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SKIN LESION DATA AUGMENTATION USING DCGAN

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Abstract - *There is scarcity of labeled medical image data available publicly. Generating medical image data is a complex and expensive task. Generally, diseases with multiple classes have imbalance dataset. Deep learning models require large number of samples and balanced dataset to work efficiently and perform with higher accuracy. To achieve efficiency augmentation of data is done. Traditional augmentation techniques give limited results. In order to tackle their problem we need more data which is a complex and expensive procedure because it involves both researcher and radiologist. So to solve both the problems we propose usage of GAN for augmenting skin lesion dataset. Data augmentation using GAN has been used for medical imaging generation purpose in past also. It has shown positive result.*

Skin lesion is part of skin which has abnormal growth and appearance from skin around it. There are seven different skin lesion classes and available dataset is highly imbalance dataset. So, using GAN we can generate synthetic lesion images to balance the dataset. The improved dataset will help to train classification model and increase its performance

Key Words: Deep Learning, Generative Adversarial Network, Skin Lesion classification, Data Augmentation.

1.INTRODUCTION

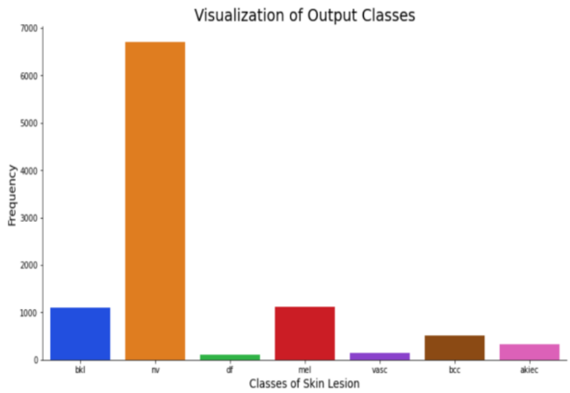
A skin lesion is an abnormal growth or appearance of a skin part compared to the skin around it. It is categorized as primary and secondary skin lesions. Divided into seven different classes. Four classes among them are cancerous. So, detecting these classes in early stage is necessary. But due to imbalance data set the deep learning model is inefficient. Data augmentation is used in such cases. Data augmentation using GAN has been used for medical imaging generation purpose in past also. It has shown positive result.

1.1 Skin Lesion Dataset

There are only 2 datasets available for skin lesion in public domain one has 10,000 samples and other has 2,000 samples. Name of Dataset is HAM10000.

There are 7 Classes in dataset each representing types of skin lesion

AKIEC has 327 Images, BCC – 514 Images, BKL has 1099 Images, DF has 115 Images, MEL has 1113 Images, NV has 6705 Images, VASC – 142 Images.

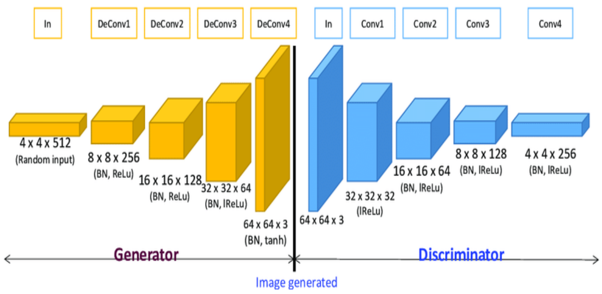


1.2 Deep Convolutional Generative Adversarial Network

In DC GAN up sampling convolutional layers are added between the input vector and the output image generated by the generator. Where as in discriminator it uses convolutional layers just like a regular convolutional neural network

2. ARCHITECTURE

We have used DCGAN (Deep Convolutional GAN) for generating new images of skin lesion classes. In any Generative Adversarial Network there are two neural networks generator and discriminator. Input to the generator network is latent space and after processing by generator we get the output tensor of shape 3X64X64. Where 3 are number of channel and 64, 64 are height and width. On the other hand discriminator takes an images tensor as input of shape 3X64X64 and gives 0/1 as output because it is a binary classifier. Generator and discriminator both are created as mentioned in official DCGAN paper.



3. WORKFLOW

We first train the discriminator on original dataset after that we generate data from generator which will be random data because we pass random latent space to generator. We pass the data generated by generator to discriminator and upon that feedback from discriminator we train generator. Discriminator classifies images into two categories original and generated it return 1 for original and 0 for generated images. We monitor loss of both generator and discriminator very closely and we also track images generated in different epochs depending upon this factor we choose our best model to generate images. After selecting best model we load the model and generate images using the best model. These generated images are then used to train the CNN classifier with original images.

4. GENERATED IMAGES

We have given both generated and original images below to show that we can augment similar images to original dataset using DCGAN.

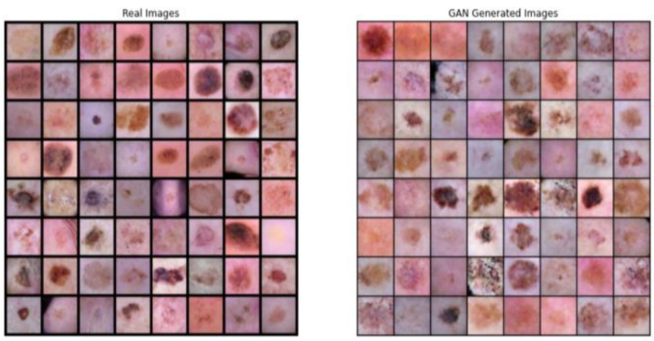


Fig 4.1: Class BKL

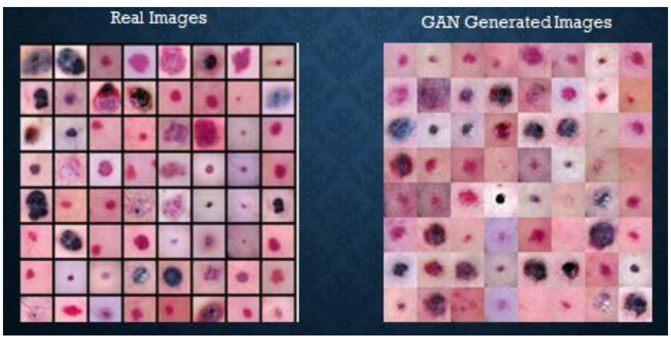


Fig 4.2: Class VASC

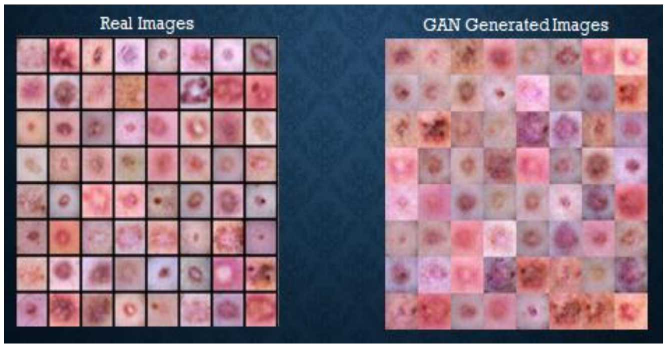


Fig 4.3: Class DF

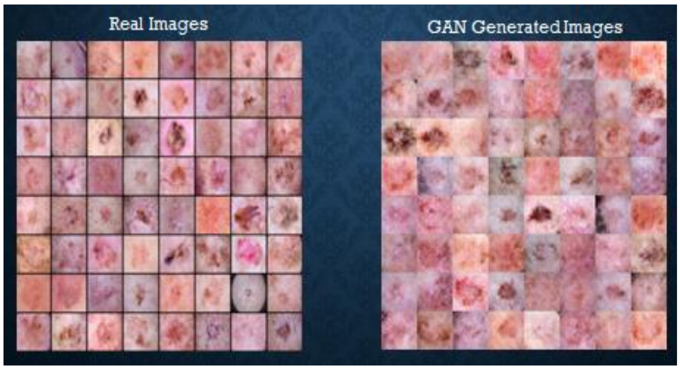


Fig 4.4: Class AKIEC

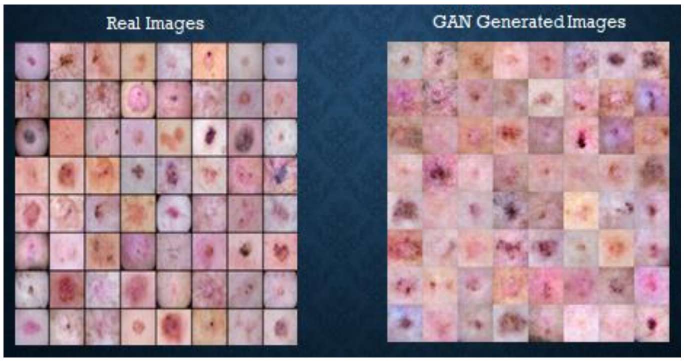


Fig 4.4: Class BCC

5. CONCLUSION

We can increase the accuracy of CNN classifier using images augmented with DCGAN. We used same classifier keeping all the parameters same while training on original dataset and original dataset with added generated images. We found out that there is improvement of 4% in accuracy which further can be increased as we improve quality of images using GAN.

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