Generative Adversarial Networks in Cancer Imaging: Applications, Challenges, Solutions

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Abstract

In this review, we assess the potential of GANs to address a number of key challenges of cancer imaging, including data scarcity and imbalance, domain and dataset shifts, data access and privacy, data annotation and quantification, as well as cancer detection, tumour profiling and treatment planning

We analyse and discuss 126 papers that apply adversarial training techniques in the context of cancer imaging and elaborate their methodologies, advantages and limitations.

This poster will discuss

- **Generative Adversarial Networks and their use cases in Cancer Imaging**
- **The challenge of early cancer detection with current imaging modalities**
- **Distributions of GANs papers per organ, and modality**
- **Research inspired by the GAN review: Conditional Mammogram Synthesis**

The theoretical underpinnings of Generative Adversarial Networks (GANs)

Two-Player MinMax Game

- **In zero-sum games, what is won on one side is a loss on the other.**
- **One Player (G) tries to minimize the same function (D) tries to maximise**

Image Generation

- **Player D (discriminator) receives an image and needs to decide where it came from**
- **It could be from the source data or generated by G (generator)**
- **D uses binary-cross-entropy loss for this classification**

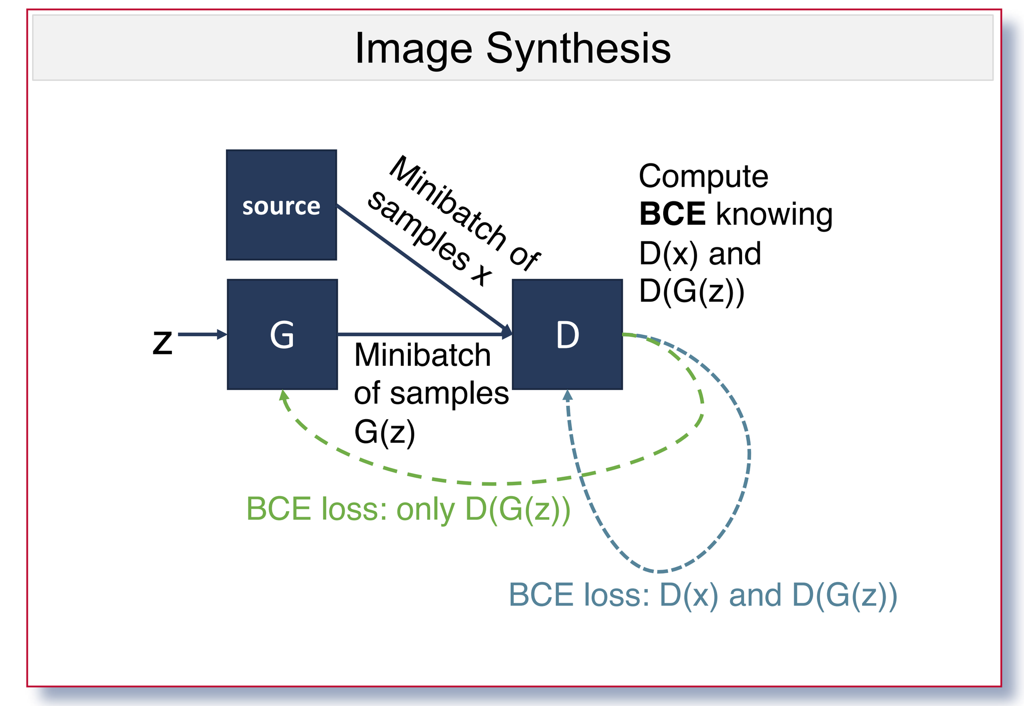
Binary-Cross-Entropy Loss of D:

$$L_D = -\mathbb{E}_{x\sim p_{data}}[logD(x)] + \mathbb{E}_{z\sim p_z}[log(1 - D(G(z)))]$$

MinMax Value function of both D and G:

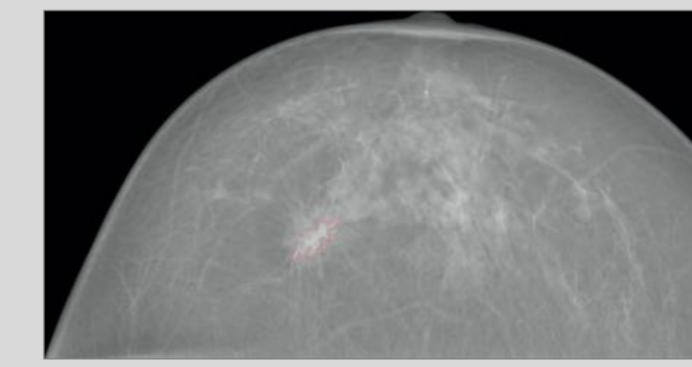
$$\min_G \max_D V(D,G) = \min_G \max_D [\mathbb{E}_{x\sim p_{data}}[logD(x)] + \mathbb{E}_{z\sim p_z}[log(1 - D(G(z)))]]$$

The Vanilla GAN Architecture



Goodfellow et al (2014)

My current research: BIRADs conditioned mammogram generation to improve tumour detection models



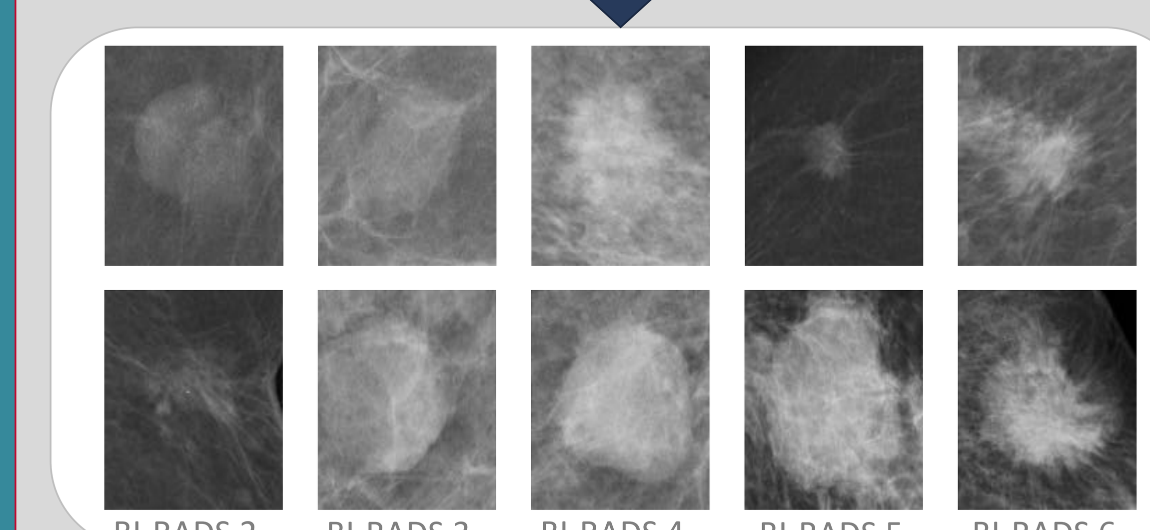
Mammography Example of a Mass with annotated ROI mask from INbreast Dataset

Category	Definition	Likelihood of cancer
BI-RADS 0	Incomplete	N/A
BI-RADS 1	Negative	Essentially 0%
BI-RADS 2	Benign	Essentially 0%
BI-RADS 3	Probably benign	>0%, but ≤2%
BI-RADS 4	Suspicious	>2%, but <95%
BI-RADS 5	Highly suggestive of malignancy	≥95%
BI-RADS 6	Known biopsy-proven malignancy	N/A

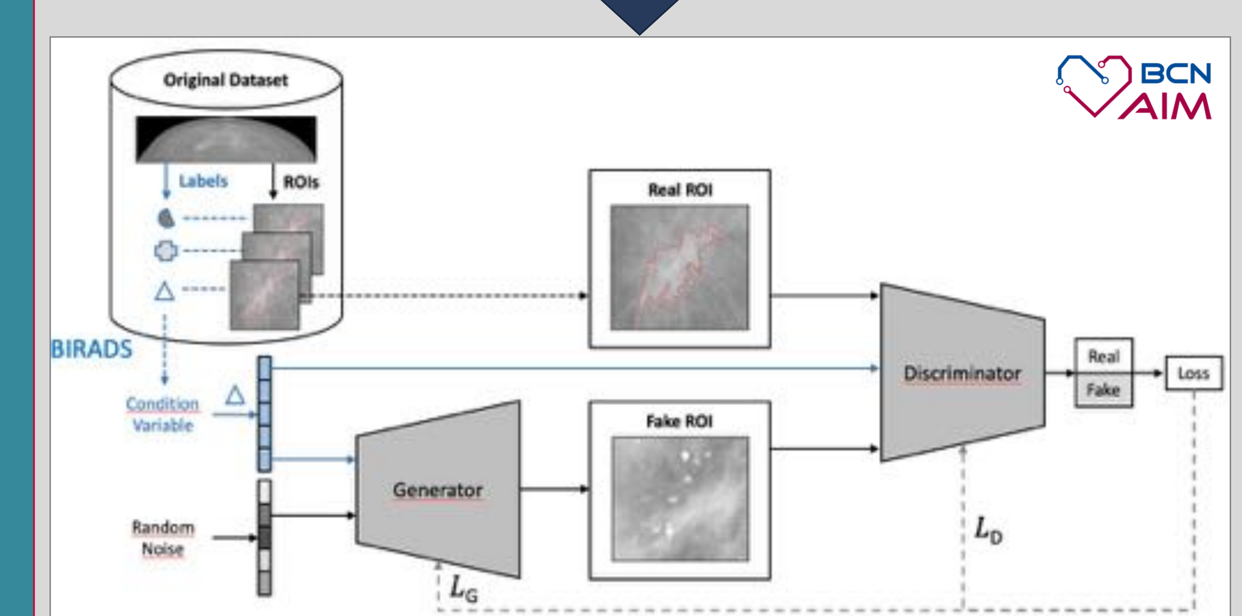
Adopted from ACR BI-RADS Atlas, Breast Imaging Reporting and Data System.

BIRADs Classification Framework, source: Von Schantz et al (2016)

Leading to



Real **Masses** from INbreast Dataset with BI-RADS classification

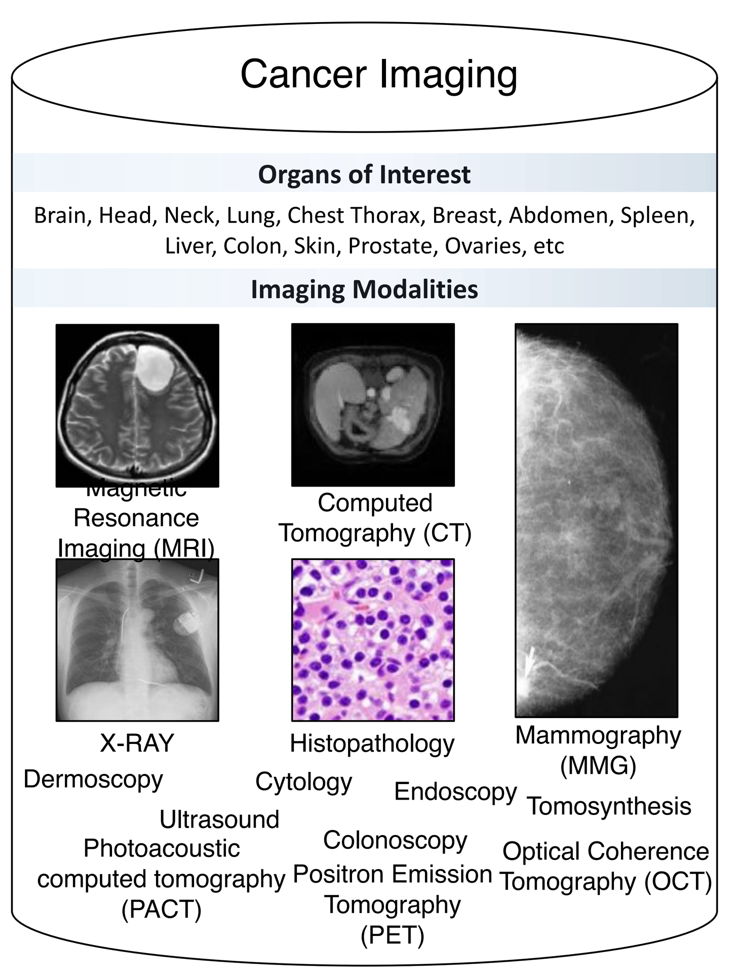


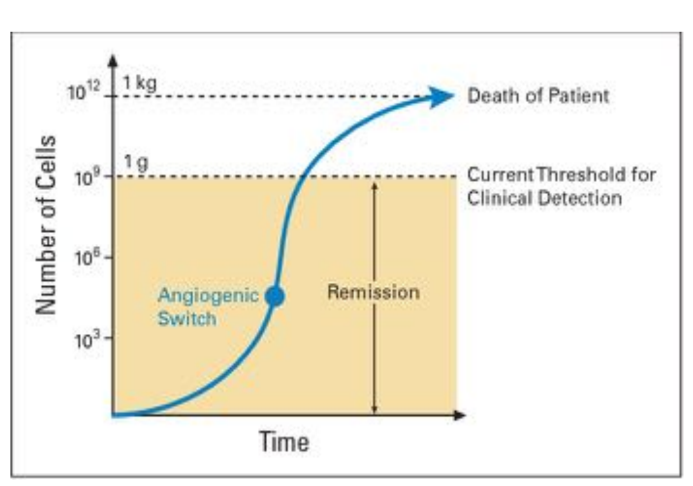
Solution Architecture: Improving cancer detection by training deep learning detection models with **controlled** synthetic training data

Cancer imaging modalities and early detection

We define Cancer Imaging as the entirety of approaches for **Research, Diagnosis, Treatment** of cancer based on medical images.

A large proportion of the global burden of cancer deaths could be prevented due to treatment and **early detection** in **cancer imaging modalities.**





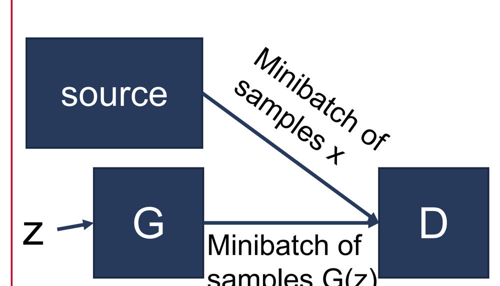
Gompertzian Tumour Growth Curve, source Frangioni (2008)

Solid tumours become detectable by radiological imaging only at an approx. size of 10^9 cells = 1cm³ after evolving from a single cell (= 10^0). → **Better detection methods are urgently needed.**

Most common GAN use-cases in cancer imaging for detection

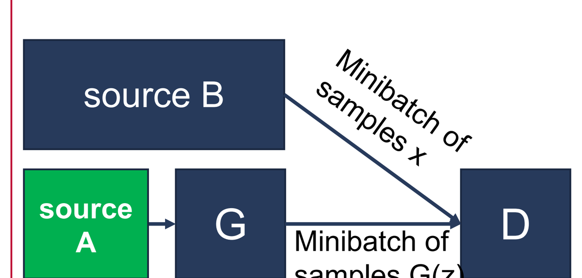
Data Augmentation

improve detection, segmentation, etc model performance with more training data



Cross Modal Image Translation

translate image to other (e.g. seen/unseen domain shifts are common in clinical practice)



Anomaly Detection

e.g. encode lesion images into latent space to find anormal (malignant) ones

Image Inpainting

e.g. add/remove artifacts, facial features, tumours etc

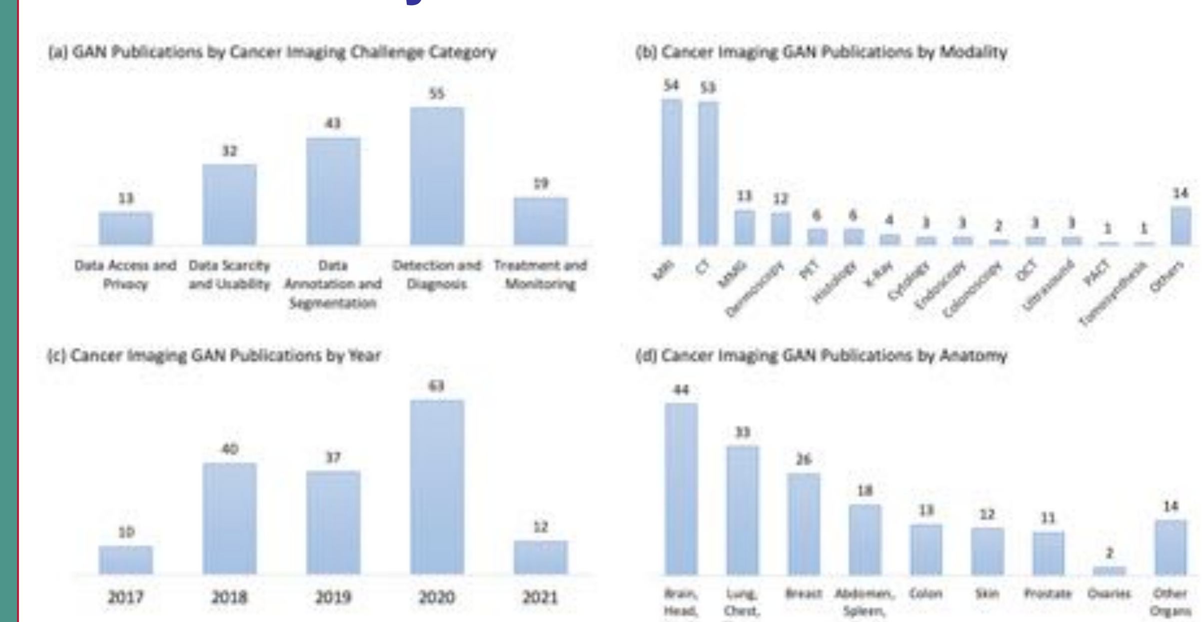
Invariant Feature Representations

e.g. make deep learning models robust against biases and domain shifts

Super-Resolution

e.g. better diagnostic image analysis

Distribution of GANs per year, organ, and modality



Conclusions

- Most work on detection and segmentation challenges, much less on privacy preservation and cancer treatment
- An extensive amount of research is devoted to organs and modalities with publicly available benchmark datasets
  - e.g. BRATS, LIDC/IDRI, DDSM
- Many of the challenges of cancer imaging are not yet addressed by the current GAN literature.
  - e.g. genotype-phenotype linked synthesis, **BIRADS conditioned mammogram synthesis**, etc.

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