ACCSCIENCE PUBLISHING

Eurasian Journal of Medicine and Oncology

REVIEW ARTICLE

Artificial intelligence in contrast-enhanced mammography: Current evidence, clinical integration, and future perspectives – a narrative review

Graziella Di Grezia[1]*, Teresa Iannaccone[2], Antonio Nazzaro[2], Leandra Piscopo[3], Salvatore Antonio Masala[3], and Mariano Scaglione[3,4]

[1]Department of Life Sciences, Health, and Healthcare Professions, Link Campus University Rome, Roma, Italy

[2]Independent Researcher, Avellino, Italy

[3]Department of Medicine, Surgery and Pharmacy, University of Sassari, Sassari, Italy

[4]Department of Radiology, James Cook University Hospital, Middlesbrough TS43BM, United Kingdom

***Corresponding author:**
Graziella Di Grezia
(g.digrezia@unilink.it)

Citation: Di Grezia G, Iannaccone T, Nazzaro A, Piscopo L, Masala SA, Scaglione M. Artificial intelligence in contrast-enhanced mammography: Current evidence, clinical integration, and future perspectives – a narrative review. *Eurasian J Med Oncol.* 2026;10(5):026250294. doi: 10.36922/EJMO026250294

Received: June 20, 2026

Revised: July 26, 2026

Accepted: August 27, 2026

Published online: September 9, 2026

Copyright: © 2026 Author(s). This is an Open-Access article distributed under the terms of the Creative Commons Attribution License, permitting distribution, and reproduction in any medium, provided the original work is properly cited.

Publisher's Note: AccScience Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Abstract

Introduction: Contrast enhanced mammography (CEM) combines standard mammographic imaging with functional enhancement patterns and is increasingly used in diagnostic and staging pathways. Artificial intelligence (AI) has shown strong potential in breast imaging, yet its application to CEM remains limited.

Objectives: This narrative expert review summarizes current evidence on AI applied to CEM, identifies methodological gaps, and outlines future directions for clinically integrated, precision-oriented models.

Methods: A narrative review of peer reviewed studies was conducted, focusing on AI for lesion detection, classification, segmentation, radiomics, workflow support, and emerging multidimensional frameworks involving CEM. Given the heterogeneity of available studies and the early developmental stage of the field, a narrative expert review was considered more appropriate than a protocol driven systematic approach.

Results: Existing studies demonstrate that AI can improve lesion conspicuity, support automated detection, and extract quantitative features from CEM. Reported performance metrics—such as area under the curve (AUC) values between 0.87 and 0.93 in small datasets—indicate promising diagnostic potential. However, progress is limited by small sample sizes, heterogeneous acquisition protocols, variability in background parenchymal enhancement, lack of external validation, and the absence of models incorporating clinical, hormonal, or multimodal information essential for real world interpretation. Emerging frameworks suggest that AI may also support multidimensional risk profiling by integrating imaging features with patient specific variables.

Conclusions: AI has the potential to enhance the diagnostic and clinical value of CEM, but meaningful implementation will require standardized acquisition, larger multicenter datasets, explainable architectures, and integration of clinical context. Future models should reflect real-world senological workflows and support personalized, risk stratified decision making.

Keywords: Contrast enhanced mammography; Artificial intelligence; Deep learning; radiomics; Breast imaging; Lesion detection; Multimodal imaging; Clinical integration

1. Introduction

Contrastenhanced mammography (CEM) has become an important component of modern breast cancer imaging, offering a combined morphological and functional assessment that enhances the detection and characterization of breast lesions. By integrating lowenergy images comparable to fullfield digital mammography with iodinebased recombined images, CEM provides enhancement patterns like those obtained with breast magnetic resonance imaging (MRI), while maintaining shorter acquisition times, lower costs, and broader accessibility. Consolidated evidence supports its high sensitivity, rapid acquisition, and utility across diagnostic, staging, and preoperative settings.[1] More recent analyses have also explored its potential role in screening, particularly for women with dense breasts or intermediaterisk profiles,[2] and state-of-the-art reviews confirm its increasing integration alongside MRI in contemporary breast imaging practice.[3,4] Although CEM is increasingly adopted in clinical practice, CEM interpretation presents unique challenges. The dual-energy subtraction process, while providing functional information, also introduces artifacts and variability related to contrast injection timing, patient positioning, and breast composition. Subtle lesions may be obscured by overlapping fibroglandular tissue or intense background parenchymal enhancement (BPE), which varies considerably with hormonal status, menopausal state, and breast density. These factors contribute to inter-reader variability—even among experienced breast radiologists—and underscore the need for standardized interpretative criteria.[5,6] Artificial intelligence (AI), with its capacity for consistent feature extraction and quantitative analysis, offers a promising avenue to address these challenges by providing reproducible lesion characterization and decision support.

As clinical use of CEM expands, interest has grown in the potential contribution of AI to improve interpretation, enhance diagnostic consistency, and support workflow optimization. The dual energy nature of CEM and its functional enhancement patterns make it particularly suitable for AI-based analysis, radiomics extraction, and precision-oriented imaging approaches. Expert perspectives suggest that AI may strengthen CEM performance by improving lesion conspicuity, reducing inter-reader variability, and enabling quantitative assessment of enhancement patterns.[5,6] The variability of real-world CEM interpretation underscores this need: subtle findings may become apparent only on delayed subtracted images, as in postpartum patients, whereas extensive multifocal enhancement patterns may require careful kinetic evaluation to differentiate benign from malignant processes, as illustrated in the representative clinical cases presented (Figures 1 and 2).

Existing research on AI applied to CEM remains limited but methodologically diverse. The literature reflects a field characterized by promising diagnostic performance across detection, classification, segmentation, and radiomics tasks, but also by persistent challenges—including heterogeneous acquisition protocols, limited explainability, and scarce prospective validation. These limitations justify the need for a narrative expert synthesis such as the present review, which aims to contextualize existing findings and identify the most relevant gaps for future research.[1-6]

Given the emerging and heterogeneous nature of AI applications in CEM, this work was conceived as an expert narrative review aimed at providing a concept-driven synthesis rather than a protocol-driven systematic assessment. This review: (i) summarizes existing studies on AI applied to CEM across detection, classification, segmentation, radiomics, workflow support, and multimodal integration; (ii) critically appraises methodological limitations, with emphasis on dataset size, validation strategies, and the impact of BPE (iii) proposes a conceptual framework for clinically integrated AI-augmented CEM workflows; and (iv) identifies gaps preventing translation from research to real-world practice, with future directions for standardized acquisition, multimodal fusion, explainability, federated learning, and equitable deployment.

2. Materials and methods

This study was conducted as an expert narrative review aimed at synthesizing current evidence and conceptual developments regarding AI applications in CEM within the broader context of breast cancer imaging. Narrative design was intentionally adopted due to the emerging nature of the field, the heterogeneity of imaging protocols, AI architectures, validation strategies, and outcome reporting, and the aim of providing an interpretative and clinically oriented synthesis rather than a protocol-driven systematic review.

A comprehensive but non-systematic literature search

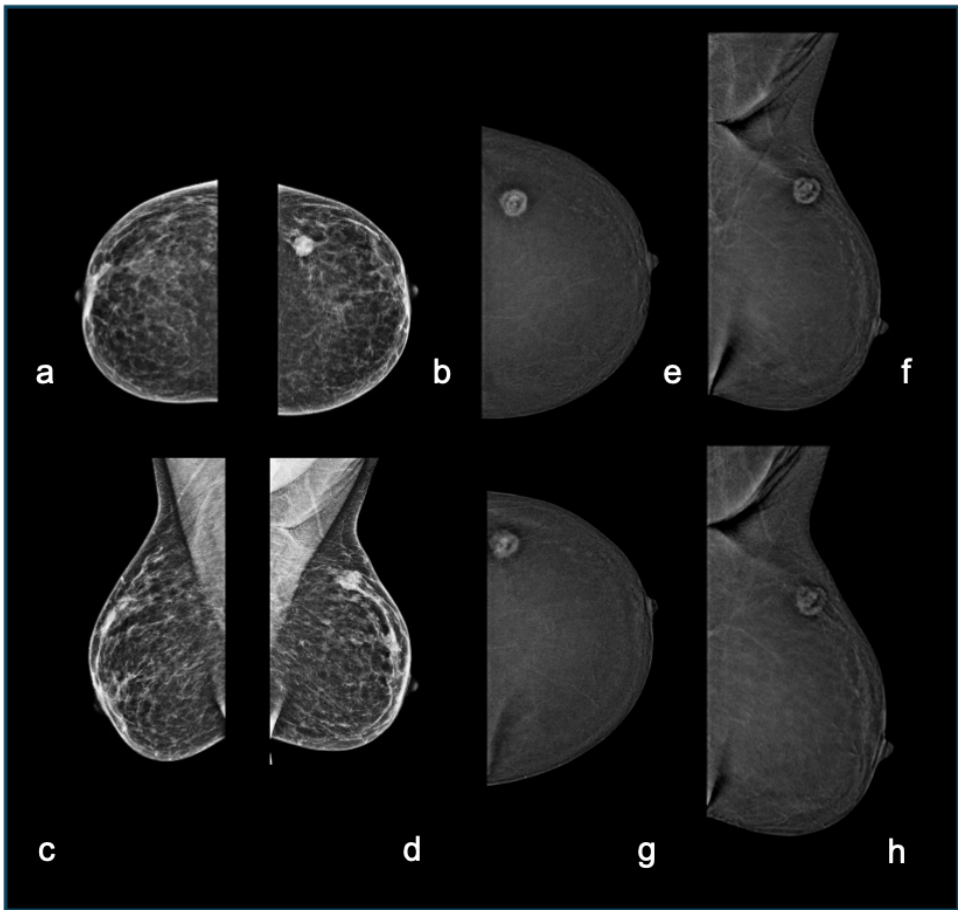


Figure 1. CEM case in a 39-year-old woman undergoing her first postpartum mammogram. (a–d) This case illustrates three specific AI applications: (1) detection algorithms could flag the subtle asymmetry in the low-energy images (a–d) that might otherwise be overlooked due to postpartum parenchymal changes; (2) segmentation models could quantify the area and volume of enhancement in the early subtracted images (e, f); and (3) classification frameworks incorporating kinetic analysis could automatically recognize the washout pattern in the delayed images (g, h) as a suspicious feature associated with malignancy. These AI capabilities could be particularly valuable in postpartum patients, where interpretation is challenging due to physiological enhancement.[7-10] Original clinical image from the authors' institution, published with patient consent.
Abbreviations: AI: Artificial intelligence; CEM: Contrast-enhanced mammography.

was performed using PubMed, Scopus, and Web of Science to identify relevant publications published between January 2010 and December 2024. The search strategy combined keywords related to "contrast-enhanced mammography," "CEM," "artificial intelligence," "deep learning," "machine learning," "radiomics," "radiogenomics," "lesion detection," "segmentation," and "breast imaging." Additional relevant studies were identified through manual screening of reference lists of key articles and recent reviews. Following the initial literature retrieval, identified studies were categorized into distinct conceptual domains, which were predefined based on preliminary scoping and clinical relevance. A substantial body of research focuses on detection and classification, evaluating models designed to differentiate benign from malignant enhancing lesions, complemented by segmentation studies that address the automated delineation of lesion boundaries and quantitative enhancement analysis.

In terms of advanced data characterization, radiomics and radiogenomics studies investigate the extraction of quantitative imaging features for molecular subtyping and risk profiling, whereas multimodal integration research explores the synergy between CEM and other diagnostic imaging modalities—such as ultrasound, MRI, and digital breast tomosynthesis—within AI frameworks. Finally, broader translational aspects are captured by workflow and equity studies, which examine practical implementation, clinical triage, and healthcare access considerations.

For each domain, representative studies were selected based on methodological rigor, novelty, and clinical relevance. When multiple studies addressed similar

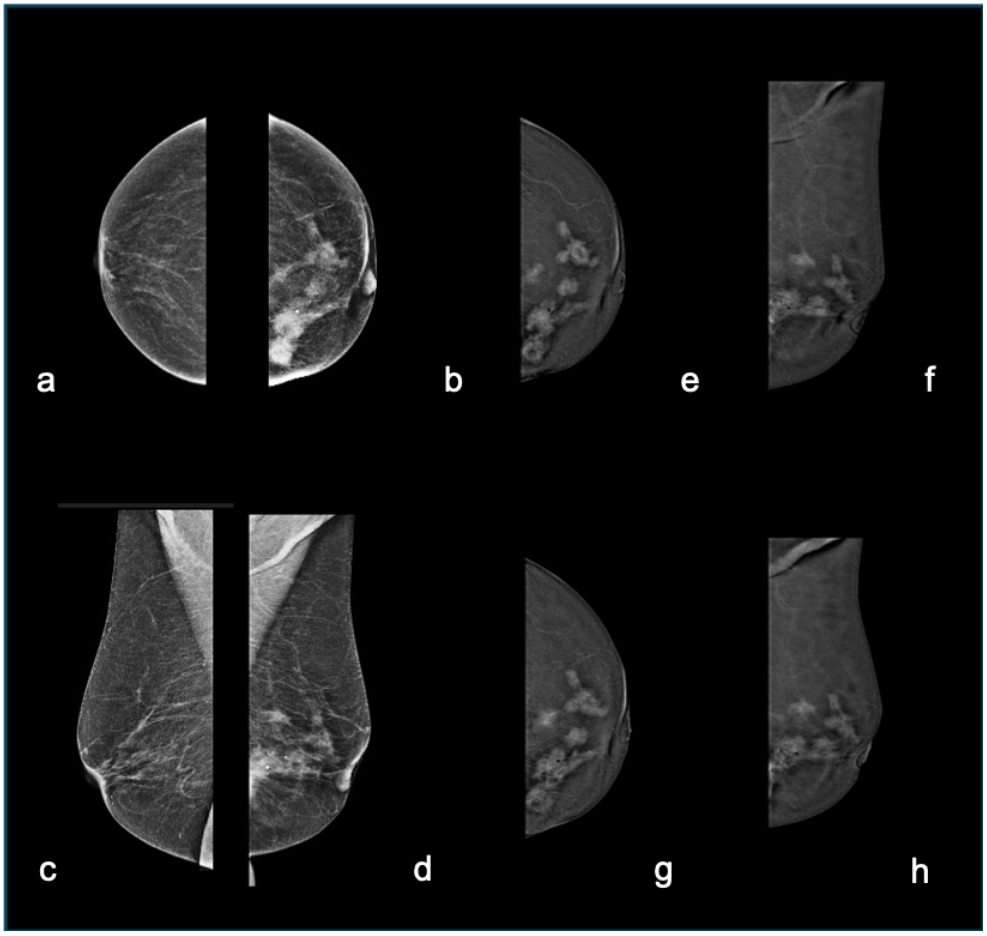


Figure 2. CEM case in a 66-year-old disabled woman presenting with an extensive palpable mass. (a–d). This case demonstrates three specific contributions of AI for extensive disease: (1) automated segmentation algorithms could map the geographic distribution of enhancement throughout the entire quadrant, providing volumetric measurements of disease extent; (2) radiomics analysis could quantify enhancement heterogeneity and textural features from multifocal confluent areas (e, f), potentially correlating with tumor aggressiveness;[11,12] and (3) hybrid CNN–radiomics models could assist in differentiating suspicious washout patterns (g, h) from benign inflammatory enhancement, supporting treatment planning and surgical decisions in this complex case.[9-18] Original clinical image from the authors' institution, published with patient consent.
Abbreviations: AI: Artificial intelligence; CEM: Contrast-enhanced mammography; CNN: Convolutional neural network.

questions, priority was given to those with larger datasets, external validation, or prospective design. Findings were synthesized thematically, with particular attention to (i) reported performance metrics and their generalizability; (ii) methodological strengths and limitations; (iii) gaps in the evidence base; and (iv) implications for clinical translation. This narrative synthesis approach, while not exhaustive, aims to provide a balanced and interpretative overview of the current state of AI in CEM.

The search yielded approximately 106 records. After removal of duplicates, 63 unique publications were screened based on title and abstract. Of these, 49 full-text articles were assessed for eligibility. Studies were excluded if they did not specifically address CEM, did not investigate AI applications, lacked sufficient methodological detail (*e.g.*, conference abstracts), or were outside the scope of AI-enhanced CEM imaging. Additional studies were identified through reference list screening.

Given the narrative nature of the review, study selection was based on conceptual relevance and methodological contribution rather than exhaustive inclusion. Representative studies were selected to cover the main domains of AI application in CEM, including detection, classification, segmentation, radiomics, multimodal integration, workflow optimization, explainability, and implementation challenges. No PRISMA flow diagram was generated, as this study was not designed as a systematic or scoping review. As detailed in Table 1, applying AI to

Table 1. Overview of AI applications and related evidence in CEM

Domain	Clinical purpose	Study type	AI methods used	Key findings	Dataset size	Validation strategy	Key metrics	Representative study
AI in CEM workflow	Review AI applications in CEM	Commentary/ perspective	DL, radiomics (literature overview)	AI shows promise for detection, segmentation, classification but is not yet standardized clinically	—	—	Conceptual synthesis	Bahl & Do (2023)[8]
Lesion classification	Differentiate benign vs malignant enhancement	Systematic review	CNN, attention-based DL	DL improves classification; multimodal and radiologist integration enhance performance	16 studies	—	AUC 0.53–0.99 (retrospective); 0.89–0.91 (prospective); accuracy ~88%–89%	Sorin *et al.* (2025)[9]
Lesion detection	Detect enhancing lesions in CEM	Original AI study	YOLO-based DL	High sensitivity; BPE affects performance; multimodal input improves detection	1673 patients (7443 images)	Train/test evaluation	AUC 0.964; Sensitivity 90%; 0.128 FP/image	Jailin *et al.* (2023)[10]
Radiomics – risk profiling	Assess BD/BPE reproducibility and systemic risk surrogates	Original AI study	DNN + linear regression	AI improves reproducibility and reduces reading time; supports risk stratification	213 patients + 500 external cases	Internal + external validation	κ 0.68→0.82; AUC 0.74–0.75; MSE ~0.64	Di Grezia *et al.* (2025)[11]
Radiomics – molecular subtype prediction	Predict breast cancer molecular subtypes	Original radiomics study	Radiomics + SVM (LE/RC/LE+RC)	CEM radiomics enables subtype prediction; LE+RC model best performance	356 patients (386 lesions; 162/160/64 split)	Internal + external test sets	AUC 0.93/0.89/0.87 (internal); 0.82/0.83/0.69 (external)	Zhu *et al.* (2024)[12]
Multicenter AI classification	Classify lesions across institutions	Original multicenter AI study	Refine Net + CBAM + XGBoost	Robust cross-center performance; DL outperforms radiomics and radiologists	1430 patients (1101/196/133 split)	Internal + external validation	AUC 0.932; 0.788–0.824 (subtasks)	Zhang *et al.* (2024)[13]
Breast cancer screening strategy	Evaluate risk-based screening approaches	Narrative review	AI discussed conceptually	Risk-based screening improves benefit–harm balance; MRI recommended for high-risk women	—	—	Evidence-based recommendations	Marcon *et al.* (2024)[14]
AI frameworks in breast imaging	Review methodological AI challenges	Narrative / methodological review	AI concepts (segmentation, classification, feature extraction)	Lack of standardization limits clinical translation	—	—	CLAIM-guided conceptual synthesis	Kinkar *et al.* (2024)[15]

Abbreviations: AI: Artificial intelligence; AUC: Area under the ROC curve; BD: Breast density; BPE: Background parenchymal enhancement; CBAM: Convolutional block attention module; CEM: Contrast-enhanced mammography; CNN: Convolutional neural network; DL: Deep learning; MRI: Magnetic resonance imaging; MSE: Mean squared error; SVM: Support vector machine.

doi: 10.36922/EJMO026250294

contrast-enhanced mammography improves diagnostic accuracy and lesion characterization across various validated datasets and key performance metrics.

2.1. Inclusion and exclusion criteria and evidence appraisal

Inclusion criteria comprised peer-reviewed original studies and relevant review articles on AI applied to CEM published between 2010 and 2024. Eligible studies included those addressing lesion detection, classification, segmentation, radiomics, multimodal integration, workflow support, or clinical implementation.

Exclusion criteria included conference abstracts without full methodological description, studies not involving CEM, purely technical AI papers without clinical relevance, and works lacking sufficient methodological transparency.

No quantitative thresholds (*e.g.*, minimum sample size) were applied due to the exploratory nature of the field. Discrepancies across studies were resolved through consensus-based discussion among the authors. When conflicting evidence was present, greater weight was given to prospective and externally validated studies due to their lower risk of bias.

As this is a narrative review, no formal risk-of-bias tool or standardized quality scoring system was applied. Instead, methodological quality and limitations of included studies were assessed qualitatively within thematic sections, with emphasis on dataset characteristics, AI model design, validation strategies, and clinical applicability.

To ensure structure and transparency, the literature was organized into predefined conceptual domains. Within each domain, representative studies were synthesized and empirical findings were clearly distinguished from expert interpretation in the Results and Discussion sections.

This review did not involve new patient-level data collection; therefore, ethical approval was not required. Clinical images included in Figures 1 and 2 were obtained from anonymized routine clinical cases with informed consent for publication.

2.2. Use of generative AI

Generative AI was used exclusively to assist in the linguistic refinement and restructuring of the manuscript text. It was not used to generate scientific content, data, analyses, figures, or interpretations. All scientific concepts, interpretations, and conclusions derive from the authors' expertise and the cited literature.

3. Results

3.1. Clinical evolution and current role of CEM

Contrast-enhanced mammography (CEM) has progressively become a central component of breast imaging workflows. Its dual energy acquisition provides simultaneous morphological and functional information, supporting diagnostic workup, preoperative staging, and selected screening applications.[1-3] Early studies demonstrated that diagnostic accuracy of CEM is comparable to MRI and superior to conventional mammography and ultrasound.[1] Subsequent analyses confirmed its utility in dense breasts and intermediate risk women,[2] while recent reviews emphasized its versatility, cost effectiveness, and patient acceptability.[3,4] Standardization of acquisition parameters and interpretative criteria has been identified as essential for reproducibility and for future AI integration.[6] Background parenchymal enhancement (BPE) and breast density have also been shown to influence lesion conspicuity and interpretative variability.[7] The clinical evidence base for CEM now includes multiple prospective studies demonstrating sensitivity comparable to MRI (ranging from 89% to 96% across published series) and significantly higher specificity than conventional mammography in dense breast populations.[1-3] Recent meta-analyses have further confirmed these findings, with pooled sensitivity estimates exceeding 90% for breast cancer detection.[4] This robust evidence has prompted the inclusion of CEM in several national and international guidelines for preoperative staging and problem-solving in indeterminate cases.[3,4]

3.2. AI in breast imaging: From conventional mammography to CEM

Artificial intelligence (AI) has demonstrated strong performance in mammography and digital breast tomosynthesis, providing the methodological and computational foundation for its application to CEM. This transition from conventional breast imaging modalities to CEM has been gradual, primarily due to limited annotated datasets, heterogeneous imaging protocols, and variability in contrast enhancement patterns.[8] The application of AI to breast imaging has evolved substantially over the past decade, transitioning from traditional machine learning approaches—which relied on handcrafted features such as texture, shape, and margin descriptors—to deep learning architectures that learn hierarchical representations directly from imaging data.[8] In mammography and digital breast tomosynthesis, AI models have demonstrated the ability to match or exceed radiologist performance in

cancer detection, particularly when used as a concurrent reading aid.[9] These successes have provided a strong foundation for extending AI techniques to CEM, where the dual-energy acquisition and functional enhancement patterns offer additional opportunities for quantitative analysis.[8,9]

A systematic review identified 16 studies evaluating AI for CEM between 2018 and 2024, reporting area under the receiver operating characteristic curve (AUC) values ranging from 0.53 to 0.99 depending on task and dataset characteristics.[9] These studies include applications in lesion detection, classification, and early radiomics-based prediction tasks, with heterogeneous performance reported across different institutions and acquisition protocols.

3.3. AI-based lesion detection and classification in CEM

Finding and classifying lesions is the most common use of AI in CEM. A model built on YOLO (You Only Look Once—a fast AI algorithm designed to locate and identify objects in images simultaneously) was trained on 7,443 images. It achieved an AUC of 0.964—a performance score from 0.5 to 1.0 that measures how well an AI distinguishes between healthy and diseased cases, with 0.964 indicating extremely high accuracy. The model performed even better when combining low-energy and recombined images.[10] The YOLO-based model achieved a sensitivity of 90% with 0.128 false positives per image. This sensitivity is comparable to the average of three expert breast radiologists (88%–92%), although the AI showed lower specificity (more false alarms). Importantly, the AI model provided consistent performance across different BPE categories. This suggests that machine-based reading may be less affected by reader fatigue and personal bias.[10]

To enable reproducible benchmarking, single-center detection architectures have demonstrated high sensitivity in locating contrast-enhancing lesions.[11] Expanding beyond simple detection, recent frameworks have integrated clinical and imaging variables to enable multidimensional risk profiling,[13] while radiomics approaches have allowed for the non-invasive preoperative prediction of breast cancer molecular subtypes.[12] Furthermore, robust multicenter evaluations have confirmed the generalizability of deep learning models in classifying complex CEM findings.[13] When combined with quantitative feature extraction, these integrative frameworks significantly improve diagnostic consistency across diverse clinical settings.[15]

Calibration techniques such as Platt scaling or isotonic regression can improve the alignment of predicted malignancy risks with observed frequencies, as demonstrated in the general machine learning literature.[16,17]

Additional studies have reported high accuracy for convolutional neural networks (CNN) based classification models, particularly when attention mechanisms or radiomics features are incorporated into learning process.[9] Radiomics-based approaches extract quantitative descriptors of lesion heterogeneity and contrast-enhancement patterns, providing complementary information that supports multidimensional risk profiling.[18,19]

Radiomics frameworks focus on the extraction and analysis of quantitative imaging features that characterize lesion heterogeneity and enhancement patterns and typically rely on feature-selection and dimensionality-reduction strategies to minimize overfitting and improve model generalizability, as widely reported in the radiomics literature.[16,19]

3.4. AI-driven segmentation and quantitative enhancement analysis

Segmentation in CEM ranges from manual tracing to fully automated deep learning approaches. While automated models show promising results, their performance is still limited by small datasets and a lack of external validation.[9] Beyond simply defining lesion boundaries, several studies have explored quantitative enhancement analysis, including pixel-based mapping, tracking contrast flow (wash-in and wash-out patterns), and radiomics (extracting quantitative data from medical images). These approaches capture functional information comparable to breast MRI, aiding in both treatment evaluation and risk assessment.[18-21]

The choice of segmentation architecture directly impacts clinical deployment. Traditional CNN and U-Net architecture (standard deep learning models designed for medical image segmentation) remain the most widely adopted solutions because they are stable, efficient, and perform well even with small datasets of a few hundred lesions. In contrast, Transformer-based models excel at capturing global spatial relationships, but they require significantly larger training datasets and greater computational resources, which limits their accessibility in routine practice.[21] To bridge this gap, hybrid models combining convolutional and visual attention mechanisms are emerging as a practical middle ground, while single-stage frameworks like YOLO (You Only Look Once) offer remarkably fast inference times for real-time clinical workflows.

To evaluate segmentation accuracy, models rely on key metrics such as the Dice similarity coefficient (DSC) (measuring total overlap between predicted and actual lesion areas) and the 95th percentile Hausdorff Distance (HD95) (measuring boundary agreement). Finally, because

lesion voxels occupy only a small fraction of the total breast volume (class imbalance), specialized loss functions like focal loss or weighted Dice formulations are essential to keep the AI sensitive to subtle, easily overlooked enhancing foci.[20,21]

3.5. Radiomics and radiogenomics applications in CEM

Radiomics applied to CEM captures enhancement-based features that reflect tumor heterogeneity, vascularity, and the surrounding microenvironment. These quantitative descriptors have been incorporated into AI frameworks aimed at personalized risk profiling, molecular subtype prediction, and prognostic assessment.[11-13] Hybrid approaches that combine radiomics with CNN have shown improved classification performance compared to CNN-only models. This suggests that handcrafted features (quantifiable mathematical properties extracted using predefined formulas, such as texture or shape) and learned features (patterns discovered independently by the AI during training) offer complementary information.[9]

Because radiomics extracts hundreds of variables from small CEM datasets, feature reduction and model optimization are vital to prevent overfitting (when an AI memorizes training data instead of learning general rules). To manage this high dimensionality, researchers use techniques like least absolute shrinkage and selection operator (LASSO; eliminates useless variables), recursive feature elimination (RFE; removes weak features step-by-step), and principal component analysis (PCA; combines correlated features). Furthermore, hyperparameter tuning via cross-validation helps ensure the model generalizes well to new patients.[12]

Features should also be evaluated for test-retest reliability using the intraclass correlation coefficient (ICC; a statistical score measuring whether feature extraction yields consistent results across repeated imaging).[22,23] These methodological steps are particularly critical in CEM, where limited dataset size and image heterogeneity can otherwise compromise the reliability of radiomics-based predictions.

3.6. Background parenchymal enhancement as a determinant of AI performance

Background parenchymal enhancement (BPE) significantly affects lesion conspicuity and AI performance in CEM. High BPE can obscure subtle enhancing foci, reduce sensitivity, and increase false positives. Recent studies have shown that AI accuracy decreases in moderate to marked BPE categories.[7] Quantitatively, BPE can be modeled as a confounding variable using conditional adversarial domain adaptation, where domain invariant feature representations are learned to reduce the impact of BPE variation on classification performance.[24,25] Emerging strategies include BPE-aware training pipelines, domain adaptation methods, and models incorporating parenchymal texture descriptors to distinguish true enhancement from background noise.[10] Standardized BPE annotation and balanced datasets are essential for developing robust and generalizable AI systems.

3.7. Multimodality imaging and AI integration

Contrast-enhanced mammography (CEM) is increasingly used alongside ultrasound, digital breast tomosynthesis (DBT; a 3D mammography technique providing depth-resolved structural details), and MRI, creating strong opportunities for multimodal AI integration. For example, automated 3D ultrasound helps detect small or non-mass lesions in dense breasts, perfectly complementing the functional contrast-enhancement patterns captured by CEM. Early multimodal AI models combining CEM with DBT or ultrasound have already demonstrated superior diagnostic accuracy compared to single-modality approaches.[11,15,26,27]

However, multimodal integration presents unique technical challenges. CEM itself naturally provides dual-energy inputs—low-energy images (similar to standard 2D mammograms) and recombined images (highlighting contrast uptake). Adding further modalities like DBT or ultrasound drastically increases input dimensionality, raising concerns about computational demands and overfitting (a scenario where the AI memorizes training data rather than learning general rules, failing on new patients).[11,14]

To address these challenges, emerging AI frameworks rely on two main integration strategies. The first is feature-level fusion, where quantitative features from each imaging modality are extracted and combined before making a classification decision. The second is decision-level fusion, where independent AI models analyze each modality separately, and their individual predictions are later combined using ensemble methods to reach a final diagnosis.[15]

3.8. AI, equity, and personalized screening strategies

Disparities in access to breast imaging remain a significant challenge, particularly for underserved populations and women with limited healthcare access. CEM has been proposed as a cost-effective alternative to MRI in resource-limited settings, and AI-enhanced CEM may further support equitable screening by improving

detection accuracy and reducing dependence on specialized radiologists.[28] AI-driven triage systems may help prioritize high-risk examinations, reduce reading times, and support risk-stratified screening pathways.[14] Ethical considerations—including algorithmic bias, data representativeness, and equitable deployment—remain essential to ensure that AI does not inadvertently widen existing healthcare disparities.

3.9. Toward an integrated AI framework for CEM

Current AI applications in CEM remain largely task specific. Recent conceptual frameworks propose unified, end-to-end AI ecosystems integrating standardized acquisition, multimodal imaging inputs, automated segmentation, hybrid radiomics–deep learning classification, and patient-specific clinical variables (Figure 3). Such models could generate individualized malignancy-likelihood scores, support biopsy decision-making, and guide personalized screening or follow-up recommendations.[8-11] Hybrid CNN–radiomics architectures (combining deep neural networks with handcrafted mathematical image features) have shown improved performance over single-modality models.

To overcome data scarcity and privacy constraints, federated learning (a machine learning technique that enables multiple hospitals to train a shared AI model collectively without sharing private patient data) offers a promising strategy. Differential privacy mechanisms can be incorporated into federated learning to provide formal data protection guarantees, while global convergence is monitored via the overall loss function.[29,30] Future work should prioritize prospective validation, cross-vendor interoperability, explainability, and seamless workflow-integrated deployment.[14,15,27,31–34]

3.10. Critical appraisal of current AI evidence in CEM

Across published studies, key methodological strengths include the use of real-world dual-energy CEM datasets and state-of-the-art architectures—such as CNN, YOLO, U-Net, and hybrid radiomics–deep learning models—targeting clinically relevant tasks like lesion detection, classification, molecular subtype prediction, and decision support.[8-15,22] Additionally, several investigations have incorporated multicenter datasets, an important step toward improving model robustness and external validity.[13,15]

Nevertheless, these findings are constrained by recurring limitations that reduce generalizability. Most studies are retrospective, single-center, and rely on relatively small datasets, which increases the risk of overfitting (AI memorizing training data rather than learning general patterns) and limits external validation.[8,9,15] Furthermore, variability in CEM acquisition protocols and image preprocessing hampers direct comparisons across studies.[1,5,15] Key imaging biomarkers, particularly BPE—reflecting normal background fibroglandular tissue enhancement on CEM—and breast density, are reported inconsistently despite their recognized impact on AI performance.[7,15] Heterogeneity in reference standards and annotation strategies also limits reproducibility.[9,22,35,36]

Another major limitation involves the definition of "ground truth" (the true diagnosis used to train the AI). While histopathology from biopsy or surgery serves as the reference standard, many retrospective studies rely partly on 12–24-month imaging follow-up for non-biopsied benign cases, introducing diagnostic uncertainty. Furthermore, institutional differences in classifying borderline lesions—such as atypical ductal hyperplasia—complicate cross-study comparisons.[9]

Finally, model calibration and explainability remain underdeveloped. Most CEM-AI studies rely solely on qualitative visual heatmap (like saliency or attention maps), which can be unreliable.[9,15-17] Future studies should adopt

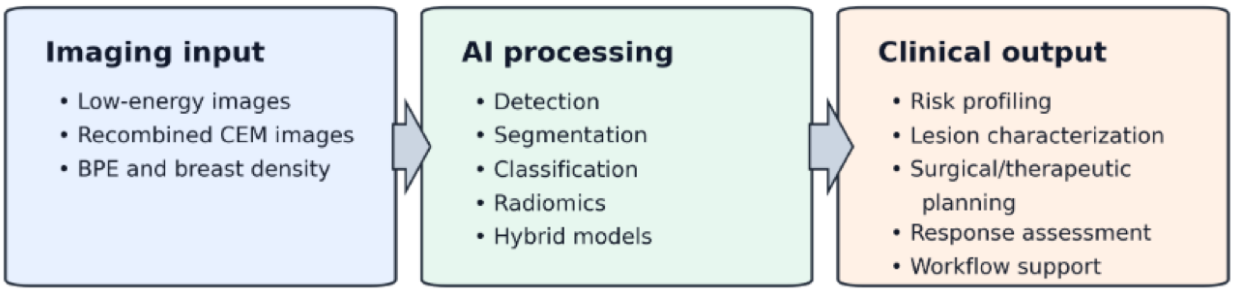


Figure 3. Work-flow schematic illustrating the integration of AI in CEM. The diagram summarizes imaging inputs (low-energy images, recombined CEM images, breast density and BPE), AI processing modules (detection, segmentation, classification, radiomics, hybrid models), and clinical outputs (risk profiling, lesion characterization, treatment planning, response assessment, workflow support). Original diagram created by the authors.
Abbreviations: AI: Artificial intelligence; BPE: Background parenchymal enhancement; CEM: Contrast-enhanced mammography.

quantitative explainability metrics, such as the pointing game (which checks if the model's highest activation point falls inside the true lesion area) or fidelity-based metrics (which measure how prediction confidence drops when key features are altered), alongside calibration analyses before clinical deployment.[16,17,35,36]

4. Discussion

4.1. Interpretation of key findings

The growing body of literature on CEM and AI reflects a rapidly evolving field shaped by technological innovation, changing clinical needs, and the limitations of conventional breast imaging. CEM has consistently demonstrated strong diagnostic performance, particularly in dense breasts and preoperative staging, reinforcing its role as a valuable complement or alternative to MRI in selected scenarios.[1-4] At the same time, breast imaging is moving toward risk-stratified pathways, multimodal integration, and precision-oriented diagnostic strategies, creating a natural context for the incorporation of AI.[14,31] Across the diverse studies reviewed, several consistent themes emerge. First, AI applied to CEM has demonstrated robust diagnostic performance across multiple tasks, with AUC values typically ranging from 0.85 to 0.95 for lesion classification—comparable to those achieved by AI in standard mammography and DBT.[9] This consistency across tasks suggests that the functional information provided by CEM is amenable to computational analysis and may offer advantages over morphological imaging alone. Second, the integration of radiomics features with deep learning architectures appears to confer additive benefit, particularly for molecular subtyping and risk profiling, where conventional CNN models may not capture the full spectrum of lesion heterogeneity.[11,12] Third, early evidence for multimodal integration—combining CEM with DBT, ultrasound, or patient-level clinical data—suggests that AI systems can leverage complementary information to improve diagnostic accuracy, although the optimal integration strategy remains to be determined.[11,15,19]

Through published studies, AI has shown the potential to improve interpretative consistency by reducing inter-reader variability, especially in subtle enhancement patterns and dense breasts. Automated detection and segmentation standardize lesion localization, while radiomics quantification reduces subjective interpretation of enhancement kinetics (Figure 4).

Large-scale detection models, including YOLO-based architectures trained on thousands of CEM images, demonstrate that AI can approach radiologist-level performance in specific tasks.[10] Systematic reviews confirm that CNN, attention-based models, and hybrid radiomics–deep learning frameworks achieve high diagnostic accuracy across detection, classification, and segmentation tasks.[9] However, these encouraging results must be interpreted cautiously due to persistent methodological limitations.

A central challenge is the heterogeneity of CEM acquisition protocols across vendors and institutions. Variability in contrast timing, dose, reconstruction algorithms, and post-processing directly affects lesion conspicuity and complicates model training and comparison. BPE and breast density further influence both radiologist interpretation and AI performance, underscoring the need for structured reporting systems and standardized descriptors.[7] These issues align with broader efforts in breast imaging to reduce variability and improve reproducibility through harmonized guidelines and consensus recommendations.[14,31]

Radiomics and hybrid AI models represent a promising direction for precision imaging. Radiomics enables the extraction of quantitative descriptors of enhancement heterogeneity, vascularity, and textural complexity—features that may correlate with tumor biology and treatment response. When integrated with deep learning architectures, radiomics supports multidimensional risk profiling and prognostic assessment. The framework proposed by Di Grezia *et al.*[11] illustrates how CEM can serve as a platform for precision imaging by combining functional enhancement with clinical and biological variables to support individualized decision-making. This evolution mirrors broader trends in breast imaging, where the focus is shifting from simple detection toward comprehensive characterization, risk stratification, and therapy guidance.[19,32]

Multimodal integration further expands the potential of AI-enhanced CEM. Automated 3D ultrasound, DBT, and MRI each provide complementary information that can be synthesized by AI systems to improve diagnostic accuracy, particularly in dense breasts or ambiguous cases.[19]

Recent recommendations from EUSOBI emphasize risk-stratified screening and the integration of supplemental imaging modalities, including CEM, particularly in women with dense breasts.[33] Surgical oncology literature similarly highlights the importance of multimodality imaging in dense-breast management.[34] The future of breast imaging is likely to involve AI models capable of integrating data across modalities and generating unified assessments that reflect the full spectrum of available information.

4.2. Methodological and practical limitations

Current evidence in CEM-AI is mainly based on small, retrospective, single-center studies with limited external validation. Heterogeneity in ground-truth definitions

and lack of consistent patient-level data splitting may affect model comparability and performance estimates. Multicenter studies often rely on pooled datasets without independent external testing, limiting generalizability. In addition, incomplete reporting of hardware specifications and inference time reduces reproducibility and hinders assessment of clinical scalability. The small sample sizes characteristic of most CEM-AI studies has practical implications that extend beyond statistical power. With datasets typically comprising fewer than 1,000 patients, deep learning models are at substantial risk of overfitting, particularly when using high-capacity architectures.[9] In this context, the reported performance metrics may reflect over-optimistic estimates of generalizability, especially when models are evaluated on data from the same institution used for training. The absence of external validation in the majority of studies further limits confidence in performance claims. It is notable that even multicenter studies often combine data for training rather than conducting true external testing, which—while representing a step forward—does not fully address generalizability concerns.[13] These methodological limitations must be acknowledged when interpreting the promise of AI in CEM.

4.3. Ethical and practical considerations

Moving from research to clinical practice will require addressing several practical considerations that are rarely discussed in the current literature. First, integration with existing PACS/RIS (picture archiving and communication system/radiology information system) environments must be seamless and real-time; any delay or additional step in the reporting workflow may reduce radiologist acceptance and diminish the potential efficiency gains.[14,31] Second, the output of AI systems must be presented in a manner that is actionable and interpretable, typically as a malignancy probability score or a highlighted region of interest, with clear visual explanations to support radiologist review.[36] Third, regulatory approval pathways (*e.g.*, FDA 510(k) clearance, CE marking) require demonstration of safety and effectiveness in prospective studies with clinically meaningful endpoints, a standard that has not yet been met for CEM-AI systems. Fourth, reimbursement models must be developed to incentivize adoption without creating financial barriers to equitable access.

AI systems for CEM must ensure transparency, explainability, and robustness to minimize potential risks in clinical use. Variability in imaging protocols, population characteristics, and vendor systems may influence model performance across different settings. Algorithmic bias and dataset imbalance remain relevant concerns for equitable deployment. Therefore, interpretable outputs are essential to support radiologist decision-making, particularly in lesion assessment and triage tasks.

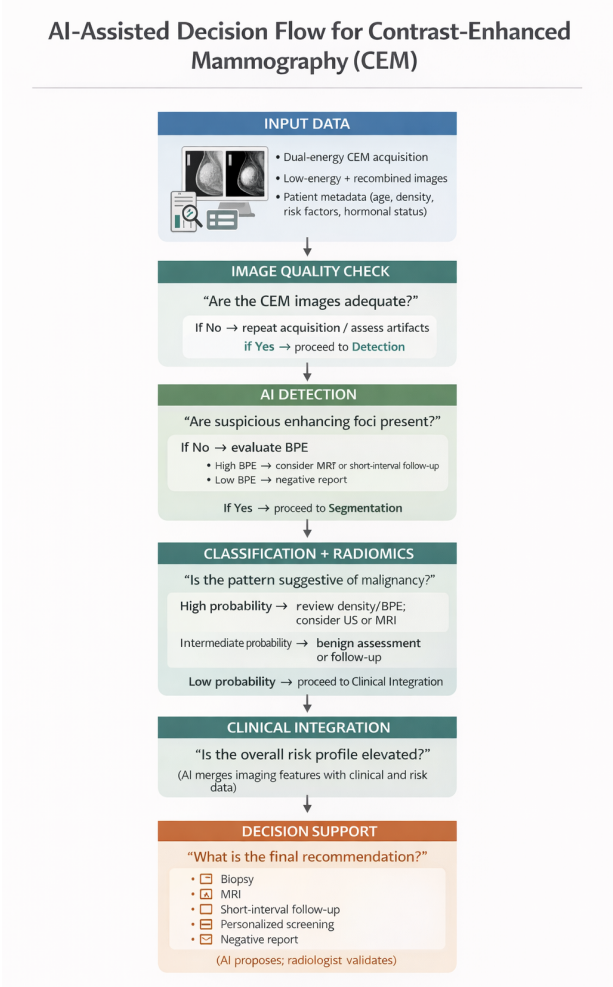


Figure 4. AI-assisted decision flow for CEM. The diagram illustrates the sequential workflow from image acquisition and quality assessment to AI-based detection, segmentation, hybrid radiomics–deep learning classification, clinical integration, and radiologist-validated decision making. Original flow-chart created by the authors.
Abbreviations: AI: Artificial intelligence; BPE: Background parenchymal enhancement; CEM: Contrast-enhanced mammography; CNN: Convolutional neural network; MRI: Magnetic resonance imaging; US: Ultrasonography.

4.4. Toward clinical integration

Clinical implementation will require seamless integration into PACS/RIS environments, enabling real-time decision support without disrupting established workflows. In resource-limited settings, AI-augmented CEM may help compensate for the scarcity of specialized breast radiologists, supporting equitable access to high-quality imaging. This is particularly relevant for

vulnerable populations, including refugee women, where optimized imaging pathways and AI-supported triage could reduce disparities in care.[28] Updated ACR Appropriateness Criteria further highlights the need for tailored supplemental screening strategies based on breast density and individual risk.[37] Within this broader evolution, CEM represents a uniquely suitable platform for AI-driven precision imaging because its dual-energy acquisition and functional enhancement patterns provide both morphological and vascular information. Recent literature highlights additional emerging directions—including molecular breast imaging integration, adaptive screening paradigms, advances in CEM-guided biopsy, and radiomics-focused standardization efforts—that may further support clinical translation.[37-49] Looking forward, several specific research priorities can be identified. First, the creation of large, publicly available CEM datasets with standardized acquisition parameters, detailed clinical annotations (including BPE, breast density, hormonal status, and histopathological correlates), and patient-level splitting would accelerate progress and enable fair comparison of methodologies. Second, prospective clinical trials are needed to evaluate AI-augmented CEM in real-world settings, with endpoints that include not only diagnostic accuracy but also workflow efficiency, reader confidence, and patient outcomes. Third, the development of explainable AI techniques specific to CEM—that provide clinically meaningful rationales for model decisions—is essential for building trust and facilitating adoption. Fourth, the use of federated learning should be scaled to multicenter settings, enabling collaborative model development without violating data privacy. Fifth, the integration of CEM-AI into screening pathways, particularly for women with dense breasts or intermediate risk, should be explored as a potential strategy to reduce disparities in access to breast imaging.[28,33]

4.5. Barriers to clinical translation

Despite the promising evidence reviewed above, several barriers currently impede the translation of AI-enhanced CEM from research to routine clinical practice.

Technical barriers include the lack of standardized acquisition protocols across vendors and institutions, which affects model generalizability and complicates multi-institutional collaboration. Variability in contrast injection timing, iodine dose, and reconstruction algorithms directly impacts enhancement patterns and, consequently, AI model performance.[7,31] The absence of standardized DICOM headers for CEM-specific parameters further complicates data aggregation.

Clinical barriers include radiologist acceptance, which depends on trust in AI outputs, perceived workflow disruption, and the availability of explainable outputs. Many radiologists express concern about over-reliance on AI and the potential for automation bias.[36] Additionally, the integration of AI into existing PACS/RIS workflows requires substantial technical infrastructure and institutional support.

Economic barriers include the costs of AI software licenses, hardware upgrades, and ongoing maintenance, which may be particularly burdensome in resource-limited settings. Reimbursement for AI-augmented services remains uncertain in many healthcare systems, potentially limiting adoption to well-resourced academic centers.[28]

Addressing these barriers will require coordinated efforts among researchers, clinicians, industry partners, regulators, and policymakers to ensure that AI-enhanced CEM achieves its potential to improve breast cancer detection and patient care.

5. Conclusions

Contrast-enhanced mammography (CEM), increasingly supported by AI, is evolving toward a more integrated role in breast cancer imaging, with benefits in lesion detection, interpretative consistency, and workflow efficiency, particularly in dense breasts and complex cases. Future progress should focus on standardized multicenter datasets, explainable and well-calibrated multimodal AI models, and robust prospective validation within clinical workflows, including transparent reporting of technical and deployment parameters. Ethical implementation requires attention to fairness, representativeness, and reduction of disparities in access to breast imaging. Advances such as federated learning and synthetic data may help address current data and privacy limitations.

The trajectory of AI in CEM mirrors the broader evolution of precision medicine—moving from simple detection toward comprehensive characterization and personalized management. This progression is not merely technological but also conceptual, reflecting a shift in how we understand breast cancer as a heterogeneous disease with varied biological behavior, prognosis, and treatment response. By integrating functional imaging with computational analysis, AI-augmented CEM offers a window into tumor biology that may ultimately transform clinical decision-making. However, this vision will only be realized through sustained commitment to rigorous methodology, interdisciplinary collaboration, and patient-centered implementation.

Overall, with coordinated interdisciplinary development, CEM may evolve into a precision imaging

platform, where AI supports earlier detection, treatment planning, and improved patient outcomes in a clinically reliable and equitable manner.

Acknowledgments

During the preparation of this manuscript, the authors used Microsoft Copilot, ChatGPT, and Gemini to assist with English language editing. The final version was reviewed and corrected by Silvia Losco, an accredited English teacher. The authors thank her for her valuable assistance in improving the English language and readability of the manuscript.

Funding

None.

Conflict of interest

Graziella Di Grezia is an Editorial Board Member of this journal, but was not in any way involved in the editorial and peer-review process conducted for this paper, directly or indirectly. The authors declare no conflicts of interest.

Author contributions

Conceptualization: Graziella Di Grezia, Mariano Scaglione
Project administration: Graziella Di Grezia
Supervision: Mariano Scaglione, Salvatore Masala
Visualization: Teresa Iannaccone, Antonio Nazzaro, Leandra Piscopo
Writing–original draft: Graziella Di Grezia, Teresa Iannaccone, Antonio Nazzaro, Leandra Piscopo
Writing–review & editing: Graziella Di Grezia, Salvatore Masala, Mariano Scaglione

Ethics approval and consent to participate

Not applicable.

Consent for publication

All figures and tables presented in this manuscript are original and were created by the authors. Clinical images (Figures 1 and 2) were fully anonymized and obtained with informed consent. No copyrighted material from third parties was used.

Availability of data

Not applicable.

References

1. Jochelson MS, Lobbes MBI. Contrast-enhanced Mammography: State of the Art. *Radiology*. 2021;299(1):36-48.

   doi: 10.1148/radiol.2021201948

2. Coffey K, Jochelson MS. Contrast-enhanced mammography in breast cancer screening. *Eur J Radiol*. 2022;156:110513.

   doi: 10.1016/j.ejrad.2022.110513

3. Di Grezia G, Mercogliano S, Marinelli L, Cuccurullo V, Scaglione M. Contrast-Enhanced Mammography in Breast Lesion Assessment. *Tomography*. 2025;11(8):93.

   doi: 10.3390/tomography11080093

4. Mann RM, Longo V. Contrast-enhanced Mammography versus MR Imaging of the Breast. *Radiol Clin North Am*. 2024;62(4):643-659.

   doi: 10.1016/j.rcl.2024.02.003

5. Zhang T, Mann RM. Contrast-enhanced mammography: better with AI? *Eur Radiol*. 2024;34(2):914-916.

   doi: 10.1007/s00330-023-10190-5

6. Bahl M. Contrast-enhanced Mammography: An Emerging Modality in Breast Imaging. *Radiology*. 2022;302(3):582-583.

   doi: 10.1148/radiol.212856

7. Di Grezia G, Nazzaro A, Schiavone L, *et al*. From Variability to Standardization: The Impact of Breast Density on Background Parenchymal Enhancement in Contrast-Enhanced Mammography and the Need for a Structured Reporting System. *Cancers*. 2025;17(15):2523.

   doi: 10.3390/cancers17152523

8. Bahl M, Do S. Artificial intelligence applied to contrast-enhanced mammography: exploring uncharted territory. *Radiology*. 2023;307(4):e231140.

   doi: 10.1148/radiol.231140

9. Sorin V, Sklair-Levy M, Glicksberg BS, *et al*. Deep learning for contrast-enhanced mammography: a systematic review. *Acad Radiol*. 2025;32(8):2497-2508.

   doi: 10.1016/j.acra.2024.11.035

10. Jailin C, Mohamed S, Iordache R, *et al*. AI-based cancer detection model for contrast-enhanced mammography. *Bioengineering*. 2023;10(8):974.

    doi: 10.3390/bioengineering10080974

11. Di Grezia G, Nazzaro A, Cisternino E, *et al*. Beyond cancer detection: an AI framework for multidimensional risk profiling on contrast-enhanced mammography. *Diagnostics*. 2025;15(21):2788.

    doi: 10.3390/diagnostics15212788

12. Zhu S, Wang S, Guo S, *et al*. Contrast-enhanced mammography radiomics analysis for preoperative prediction of breast cancer molecular subtypes. *Acad Radiol*. 2024;31(6):2228-2238.

    doi: 10.1016/j.acra.2023.12.005

13. Zhang H, Lin F, Zheng T, *et al*. Artificial intelligence–based classification of breast lesion from contrast-enhanced mammography: a multicenter study. *Int J Surg*. 2024;110(5):2593-2603.

doi: 10.1097/JS9.0000000000001076

14. Marcon M, Fuchsjäger MH, Clauser P, Mann RM. ESR Essentials: screening for breast cancer—general recommendations by EUSOBI. *Eur Radiol*. 2024;34(10):6348-6357.

doi: 10.1007/s00330-024-10740-5

15. Kinkar KK, Fields BKK, Yamashita MW, Varghese BA. Empowering breast cancer diagnosis and radiology practice: advances in artificial intelligence for contrast-enhanced mammography. *Front Radiol*. 2024;3:1326831.

doi: 10.3389/fradi.2023.1326831

16. Guo C, Pleiss G, Sun Y, Weinberger KQ. On calibration of modern neural networks. *Proc Mach Learn Res*. 2017;70:1321-1330.

17. Niculescu-Mizil A, Caruana R. Predicting good probabilities with supervised learning. *Proc Int Conf Mach Learn*. 2005:625-632.

doi: 10.1145/1102351.1102430

18. Di Grezia G, Iannaccone T, Nazzaro A. Bifurcated networks for breast density & cancer risk. *Diagnostics*. 2026;16(5):770.

doi: 10.3390/diagnostics16050770

19. Di Grezia G, Gatta G, Brunese L, Falco G. State-of-the-art in integrated breast imaging. *Biomed Res Int*. 2019;2019:7596059.

doi: 10.1155/2019/7596059

20. Lin TY, Goyal P, Girshick R, He K, Dollár P. Focal loss for dense object detection. *IEEE Trans Pattern Anal Mach Intell*. 2020;42(2):318-327.

doi: 10.1109/TPAMI.2018.2858826

21. Milletari F, Navab N, Ahmadi SA. V-Net: fully convolutional neural networks for volumetric medical image segmentation. *Proc IEEE Int Conf 3D Vis*. 2016:565-571.

doi: 10.1109/3DV.2016.79

22. Zwanenburg A, Vallières M, Abdalah MA, *et al*. The Image Biomarker Standardization Initiative: Standardized quantitative radiomics for high-throughput image-based phenotyping. *Radiology*. 2020;295(2):328-338.

doi: 10.1148/radiol.2020191145

23. Tibshirani R. Regression shrinkage and selection via the lasso. *J R Stat Soc Series B*. 1996;58(1):267-288.

doi: 10.1111/j.2517-6161.1996.tb02080.x

24. Ganin Y, Ustinova E, Ajakan H, *et al*. Domain-adversarial training of neural networks. In: *Advances in Computer Vision and Pattern Recognition*. Cham, Switzerland: Springer International Publishing; 2017:189-209.

doi: 10.1007/978-3-319-58347-1_10

25. Ji W, Chung ACS. Unsupervised domain adaptation for medical image segmentation using transformer with meta attention. *IEEE Trans Med Imaging*. 2024;43(2):820-831.

doi: 10.1109/TMI.2023.3322581

26. Guan H, Liu M. Domain Adaptation for Medical Image Analysis: A Survey. *IEEE Trans Biomed Eng*. 2022;69(3):1173-1185.

doi: 10.1109/TBME.2021.3117407

27. Galati F, Moffa G, Pediconi F. Breast imaging: Beyond the detection. *Eur J Radiol*. 2022;146:110051.

doi: 10.1016/j.ejrad.2021.110051

28. Di Grezia G, Iannaccone T, Gatta G. Optimizing Breast Imaging: Needs and Opportunities for Refugee Women in Italy and Low-Income Countries. *Eur J Breast Health*. 2025;21(3):281-282.

doi: 10.4274/ejbh.2025.2025-3-1

29. McMahan B, Moore E, Ramage D, Hampson S, Arcas BA. Communication efficient learning of deep networks from decentralized data. *Proc Int Conf Artif Intell Stat*. 2017;54:1273-1282.

30. Abadi M, Chu A, Goodfellow I, *et al*. Deep learning with differential privacy. In: *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*. New York, NY: ACM; 2016:308-318.

doi: 10.1145/2976749.2978318

31. Yong-Hing CJ, Gordon PB, Appavoo S, *et al*. Addressing Misinformation About the Canadian Breast Screening Guidelines. *Can Assoc Radiol J*. 2023;74(2):388-397.

doi: 10.1177/08465371221120798

32. Arıbal E. Future of Breast Radiology. *Eur J Breast Health*. 2023;19(4):262-266.

doi: 10.4274/ejbh.galenos.2023.2023-8-3

33. Kilburn-Toppin F, Allajbeu I, Healy N, Gilbert FJ. Supplemental Screening With MRI in Women With Dense Breasts: The European Perspective. *J Breast Imaging*. 2025;7(2):131-140.

doi: 10.1093/jbi/wbae091

34. Upadhyay N, Wolska J. Imaging the dense breast. *J Surg Oncol*. 2024;130(1):29-35.

doi: 10.1002/jso.27661

35. Pineau J, Vincent-Lamarre P, Sinha K, *et al*. Improving reproducibility in machine learning research. *J Mach Learn Res*. 2021;22(164):1-20.

36. Heil BJ, Hoffman MM, Markowetz F, *et al*. Reproducibility standards for machine learning in the life sciences. *Nat*

Methods. 2021;18(10):1132-1135.

doi: 10.1038/s41592-021-01256-7

37. Paulis LV, Lewin AA, Weinstein SP, *et al*. ACR Appropriateness Criteria and Supplemental Breast Cancer Screening Based on Breast Density: 2024 Update. *J Am Coll Radiol*. 2025;22(5S):S405-S423.

doi: 10.1016/j.jacr.2025.02.023

38. Smith KA, Hunt KN, Rauch GM, Fowler AM. Molecular breast imaging in the screening setting. *J Breast Imaging*. 2023;5(3):240-247.

doi: 10.1093/jbi/wbad011

39. Van Baelen K, Sawyer E, Van Cauwenberge J, *et al*. Clinical challenges and proposed solutions for patients with invasive lobular breast cancer. *Ann Oncol*. 2025;36(11):1285-1298.

doi: 10.1016/j.annonc.2025.07.008

40. van Nijnatten TJA, Morscheid S, Baltzer PAT, *et al*. Contrast-enhanced breast imaging: current status and future challenges. *Eur J Radiol*. 2024;171:111312.

doi: 10.1016/j.ejrad.2024.111312

41. Weaver OO, Berg WA. Contrast-enhanced mammography-guided biopsy: a step-by-step guide. *AJR Am J Roentgenol*. 2025;225(4):e2533038.

doi: 10.2214/AJR.25.33038

42. Cömert D, van Gils CH, Veldhuis WB, Mann RM. Challenges and changes of the breast cancer screening paradigm. *J Magn Reson Imaging*. 2023;57(3):706-726.

doi: 10.1002/jmri.28495

43. Tsarouchi MI, Hoxhaj A, Mann RM. New approaches and recommendations for risk-adapted breast cancer screening. *J Magn Reson Imaging*. 2023;58(4):987-1010.

doi: 10.1002/jmri.28731

44. Goh Y, Quek ST, Pillay P, Chou CP. Evaluation of architectural distortion with contrast-enhanced mammography. *Clin Radiol*. 2024;79(3):163-169.

doi: 10.1016/j.crad.2023.11.021

45. Sitges C, Mann RM. Breast MRI to screen women with extremely dense breasts. *J Magn Reson Imaging*. 2025;62(1):58-72.

doi: 10.1002/jmri.29716

46. Yang ML, Bhimani C, Roth R, Germaine P. Contrast-enhanced mammography: focus on frequently encountered benign and malignant diagnoses. *Cancer Imaging*. 2023;23(1):10.

doi: 10.1186/s40644-023-00526-1

47. Alcantara R, Azcona J, Pitarch M, *et al*. Contrast-enhanced mammography-guided biopsy: principles, challenges, and opportunities. *Insights Imaging*. 2025;16(1):262.

doi: 10.1186/s13244-025-02148-6

48. Nicosia L, Gnocchi G, Gorini I, *et al*. History of mammography: analysis of breast imaging diagnostic achievements over the last century. *Healthcare*. 2023;11(11):1596.

doi: 10.3390/healthcare11111596

49. Siviengphanom S, Gandomkar Z, Lewis SJ, Brennan PC. Mammography-based radiomics in breast cancer: a scoping review of current knowledge and future needs. *Acad Radiol*. 2022;29(8):1228-1247.

doi: 10.1016/j.acra.2021.09.025