DCGANs for Realistic Breast Mass Augmentation in X-ray Mammography

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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 poor generalisation. GANs [1] were introduced in 2014 and have been used in many different applications ranging from image synthesis to image translation and super resolution. In this work, we used 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. Materials

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

① Read Image **I** (processed).

② Create groundtruth **GT.**

③ Apply histogram normalisation to get **I'**.

④ Create **Mask** using non-zero thresholding.

⑤ Using I', GT, and Mask, extract patches.

Outcome:

5K mass lesion patches
147K normal tissue patches.

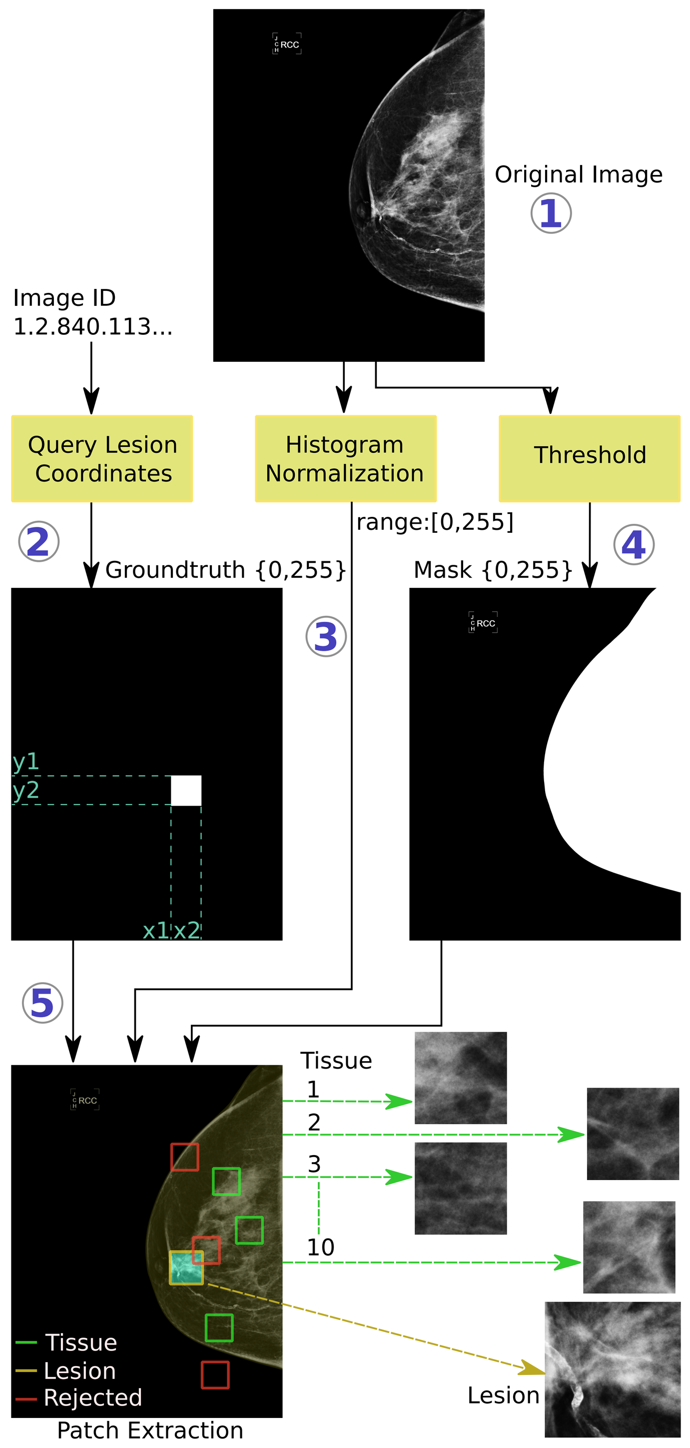

Fig. 1: Dataset preparation.

3.a Methods(1): DCGAN Training

① **S**ample a noise batch from N(mean=0, sd=1).

② **F**orward z through G, G(z).

③ **F**orward real and fake batches through D.

④ **C**alculate LD.

⑤ **U**pdate D.

⑥ **C**alculate LG.

⑦ **U**pdate G.

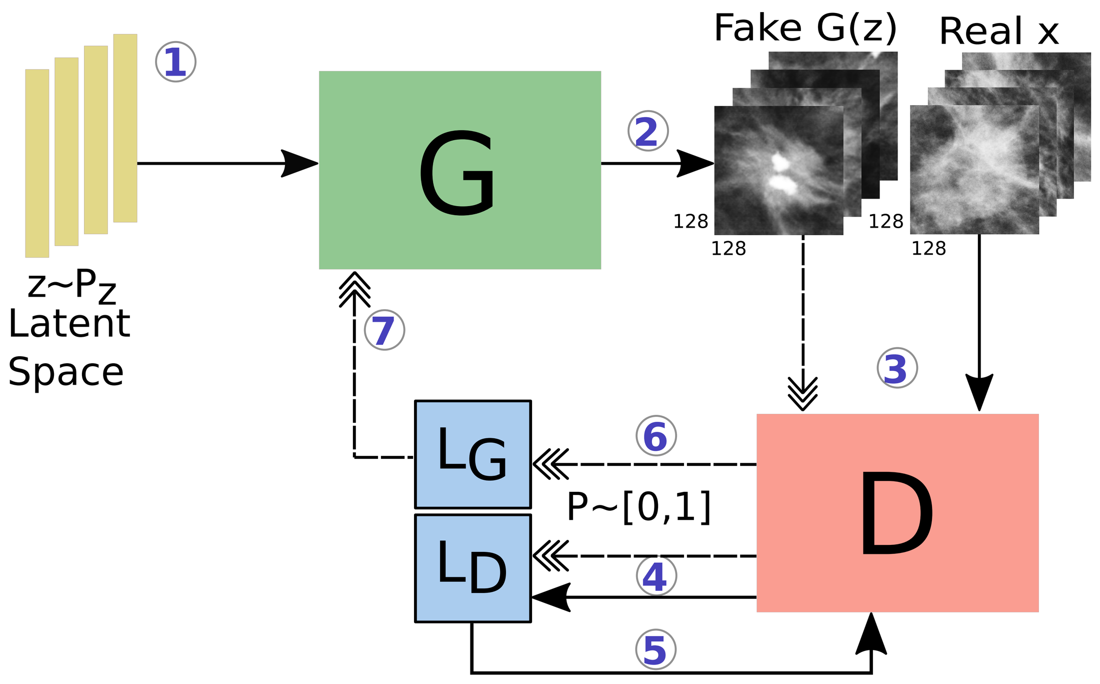

Fig. 2: The top view of training DCGAN. Dotted arrows refer to fake values.

3.b Methods(2): Augmentation

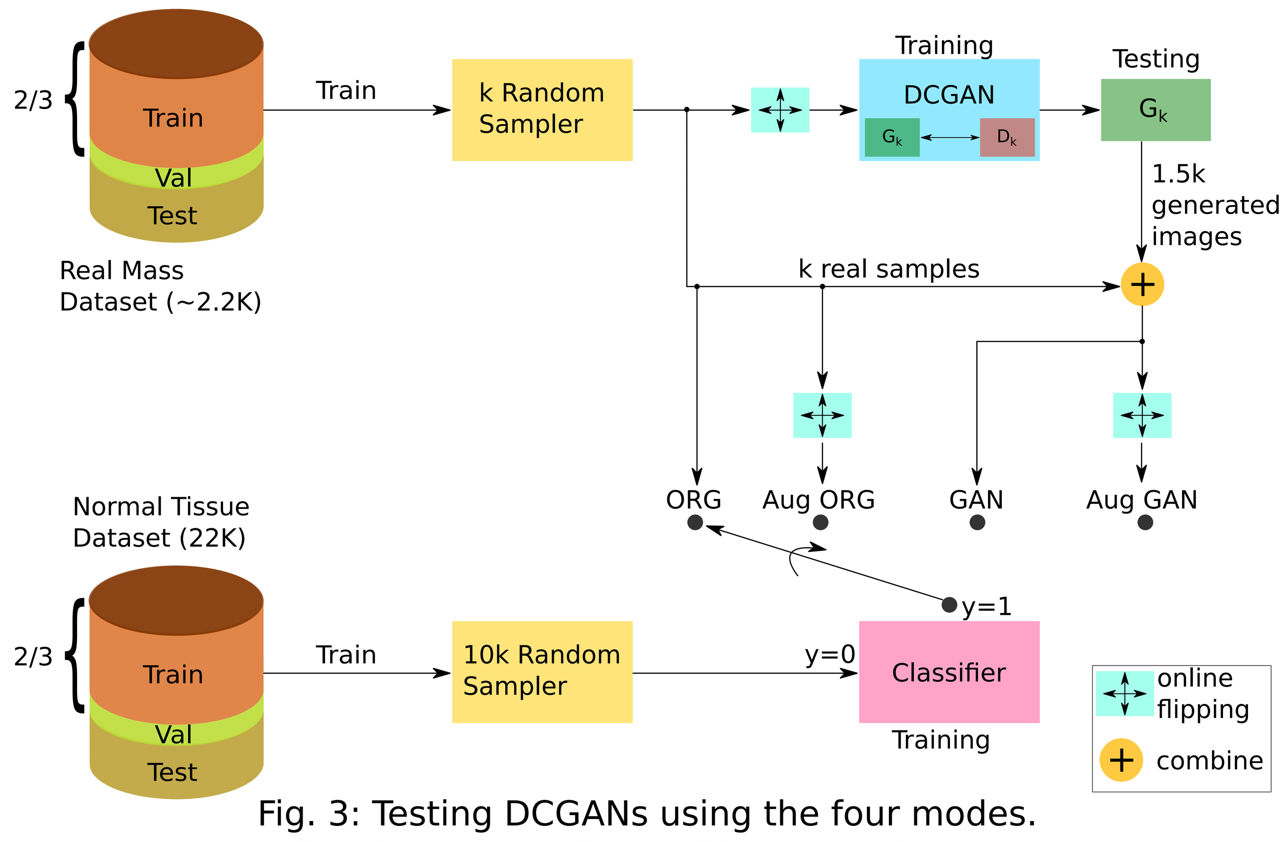

Fig. 3: Testing DCGANs using the four modes. Val and test are using real images only.

ORG:
real unbalanced (1:10).

Aug ORG:
flipping(ORG).

GAN:
ORG + fake.

Aug GAN:
flipping(ORG + fake).

4. Results

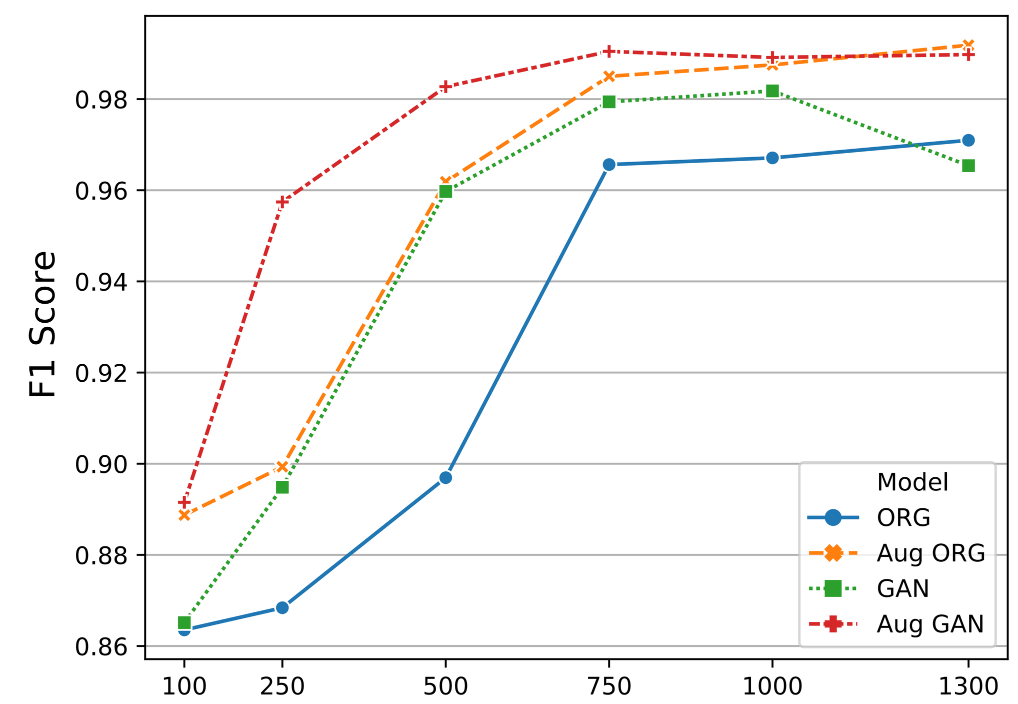

Fig. 4: Real Positive Training Sample Size (k)

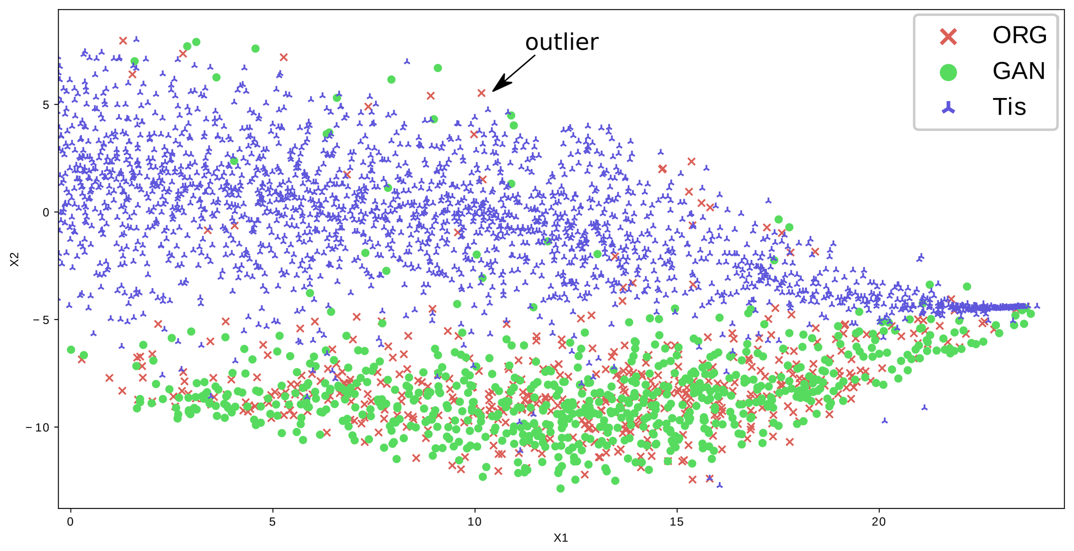

Fig. 5: t-Stochastic Neighbor Embedding (t-SNE) distribution of real and fake lesions, and normal tissue.

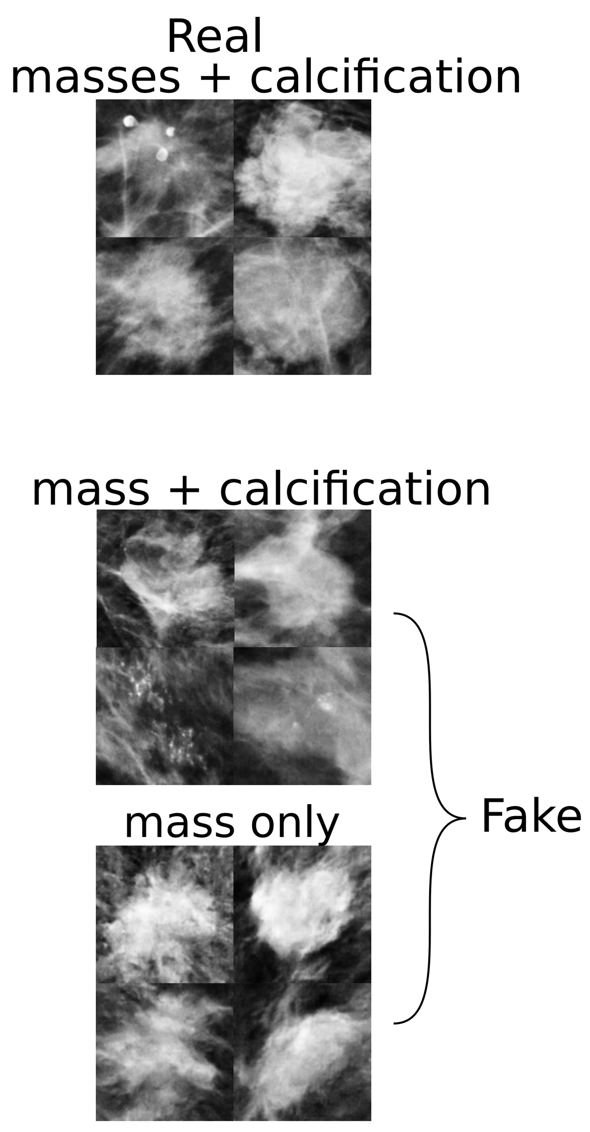

Fig. 6: samples from the real and the synthetic distribution

5. Conclusion

- G generates mass and/or calcification.
- High realism and diversity.
- Best Frechet Inception Distance of 16.
- GANs support inliers.
- GANs fill in (interpolate) gaps.
- GAN + flipping outperforms GAN alone.
- GANs are sensitive to hyperparameters but powerful.
- Synthesis and flipping are independent.

6. Acknowledgement

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For more details about this work, scan the QR code at the top.

7. References

[1] J. Goodfellow et al, 2014. Generative Adversarial Nets, in Advances in Neural Information Processing Systems.
[2] Radford et al, 2016. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks.
[3] Halling-Brown et al, 2014. The oncology medical image database (omi-db).