Multi-View Generative Models for Breast Cancer Screening

Neural Network - Project

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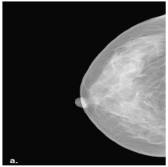
Motivations and Aim

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, synthesizing complementary views

PatchGAN-style Discriminator enforcing realistic and coherent image fidelity.

Input

* CC mammogram image
* Lesion mask corresponding to the CC image
* Radiomic feature vector

Output

Synthetic MLO mammogram corresponding to the input CC, preserving anatomical structure and lesion-specific features.

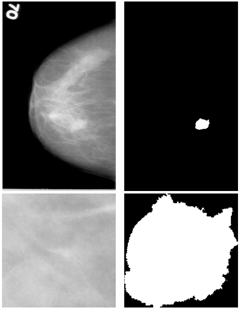
$$\mathcal{L}_G = \lambda_{GAN}\mathcal{L}_{GAN} + \mathcal{L}_{view} + \lambda_{L1}\mathcal{L}_{L1} + \lambda_{percep}\mathcal{L}_{percep} + \lambda_{SSIM}\mathcal{L}_{SSIM} + \lambda_{rad}\mathcal{L}_{rad}$$

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

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.
- **Checkpointing & logging** → results.csv.

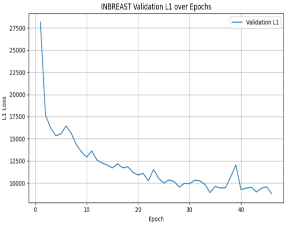
Results Analysis - Quantitative metrics

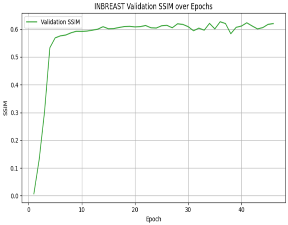
Evaluation Metrics

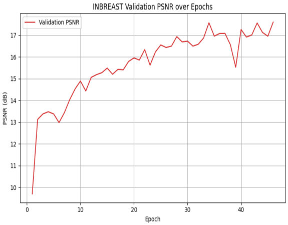
- **L1** (Mean Absolute Error)
- **SSIM** (Structural Similarity Index Measure)
- **PSNR** (Peak Signal-to-Noise Ratio)

Loss	Value
loss_G	1.7476
loss_D	0.0350
loss_GAN	0.6441
loss_L1	0.1885
loss_percep	0.6301
loss_rad	0.2120

Metric	L1	SSIM	PSNR
Val	10977.29	0.6431	16.49 dB
Test	11519.74	0.6156	16.26 dB



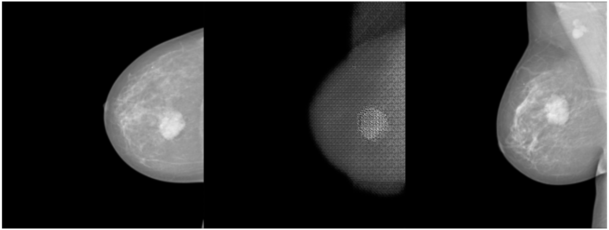




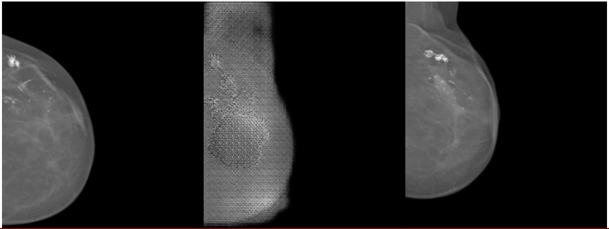
Results Analysis - Qualitative Metrics

Visualizations:

MLO output from training



MLO output from test



Limitations and Future Works

Main Limitations

- **Dataset Size and Diversity**: Limited training data may reduce generalization capability.
- **Metric Limitations**: SSIM, PSNR, and L1 measure image similarity but do not fully reflect clinical relevance or lesion-level fidelity.
- **Computational Resources**: High-resolution training requires substantial GPU memory and time, limiting scalability.

Future Works

* **Multi-Modal Integration** using attention or fusion.
* Feed in **Multi-View Classification Systems** the generated output to exploit interview correlations and improve lesion detection.
* Introduce **Clinical Evaluation Metrics**
* Additional **Data Augmentation** and **Synthetic Data** generation
* Explore **Diffusion Models** for higher fidelity synthesis (considering computational requirements)

Thank you for listening!

Multi-View Generative Learning for Mammography

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