GAN (GENERATIVE ADVERSARIAL NETWORKS) FOR REALISTIC DATA AUGMENTATION AND LESION SIMULATION IN X-RAY BREAST IMAGING

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1. Introduction

Medical datasets are usually costly to label. This reduces the availability of large annotated medical datasets. As a result, supervised machine learning tools, when used in medical applications, commonly suffer from problems related to lack of generalisation. GANs [1] were introduced in 2014 and have been used in many different applications ranging from image synthesisation, to image translation, and in super resolution problems. In this work, we use Deep Convolutional GAN (DCGAN) [2] to generate synthetic mammographic lesion patches of size 128 x 128 pixels in order to use them to:

- Augment an imbalanced dataset to improve classification performance.
- Provide specialists with photo-realistic mammographic lesions.

2. Dataset

OPTIMAM [3] dataset has 79K processed and unprocessed images.

1. Read Image **I**.
2. Create groundtruth **GT** from lesion coordinates.
3. Apply histogram normalisation to get **I'**.
4. Create corresponding **Mask** using non-zero thresholding.
5. Using I', GT, and Mask, extract patches.

Outcome:
5K lesion patches and 147K normal tissue patches.

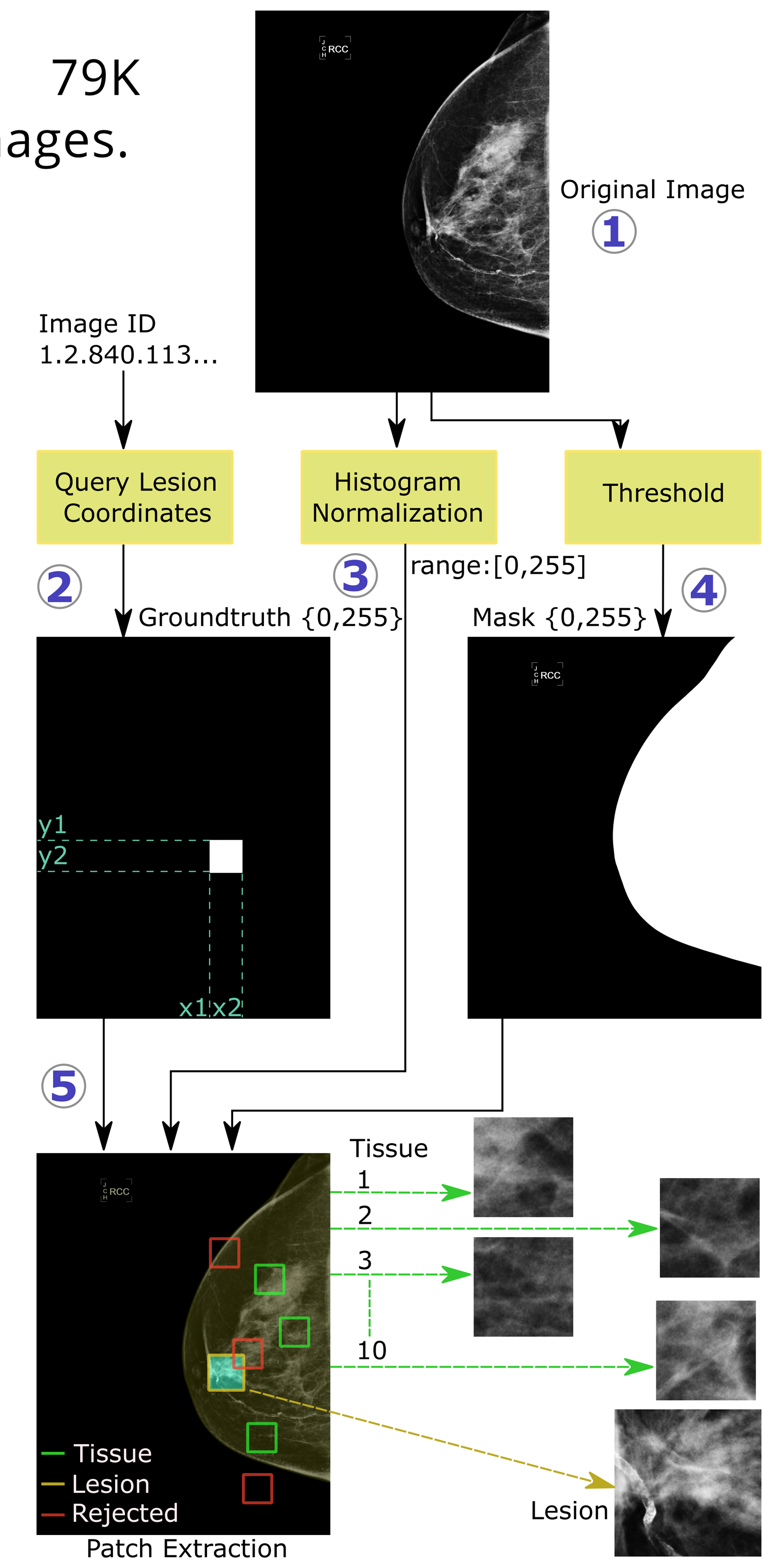

Figure 1: Dataset preparation.

3.a Methods(1): DCGAN

In GANs, two networks should be trained simultaneously, namely: Generator (**G**) and Discriminator (**D**). D learns to capture real images among fake ones, while G tries to fool D.

1. Generate a noise batch from N(mean=0, sd=1).
2. Forward z through G to get G(z).
3. Forward real and fake batches through D.
4. Calculate LD.
5. update D.
6. Calculate LG.
7. update G.

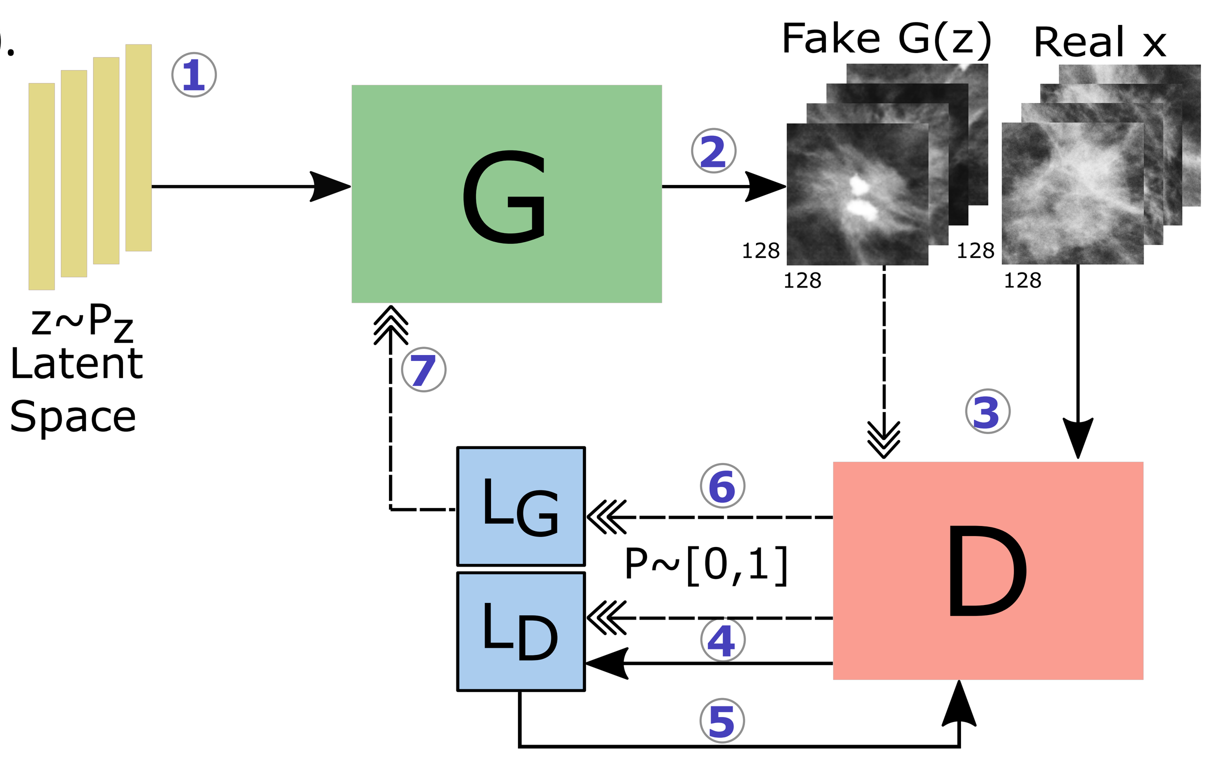

Figure 2: The top view of training DCGAN. Dotted arrows refer to fake values.

3.b Methods(2): Augmentation

- **ORG**: real unbalanced (1:10).
- **GAN**: ORG + fake.
- **Aug ORG**: flipping(ORG).
- **Aug GAN**: flipping(ORG + fake).

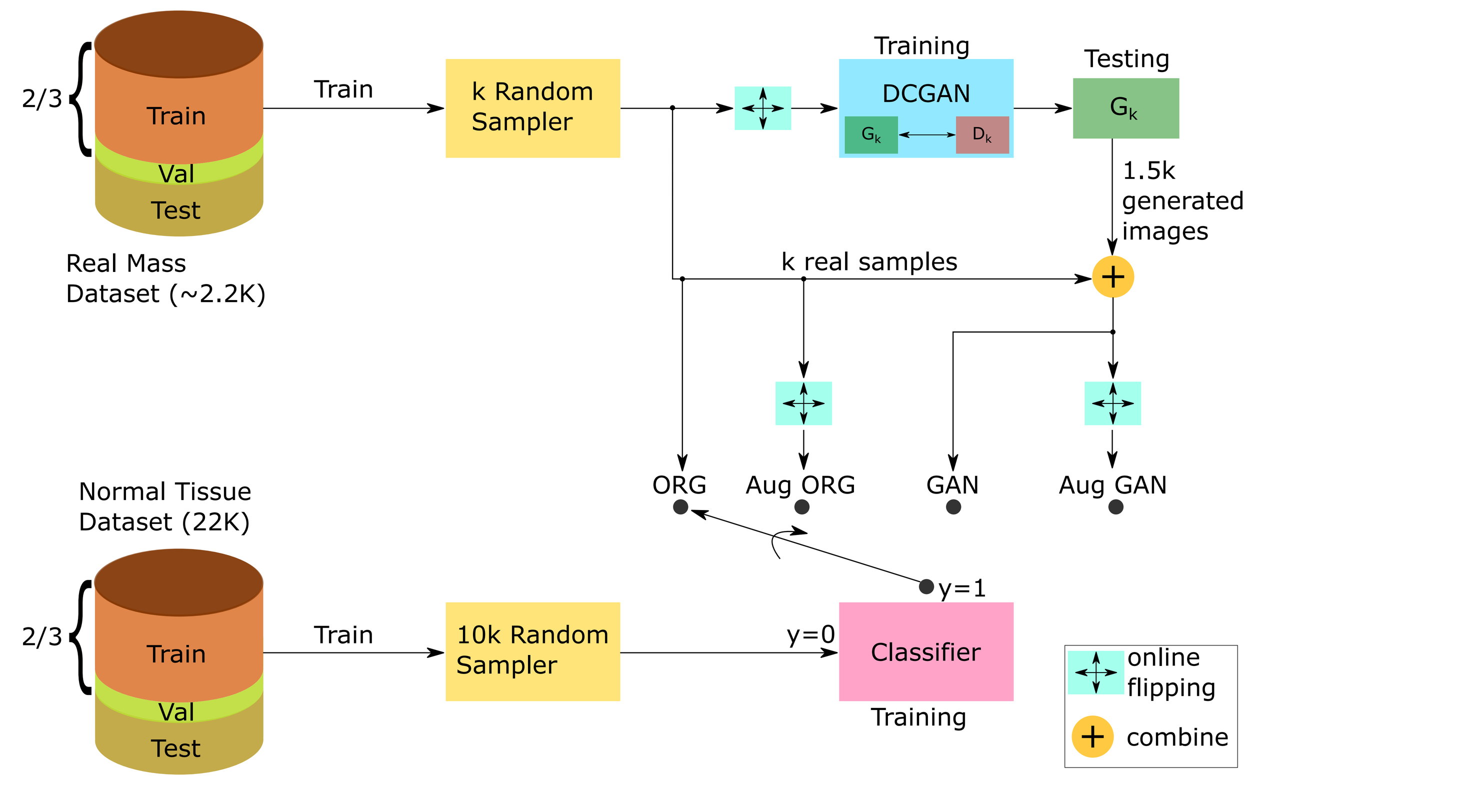

Figure 3: Augmentation as a function of training size.

4. Results

- G generates mass and/or calcification.
- High realism and diversity.
- Best Frechet Inception Distance of 16.

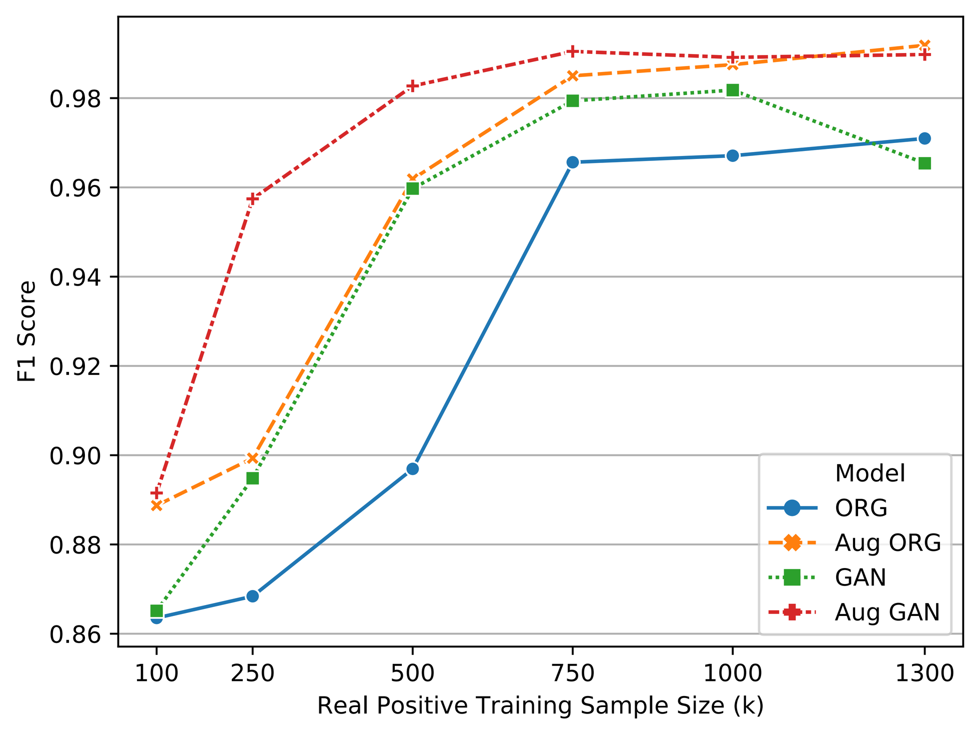

Figure 4: F1 score for all modes.

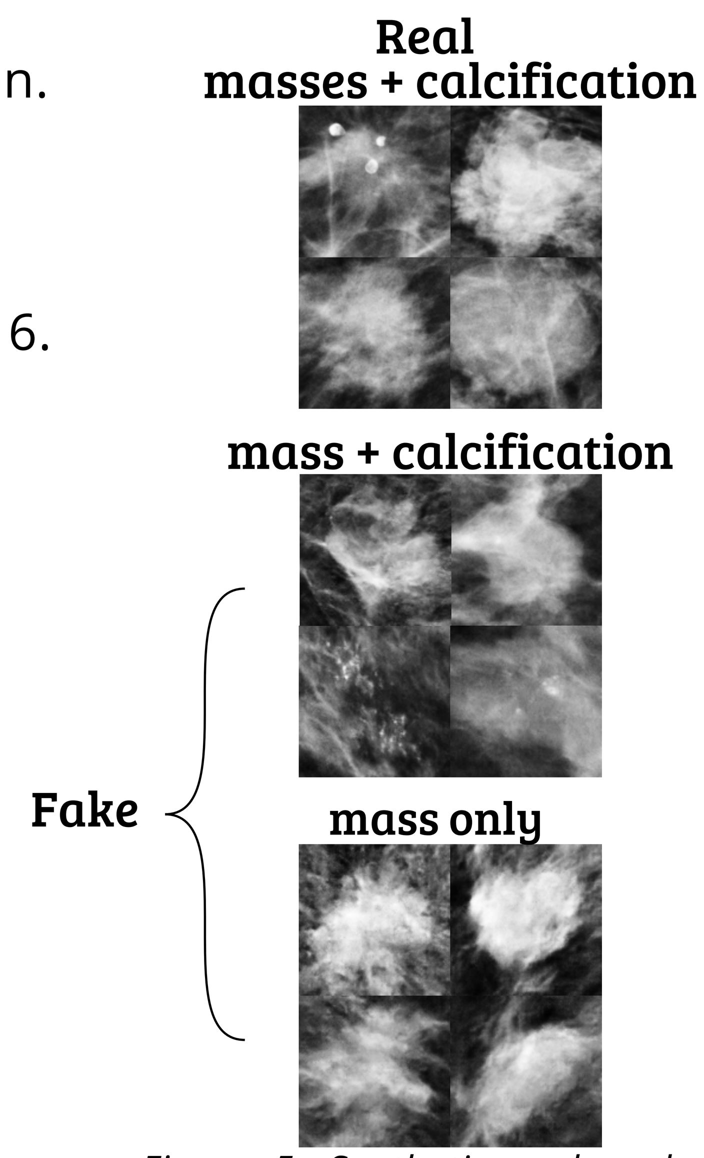

Figure 5: Synthetic and real lesions

5. Conclusion

- GANs support inliers.
- GANs fill in (interpolate) gaps.
- GAN + flipping outperforms GAN alone.

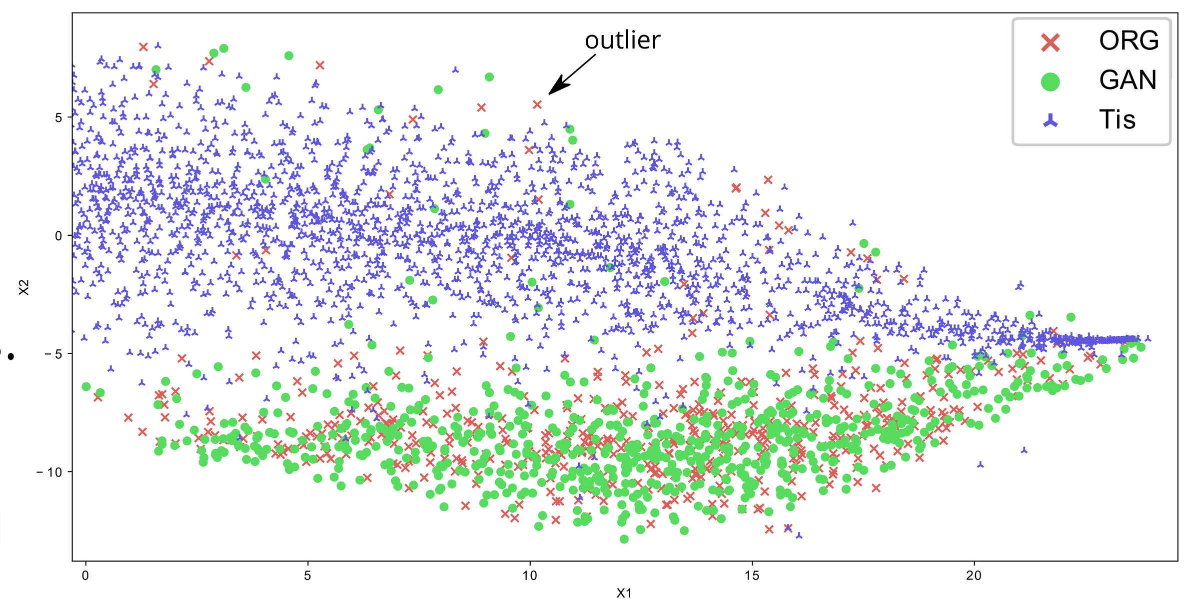

Figure 6: t-Stochastic Neighbor Embedding (t-SNE) distribution of real and fake lesions, and normal tissue.

- GANs are sensitive to hyperparameters but powerful.
- Fake synthesisation and traditional augmentation are independent.

6. References

[1] J. Goodfellow et al, 2014. Generative Adversarial Nets, in: Ghahramani, Z., Welling, M., Cortes, C., Lawrence, N.D., Weinberger, K.Q. (Eds.), Advances in Neural Information Processing Systems 27. Curran Associates, Inc., pp. 2672–2680.
[2] Radford et al, 2016. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks, in: 2016 International Conference on Learning Representations (ICLR).
[3] Halling-Brown et al, 2014. The oncology medical image database (omi-db), in: Proc. SPIE 9039 Medical Imaging 2014: PACS and Imaging Informatics: Next Generation and Innovations.

7. Acknowledgement

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Scan me

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