Cycle-GAN based Data Augmentation for Melanoma Image Classification

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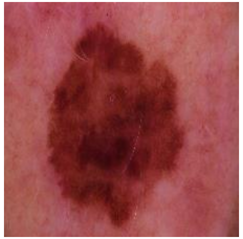
Background

Benign

Malign

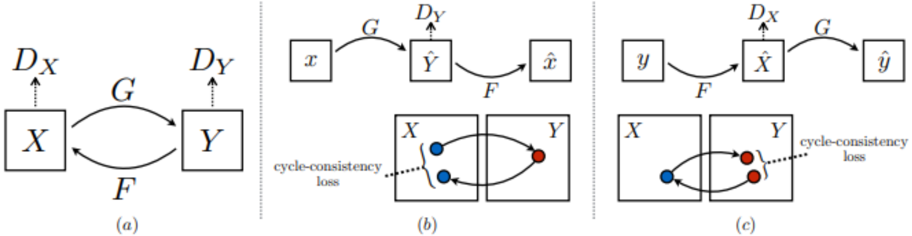


- Skin cancer is the most prevalent type of cancer, and its early and accurate detection is desirable.
- Melanoma is responsible for 75% of skin cancer deaths.
- This project deals with **detecting Melanoma using skin lesion images.**
- The highly imbalanced SIIM-ISIC Melanoma Classification dataset containing ‘benign’ (majority class) and ‘malign’ (minority class) samples has been used.
- **‘Malign’ samples data augmentation is essential** to train robust deep learning binary classifiers.

Proposed Approach

- **To tackle the class imbalance and less data, CycleGANs have been used to generate synthetic ‘malign' samples.** They are suitable for unpaired image-to-image translation.
- Pairs of ‘benign’ and ‘malign’ images are fed to the generators that learn to generate fake samples. The discriminator learns to differentiate between real and fake.
- Required number of synthetic ‘malign’ samples were generated by feeding ‘benign’ samples into the generator.
- Using the new balanced dataset and transfer learning, binary classification have been performed.

Technical Details



- **Generator** - three down-sampling convolutional layers, followed by nine residual blocks, and three up-sampling convolutional layers.
- **Residual Blocks** - two convolutional layers and a skip connection.
- **Discriminator** – PatchGAN discriminator with five convolutional layers.
- **Loss function** - $L(G_{AB}, G_{BA}, D_A, D_B) = L_{GAN}(G_{AB}, D_B, A, B) + L_{GAN}(G_{BA}, D_A, A, B) + \lambda L_{cyc}(G_{AB}, G_{BA})$

$$G_{AB}, G_{BA} = arg \min_{G_{AB}, G_{BA}} \min_{D_A, D_B} L(G_{AB}, G_{BA}, D_A, D_B)$$

- GAN loss – MSE loss, Cycle loss – L1 loss, Discriminator loss – MSE loss
- **Cycle-GAN** – trained for 720 epochs with Adam optimization, an initial learning rate of 0.0002, and $\lambda = 10$.
- **Binary classifier** – EfficientNet transfer learning with BCE loss.

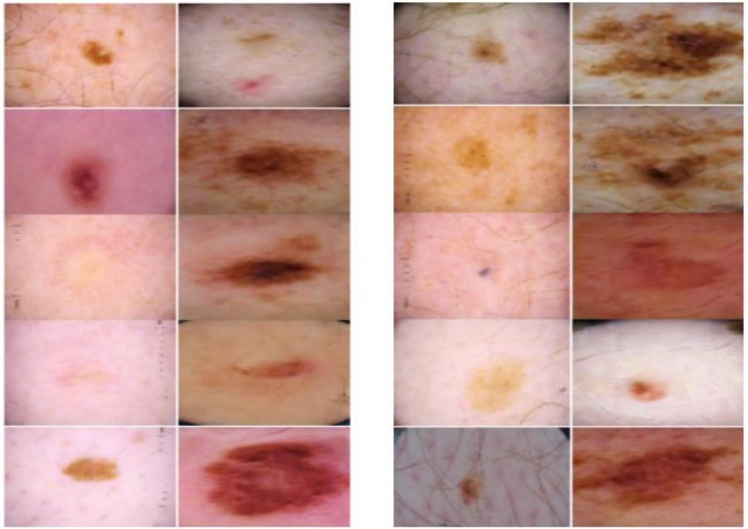
Contributions (Novelty)

- Traditional data augmentation techniques like flipping, rotating, cropping is considered baseline.
- Firstly, I used PatchGAN discriminator which tries to classify each pixel (uses MSE loss) in a patch (14x14 in this case) as real or fake instead of the whole image (uses BCE loss).
- Used LeakyReLU activation function everywhere in generator and discriminator instead of ReLU.
- Introduced label smoothing as a way of regularization.

Results & Conclusion

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

Example of synthetic CycleGAN-generated ‘malign’ samples.



The second and fourth columns are CycleGAN generated synthetic ‘malign’ samples from the respective ‘benign’ samples in the first and third columns.

- Generating synthetic minority class samples using **CycleGAN is a better method for data augmentation.**
- It also solves the problem of class imbalance which is prevalent in medical imaging.
- There is variability in the generated images.