good by expert evaluation. Overall, the implemented DCGAN-based model generates realistic CT image of vertebral column fracture.

VI. CONCLUSION

In the present research work, synthetic complete burst fracture images were generated for the first time using DCGAN. From the results it is evident that the generated fractured images were able to deceive the orthopaedician. Further improvements can be explored by readjusting the parameters of the model to get more accurate images. These generated images could be used along with the real images thereby increasing the training data set in the classification process which increases the accuracy of the classification process. In the future work, we can aim to generate different vertebral column fracture images. And evaluation can be expanded with inclusion of more orthopaedician and experts.

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