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Beyond Masses and Calcifications: A Review of Architectural Distortion Detection for Early Breast Cancer Diagnosis

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A B S T R A C T

Architectural distortion (AD) in mammograms is a subtle yet critical marker of early breast cancer, often appear up to two years before other findings like masses and calcifications. Despite its clinical significance accounting for up to 45% of missed breast cancers AD remains diagnostically challenging due to its subtle patterns, overlap with dense breast tissue, and the reliance on radiologist expertise. This review synthesizes the evolution of AD detection methodologies, from early handcrafted feature-based approaches to advanced machine learning (ML) and deep learning (DL) techniques. The performance of these methods is evaluated, highlighting the superior results achieved by modern deep learning models, such as U-Net and attention-based networks, which automate feature extraction. However, challenges persist, including limited annotated datasets and high false-positive rates, which hinder clinical adoption. The need for standardized datasets, multimodal imaging integration, and collaborative efforts to develop AD-specific datasets and hybrid AI-human workflows is emphasized. Bridging technical innovations with clinical practice is essential to improving early breast cancer diagnosis and ensuring more accurate and widespread detection of architectural distortion.

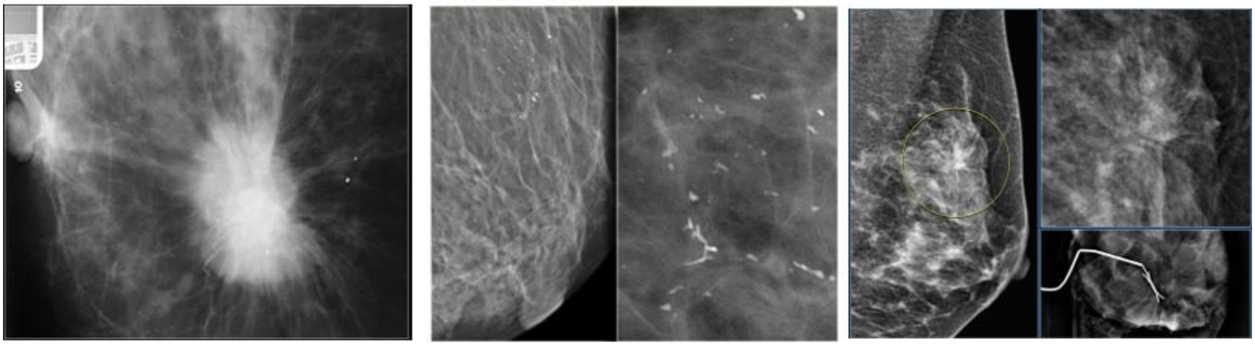
K E Y W O R D S

Architectural distortion, Breast cancer, Machine learning, Deep learning.

1. INTRODUCTION

Breast cancer remains the most prevalent cancer among women worldwide, accounting for nearly 25% of all cancer diagnoses and 15% of cancer-related deaths globally [1]. Early detection plays a crucial role in improving survival rates, with studies indicating that localized breast cancer has a 99% five-year survival rate compared to 30% for metastatic cases [2]. Mammography is the cornerstone of breast cancer screening, identifying abnormalities such as masses, calcifications, and architectural distortion (AD). While masses and calcifications are well-studied, AD characterized by radiating spicules or disrupted breast parenchyma without a distinct mass remains an underrecognized yet critical marker of early malignancy. Figure 1 illustrates various mammogram images: (a) a suspicious mass, (b) a micro-classification, (c) a distortion of the normal breast architecture on oblique view (yellow circle) and magnification view [3]. These images provide visual examples of the different abnormalities that can be detected via mammography.

In Egypt, breast cancer is the most prevalent cancer among women, accounting for approximately 38.8% of all female cancer cases. Diagnoses frequently occur in younger women, often at more advanced stages due to historically lower early detection rates [4,5]. However, recent public health initiatives, such as the 100 Million Healthy Lives campaign launched in 2019, have improved early detection and awareness. By October 2020, 8.5 million women received free screenings through the program, and as of mid-2021, around 16 million women had participated. These efforts have contributed to increased awareness, with the Egyptian Ministry of Health expanding oncology centers and prioritizing early detection and treatment strategies to reduce breast cancer mortality across the country [6,7].



(a) (b) (c)

Figure 1: Field Mammogram image showing: (a) A suspicious mass. (b) A micro classification. (c) A distortion of the normal breast architecture on oblique view (yellow circle) and magnification view [3].

Architectural distortion is a diagnostic challenge due to its subtle presentation, often mimicking benign conditions like radial scars or post-surgical changes [8]. Its association with malignancy is strong, with studies suggesting that 25–75% of AD cases prove cancerous on biopsy [9]. This challenge is compounded by its lack of well-defined borders and its tendency to mimic overlapping dense tissue, which is particularly problematic in women with dense breasts, affecting up to 40% of those screened [10]. via mammography.

The importance of AD detection lies in its potential to detect malignancies in cases where masses or calcifications may not be present. Radiologists identify AD through spiculated lines or focal retractions of the parenchyma, but these patterns can be difficult to discern, especially in dense breast tissue, which reduces screening sensitivity by up to 50% [11]. Furthermore, the reliance on radiologist expertise in manual interpretation introduces challenges due to time-intensive processes (10–15 minutes per case) and the risk of inter-observer variability, which can be as high as 30% [12]. Alarmingly, AD accounts for 12% of missed cancers in retrospective screenings, highlighting the need for automated, standardized detection systems to support radiologists and reduce diagnostic errors [11].

2. METHODOLOGY

This systematic review evaluates the advancements in AD detection techniques and their impact on early breast cancer diagnosis. The studies included in this review were categorized into three methodological groups to assess their contributions to AD detection: traditional methods, machine learning approaches, and deep learning approaches. Each category represents a distinct level of computational complexity and automation, with varying levels of accuracy and sensitivity in detecting AD.

2.1. Traditional Methods

Traditional segmentation techniques primarily include manual and semi-automated approaches. While foundational in medical imaging, these methods have notable limitations. Manual segmentation, performed by radiologists or technicians, requires delineation of regions of interest (ROIs) on medical images. Although accurate, this method is labor-intensive and prone to inter-observer variability. As noted by [13], manual segmentation is time-consuming and may yield inconsistent results, especially in complex cases with subtle distortions.

Thresholding is a basic segmentation technique that separates image regions based on pixel intensity. Despite its simplicity, it often fails to capture intricate details in AD detection. According to [14], thresholding requires fine-tuned values to avoid loss of crucial structural information. Similarly, edge detection methods, such as Canny and Sobel operators, emphasize boundary identification but are sensitive to noise and variations in image quality, as highlighted by [15]. These techniques often necessitate additional processing for refined segmentation.

Several researchers have sought to improve traditional methods. Nemoto et al. [16] introduced a novel algorithm combining the point convergence index with spiculation likelihood to detect AD, significantly reducing false positives from 84.48 to 0.80 per image while maintaining 80% sensitivity. Rangayyan et al. [17] utilized directional filtering to model normal breast architecture, achieving 81% sensitivity on the MIAS dataset, demonstrating its potential for early AD detection. Anand and Rathna [18] employed a contourlet transform-based approach, leveraging multi-scale and directional analysis, reporting an 87% accuracy on the MIAS dataset. However, its computational intensity limited real-time clinical application.

Banik et al. [19] applied Gabor filters and phase-portrait analysis, extracting features like fractal dimension and angular power entropy, achieving an AUC of 0.78 with a neural network classifier. Matsubara et al. [20] developed an automated detection method using directional and background filters to analyze linear structures, achieving 81% sensitivity with 2.5 false positives per image in a dataset of 174 AD cases and 580 controls.

2.2. Machine Learning Approaches

Machine learning (ML) techniques have significantly advanced the field of medical image analysis by improving segmentation accuracy and robustness. Two prominent ML approaches are Support Vector Machines (SVMs) and Random Forests. SVMs are a class of supervised learning algorithms used for classification and regression tasks. In medical image segmentation, SVMs can classify pixels or regions based on extracted features such as texture or intensity. According to [21], SVMs offer robust performance in distinguishing between different types of tissue or abnormalities, particularly when combined with feature extraction techniques like Histogram of Oriented Gradients (HOG) or texture descriptors.

Netprasat et al. [22] employed a machine learning approach to detect AD, using SVMs to classify suspicious regions in mammograms. Their method focused on extracting texture and intensity features, which were then fed into the SVM for classification. Like Rangayyan's study, this research also utilized the MIAS dataset for testing, which provided a consistent comparison point. The study reported a detection accuracy of 90%, which was a marked improvement over more traditional image analysis techniques. This increase in accuracy highlights the potential of machine learning to enhance mammographic analysis, especially in distinguishing between malignant and benign patterns. Nevertheless, the study suggested that additional work could be done to optimize the feature extraction process to further improve detection rates.

Raaj and Thirumurugan [23] developed a hybrid classification approach for AD detection that combined two machine learning techniques: Support Vector Machines (SVMs) and k-nearest neighbors (k-NN). The features were extracted using the Gray Level Co-occurrence Matrix (GLCM), a texture-based method widely used in image analysis. This dual approach allowed the system to leverage the strengths of both classifiers, leading to improved performance. Tested on the MIAS dataset as well as private datasets, the method achieved a sensitivity rate of 85%, demonstrating its robustness across different datasets. The combination of two classifiers provided more flexibility in capturing complex patterns of AD in mammograms. However, while the hybrid model showed promise, further evaluation on larger datasets was suggested to confirm its generalizability.

Du et al. [24] took a more advanced approach by combining a non-subsampled contourlet transform (NSCT) with an improved pulse-coupled neural network (PCNN) for detecting AD in mammograms. The use of NSCT allowed for the extraction of multi-scale, multi-directional features, which were crucial for capturing the subtle patterns characteristic of AD. This method was applied to both the DDSM (Digital Database for Screening Mammography) and private datasets, achieving a sensitivity of 92%. The high sensitivity demonstrated the power of combining multi-resolution analysis with neural networks in detecting subtle architectural distortions that are often missed by traditional methods. While the results were highly promising, the computational complexity of the method was noted as a potential barrier to widespread clinical implementation, suggesting the need for further optimization.

Random Forests, an ensemble learning method, aggregate predictions from multiple decision trees to improve classification accuracy. In segmentation tasks, Random Forests leverage various features to differentiate between normal and distorted tissue regions. Research by [25] demonstrates that Random Forests can handle diverse image characteristics and improve segmentation outcomes compared to simpler methods. However, these methods still face challenges related to feature selection and computational complexity.

2.3. Deep Learning Techniques

Deep learning has revolutionized medical image segmentation by providing advanced methods that offer high accuracy and adaptability. Convolutional Neural Networks (CNNs) and other neural network architectures are at the forefront of this transformation. CNNs are designed to automatically and adaptively learn spatial hierarchies of features from input images. They have demonstrated significant success in segmenting medical images, including architectural distortions. [26] shows that CNNs can learn complex patterns and features from large datasets, allowing for precise segmentation of subtle distortions. The ability of CNNs to perform end-to-end learning and feature extraction reduces the need for manual feature engineering and enhances overall segmentation performance.

The U-Net architecture, introduced by [27], is a specific type of CNN tailored for biomedical image segmentation. Its U-shaped structure consists of a contracting path to capture context and a symmetric expanding path for precise localization. [27, 28] highlight the effectiveness of U-Net in segmenting medical images, including mammographic images with architectural distortions. The U-Net's skip connections help retain fine-grained details, which is crucial for accurately delineating distortions. GANs have emerged as a powerful tool for enhancing image segmentation results by generating synthetic data or improving image quality. GANs consist of two neural networks, a generator and a discriminator, that compete in a game-theoretic framework. [29] discusses recent developments in applying GANs to medical imaging, including their use for data augmentation and improving segmentation performance by generating high-quality synthetic images. GANs help address issues related to data scarcity and variability, thereby enhancing the robustness of segmentation models.

Kulkarni and Rabidas [30] developed a novel deep dilated fully convolutional neural network (DDFCNN) tailored for detecting various breast cancer abnormalities, including architectural distortion (AD), masses, and microcalcifications, within mammogram images. The DDFCNN architecture incorporates a multi-scale feature extraction module, allowing it to capture a diverse range of abnormal patterns by using convolutional filters of varying sizes. Additionally, the dilation module within DDFCNN preserves high-resolution image details, essential for accurately localizing abnormalities in dense breast tissue. Their extensive evaluations on both the DDSM and mini-MIAS datasets reveal significant improvements in accuracy, with the DDFCNN achieving 92.67% accuracy for AD detection on the DDSM dataset, accompanied by a false-positive rate of 0.46. Similarly, on the mini-MIAS dataset, the model attained a 95.07% accuracy rate with a false-positive rate of 0.31. The findings underscore DDFCNN's potential as a robust tool for early breast cancer screening, with enhanced detection accuracy and reduced false positives compared to previous approaches, thus holding promise for improving early diagnostic outcomes in clinical settings.

Ou, Weng, and Chang [31] introduced a structure fusion attention model aimed specifically at detecting architectural distortion in mammograms. This model employs a novel attention mechanism to selectively focus on key regions within mammographic images, effectively capturing subtle and irregular AD patterns that are challenging to detect with traditional techniques. By enhancing the localization of these patterns, the model achieves both high detection accuracy and precision in identifying early signs of malignancy. Their approach highlights the efficacy of advanced attention mechanisms in improving AD detection, offering a potential advancement for early breast cancer diagnosis through enhanced image detail analysis.

Table 1 clearly organizes the method, dataset, and results for each study. It shows that traditional methods like thresholding and edge detection have limitations, while machine learning and deep learning methods have gradually improved detection and segmentation accuracy through feature extraction and complex models like SVMs and CNNs. This comprehensive analysis demonstrates the shift from traditional methods toward ML and DL approaches, which offer improved sensitivity, accuracy, and efficiency for early AD detection in mammograms.

Table 1: Summary of techniques for detecting and segmenting architectural distortion.

Research	year	Dataset	method	Results
Nemoto et al.[10]	2008	25 CR mammograms	Novel algorithm combining point convergence index with spiculation likelihood for detecting AD.	Sensitivity: 80% with 0.80 FPPI.
Banik et al.[11]	2012	Not specified	Gabor filters and phase-portrait analysis for AD detection, calculating various features for refined classification.	AUC: 0.76
Rangayyan et al. [12]	2013	MIAS dataset	Directional filtering for AD detection by modeling normal breast architecture.	Sensitivity: 81%
Anand, S., & Rathna, R. A. V. [13]	2013	MIAS dataset	Contourlet transform-based AD detection, emphasizing directional and multi-scale features.	Accuracy: 87%
Netprasat et al. [14]	2014	MIAS dataset	SVM classifier with texture and intensity features for AD detection in mammograms.	Accuracy: 90%
Matsubara et al. [15]	2015	174 AD cases and 580.	Automated method using directional and background filters to detect linear structures for AD.	sensitivity: 81% with 2.5 FPPI.
Du, G., Dong, M., Sun, Y., et al.[16]	2019	DDSM and private datasets	Non-subsampled contourlet transform (NSCT) combined with PCNN for multi-scale, multi-directional feature extraction.	Sensitivity: 92%
Raaj, R. S., & Thirumurugan, P. [17]	2021	MIAS and private datasets	Hybrid SVM and k-NN classification approach using Gray Level Co-occurrence Matrix (GLCM) for feature extraction.	Sensitivity: 85%
Kulkarni, S., & Rabidas, R. [18]	2024	DDSM, mini-MIAS	Deep Dilated Fully Convolutional Network (DDFCNN) for multi-abnormality detection.	Accuracy for AD: 92.67% (DDSM, FPR 0.46); 95.07% (mini-MIAS, FPR 0.31)
Ou, T.-W., Weng, T.-C., & Chang, R.-F. [19]	2024	Not specified	Structure Fusion Attention Model with attention mechanisms for fine-grained AD detection.	Enhanced sensitivity in identifying subtle AD patterns

3. PUBLIC DATASETS AND LIMITATIONS

Public mammography datasets have played a pivotal role in advancing research on architectural distortion (AD) detection. However, several inherent limitations, particularly the lack of AD-specific annotations and pronounced class imbalance, present substantial challenges for the development of reliable automated systems. In the following section, we critically examine three major datasets, highlighting their respective constraints. A comparative overview of these datasets is summarized in Table 2.

The Digital Database for Screening Mammography (DDSM), curated in the 1990s, contains over 2,500 scanned film mammograms from screening exams, including approximately 250 cases with architectural distortion. While it remains a foundational resource, its utility is limited by low resolution, outdated technology, and sparse AD annotations. Images are digitized at 50 µm/pixel, resulting in poor spatial clarity compared to modern full-field digital mammography (FFDM) systems. Additionally, film mammograms lack the dynamic range and contrast of digital systems, complicating AD detection in dense tissue. AD cases are not explicitly labeled, requiring manual extraction from textual pathology reports. Despite these shortcomings, the DDSM has been widely used to validate traditional methods, such as the work by Banik et al. (2012), which achieved an AUC of 0.76 using Gabor filters on DDSM images.

The Mammographic Image Analysis Society (MIAS) database comprises 322 medio-lateral oblique (MLO) view mammograms digitized at 50 µm/pixel. While it provides region-of-interest (ROI) annotations for masses and calcifications, it lacks explicit AD labels, requiring researchers to infer AD cases from pathology reports or visual inspection, introducing subjectivity. Moreover, the dataset exhibits limited diversity as all images are from the same acquisition system, reducing generalizability. With only 15–20 suspected AD cases, MIAS is insufficient for training deep learning models. Studies like Rangayyan et al. (2013) leveraged MIAS to test directional filtering techniques, achieving 81% sensitivity, but the dataset’s constraints necessitate caution in extrapolating results to clinical settings.

Table 2: Comparison of Public Mammography Datasets.

Dataset	Resolution	AD Cases	Annotations	Key Limitations
DDSM	50 µm/pixel	~250	Text-based pathology	Low resolution, film artifacts
MIAS	50 µm/pixel	~15	ROI masks (no AD labels)	Small size AD cases
INbreast	70 µm/pixel	~15	ROI masks + BI-RADS	Sparse AD cases, class imbalance

The INbreast database, released in 2012, is a high-resolution FFDM dataset containing 410 mammograms (115 cases) acquired with a Siemens Mammomat Inspiration system at 70 µm/pixel resolution. It offers detailed annotations, high image quality, and diverse cases, including normal, benign, and malignant exams across breast density categories. However, it has critical limitations for AD research. Only 12–15 cases (≈12%) include architectural distortion, with most annotations focused on masses and calcifications. The class imbalance, with an AD to non-AD ratio of ≈1:10, leads models to prioritize majority classes during training. Additionally, with only 115 cases, it is inadequate for training data-hungry deep learning architectures like transformers. Kulkarni & Rabidas (2024) tested their Deep Dilated FCNN on INbreast but achieved lower accuracy (85%) compared to DDSM (92.67%) due to limited AD samples.

4. FUTURE DIRECTIONS

4.1. Enhancing Data Quality and Annotation

The development of robust AD detection systems hinges on addressing critical gaps in existing datasets. Future efforts must prioritize comprehensive annotations that explicitly label architectural distortions, including spiculation patterns and associated BI-RADS categories, to standardize training and evaluation. Synthetic data augmentation, particularly through generative adversarial networks (GANs) and diffusion models, can mitigate class imbalance by synthesizing realistic AD cases in diverse breast densities. For instance, Avanzo et al. (2021) [32] demonstrated the potential of GANs to enhance medical imaging pipelines, though their work highlighted challenges in ensuring synthetic data fidelity across modalities.

4.2. Advancing AI Architectures and Hybrid Models

The integration of transformer-based models with convolutional neural networks (CNNs) represents a promising frontier for capturing both local texture details and global contextual relationships in mammograms. Chen et al. (2023) [33] showcased the effectiveness of the Swin Transformer in breast cancer detection, achieving state-of-the-art performance by leveraging hierarchical feature learning. Hybrid architectures combining CNNs with transformer self-attention mechanisms could similarly enhance sensitivity to subtle AD patterns obscured by dense tissue. Furthermore, attention mechanisms, such as those in Li et al.'s (2022) [34] Dual Attention Networks, prioritize clinically relevant regions (e.g., spiculation convergence points), improving detection accuracy while maintaining computational efficiency. Pretraining vision transformers (ViTs) on large-scale medical imaging datasets may further reduce dependency on scarce AD-specific data.

4.3. Advancing AI Architectures and Hybrid Models

To translate AD detection tools into clinical practice, reducing false-positive rates is imperative. Multi-stage pipelines could first screen mammograms using high-sensitivity CNNs, followed by a second-stage classifier (e.g., SVM or random forest) to filter false alarms using clinical metadata and lesion morphology. Samala et al. (2020) [35] demonstrated the efficacy of deep convolutional neural networks (DCNNs) in reducing false positives for mass detection, a framework adaptable to AD through ensemble learning. Combined view analysis of craniocaudal (CC) and mediolateral oblique (MLO) mammograms, paired with explainable AI tools, would enable radiologists to validate AI findings against multi-angle evidence, fostering trust and reducing unnecessary biopsies.

5. CONCLUSION

Architectural Distortion (AD) detection remains a formidable challenge in mammography due to its inherently subtle patterns and the scarcity of high-quality, annotated datasets. Unlike masses and calcifications, AD often manifests as faint disruptions in breast tissue architecture, requiring both computational precision and clinical expertise to identify. Despite these hurdles, early detection of AD is critical, as it can signify malignancy at stages where treatment is most effective, potentially saving countless lives through timely intervention.

Deep learning models, such as U-Net and DDFCNN, have demonstrated superior sensitivity (85–92%) compared to traditional methods, automating feature extraction and reducing reliance on error-prone manual analysis. However, their performance is constrained by limited and imbalanced datasets, which skew training and validation outcomes. Future research must prioritize large-scale, diverse dataset curation to address class imbalance and improve generalizability. To translate these advancements into clinical practice, reducing false-positive rates through multi-stage detection pipelines and ensemble learning remains imperative. Simultaneously, efforts to enhance clinical utility will foster radiologist trust and adoption. By bridging these gaps, automated AD detection systems can minimize diagnostic delays, reduce unnecessary biopsies, and ultimately curb global breast cancer mortality rates.

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