

Deep Learning–Based Ultrasound Lesion Segmentation & Subtype Classification

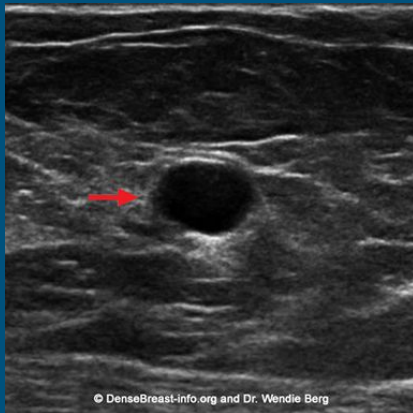
Presenter: Varsha V-ML Undergraduate Researcher

Affiliation: Lampe Joint Department of Biomedical Engineering

Funding: NSF Graduate Research Fellowship

Introduction- Breast Cancer Ultrasound

- Mammography Partner: Ultrasound complements X-rays, especially in dense breasts where tumors hide.
- Safe & Accessible: No ionizing radiation, lower cost, widely available in clinics and mobile units.
- Real-Time Guidance: Instant feedback for lesion detection and biopsy needle placement.



Significance

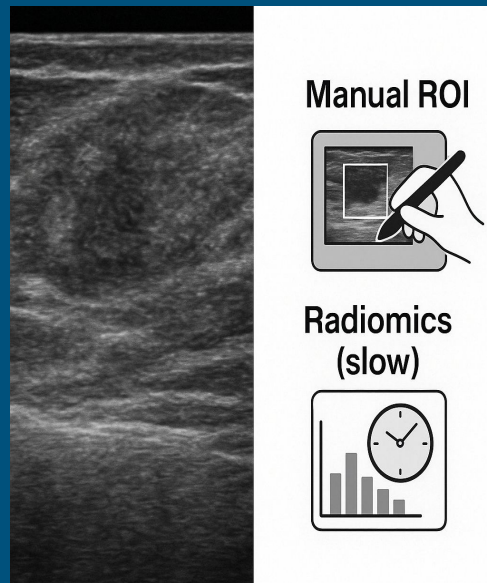
Remaining Gaps

1. Manual Steps: Someone still has to outline the tumor
2. Speed vs. Detail with current computer tools: Fast models miss small features; detailed ones lag behind
3. No One-Click Tool: No single, real-time, scanner-diagnostic system

Past Attempts with AI

- Radiomics + Statistics (Ferre et al. 2023): Good AUC (~ 0.82), but needed radiologists to draw masks by hand
- Vision Transformers (Pacal 2022): High accuracy ($\sim 89\%$), yet processed whole frames slowly—no live guidance
- LightGBM Models (Michael 2022): Very fast and accurate, but relied on pre-computed features and separate steps

B-mode Breast
US of dense
tissue



Aim 1 – Automated Attention-Enhanced Segmentation

Evaluation (50 Held-Out Scans)

Goal

- AI draws tumor outlines fully automatically—no more hand-tracing.

Model

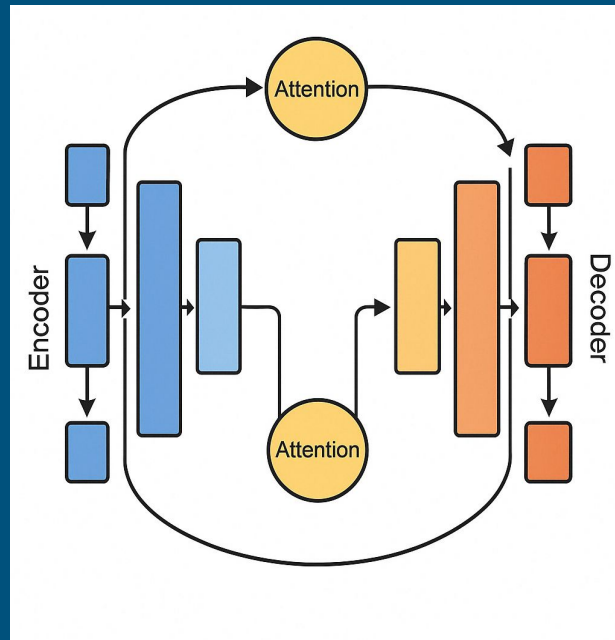
- Residual U-Net (U-shaped encoder-decoder)
- Spatial & channel attention modules highlight the tumor region

Training

- 100 expert-annotated B-mode ultrasound volumes

Loss Function

- Dice loss: rewards overlap between AI mask and expert mask
- Focal loss: emphasizes hard-to-classify pixels



- Overlap vs. 2 Radiologists

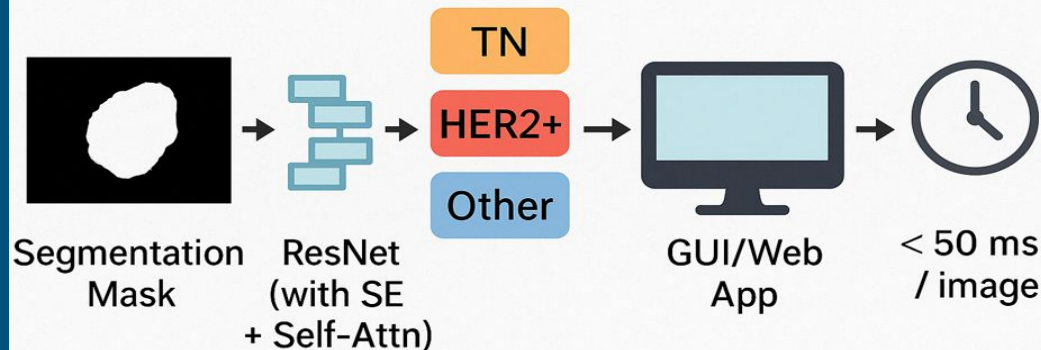
- *Dice coefficient* (0 = no overlap → 1 = perfect match)
- *Intersection over Union* (shared area ÷ total area)

- **Benchmark: AI's agreement matches or exceeds radiologist-radiologist consistency ($p < 0.05$)**

Aim 2

Hypothesis

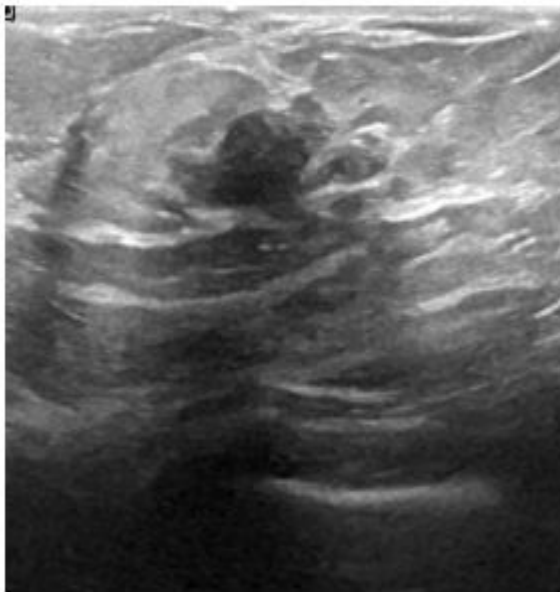
Using the AI-generated tumor outline as a guide will let our ResNet classifier distinguish subtypes (triple-negative, HER2+, other) with an AUC ≥ 0.85 —far above the 0.55 baseline.



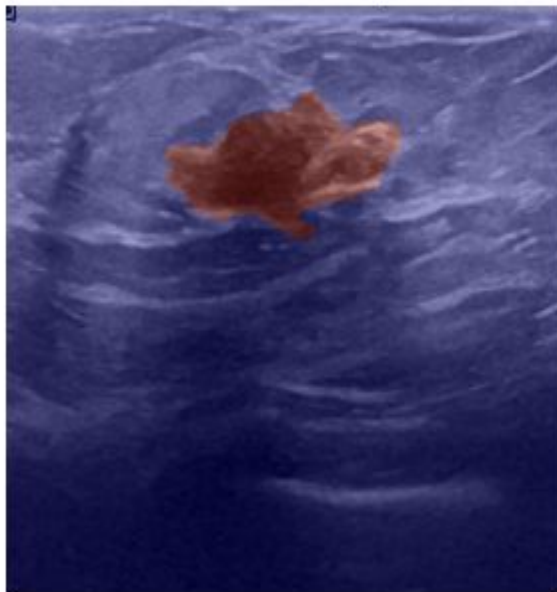
- AUC of ROC Curve: Target ≥ 0.85 for each subtype comparison (triple-negative vs. others, HER2+ vs. others).
- Accuracy: Percentage of correct subtype calls.
- Latency: End-to-end inference (mask \rightarrow subtype) in < 50 ms per image on multiple commercial scanners.
- Cross-Scanner Validation: $\geq 95\%$ of images processed within the time limit across three different ultrasound machines.

Preliminary Data

Raw US



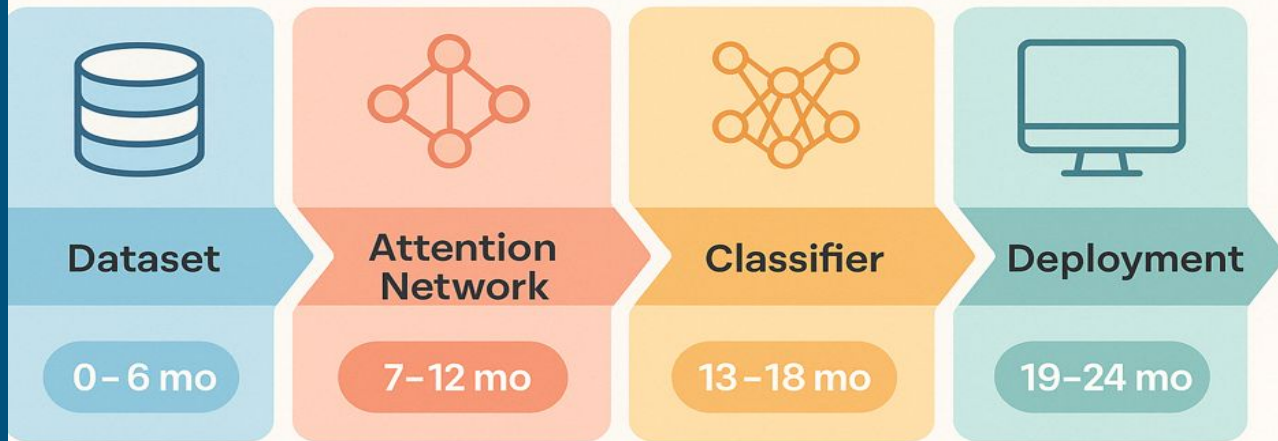
Mask Overlay



Baseline pipeline:
crop→lightweight
ResNet on N=130

Accuracy 65 %,
AUC 0.55 (vs 0.50),
0.11 s/image

Timeline & Logistics

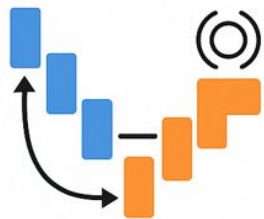


Broader Impacts

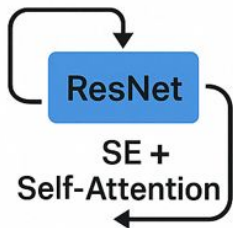
- Reduce false positives & unnecessary biopsies
 - Fewer invasive procedures → less patient anxiety & cost
- Accelerate bedside decision-making
 - Immediate AI-guided insights → earlier intervention
- Democratize care in resource-limited settings
 - Rural/underserved clinics gain expert-level US interpretation
- Foster global collaboration & innovation
 - Open-source models enable adaptation to new diseases/modalities
- Standardize imaging & improve equity
 - Consistent analysis everywhere → fairer access to life-saving diagnostics



Intellectual Merit



U-Net +
Attention



Real-Time



Real-Time



Cross-
Platform

- **Interactive GUI/Web App:** One-click attention-guided segmentation + classification wrapped in a user-friendly interface for bedside use.
- **Real-time, cross-platform inference:** Runs in <50 ms/image on varied clinical ultrasound scanners.
- **Open-source** release: Full GUI and codebase published publicly to drive global adaptation and extension.

**— So Let's Revolutionize Healthcare with
AI-Powered Ultrasound: Precision Cancer
Insights in <50 ms**

References

1. Ferre R, Elst J, Senthilnathan S, et al. Machine learning analysis of breast ultrasound to classify triple-negative and HER2+ breast cancer subtypes. *Breast Dis.* 2023;42:59–66.
2. Pacal I. Deep learning approaches for classification of breast cancer in ultrasound (US) images. *J Inst Sci Technol.* 2022;12(4):1917–1927.
3. Michael E, Ma H, Li H, Qi S. An optimized framework for breast cancer classification using machine learning. *Biomed Res Int.* 2022;2022:8482022.
4. Becker AS, Mueller M, Stoffel E, et al. Classification of breast cancer in ultrasound imaging using a generic deep learning analysis software: a pilot study. *Br J Radiol.* 2018;91(1083):20170576.