CYCLE-GAN BASED DATA AUGMENTATION FOR MELANOMA IMAGE CLASSIFICATION

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ABSTRACT

Skin cancer is the most prevalent type of cancer and its early and accurate detection is desirable. This project deals with detecting Melanoma using skin lesion images. The highly imbalanced SIIM-ISIC Melanoma Classification dataset containing 'benign' and 'malign' samples has been used. To tackle the class imbalance, CycleGANs have been used to generate synthetic 'malign' samples.

1. INTRODUCTION

Melanoma detection is a binary classification problem. The dataset has around 32,000 'benign' samples and only 584 'malign' samples. In addition, there are around 10,000 test samples. Deep Learning models are biased towards majority class. Oversampling of minority class image samples using data augmentation becomes essential. CycleGANs [1] is a variant of GAN [2] which performs image to image translation. Pairs of 'benign' and 'malign' samples are fed into the model and it learns to transform 'benign' samples to 'malign' samples and vice versa. Using the CycleGAN-generated new samples, the dataset is balanced. A binary classifier is trained by fine-tuning EfficientNet weights. The perfomance of CycleGAN-based data augmentation has been compared with traditional data augmentation (rotation, flipping, random-cropping) techniques.

2. TECHNICAL DETAILS

The CycleGAN consists of two generators (G_{AB} and G_{BA}), and two discriminators (D_A and D_B). The generator network involves three downsampling convolutional layers, followed by nine residual blocks, and three upsampling convolutional layers. Each residual block has two convolutional layers and a skip connection. The discriminator is a PatchGAN [3] discriminator consisting of five convolutional layers. The loss term includes two components. The first is the least squared GAN loss [4]. A cycle consistency loss has been included which is L1-norm between generated and original images. The total loss is given as $L(G_{AB}, G_{BA}, D_A, D_B) = L_{GAN}(G_{AB}, D_B, A, B) + L_{GAN}(G_{BA}, D_A, A, B) + \lambda L_{cyc}(G_{AB}, G_{BA})$. λ is chosen to be equal to 10. The objective is to solve $G_{AB}, G_{BA} = arg \min_{G_{AB}, G_{BA}} \min_{D_A, D_B} L(G_{AB}, G_{BA}, D_A, D_B)$. The CycleGAN was trained for 720 epochs with an initial learning rate of 0.0002. After generating synthetic 'malign' samples, a total of around 32,000 'malign' were available, thereby balancing the dataset. Now, the pre-trained EfficientNet [5] weights were tuned for the binary classification task and tested on test set of around 10,000 images.

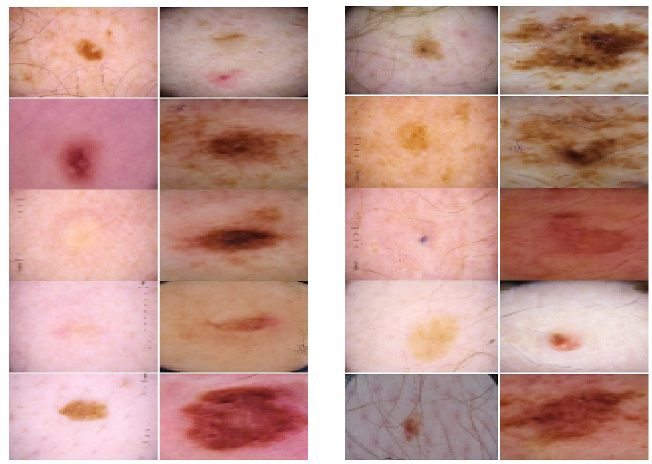

Fig. 1. The second and fourth columns are CycleGAN-generated synthetic 'malign' samples from the respective 'benign' samples in the first and third columns.

3. RESULTS

Method	Test ROC-AUC
Flipping, Cropping, Rotating	0.79
CycleGAN baseline	0.87
CycleGAN label smoothing	0.89

4. CONTRIBUTIONS

Firstly, I used PatchGAN discriminator which tries to classify each pixel (uses MSE loss) as real or fake instead of the whole image (uses BCE loss). I changed all the activation functions in generator and discriminator to leaky relu. It reduced the number of sparse gradients and also improved the overall performance. The other approach I contributed is introducing label smoothing. That also performed better than the baseline approach.

5. RESOURCES

[1] Dataset Link [2] Github link of my implementation

6. REFERENCES

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