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# The Critical Role of Multimodal Imaging in Breast Cancer Diagnosis

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**ABSTRACT:** Breast cancer remains one of the leading causes of cancer-related mortality among women worldwide. Early and accurate detection is critical to improving patient outcomes, yet relying solely on a single imaging modality such as ultrasound, mammography, or histopathology may lead to misdiagnosis or under-detection of malignancies. Each modality offers unique insights: ultrasound captures real-time structural and vascular information, mammography highlights microcalcifications and dense tissue patterns, while histopathology provides definitive cellular-level confirmation. However, no single method is sufficient to comprehensively characterize breast lesions due to varying tumor presentations and limitations in sensitivity or specificity. This paper emphasizes the necessity of a multimodal approach that integrates findings from all three techniques to enhance diagnostic accuracy and minimize false positives and negatives. We discuss the complementary roles of these modalities and advocate for standardized multimodal protocols in clinical breast cancer evaluation.

**KEYWORDS:** Breast Cancer Detection, Multimodal Imaging, Ultrasound, Mammography, Histopathology, Diagnostic Accuracy, Medical Image Analysis, Complementary Modalities, Malignant Tumor Confirmation, Multimodal Diagnosis.

## I. INTRODUCTION

Breast cancer remains one of the most prevalent and life-threatening cancers affecting women globally. Despite substantial advancements in imaging technologies and artificial intelligence (AI) driven diagnostics, the early and accurate detection of malignant breast cancer continues to pose significant challenges. Traditionally, diagnostic evaluation has relied on a single imaging modality such as ultrasound, mammography, or histopathology. However, relying on any one of these techniques in isolation often results in false positives, where benign lesions are mistaken as malignant, or false negatives, where malignant tumors go undetected. According to estimates for 2024, over 2.4 million women were diagnosed with breast cancer worldwide, with more than 706,342 deaths, highlighting the urgent need for improved diagnostic systems. In India alone, the year 2024 witnessed over 240,309 new breast cancer cases and approximately 100,614 deaths, making it the most common and deadly cancer among Indian women. These alarming figures underscore the necessity of adopting more integrated, multimodal diagnostic strategies to improve early detection and treatment outcomes. Each imaging modality used in breast cancer detection offers unique diagnostic advantages while also presenting notable limitations.

Ultrasound is widely accessible, non-invasive, and cost-effective, making it valuable for real-time imaging and preliminary screening, particularly in younger women and low-resource settings. It excels in differentiating cystic from solid masses and assessing vascularity through Doppler techniques. However, ultrasound is often operator-dependent and may lack specificity, especially in dense breast tissue, where lesion borders and internal features can be challenging to interpret.

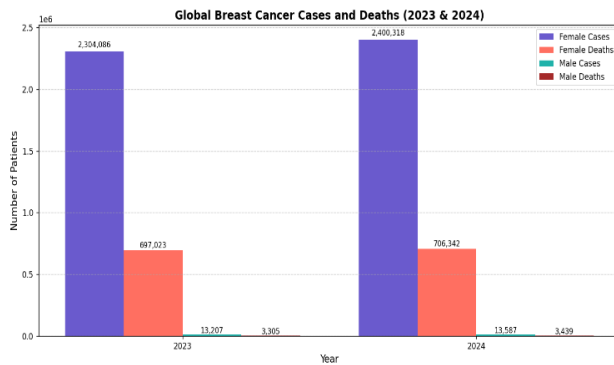


Figure 1: Global breast cancer cases

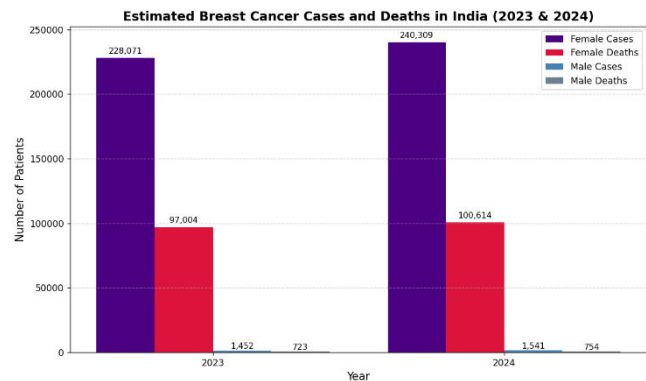


Figure 2: Indian breast cancer cases

Mammography is a cornerstone of population-level breast cancer screening and is particularly effective at detecting microcalcifications, architectural distortions, and subtle tissue asymmetries hallmarks of early malignancy. It has contributed significantly to reducing breast cancer mortality through early detection. However, its performance diminishes in women with dense breasts, where overlapping tissue can mask tumors. Moreover, it involves low-dose radiation exposure, which limits repeated use, especially in high-risk groups.

In contrast, histopathology is considered the gold standard for breast cancer diagnosis. It provides microscopic and molecular-level analysis of tissue, enabling the accurate classification of tumor type, grade, hormonal status (ER/PR), HER2 expression, and other biomarkers crucial for personalized treatment planning. Despite its unmatched diagnostic precision, histopathology is invasive, requiring tissue biopsy or surgical excision, and is usually performed only after imaging suggests a potential abnormality introducing delays and depending heavily on the accuracy of prior imaging.

Recent research efforts have largely focused on enhancing model architectures, improving training performance, or applying deep learning techniques on individual modalities. Some researchers have started to incorporate patient statistical data such as age, family history, hormonal status, and genetic markers along with imaging data to improve prediction models. While this direction is promising, it still often lacks the practical integration of multiple medical imaging modalities in a unified diagnostic framework.

A multimodal imaging approach, combining ultrasound, mammography, and histopathological data, has the potential to overcome the inherent limitations of each modality and provide a more comprehensive, accurate, and reliable assessment. Such an approach aligns with how clinicians evaluate breast cancer in real-world scenarios through a holistic interpretation of various types of medical data. This paper highlights the critical need to move beyond isolated improvements in AI models and towards developing clinically viable, multimodal diagnostic systems that reflect real-world diagnostic workflows. We argue that the true path to improved breast cancer detection lies not only in better algorithms but in better integration of diverse, complementary diagnostic modalities.

## II. LITERATURE SURVEY

**Ultrasound based detection:** Ultrasound is a commonly used non-invasive imaging modality in breast cancer diagnosis, especially in younger women and those with dense breast tissue. The study by Iacob et al. (2024) emphasized the significance of ultrasound as a primary screening tool in low- and middle-income countries due to its affordability and accessibility [1]. Despite its advantages such as real-time imaging and absence of radiation, limitations include operator dependency and reduced specificity. Recent advances like Automated Breast Ultrasound (ABUS) aim to reduce these issues by standardizing the imaging process. Additionally, a comprehensive review by Dan et al. (2023) emphasized the potential of ultrasound (US) as a primary screening tool in low- and middle-income countries (LMICs), especially in younger women and those with dense breasts where mammography is less effective. The study highlighted how advancements in handheld and automated breast ultrasound (ABUS), combined with artificial intelligence (AI) and deep learning (DL) techniques[2], can enhance screening accuracy and accessibility in resource-limited settings.



Portable US devices powered by AI have shown comparable diagnostic accuracy to experienced radiologists, making them a viable alternative for early breast cancer detection in underserved regions.

**Mammography based detection:** Mammography is the standard imaging modality for population-wide breast cancer screening. It is particularly useful for detecting microcalcifications and architectural distortions. The review by Abhisheka et al. (2023) highlights that digital mammography remains a core method despite its limitations in dense breast tissue [3]. It also underlines the use of deep learning techniques to enhance detection performance. A study by Kumar Saha et al. (2024) introduced a novel approach to breast cancer classification from mammograms using a segmentation-based transformer model. By incorporating the 'Segment Anything Model' (SAM) [4] for region of interest extraction and applying transfer learning on a modified Pyramid Transformer (PTr) architecture, the model achieved outstanding results. Their approach reported a binary classification accuracy of 99.96% and an AUC of 99.98%, outperforming other deep learning models such as ViT, EfficientNetB7, and MobileNetV3.

**Histopathological based detection:** Histopathological analysis is the gold standard for definitive diagnosis of breast cancer. With the digitization of pathology slides, machine learning models have been applied for accurate classification of cancer subtypes. These methods are highly accurate but are limited by their invasive nature and high cost, making them suitable primarily for confirmatory diagnostics. The study by Drioua et al. (2023) explored U-Net and autoencoder architectures for tumor segmentation in histopathological images [5], demonstrating high precision. Robin et al. emphasized that U-Net-based models can work effectively even with small annotated datasets [6]. with patient-specific statistical data, including age, breast density, and medical history. This hybrid approach was tested using both soft voting and feature concatenation methods to integrate predictions from deep learning and traditional machine learning models. The system achieved a maximum classification accuracy of 93% and an AUC-ROC of 100%, demonstrating that integrating both image and non-image data significantly enhances the performance and robustness of breast cancer diagnosis systems. The study also emphasized that using images from both breasts (CC and MLO views) improves diagnostic accuracy over single-side analysis.

**Multimodal and Statistical Data Inclusion:** Multimodal learning, which integrates data from imaging (e.g., mammography, ultrasound) and non-imaging sources (e.g., clinical data, genomics), has shown promising results in improving classification and prediction performance. Nakach et al. (2024) [7] conducted a systematic review of 47 studies using multimodal deep learning fusion, revealing enhanced performance over unimodal systems. Kayikci and Khoshgoftaar (2023) developed a gated attention-based multimodal model [8] that combined gene expression, copy number variation, and clinical data for breast cancer classification. A recent study by Sunba et al. (2024) introduced a multimodal CAD system that integrates four-view mammographic images with patient data (e.g., age, breast density, medical history). Using soft voting and feature concatenation, the system achieved 93% accuracy and 100% AUC-ROC, highlighting the effectiveness of combining imaging and clinical data for improved breast cancer diagnosis [9].

### III. PROBLEM STATEMENT

Breast cancer continues to cast a long shadow over women's health, claiming countless lives due to one critical issue: delayed or inaccurate diagnosis. Despite the explosion of medical imaging technologies and AI-powered diagnostics, the global medical community is still grappling with a fundamental limitation the over-reliance on single-modality scans.

A mammogram might miss a tumor hiding in dense tissue. An ultrasound might struggle to distinguish between benign and malignant lesions. Histopathology, while highly precise, is invasive, slow, and comes too late in the diagnostic process for many. Each modality tells only part of the story, like trying to solve a puzzle with missing pieces.

This fragmented approach can result in false alarms that trigger unnecessary biopsies, or worse, missed malignancies that are caught too late for effective treatment. In a country like India, where disparities in healthcare access, equipment quality, and trained radiologists are stark, this challenge is even more magnified.

So, the question arises **why are we still treating breast cancer detection as a one-size-fits-all problem?**

To overcome this diagnostic blindspot, we must embrace a new paradigm, multimodal fusion. By combining the power of mammography, ultrasound, histopathology, and potentially even MRI or CT, we can construct a fuller, clearer, and

more actionable picture of what's happening inside the body. This isn't just a technical upgrade it's a life-saving evolution in how we detect and treat one of the deadliest diseases affecting women today.

#### IV. OBJECTIVES

The primary objective of this study is to explore and emphasize the critical need for a multimodal diagnostic approach in the detection and confirmation of breast cancer. While significant advancements have been made in deep learning architectures and imaging techniques, the majority of research efforts remain focused on improving the performance of models based on single imaging modalities, such as ultrasound, mammography, or histopathology.

This study aims to shift the perspective from isolated modality-based improvements to a more holistic, integrative view that mirrors real-world clinical decision-making, where multiple imaging results are often combined to reach an accurate diagnosis. Furthermore, the paper intends to identify the research gap in current literature that largely overlooks the practical implementation and feasibility of multimodal systems in clinical practice.

##### Specific Objectives Include:

1. **To analyze the limitations** of relying solely on a single imaging modality (ultrasound, mammography, or histopathology) for accurate breast cancer detection.
2. **To evaluate the complementary strengths** of each modality in diagnosing various breast tissue abnormalities, especially in complex cases or dense breast tissues.
3. **To highlight the clinical significance** of combining multiple imaging modalities for a more reliable and confident diagnosis, reducing false positives and negatives.
4. **To identify gaps** in current literature where most studies focus on improving individual model accuracy, but lack consideration of real-world implementation using multimodal data.
5. **To advocate for a shift in research direction** towards building multimodal frameworks and datasets that mirror actual diagnostic procedures used by radiologists and pathologists.

#### V. COMPARATIVE ANALYSIS OF MODALITIES

In the clinical diagnosis of breast cancer, various imaging modalities play critical roles. Each of these techniques offers unique advantages while also exhibiting certain limitations. Understanding these differences is essential for assessing their individual and combined diagnostic value in real-world applications.

**Ultrasound** is a non-invasive, real-time imaging technique that uses high-frequency sound waves to visualize internal breast structures. It is particularly useful for evaluating cystic versus solid masses and is often recommended for younger women and patients with dense breast tissue.

- **Strengths:** Non-ionizing, cost-effective, portable, effective in dense breast tissue
- **Limitations:** Operator-dependent, lower specificity, less effective at detecting microcalcifications

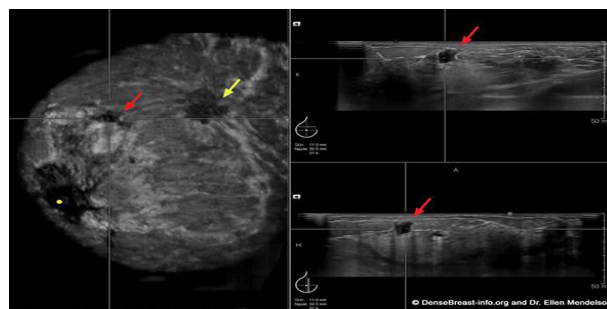
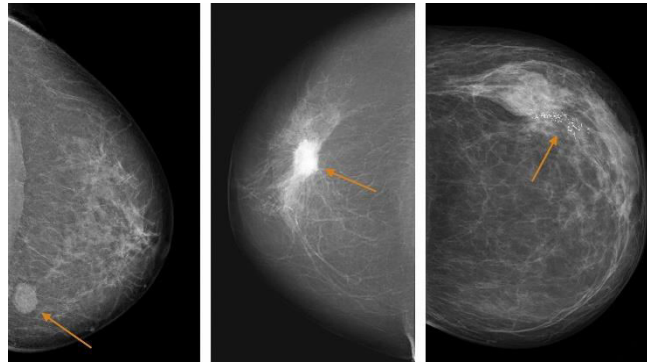


Figure 3: Ultrasound image of Breast

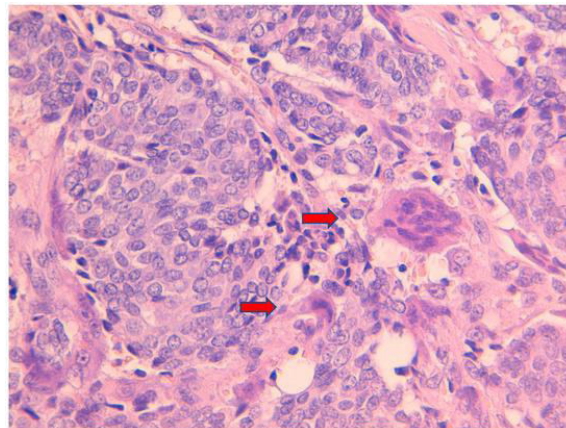
**Mammography** is a widely used screening tool that employs low-dose X-rays to detect breast abnormalities, especially calcifications and architectural distortions. It remains the gold standard for population-level screening programs.

- **Strengths:** High resolution, good at detecting microcalcifications, widely accessible
- **Limitations:** Reduced sensitivity in dense breasts, uses ionizing radiation, less effective in younger women



**Figure 4:** Mammography of a breast

**Histopathological** analysis involves the microscopic examination of biopsy or surgical tissue samples. It is the definitive method for diagnosing breast cancer and grading tumors based on cellular characteristics.



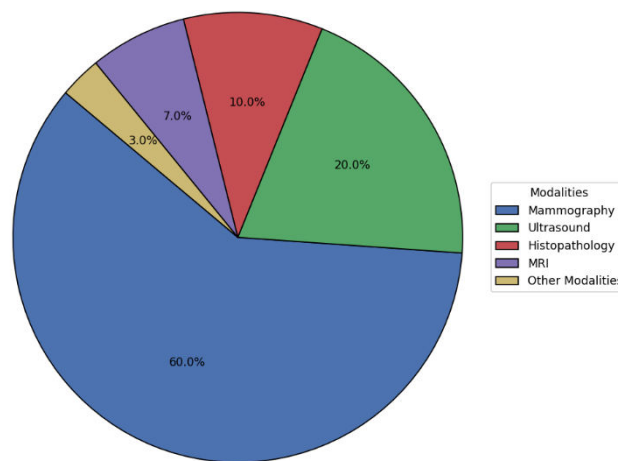
**Figure 5:** Histology of breast

- **Strengths:** Gold standard for confirmation, provides cellular-level details, essential for tumor grading
- **Limitations:** Invasive, requires prior suspicion, time-consuming, not suitable for screening

**Table 1:** Comparison of Imaging modalities in breast cancer

| Feature / Modality | Ultrasound                      | Mammography                       | Histopathology                       |
|--------------------|---------------------------------|-----------------------------------|--------------------------------------|
| Type of Technique  | Real-time imaging (sound waves) | X-ray based imaging               | Microscopic tissue examination       |
| Invasiveness       | Non-invasive                    | Non-invasive                      | Invasive                             |
| Ideal for          | Dense breasts, younger women    | Early detection, screening        | Confirmation after imaging suspicion |
| Radiation Exposure | None                            | Yes (low dose)                    | None (but involves tissue removal)   |
| Detection Ability  | Good for masses, cysts          | Excellent for calcifications      | Definitive diagnosis                 |
| Sensitivity        | Moderate                        | High (but lower in dense breasts) | Very high                            |
| Specificity        | Moderate                        | High                              | Highest                              |
| Cost               | Low to moderate                 | Moderate                          | High                                 |
| Accessibility      | Widely available                | Widely available                  | Requires lab facilities              |

The pie chart illustrates the global distribution of breast cancer diagnostic modality usage. Mammography, accounting for 60%, remains the most widely utilized screening tool due to its accessibility and effectiveness in detecting early-stage abnormalities. Ultrasound follows with 20%, primarily used as a supplementary technique, especially for patients with dense breast tissue. Histopathology contributes 10%, serving as the gold standard for confirmatory diagnosis. MRI, with 7%, is reserved for high-risk cases due to its cost and sensitivity, while other modalities like PET and CT scans comprise the remaining 3%. This visualization underscores the dominant role of imaging-based techniques in global breast cancer diagnostics.



**Figure 5:** Global distribution of breast cancer diagnostic modality usage

## VI. INTEGRATION CHALLENGES

In the context of this research, the focus lies in using multimodal medical images specifically ultrasound, mammography, and histopathology for the classification and prediction of breast cancer. Although this approach aims to improve diagnostic accuracy by leveraging the complementary strengths of each modality, several challenges emerge when attempting to integrate such diverse data types in a single analytical framework.



### 1. Multimodal dataset availability

One of the most pressing challenges is the lack of publicly available datasets that contain all three imaging modalities for the same set of patients. Most existing datasets are unimodal, making it difficult to train and validate models that require cross-modal data. The scarcity of aligned multimodal datasets limits the ability to explore the true potential of multi-input learning systems.

### 2. Alignment and Synchronization of modalities

Each imaging modality captures breast tissue at a different resolution, scale, and spatial perspective, which poses challenges in feature-level integration. For example, histopathology offers cellular-level detail, while mammograms provide macro-level anatomical context. Aligning these modalities for meaningful feature fusion requires advanced preprocessing, normalization, and possibly region correspondence techniques, which adds complexity to the pipeline.

### 3. Heterogeneous data representations

Ultrasound, mammography, and histopathology images differ significantly in data formats, noise characteristics, contrast levels, and image sizes. Training a unified model that can handle such heterogeneity demands careful design of modality-specific preprocessing and feature extraction modules, possibly using separate CNN branches or transformer encoders for each modality.

### 4. Feature fusion strategy

A key consideration in multimodal classification is how and when to fuse information from different modalities. Early fusion (at the input level) may not be effective due to different resolutions and structures, while late fusion (at decision level) risks losing cross-modal correlations. Designing a robust and interpretable fusion mechanism such as attention-based or transformer-driven architectures is both a technical and research challenge.

### 5. Evaluation and Benchmarking

There is a lack of standardized evaluation frameworks for multimodal classification in medical imaging. Different studies adopt varying metrics, data splits, and fusion strategies, making it difficult to compare approaches or replicate results. Establishing common benchmarks for multimodal breast cancer classification is necessary for meaningful progress.

## VII. CONCLUSION

This paper presents a detailed discussion on the necessity of adopting multimodal approaches for breast cancer detection, particularly by integrating ultrasound, histopathology, and mammography imaging techniques. Leveraging multiple modalities offers a comprehensive understanding of breast tissue characteristics, which can potentially enhance diagnostic accuracy, robustness, and consistency. By examining the strengths and limitations of each modality, this paper highlights the importance of combining these imaging techniques to achieve a more reliable and accurate diagnostic process.

## VIII. FUTURE ENHANCEMENT

Future research in breast cancer detection utilizing multimodal approaches can focus on the development of sophisticated fusion architectures capable of integrating heterogeneous imaging modalities, including ultrasound, histopathology, and mammography. Advancements in cross-modal learning, transfer learning, and attention mechanisms could significantly enhance diagnostic accuracy by capturing complementary information from various modalities. Additionally, constructing large-scale, annotated multimodal datasets representative of diverse patient populations will be essential to ensure generalization and clinical applicability.



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