Multi-View Generative Models for Breast Cancer Screening

Neural Network - Project

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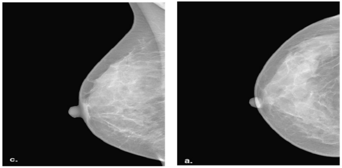
Motivations and Aim

Motivation

- Breast cancer is the most common malignancy in women
- **Mammography** is a gold standard
- Main challenges:
  - ∗ Limited data availability
  - ∗ Inter-view variability
    - → Cranio-caudal **CC**
    - → Mediolateral oblique **MLO**

Idea

Develop **multi-view generative models** to synthesize realistic and coherent CC/MLO mammograms, handling the trade-off between **breast shape preservation** and **image sharpness**.



Method - Radiomics-Conditioned cGAN

Task

Perform **multi-view mammogram synthesis**, generating complementary views (e.g., MLO from CC) conditioned on radiomic features.

Conditional GAN model (**cGAN**)

UNet-based Generator with residual connections, conditioned on radiomic features

PatchGAN-style Discriminator with dual heads for real/fake discrimination and view classification

Input

- Real CC view
- Lesion mask of real CC view
- Radiomic feature vector

Output

Synthetic MLO view

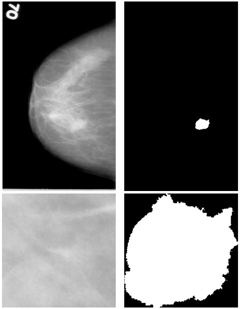
$$\mathcal{L}_G = \lambda_{GAN}\mathcal{L}_{GAN} + \mathcal{L}_{view} + \lambda_{L1}\mathcal{L}_{L1} + \lambda_{percep}\mathcal{L}_{percep} + \lambda_{SSIM}\mathcal{L}_{SSIM} + \lambda_{rad}\mathcal{L}_{rad}$$

$$\mathcal{L}_D = \mathcal{L}_{D,GAN} + \mathcal{L}_{D,view}$$

Implementation

Generative Framework

- **CBIS-DDSM** and **INbreast datasets**, containing high-resolution mammograms and radiomic features.
- **Pre-processing stage** for converting, analysing and loading mammogram images and metadata
- **Radiomic features extraction** through cropped ROIs and metadata for generating radiomic vectors



Training setup

* **Optimizer:** Adam (lr = 2e-4 for generator/discriminator)
* **Batch size:** 4 with gradient accumulation to handle memory limits.
* **Stability measures:** Gradient clipping and Early stopping based on validation SSIM.
* **Evaluation metrics:** L1, SSIM, PSNR; qualitative inspection of generated MLO images.

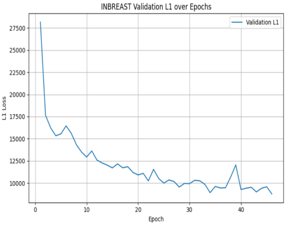
Results Analysis - Quantitative metrics

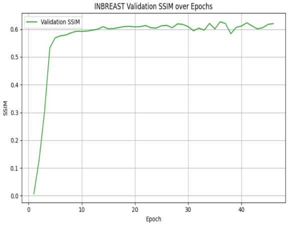
Evaluation Metrics

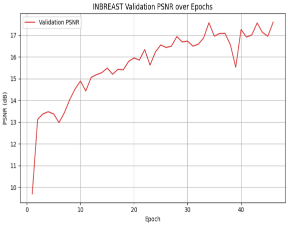
- **L1** (Mean Absolute Error)
- **SSIM** (Structural Similarity Index Measure)
- **PSNR** (Peak Signal-to-Noise Ratio)

Loss	Value
loss_G	1.8945
loss_D	0.0549
loss_GAN	0.3795
loss_L1	0.1342
loss_percep	0.7779
loss_rad	0.5557

Metric	L1	SSIM	PSNR
Val	9444.5792	0.6268	17.07 dB
Test	8831.1843	0.6285	17.27 dB



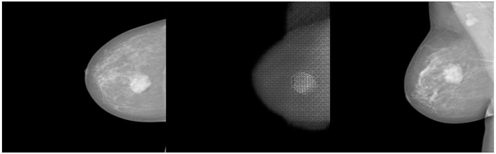




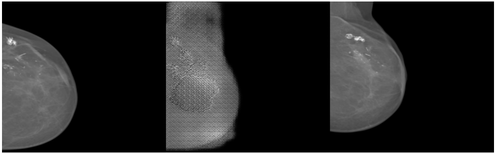
Results Analysis - Qualitative Metrics

Visualizations

MLO output from training



MLO output from test



- **Global Relations**
  Breast shape well preserved.
  Contours anatomically consistent.
- **Local Relations**
  Lesions transferred across views.
  Masses reasonably preserved, calcifications lose fine details.
  Slight blurring.
- Background plausible but smoother than real images

Training image retain better lesion alignment and detail
Test image maintain global consistency but weaker local fidelity

Limitations and Future Works

Main Limitations

- **Dataset Size and Diversity**: Limited training data reduce generalization capability.
- **Metric Limitations**: SSIM, PSNR, and L1 measure image similarity but do not fully reflect clinical relevance or lesion-level fidelity.
- **Computational and memory requirements**: the extension to more advanced models (e.g., diffusion models) results impractical for current setup

Future Works

* Feed in **Multi-View Classification Systems** the generated output.
* Extend to **Multi-View Analysis**, enabling double comparison across **ipsilateral** and **bilateral** views.
* Investigate the use of **Hypercomplex Neural Networks** to better capture inter-view correlations and multimodal relations.
* Explore **Diffusion Models** for higher fidelity synthesis

Thank you for listening!

Multi-View Generative Learning for Mammography

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