

Breast Tumor Ultrasound: Clinical Applications, Diagnostic Features, and Integration with AI

Majd Oteibi^{*1}, Adam Tamimi², Kaneez Abbas³, Gabriel Tamimi⁴, Danesh Khazaei⁵, Hadi Khazaei⁶

^{1,2,4}Validus Institute Inc

³Athreya Med Tech

⁵Portland State University

⁶Portland State University/ Athreya Med Tech

^{*}Corresponding Author

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ABSTRACT

Breast tumor ultrasound has become a cornerstone technique in both the screening and diagnosis of breast cancer due to its accessibility, non-invasiveness, and high sensitivity. This is especially true in dense breast tissue, where mammography may be less effective. Clinically, ultrasound is employed to distinguish between benign and malignant lesions, guide biopsies, and monitor treatment response. Essential diagnostic features include shape (irregular vs. round/oval), margins (non-circumscribed, spiculated), internal echotexture, and posterior acoustic phenomena. Benign lesions tend to appear as smooth, well-circumscribed, and homogeneous, whereas malignancies often present as irregular, hypoechoic masses with non-circumscribed margins and posterior shadowing.

Recent advances focus on the integration of artificial intelligence (AI) with breast ultrasound. AI-enhanced ultrasound systems, including deep learning radiomics and commercial decision support tools, can improve diagnostic accuracy, consistency, and efficiency. This approach helps with facilitating earlier detection and helps in reducing unnecessary biopsies, particularly for less experienced radiologists. Automated Breast Ultrasound (ABUS) combined with AI radiomics extracts high-dimensional image features, supporting predictive modeling for disease characterization and treatment planning.

The accompanying illustrations detail typical ultrasound appearances of benign and malignant breast masses, highlight key ultrasound features, and showcase an AI-assisted workflow. The included flowchart demonstrates the clinical algorithm: from initial patient presentation, through ultrasound image acquisition and feature characterization, to AI-integrated decision support and follow-up management steps.

This convergence of advanced imaging and AI integration marks a paradigm shift in breast cancer care, enabling more precise, timely, and cost-effective pathways from detection to management.

Keywords: Breast cancer, Ultrasound, Synthetic Tissue, AI technology, Innovation

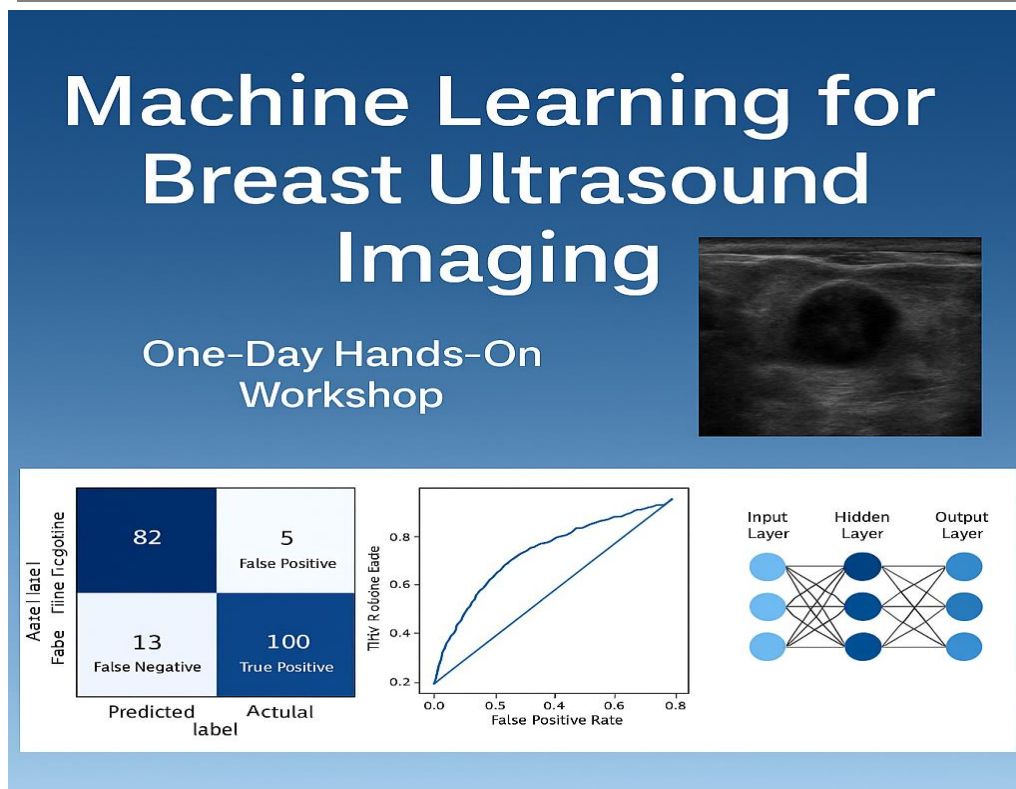


Figure 1. Image summary of the steps of breast ultrasound imaging and machine learning process.

INTRODUCTION

Breast cancer is the most common cancer in women globally. It is the second leading cause of cancer death in women globally. In 2022, there were 2.3 million new cases of breast cancer globally. Death rates were highest in low-income countries due to later diagnoses and access.

That's where the breast ultrasonography techniques that will be discussed in this article show promise in the search for more accessible, less intrusive, and more affordable breast cancer screening methods.

Ethics Statements

Animal Studies:

This manuscript did not present any information involving animal subjects

Human Studies:

No human subjects are involved in this manuscript.

Studies involving human subjects

Financial Disclosures

No financial disclosures to make in this manuscript

Conflict of Interest:

No conflict of interest presented in this manuscript

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Disclaimer:

The following manuscript explores an original experiment that was done by the Validus Institute Inc team and collaborators from the Materials and Mechanical Engineering lab at Portland State University. The experiment is original, and not all aspects discussed in this experiment will have references to prior published articles. All the images marked as courtesy of Validus Institute Inc were taken by Validus Institute Director Dr. Majd Oteibi to document that progression of this research project.

Overview of Breast Ultrasound Modalities and Clinical Applications

Ultrasound imaging is a non-invasive diagnostic tool that uses high-frequency sound waves to create real-time images of internal structures. It is widely used to assess and differentiate between benign and malignant tumors, particularly in organs like the breast (Table 1).

Table 1. Ultrasound Features of Benign vs. Malignant Breast Tumors

Feature	Benign Lesions	Malignant Lesions
Shape	Oval or round	Irregular, lobulated
Margins	Smooth, circumscribed	Indistinct, spiculated, angular
Orientation	Wider-than-tall (parallel to skin)	Taller-than-wide (non-parallel; perpendicular growth)
Echogenicity	Isoechoic or hyperechoic; homogeneous	Hypoechoic; heterogeneous
Posterior Features	Posterior acoustic enhancement (bright behind)	Posterior shadowing (dark behind), or none
Internal Echo Pattern	Uniform, possible cystic areas	Heterogeneous; internal echoes vary; may show necrosis
Calcifications	Coarse, macrocalcifications (if present)	Microcalcifications (tiny, punctate, suspicious)
Vascularity (Doppler)	Minimal or peripheral	Increased internal or central vascularity
Compressibility	Compressible	Non-compressible
Mobility	Mobile on palpation/ultrasound probe pressure	Fixed or less mobile
Elasticity (if elastography is used)	Soft or intermediate	Stiffer than the surrounding tissue

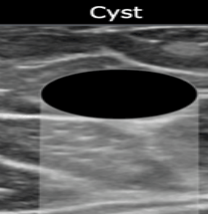

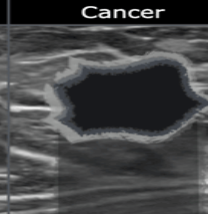
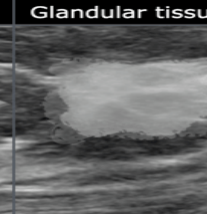
Cyst	Fibroadenoma	Cancer	Glandular tissue
			
Anechoic pattern	Hypoechoic	Hypoechoic	Hyperechoic
Oval or round shape	Most common: • oval or round Less frequent: • lobulated	Most common: • irregular shape Less frequent: • round or oval	Locally prominent glandular tissue
Circumscribed margin	Circumscribed margin	Margin is not circumscribed: • Indistinct • angular • microlobulated • spiculated	
Horizontal orientation	Horizontal orientation	Vertical orientation	
Posterior Enhancement	Sometimes minimal posterior enhancement	Frequently posterior shadowing	No feature
No calcifications	May have gross calcifications	May have small calcifications in or outside mass	No

Table 2. Summary of the classification of breast lesion types and how each can appear on the ultrasound

Typical Benign Lesions (Examples):

- **Fibroadenoma:** Oval, smooth, hypoechoic, wider-than-tall, with gentle lobulations.
- **Cyst:** Anechoic (black), posterior enhancement, well-defined.
- **Lipoma:** Isoechoic or hyperechoic, compressible, thin capsule.

Typical Malignant Lesions (Examples):

- **Invasive Ductal Carcinoma (IDC):** Irregular shape, spiculated margins, hypoechoic, posterior shadowing, taller-than-wide.
- **Invasive Lobular Carcinoma (ILC):** May appear subtle or ill-defined, often hypoechoic with minimal shadowing.

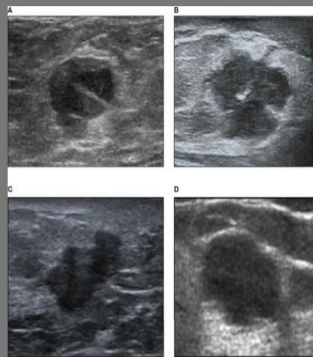


Figure 2. Ultrasound images of different breast tissue based on Malignant vs Benign clinical correlation

The Breast Imaging-Reporting and Data System (BI-RADS), developed by the American College of Radiology, serves as a standardized framework for interpreting and reporting breast imaging findings, including ultrasound examinations. The BI-RADS Ultrasound Classification categorizes lesions based on their sonographic characteristics, providing an estimate of the likelihood of malignancy and guiding appropriate clinical management. This system enhances communication between radiologists and referring clinicians and facilitates consistency in decision-making and follow-up recommendations. Table 2 summarizes the BI-RADS ultrasound categories, associated risk of malignancy, and corresponding clinical actions.

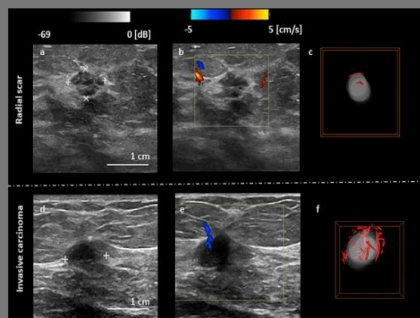


Table 3. BI-RADS Ultrasound Classification (Breast Imaging-Reporting and Data System)

Category	Description	Risk of Malignancy	Typical Action
BI-RADS 1	Negative	0%	Routine screening
BI-RADS 2	Benign finding	0%	Routine screening
BI-RADS 3	Probably benign	<2%	Short-interval follow-up (e.g., 6 months)
BI-RADS 4A	Low suspicion for malignancy	~2–10%	Recommend biopsy
BI-RADS 4B	Moderate suspicion	~10–50%	Recommend biopsy
BI-RADS 4C	High suspicion	~50–95%	Recommend biopsy
BI-RADS 5	Highly suggestive of malignancy	>95%	Immediate biopsy or surgical consultation
BI-RADS 6	Known biopsy-proven malignancy	100% (by definition)	Treatment planning

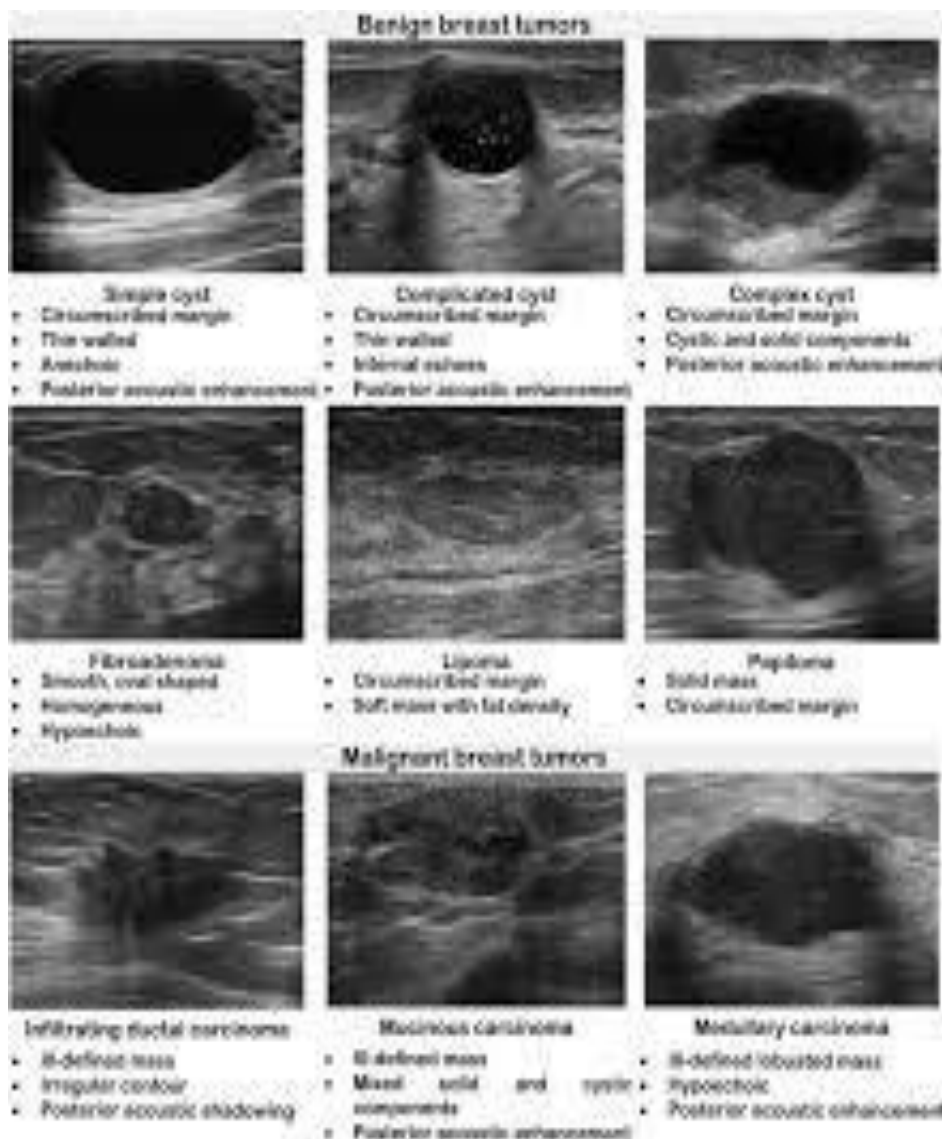


Table 4. BI-RADS Ultrasound Classification (Breast Imaging-Reporting and Classification)

Examples of Ultrasound Findings by Category

BI-RADS 2 (Benign):

- Oval, smooth, well-circumscribed fibroadenoma
- Simple cyst (anechoic, posterior enhancement, no internal echoes)
- Lipoma or intramammary lymph node

BI-RADS 3 (Probably Benign):

- Hypoechoic, oval lesion with circumscribed margins
- Wider-than-tall
- Stable fibroadenoma in young women

BI-RADS 4 (Suspicious):

- Irregular, hypoechoic mass
- Angular or indistinct margins
- Slight posterior shadowing or mixed posterior features

BI-RADS 5 (Highly Suspicious):

- Irregular or spiculated mass
- Taller-than-wide
- Strong posterior shadowing
- Marked internal vascularity
- Associated suspicious lymph nodes

METHODS/INTERVENTION

Creating synthetic tissue components, process and steps

The creation of synthetic phantom breast tissue plays a vital role in developing and validating AI-based ultrasound imaging systems. For this purpose, a multilayered phantom was constructed utilizing a controlled polyvinyl chloride (PVC) matrix plasticized with dioctyl terephthalate (DEHT) softener to emulate the acoustic and mechanical properties of human breast tissue. PVC was selected as the primary matrix material for this phantom due to its superior durability and long shelf life compared to traditional gelatin-based phantoms, which, while simpler to prepare, are prone to degradation over time and offer limited usability for prolonged imaging studies.

A ratio of 16.7 grams of PVC powder was combined with 100 milliliters of DEHT softener, producing a 16.7% w/v mixture. This blend was initially homogeneous and runny, appearing as a milky white liquid upon mixing. The mixture was steadily heated with constant stirring (Figure 3 A-B). All heating steps were conducted under a fume hood to ensure safe handling of any fumes or vapors generated during the process. As the temperature approached approximately 130°C, the solution thickened and developed a honey-like viscosity (Figure 3C). Continued heating to approximately 170°C led to a decrease in viscosity and the mixture acquired an amber-clear appearance, indicating readiness for molding (Figure 3D).

Prior to casting, a cube mold was coated internally with mineral oil to facilitate demolding. The hot PVC-DEHT mixture was first poured as a thin base layer and allowed to cool briefly, just enough for the polymer to support added features without significant deformation. Artificial lesions, in our case, 3D-printed with ABS, were then placed on top of the partially solidified base (Figure 3E), after which a second aliquot of the hot mixture was poured to fully encapsulate these inclusions. Following a similar cooling interval, a silicone breast implant was positioned atop the set lesion layer. A final portion of the mixture was applied to submerge the implant, leaving only a portion of the nipple-areolar complex exposed to replicate anatomical fidelity (Figure 3 F-G).

After assembly, the phantom was allowed to cool to room temperature to ensure complete solidification. The finished construct could be easily removed from the mold, yielding a stable, layered model suitable for ultrasound investigation. This fabrication protocol provides a reproducible approach for generating physiologically relevant phantoms intended for AI/ML training and imaging research.

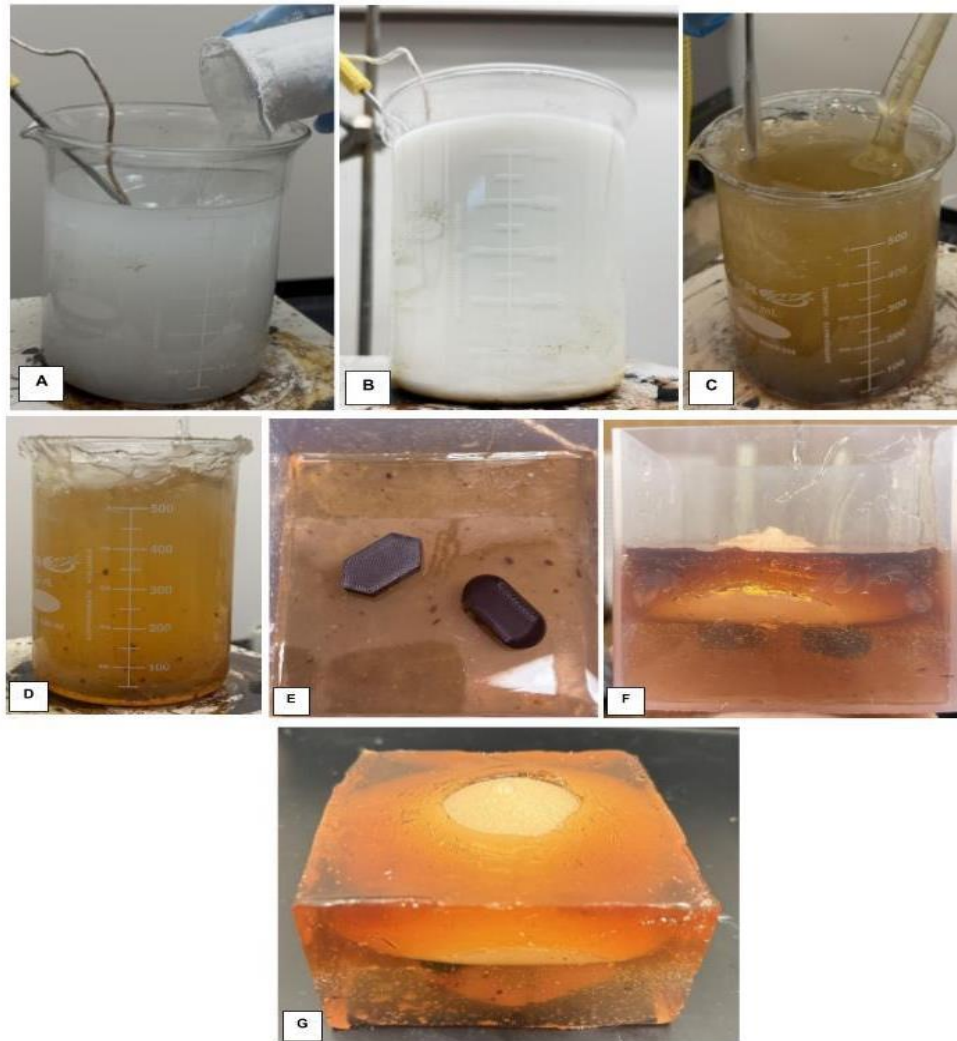


Figure 3. Fabrication and structure of the synthetic breast phantom. (A) Addition of powdered PVC into DEHT under heating and stirring. (B) Homogeneous, milky-white dispersion after full mixing. (C) Thickening of mixture at ~130 °C with honey-like viscosity. (D) Final amber-clear solution at ~170 °C, maple syrup consistency. (E) 3D-printed lesions prior to embedding. (F) Molded phantom showing stratified layers and embedded structures. (G) Fully cured phantom removed from mold, with visible breast implant and exposed nipple–areolar complex. Courtesy of Validus Institute Inc and PSU collaborators, 2025

Using the ultrasound probe and the process of capturing ultrasound images

The Butterfly iQ probe was selected for this study due to its portability, user-friendly interface, and ability to deliver imaging quality comparable to conventional ultrasound machines. The study utilized the Butterfly iQ in conjunction with the Butterfly App on a 10th Generation Apple iPad. Real-time imaging was displayed on the app interface as the probe was applied to a surface, and connected to the Ipad via USB-C.

The ultrasound procedure began with the application of conductive gel to the probe. As sound waves travel more effectively through fluid mediums, the gel facilitates optimal transmission by reducing air interference between the probe and the skin. With the gel applied, the probe was placed in contact with the general area of concern. It is important to establish a consistent orientation during scanning by referencing the probe's side light indicator, which identifies the probe's lateral orientation relative to the patient.

The Butterfly probe provides a downward-facing view, where the upper portion of the screen represents the most superficial structures. Proper grip and pressure must be maintained to ensure consistent contact and high-quality imaging. The scanning process involves first sweeping across the transverse axis, followed by the longitudinal axis, adjusting planes as needed to fully evaluate the region of interest. Images were interpreted live through the Butterfly App interface during the scanning process.

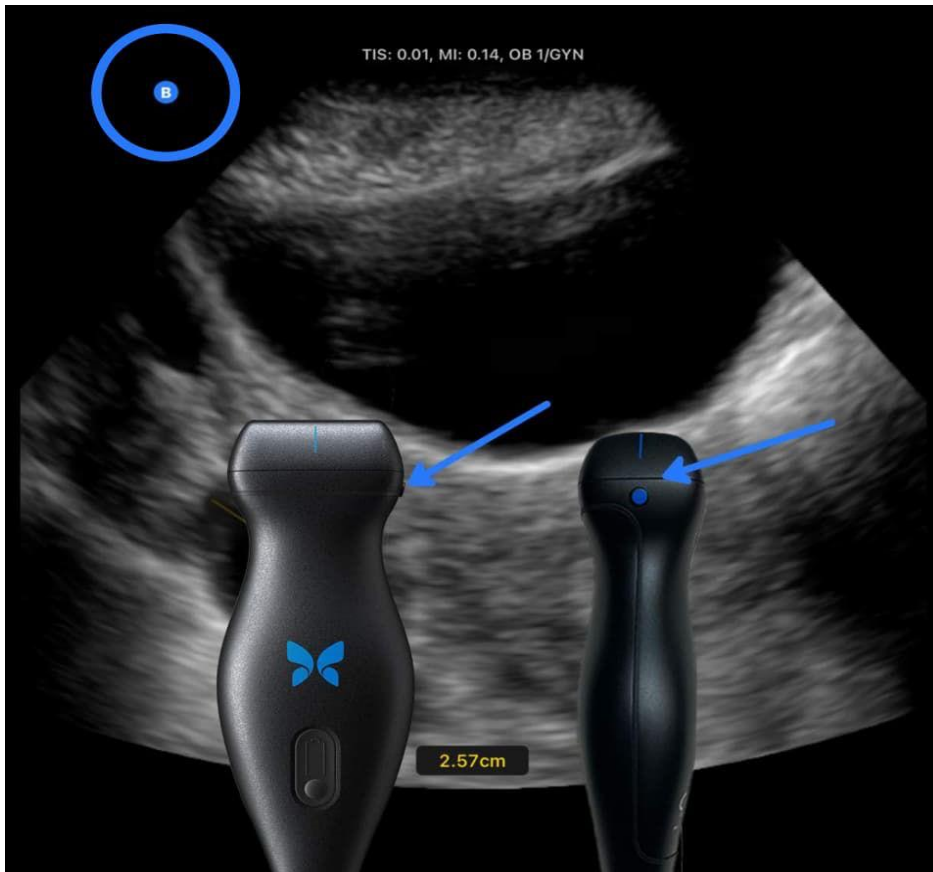


Figure 4: www.butterfly-network.com

Techniques for handling a butterfly IQ probe are similar to conventional ultrasound devices, as the user must be aware of orientation, proper “pencil” grip and hand positioning. The user can adopt the “PART” technique to ensure optimal image acquisition. This includes adjusting pressure gently to maintain good contact without distorting tissue, angling the probe to better visualize deeper structures, rotating it 90 degrees to alternate between transverse and longitudinal planes, and tilting the probe sideways, upwards, or downwards to sweep through different tissue layers. Additionally, effective image optimization involves adjusting depth and gain settings on the interface as needed. Utilizing the app’s preset modes for organs such as vascular, MSK, or abdominal can further enhance image quality tailored to the anatomical region being assessed.

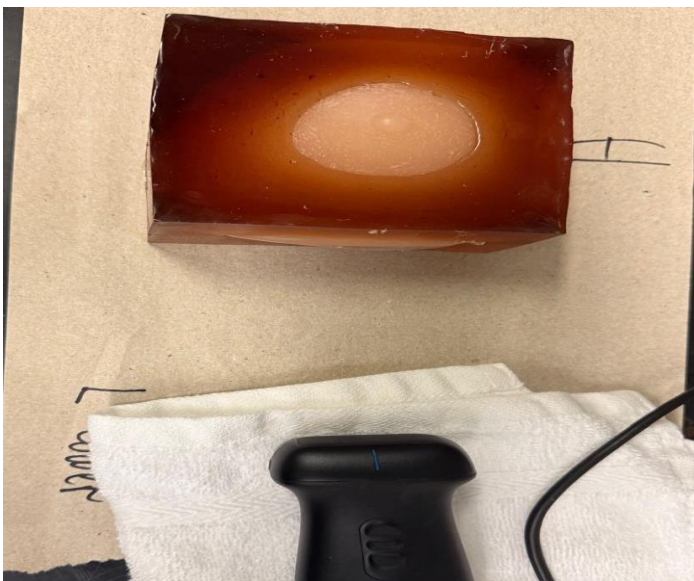


Figure 5. Synthetic tissue used and ultrasound probe used to capture images Butterfly IQ3 probe.

www.butterflynetwork.com, and synthetic tissue image. Courtesy of Validus Institute Inc, 2025

In this experiment, the following presets were used; soft tissue, small organ, and musculoskeletal (MSK). These were used because of the depth of the specific lesions and tissue since the team took images of different synthetic tissues.

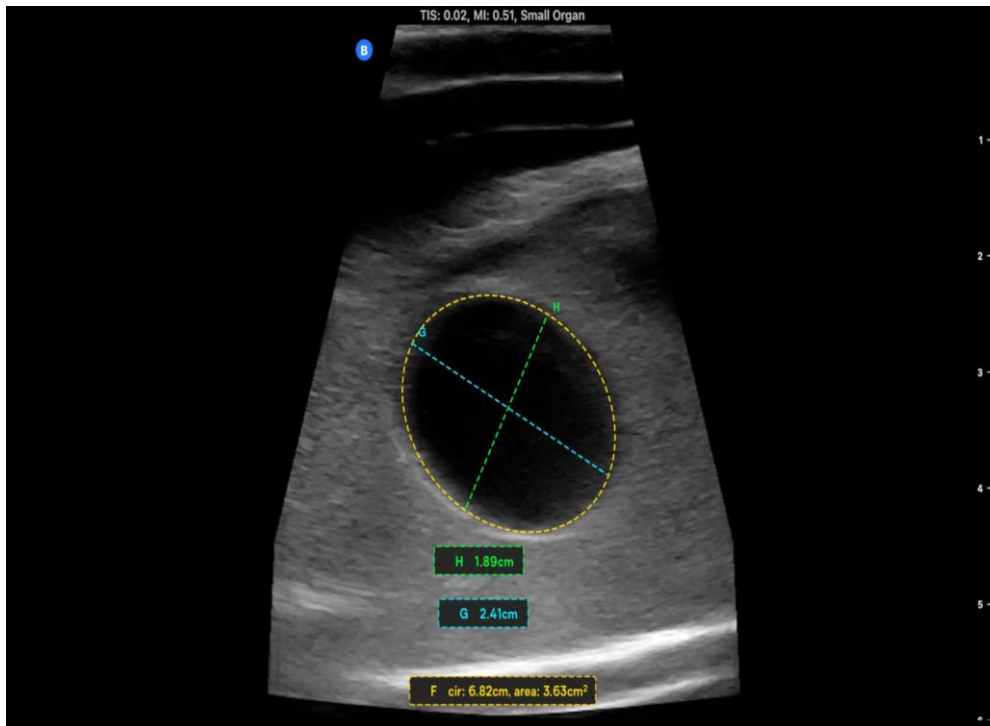


Figure 6. Ultrasound image captured using synthetic tissue. The image shows the measurements of the breast tissue. Using the ellipse and the lines both vertical and horizontal to start the annotation process. Courtesy of Validus Institute Inc., 2025

Understanding the ultrasound images and annotation process

Depending on the device being utilized, images are shown in real time on the interface. In this A10th generation iPad Air was used in this testing; the Butterfly I Q 3 was used and the gadget is USB-C compliant.

To start the annotation process, the researcher added an ellipse, line, or notes that are seen from the screen after the live broadcast has been frozen to take an image.

The size of the breast image that was taken, was identified and marked. The handling of the probe direction of the transverse or longitudinal direction was identified and marked.

The position of the cyst arrangement of the breast side that was taken, whether it was taken proximally or distally in relation to the hypothetical patient's head, were all marked with annotations for both benign cystic lesions and solid masses.

The edges of benign cystic lesions are shown by an ellipse. To display the lesions' measurements, lines were added. For malignant lesions the annotation process involves line measurements both horizontal and vertical. It also labels the organ name, transverse vs longitudinal and the location of the tumor in relation to the side of the breast captured in the image taken during this time.

To capture the borders of the cystic lesion, we clicked on the elliptical tab. The elliptical shape to shows the margins of the legion where we draw an oval shape or circle depending on the shape of the cyst. We then employed both vertical and horizontal lines to show the measurements of the cysts. The side of the breast that was photographed and the type of organ were identified to apply annotations for both benign cyst and solid masses. This work is based on the original experiment of the team during this experiment. For solid mass annotations were used by identifying the type of organ, side of the breast that was captured in the image as listed above.

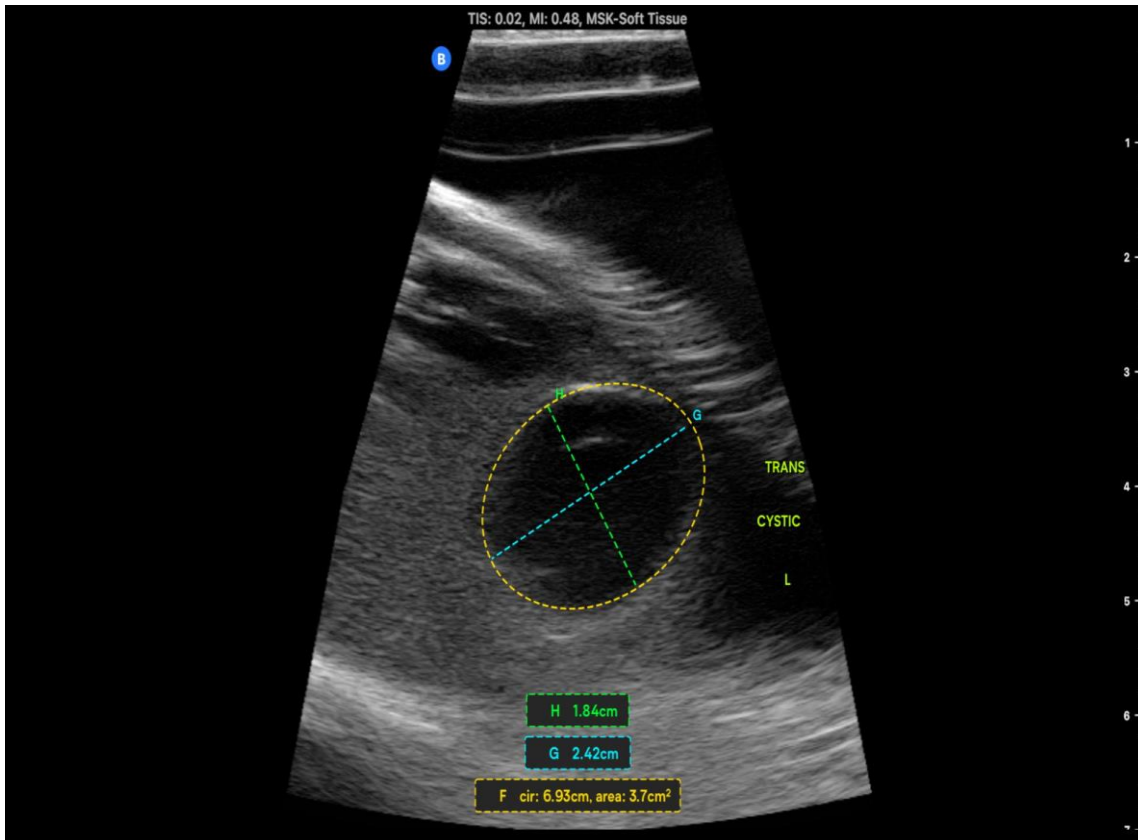


Figure 7. Left cystic breast ultrasound image. Taken as a transverse position using the synthetic tissue model. Measurements and annotations are shown in the picture. After the measurements are taken we start the annotation process by marking the side of the lesion, name of the lesion and the position of the ultrasound hand probe. Here we see an oval cystic lesion of the left breast with regular and clearly marked edges. Courtesy of Validus Institute Inc, 2025

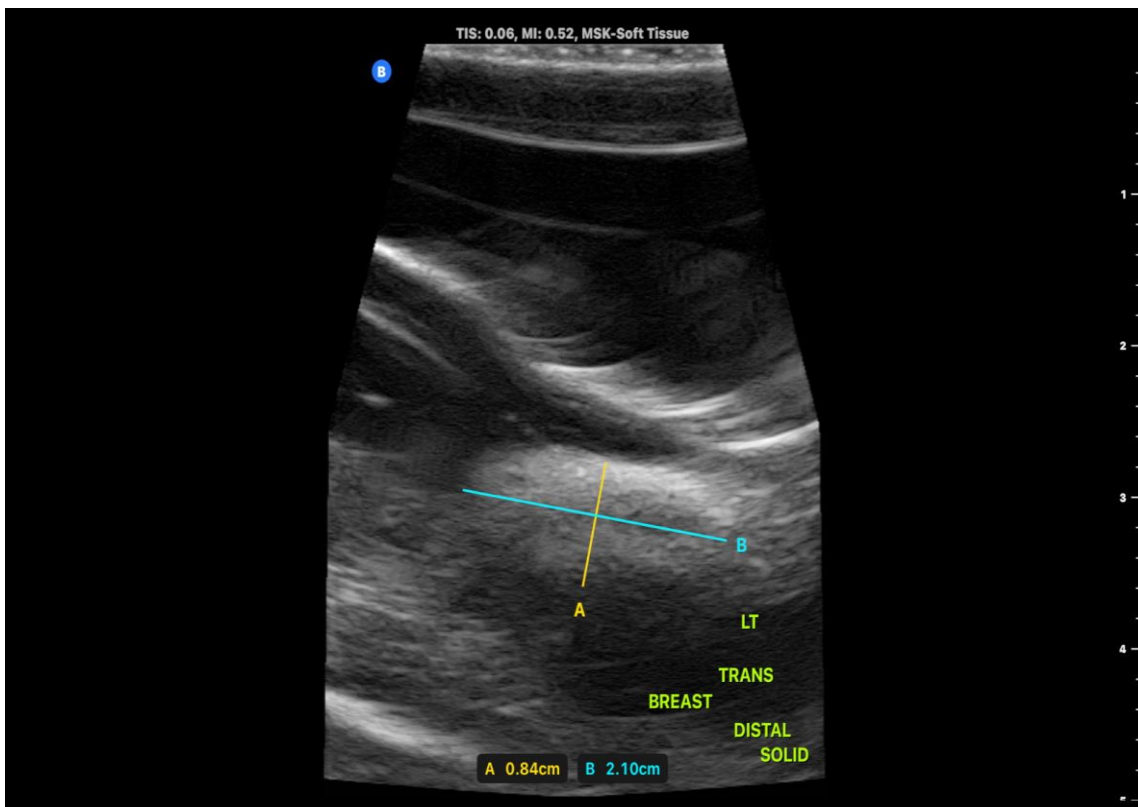
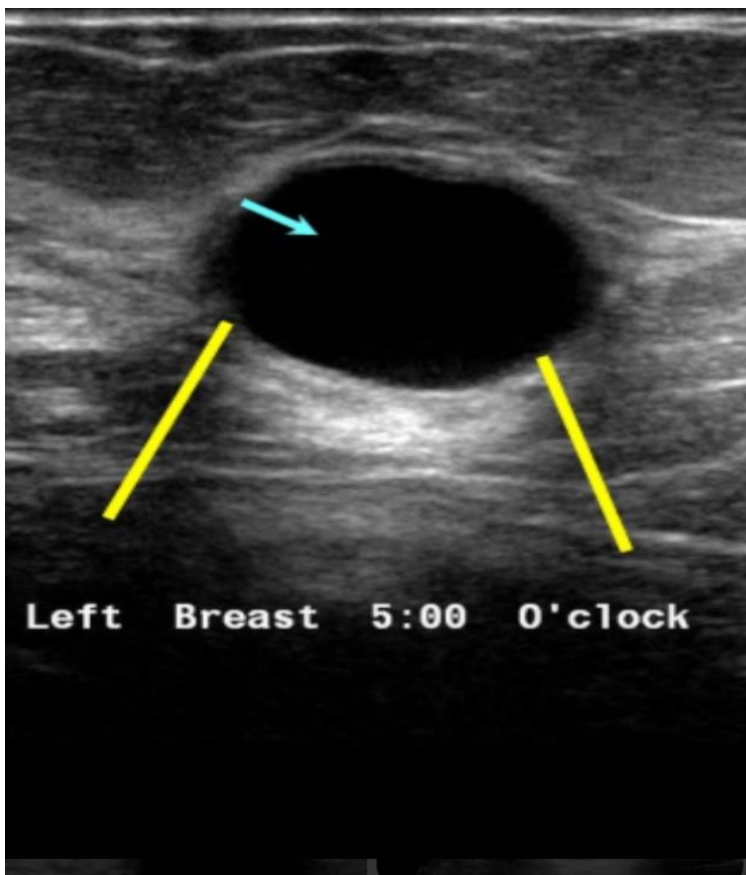


Figure 8. Left solid breast ultrasound image. Taken as a transverse position using the synthetic tissue model. Measurements and annotations are shown in the picture. Courtesy of Validus Institute Inc, 2025



Q malignant breast cancer vs cyst ultrasound in

OUTCOME AND FUTURE RESEARCH

The integration of conventional breast ultrasound with artificial intelligence (AI) represents a transformative advancement in breast cancer diagnosis and management. This innovation significantly enhances diagnostic accuracy and streamlines clinical workflows, especially in settings where radiological expertise may be limited. AI-assisted platforms have proven effective in differentiating benign from malignant lesions with higher consistency, reducing inter-observer variability, and minimizing unnecessary biopsies. Features like deep learning-based radiomics and Automated Breast Ultrasound (ABUS) have allowed the extraction and analysis of complex imaging biomarkers, supported personalized treatment strategies and improved patient outcomes. The clinical algorithm described ranging from initial imaging to AI-supported decision-making demonstrates the potential for integrated systems to provide more efficient and accurate diagnostic pathways.

Limitations:

There are constraints of using synthetic tissue because of the limitations of the breast side that can have a synthetic tissue mimicked, which can lead to bias in labeling the image captured from synthetic tissues.

Also, the limitation of the handle probe and a specific portable ultrasound probe, can be influenced by users training and affect the credibility of the image results and the research results. That's where training staff to provide proper ultrasound techniques and capturing images is a crucial part of the ultrasound screenings and training as well as synthetic tissue development. The other limitation was limited available information that can be replicated. This experiment is original in its design and thus our team went through many trials before perfecting it and coming up with the best approach to conduct this experiment.

Another limitation is limited funding options and the small data sample that was used. That is why it is important to consider other funding resources, such as grants or other small business loans that can support this research, to be able to conduct this study with a bigger sample size and resources to test this theory and replicate it on a bigger scale. This is an important step to reach the stage where we can train the AI model and produce reliable and valid AI integrative models in the future.

Future Research:

Future research in breast ultrasound and AI integration will likely focus on the following areas:

1. **Improved Model Generalizability:** Continued work is needed to train AI models on more diverse, multi-institutional datasets to ensure robust performance across different populations, equipment vendors, and clinical environments.
2. **Real-Time AI Integration:** Development of real-time, point-of-care AI solutions that assist clinicians during live scanning, offering dynamic feedback to enhance diagnostic accuracy and reduce scanning time.
3. **Multimodal Imaging Fusion:** Research into fusing AI-enhanced ultrasound with mammography, MRI, or elastography could yield more comprehensive diagnostic systems that capitalize on the strengths of each modality.
4. **Predictive and Prognostic Modeling:** Expanding the role of AI from diagnosis to long-term outcome prediction, including recurrence risk, treatment response, and survival analysis, by combining imaging data with genomic, clinical, and pathological information.
5. **Validation through Prospective Clinical Trials:** Large-scale, prospective validations are needed to assess real-world effectiveness, cost-benefit ratios, and clinical outcomes driven by AI-assisted ultrasound systems.
6. **Ethical and Regulatory Frameworks:** Establishing clear guidelines and standards around the deployment, transparency, and interpretability of AI in breast imaging to ensure safe, equitable, and trustworthy clinical use.

In summary, the coupling of ultrasound imaging with AI holds the promise of redefining breast cancer care by enabling earlier detection, better risk stratification, and more personalized treatment strategies.

Then add to this the integration of synthetic tissue models in breast ultrasound screening has yielded several promising outcomes, significantly advancing our research in a practical way. One of the most notable benefits is the ability to standardize and enhance training for radiologists and sonographers. Synthetic tissue phantoms, engineered to mimic the acoustic and mechanical properties of human breast tissue, allow for repeated, consistent practice without risk to patients. This has improved diagnostic accuracy, particularly in detecting subtle lesions or abnormalities in dense breast tissue.

Synthetic tissues have proven useful for capturing reliable images and capturing multiple images from many different angles of the breast and using both transverse and longitudinal probe handling during the capturing of the ultrasound images. Furthermore, synthetic tissue enables the safe integration and testing of AI algorithms. By generating controlled scenarios with known pathologies as was demonstrated in our experiment. The use of synthetic models allows for training and validation of machine learning systems in a reproducible environment.

CONCLUSION

The use of synthetic tissue and ultrasound images of the breast has demonstrated that it is a reliable technique to use. As synthetic tissue-supported imaging and AI modelling improve lesion characterization, clinicians can more confidently distinguish benign from suspicious masses. A potential prospect for non-invasive, easily accessible, and reasonably priced screening in a variety of healthcare settings is the combination of portable ultrasonography and artificial intelligence.

The AI assisted ultrasound training will allow the interpretation of the lesions. This will lead to the reduction in invasive procedures as less core biopsies will be needed. By providing a stable reference, these models support ongoing quality assurance, reducing variability between screenings and across different equipment or operators. The training of AI assisted ultrasound technologies using synthetic tissue modules as was demonstrated in our experiment shows promising results. This reduces the ethical concerns and logistical limitations of relying solely on human subjects and accelerates the development of robust, generalizable AI tools for early breast cancer detection.

The use of AI assisted ultrasound imaging has the potential to revolutionize the treatment of breast cancer by facilitating improved risk assessment, earlier detection, and more individualized treatment plans. Thorough validation, interdisciplinary cooperation, and ongoing learning integrated into clinical workflows will be essential for long-term success of this innovative process.

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“The Biomedical Data Science Innovation Lab (BDSIL; <https://www.innovation.lab.virginia.edu/>), through support from the National Institute of General Medical Sciences (NIGMS; NIH Grant# [R25GM139080](#)), is an intensive, interdisciplinary research training and team science program designed to catalyze novel collaborations between early-career investigators from biomedical and quantitative backgrounds. Through a carefully structured combination of mentorship, creativity training, facilitated ideation, and collaborative grant development, BDSIL provides participants with the tools, environment, and professional support needed to generate high-impact, data-driven research proposals. The program emphasizes cross-disciplinary communication, the co-creation of new ideas at the interface of biomedicine and data science, and the development of innovative solutions to complex health-related challenges. Participation in the BDSIL fostered lasting research partnerships and offered invaluable guidance from expert mentors, ultimately accelerating the trajectory of the work described in this manuscript.” -courtesy of Dr. John Darrell Van Horn, Ph.D., M.Eng., FOHBM

Special thanks to Dr. John Darell Von Horn for sharing this detailed summary and the BDSIL team as well as all the mentors for their stimulating questions during this learning experience.. Based on their stimulating questions and ideas my team will take this project further and develop a study to involve multi-omics as part of our new research, which will be part of our new upcoming paper and research project for 2025-2026. Thank you for all your valuable insights.

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