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Research paper

Applications of Artificial Intelligence and Radiomics in Contrast-Enhanced Mammography: A Recent Systematic Analysis

Norhayati Mohd Zain [1] *, Wan Azani Mustafa [2, 3]

[1] *Medical Imaging Department, School of Integrative Medicine & Life Sciences, KPJ Healthcare University, 71800 Nilai, Malaysia*
[2] *Faculty of Electrical Engineering Technology, Universiti Malaysia Perlis, UniCITI Alam Campus, Sungai Chuchuh, 02100 Padang Besar, Perlis, Malaysia*
[3] *Advanced Computing (AdvCOMP), Centre of Excellence, Universiti Malaysia Perlis (UniMAP), Pauh Putra Campus, 02600 Arau, Perlis, Malaysia*
**Corresponding author E-mail: norhayati@kpju.edu.my*

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Abstract

This systematic literature review investigates the recent advancements in the applications of Artificial Intelligence (AI) and Radiomics in Contrast-Enhanced Mammography (CEM), focusing on their diagnostic, predictive, and prognostic value in breast cancer imaging. The study aims to synthesize current evidence on the integration of AI-based algorithms and radiomic approaches that enhance lesion detection, classification, and clinical interpretation. The review follows the PRISMA protocol to ensure methodological rigor and transparency. A comprehensive search was conducted across Scopus and PubMed databases using the keywords contrast, mammography, and artificial intelligence, retrieving relevant studies published in 2025. After applying inclusion and exclusion criteria, 36 primary studies were selected for qualitative synthesis. The analysis identified three major thematic domains: (1) AI architectures and classification/detection models, (2) Radiomics and multi-modality predictive/prognostic models, and (3) Segmentation, microcalcification, and data-tooling for detection. The findings revealed that hybrid and ensemble deep learning models significantly improved diagnostic performance, while radiomics-based approaches enhanced molecular subtype prediction, risk stratification, and treatment planning. Furthermore, advances in segmentation and synthetic data augmentation improved lesion localization and model robustness, supporting more accurate and reproducible image interpretation. Despite methodological progress, challenges persist regarding data standardization, model explainability, and clinical validation across diverse populations. The review concludes that integrating AI and radiomics within CEM holds substantial potential for transforming breast cancer diagnostics by improving precision, interpretability, and clinical decision-making. Continued development of standardized frameworks and multicenter validation is essential to ensure reliable, ethical, and clinically applicable AI adoption in breast imaging practice.

Keywords: *Artificial Intelligence; Radiomics; Contrast-Enhancement Mammography.*

1. Introduction

Breast cancer is a major contributor to illness and death among women globally, highlighting the ongoing need for improved imaging techniques that support earlier diagnosis, better tumor assessment, and more tailored treatment strategies. Traditional mammography, while widely used, faces limitations in sensitivity and specificity, particularly in women with dense breast tissue. Contrast-enhanced mammography (CEM) has emerged as a promising modality, offering enhanced visualization of tumor vascularity and morphology, and demonstrating diagnostic performance comparable to magnetic resonance imaging (MRI) but with greater accessibility and lower cost ((Jochelson & Lobbes, 2021); Kinkar et al., 2024). In parallel, the rapid evolution of artificial intelligence (AI) and radiomics has transformed medical imaging analysis, enabling the extraction of high-dimensional quantitative features from images and the development of predictive models that can support clinical decision-making (Kinkar et al., 2024; Pesapane et al., 2023). The integration of AI and radiomics with CEM holds significant potential to address current diagnostic challenges, improve lesion characterization, and facilitate individualized patient management.

Recent research consistently shows that AI and radiomics enhance the diagnostic accuracy of CEM for breast cancer detection and characterization. AI-based models, particularly those leveraging deep learning and advanced machine learning algorithms, have shown superior performance in differentiating benign from malignant lesions compared to traditional radiomics models and even experienced radiologists. For instance, a multicenter study employing a deep learning model with attention mechanisms achieved an area under the curve (AUC) of

0.932 in external validation, outperforming both radiomics and clinical models (H. Zhang et al., 2024). Similarly, AI algorithms have been effective in classifying in situ versus invasive carcinoma and in predicting molecular subtypes, such as HER2 status, with high accuracy (Zhang et al., 2024; (S. Wang et al., 2021); (Zhu et al., 2023)). These findings underscore the potential of AI-enhanced CEM to serve as a robust, non-invasive tool for comprehensive breast cancer assessment.

Radiomics, the process of extracting quantitative features related to tumor size, shape, intensity, and texture from medical images, has been extensively applied to CEM for tumor characterization and prognostic prediction ((Petrillo et al., 2024); (Nicosia et al., 2025); Kinkar et al., 2024). Studies have shown that radiomic features, when combined with clinical data, can improve the prediction of disease-free and overall survival, as well as the likelihood of specific histological outcomes and molecular subtypes (Nicosia et al., 2025; Zhu et al., 2023). For example, radiomics models based on both low-energy and recombined CEM images have achieved AUCs above 0.80 for predicting luminal, HER2-enriched, and triple-negative breast cancer subtypes, supporting their utility in guiding individualized treatment strategies (Zhu et al., 2023). Moreover, the integration of radiomics with AI-driven feature selection and classification methods, such as random forests and support vector machines, has further enhanced diagnostic performance ((Massafra et al., 2021); (Beuque et al., 2023)).

Despite these advances, several challenges remain in the clinical implementation of AI and radiomics in CEM. Manual segmentation of lesions, a common step in radiomics workflows, is time-consuming and subject to inter-operator variability, highlighting the need for automated or semi-automated segmentation solutions (Petrillo et al., 2022; Beuque et al., 2023). Additionally, the interpretability of complex AI models and the standardization of data acquisition and analysis protocols are critical for ensuring reproducibility and clinical adoption (Kinkar et al., 2024; Pesapane et al., 2023). Recent guidelines, such as the Checklist for Artificial Intelligence in Medical Imaging (CLAIM), have been proposed to address these issues and promote rigorous evaluation and reporting of AI studies in breast imaging (Kinkar et al., 2024).

In summary, the combination of AI and radiomics with contrast-enhanced mammography marks a major step forward in breast cancer imaging technology (Figure 1). These technologies have demonstrated high diagnostic accuracy for lesion classification, molecular subtype prediction, and prognostic assessment, with the potential to support personalized patient care. Ongoing research is focused on overcoming technical and methodological barriers to facilitate the widespread adoption of these tools in clinical practice (Zhang et al., 2024; Kinkar et al., 2024; Zhu et al., 2023; Pesapane et al., 2023).

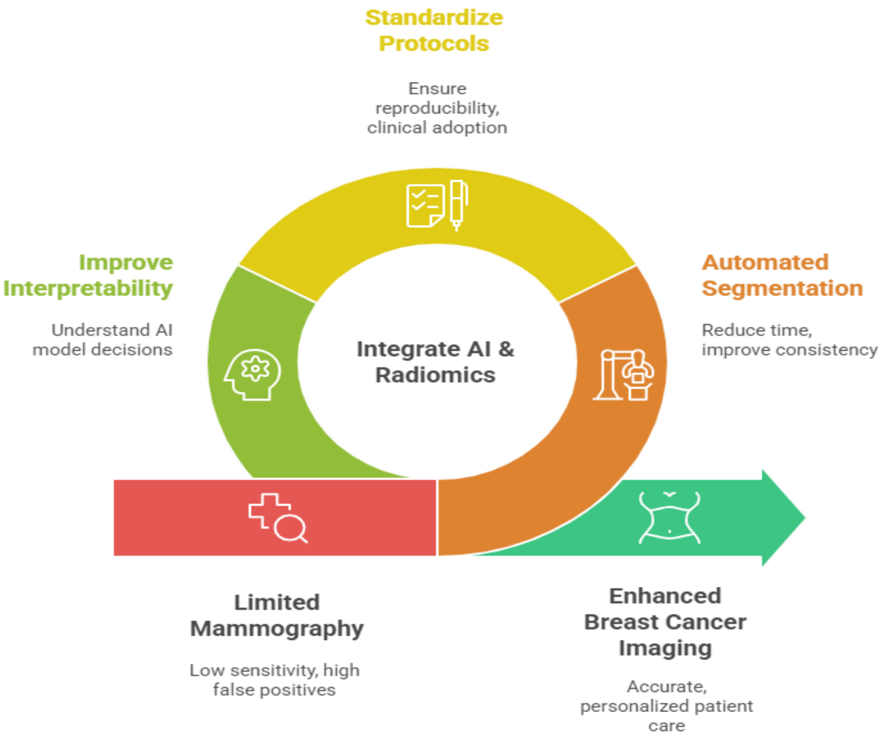

Fig. 1: The concept map of AI-Enhanced CEM for Breast Cancer.

2. Research Question

In a systematic literature review, the formulation of research questions is the central element that drives every stage of the review. These questions determine the boundaries and purpose of the investigation, influencing which publications are selected or excluded to preserve accuracy and relevance. When the questions are specific and well-structured, the search strategy becomes methodical and far-reaching, ensuring that all significant evidence on the subject is identified while reducing the risk of bias. They also act as a roadmap for organizing extracted information, allowing the results to be analyzed and presented logically. By outlining clear limits, research questions keep the review sharply focused and prevent unnecessary deviation from its intended aims. Additionally, they promote openness and repeatability, allowing future researchers to follow the same process or extend the work confidently. In essence, strong research questions give an SLR its direction and value, whether the goal is to highlight gaps in existing knowledge, assess outcomes of interventions, or explore new developments, making them the backbone of a robust and purposeful review.

Specifying the Research Questions (RQs) is the most critical task during the planning phase and remains central throughout any systematic literature review (SLR), as it shapes and directs the entire review methodology (B, Kitchenham, 2007). Given that this SLR aims to explore and assess the current advancements within the selected domain, a systematic structure is crucial to maintain a clear and focused review direction. For this study, the PICo framework was employed as a guiding strategy, following the approach recommended by C. Lockwood et al. (2015). Designed primarily for qualitative inquiries, PICo incorporates three core elements, Population, Interest, and Context, which help formulate specific and well-aligned research questions.

In the PICo structure, the Population (P) identifies the particular individuals or groups being examined, which may include a certain demographic, patient subgroup, or broader community. The Interest (I) highlights the primary topic, phenomenon, or aspect under study, such as a specific experience, behavior, intervention, or concern. Meanwhile, the Context (Co) outlines the surrounding conditions where the research is situated, which can involve the geographical setting, cultural influences, or social environment relevant to the investigation. By applying the PICo framework, research questions can be constructed in a systematic and organized manner. This approach ensures that each element of the study is explicitly defined, facilitating a more precise literature search and enhancing the overall focus and coherence of the SLR. This study achieved one research question as below;

1) RQ1: For adult women receiving contrast-enhanced mammography (P), does the application of advanced AI architectures (ensembles, transformer–CNN hybrids, and attention-based models) (I), compared with conventional single-architecture CNNs or radiologist-alone interpretation, improve detection and classification accuracy and clinical interpretability of breast lesions in routine CEM practice (Co)?
2) RQ2: In patients evaluated with contrast-enhanced mammography and complementary imaging (P), does a multi-modality radiomics model that fuses intra- and peritumoral features from CEM, DCE-MRI and ultrasound (I), versus single-modality radiomics or standard clinical models, provide superior prediction of molecular subtype, biopsy outcome, or long-term prognosis in multicenter validation (Co)?
3) RQ3: For mammographic imaging datasets containing annotated lesions and microcalcifications (P), does the combination of robust anatomical segmentation, task-aware synthetic microcalcification augmentation, and attention-guided data strategies (I), compared with models trained on real data alone, improve sensitivity and localization accuracy for microcalcification clusters and reduce missed non-palpable carcinomas in CEM/DBT across external test sets (Co)?

3. Materials and Methods

The PRISMA framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), as outlined by Page et al. (2020), is broadly recognized as a standard protocol for performing systematic reviews. Its purpose is to promote a clear, thorough, and structured review process. By adhering to PRISMA, researchers enhance the reliability and credibility of their findings through well-defined steps that involve locating, evaluating, and selecting studies relevant to the research focus. The framework also underscores the role of randomized research in minimizing bias and strengthening the overall quality of evidence. In this SLR, Scopus and PubMed were chosen as the primary sources of literature because of their broad scientific coverage and established authority as trusted databases.

The PRISMA workflow is organized into four essential phases: identification, screening, eligibility, and data extraction. In the identification phase, a comprehensive search is carried out across selected databases to gather all studies that may be relevant to the topic. The screening phase then applies predefined inclusion and exclusion criteria to remove publications that do not align with the review's objectives or quality standards. Next, the eligibility phase involves a closer evaluation of the remaining articles to confirm that they fully satisfy the criteria for inclusion. Finally, during the data extraction phase, pertinent information from the selected studies is collected, categorized, and synthesized to draw meaningful conclusions. This systematic process enhances research quality and transparency, ensuring that the final review presents trustworthy evidence to support ongoing scholarship and inform professional practice.

3.1. Identification

For this review, an extensive literature search was performed across the Scopus and PubMed databases. These two sources were chosen because they provide broad access to reputable, peer-reviewed publications within medical imaging, radiology, and artificial intelligence research. Using the predetermined search terms, "artificial intelligence," "radiomics," and "contrast-enhanced mammography (CEM)". A total of 2,889 studies were initially identified, with 2,183 retrieved from Scopus and 706 from PubMed. This substantial volume of records reflects the rapid expansion of research in AI-driven diagnostic imaging and the increasing integration of radiomics for enhanced lesion characterization in breast cancer detection. The database selection and keyword strategy were designed to ensure inclusivity, capturing studies across clinical, computational, and imaging science domains to represent a holistic evidence base for the topic (Table 1).

The large number of records identified highlights both the scientific relevance and the growing academic interest in the intersection of AI and CEM. The post-pandemic acceleration of digital transformation in medical imaging and the widespread adoption of data-driven diagnostic tools have contributed significantly to this research surge. Moreover, the inclusion of two premier indexing databases ensures the retrieval of diverse yet credible sources, minimizing publication bias and enhancing the comprehensiveness of the review. The high volume of initial records also underscores the necessity for rigorous screening and eligibility procedures, as mandated by the PRISMA framework, to refine the dataset to the most pertinent studies. Ultimately, this systematic identification process establishes a robust foundation for subsequent analytical phases, ensuring methodological rigor and enhancing the scientific reliability of the review's findings.

Table 1: The Search String

Scopus	TITLE-ABS-KEY ((contrast OR enhance*) AND (mammogram OR mammography) AND (AI OR "artificial Intelligence" OR "deep learning" OR "machine learning" OR radiomic*)) AND (LIMIT-TO (PUBYEAR, 2025)) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (PUBSTAGE, "final")) AND (LIMIT-TO (LANGUAGE, "English")) Date of Access: November 2025
Pubmed	Search: (contrast OR enhance*) AND (mammogram OR mammography) AND (AI OR "artificial Intelligence" OR "deep learning" OR "machine learning" OR radiomic*) Filters: Adaptive Clinical Trial, Address, Autobiography, Bibliography, Biography, Books and Documents, Case Reports, Classical Article, Clinical Conference, Clinical Study, Clinical Trial, Clinical Trial, Phase I, Clinical Trial, Phase II, Clinical Trial, Phase III, Clinical Trial, Phase IV, Clinical Trial Protocol, Collected Work, Comment, Comparative Study, Congress, Consensus Development Conference, Consensus Development Conference, NIH, Controlled Clinical Trial, Corrected and Republished Article, Dataset, Dictionary, Directory, Duplicate Publication, Editorial, Electronic Supplementary Materials, English Abstract, Equivalence Trial, Evaluation Study, Expression of Concern, Festschrift, Government Publication, Guideline, Historical Article, Interactive Tutorial, Interview, Introductory Journal Article, Lecture, Legal Case, Legislation, Letter, Meta-Analysis, Multicenter Study, Network Meta-Analysis, News, Newspaper Article, Observational Study, Overall, Patient Education Handout, Periodical Index, Personal Narrative, Portrait, Practice Guideline, Pragmatic Clinical Trial, Preprint, Published Erratum, Randomized Controlled Trial, Randomized Controlled Trial, Veterinary, Research Support, American Recovery and Reinvestment Act, Research Support, N.I.H., Extramural, Research Support, N.I.H., Intramural, Research Support, Non-

	U.S. Gov't, Research Support, U.S. Gov't, Research Support, U.S. Gov't, Non-P.H.S., Research Support, U.S. Gov't, P.H.S., Retracted Publication, Retraction of Publication, Clinical Trial, Veterinary, Observational Study, Veterinary, English, from 2025/1/1 - 2025/11/8 Date of Access: November 2025

3.2. Screening

During the screening phase of this systematic review, all records retrieved from the initial search were carefully examined for relevance and quality. Out of the 2,889 studies identified in the identification stage, 345 articles were retained after the first-level screening, 323 from Scopus and 22 from PubMed. This refinement was guided by predefined inclusion and exclusion criteria to ensure that only studies closely aligned with the objectives of the review were considered (Table 2). The screening primarily involved evaluating titles and abstracts to verify their focus on artificial intelligence, radiomics, and contrast-enhanced mammography (CEM). Furthermore, six duplicate records were detected and removed to preserve the accuracy and integrity of the dataset.
Following this, 2,544 records were excluded based on specific criteria designed to enhance methodological rigor and ensure the inclusion of only high-quality, peer-reviewed studies. Excluded articles were those published before 2025, written in non-English languages, or categorized as conference proceedings, book chapters, reviews, or “in press” papers. This filtering ensured that the remaining dataset comprised only original research articles with complete and verifiable findings, consistent with PRISMA recommendations. The substantial number of excluded records highlights the necessity of a stringent screening approach in a rapidly evolving research field, where the proliferation of non-peer-reviewed and secondary publications is common. Consequently, this phase yielded a refined, reliable, and language-consistent body of literature, forming a strong empirical foundation for the subsequent eligibility and inclusion stages of the systematic review.

Table 2: The Selection Criterion in Searching

Criterion	Inclusion	Exclusion
Language	English	Non-English
Time line	2025	< 2025
Literature type	Journal (Article)	Conference, Book, Review
Publication stage	Final	In-press
Subject	Medicine	Besides Medicine

3.3. Eligibility

In the eligibility phase, 339 articles were subjected to a thorough assessment. Each study’s title, abstract, and full text were thoroughly reviewed to confirm their compliance with the inclusion criteria and alignment with the review’s specific objectives. During this process, 302 articles were excluded for reasons such as being outside the scope of the field, having titles or abstracts that did not correspond to the study’s focus, lacking full-text availability, or failing to provide empirical evidence. As a result, 37 studies satisfied all eligibility requirements and were advanced to the final stage of the systematic review.

3.4. Data abstraction and analysis

This study utilized an integrative analysis approach to review and combine findings from diverse research designs, with a particular focus on qualitative studies. The primary aim was to identify key topics and subtopics relevant to the research focus. Data collection constituted the initial step in developing these themes. As exemplified in Figure 2, the authors carefully analyzed 39 selected publications (Table 3) to extract statements or content pertinent to the study’s objectives. Next, the authors evaluated the most significant current studies concerning the application of artificial intelligence and radiomics in contrast-enhanced mammography (CEM). Both the methodologies and findings of these studies were examined in detail. The authors then work together to derive themes grounded in the evidence within the context of this review. A detailed log was maintained throughout the analysis process to document reflections, interpretations, and observations related to data synthesis. To finish, the authors reviewed and cross-verified the findings to maintain consistency in the development of themes. Any discrepancies in interpretation were resolved through collaborative discussion among the authors to achieve consensus.

Table 3: Number and details of Primary Studies (PS) Database

PS	Authors	Title	Year	Journal
1	(X. Wang et al., 2025)	Predicting short- to long-term breast cancer risk from longitudinal mammographic screening history	2025	npj Breast Cancer
2	(Ergün et al., 2025)	BCECNN: an explainable deep ensemble architecture for accurate diagnosis of breast cancer	2025	BMC Medical Informatics and Decision Making
3	(Lafcı et al., 2025)	Application of Radiomics Analysis on Mammography for Differentiating Benign and Malignant Masses	2025	SN Comprehensive Clinical Medicine
4	(Varshney et al., 2025)	Hybrid and optimized feature fusion for enhanced breast cancer classification	2025	Network Modeling Analysis in Health Informatics and Bioinformatics
5	(D. Zhang et al., 2025)	Deep learning on routine full-breast mammograms enhances lymph node metastasis prediction in early breast cancer	2025	npj Digital Medicine
6	(Wu et al., 2025)	Multi-modality radiomics diagnosis of breast cancer based on MRI, ultrasound and mammography	2025	BMC Medical Imaging
7	(Ma et al., 2025)	Contrast-enhanced mammography-based interpretable machine learning model for the prediction of the molecular subtype breast cancers	2025	BMC Medical Imaging
8	(Pacal & Attallah, 2025)	InceptionNeXt-Transformer: A novel multi-scale deep feature learning architecture for multimodal breast cancer diagnosis	2025	Biomedical Signal Processing and Control
9	(Hashem et al., 2025)	Can artificial intelligence and contrast-enhanced mammography be of value in the assessment and characterization of breast lesions?	2025	Egyptian Journal of Radiology and Nuclear Medicine
10	(Chen & Martel, 2025)	Enhancing breast cancer detection on screening mammogram using self-supervised learning and a hybrid deep model of Swin Transformer and convolutional neural networks	2025	Journal of Medical Imaging
11	(Camp et al., 2025)	Impact of synthetic data on training a deep learning model for lesion detection and classification in contrast-enhanced mammography	2025	Journal of Medical Imaging

12	(Abdelhalim et al., 2025)	A deep learning framework for accurate mammographic mass classification using local context attention module	2025	Medical Physics
13	(Krishna et al., 2025)	Enhancing Breast Cancer Diagnosis With Attention Branch Network and Thermographic Imaging	2025	International Journal of Imaging Systems and Technology
14	(Sierra-Franco et al., 2025)	Towards Automated Semantic Segmentation in Mammography Images for Enhanced Clinical Applications	2025	Journal of Imaging Informatics in Medicine
15	(Ismail et al., 2025)	Application of Tuning-ensemble N-Best in Auto-Sklearn for Mammographic Radiomic Analysis for Breast Cancer Prediction	2025	Current Medical Imaging
16	(Q. Wang et al., 2025)	Dual-Modality Virtual Biopsy System Integrating MRI and MG for Noninvasive Predicting HER2 Status in Breast Cancer	2025	Academic Radiology
17	(Niranjana et al., 2025)	Performance analysis of novel hybrid\ deep learning model IEU Net++ for multiclass categorization of breast mammogram images	2025	Biomedical Signal Processing and Control
18	(Mansour, Kamal, et al., 2025)	Enhancing detection of previously missed non-palpable breast carcinomas through artificial intelligence	2025	European Journal of Radiology Open
19	(Nicosia et al., 2022)	Preliminary Evaluation of Radiomics in Contrast-Enhanced Mammography for Prognostic Prediction of Breast Cancer	2025	Cancers
20	(Ra et al., 2025)	Enhancing radiomics features via a large language model for classifying benign and malignant breast tumors in mammography	2025	Computer Methods and Programs in Biomedicine
21	(Liu et al., 2025)	A Radiomic-Clinical Model of Contrast-Enhanced Mammography for Breast Cancer Biopsy Outcome Prediction	2025	Academic Radiology
22	(Ciurescu et al., 2025)	AI in 2D Mammography: Improving Breast Cancer Screening Accuracy	2025	Medicina (Lithuania)
23	(Li et al., 2025)	An explainable and comprehensive BI-RADS assisted diagnosis pipeline for mammograms	2025	Physica Medica
24	(Panambur et al., 2025)	Attention-guided erasing for enhanced transfer learning in breast abnormality classification	2025	International Journal of Computer Assisted Radiology and Surgery
25	(Mansour, Mokhtar, et al., 2025)	Artificial intelligence reading digital mammogram: enhancing detection and differentiation of suspicious microcalcifications	2025	British Journal of Radiology
26	(Van Camp et al., 2025)	An automated toolbox for microcalcification cluster modeling for mammographic imaging	2025	Medical Physics
27	(Idress et al., 2025)	Hybrid segmentation and 3D Imaging: Comprehensive framework for breast cancer patient segmentation and classification based on digital breast tomosynthesis	2025	Biomedical Signal Processing and Control
28	(Vijetha et al., 2025)	A Sisters Similarity Neural Network SSNN Model for Generalization and Detection of Mammographic Breast Cancer Lesion Abnormalities	2025	Journal of Cancer Research Updates
29	(Yang et al., 2025)	Radiomics Integration of Mammography and DCE-MRI for Predicting Molecular Subtypes in Breast Cancer Patients	2025	Breast Cancer: Targets and Therapy
30	(Nour & Boufama, 2025)	Hybrid deep learning and active contour approach for enhanced breast lesion segmentation and classification in mammograms	2025	Intelligence-Based Medicine
31	(la Moglia & Almustafa, 2025)	Breast cancer prediction using machine learning classification algorithms	2025	Intelligence-Based Medicine
32	(F. Wang et al., 2025)	TopoTxR: A topology-guided deep convolutional network for breast parenchyma learning on DCE-MRIs	2025	Medical Image Analysis
33	(Satake et al., 2025)	Predictive Performance of Radiomic Features Extracted from Breast MR Imaging in Postoperative Upgrading of Ductal Carcinoma in Situ to Invasive Carcinoma	2025	Magnetic Resonance in Medical Sciences
34	(Shi et al., 2025)	Development and validation of an intratumoral-peritumoral deep transfer learning fusion model for differentiating BI-RADS 3–4 breast nodules	2025	Gland Surgery
35	(Xu et al., 2025)	Enhancing Specificity in Predicting Axillary Lymph Node Metastasis in Breast Cancer through an Interpretable Machine Learning Model with CEM and Ultrasound Integration	2025	Technology in Cancer Research and Treatment
36	(Puttegowda et al., 2025)	Advanced Machine Learning Techniques for Prognostic Analysis in Breast Cancer	2025	Open Bioinformatics Journal

3.5. Quality of appraisal

Following the guidelines proposed by Kitchenham and Charters (Kitchenham, 2007), after selecting the primary studies, it is necessary to evaluate their research quality and perform a quantitative comparison. In this study, the quality assessment approach by Anas Abouzahra et al. (Abouzahra et al., 2020) was adopted, which includes six quality assessment (QA) criteria for the SLR. Each criterion was rated using a three-point scale: “Yes” (Y) with a score of 1 if the criterion was fully satisfied, “Partly” (P) with a score of 0.5 if it was partially met with minor limitations, and “No” (N) with a score of 0 if it was not met.

- QA1. Is the study’s purpose clearly articulated?
- QA2. Are the significance and practical relevance of the work well presented?
- QA3. Is the methodology clearly described and justified?
- QA4. Are the key concepts and theoretical approach clearly defined?
- QA5. Does the study include comparisons with or evaluations against similar work?
- QA6. Are the limitations and potential weaknesses of the study explicitly acknowledged?

The table presents the quality assessment (QA) process employed to evaluate each study according to predefined criteria. Three experts independently reviewed the studies based on these criteria, assigning one of three possible ratings for each: “Yes” (Y) if the criterion was fully met, “Partly” (P) if it was partially satisfied with some limitations, or “No” (N) if it was not met. A detailed explanation of this assessment process is provided below. Each expert independently evaluates the study based on the established criteria, and their individual scores are then combined to calculate a total score. To advance to the next stage, a study must achieve a cumulative score greater than 3.0. This cutoff ensures that only studies meeting the required quality standards are considered for further analysis.

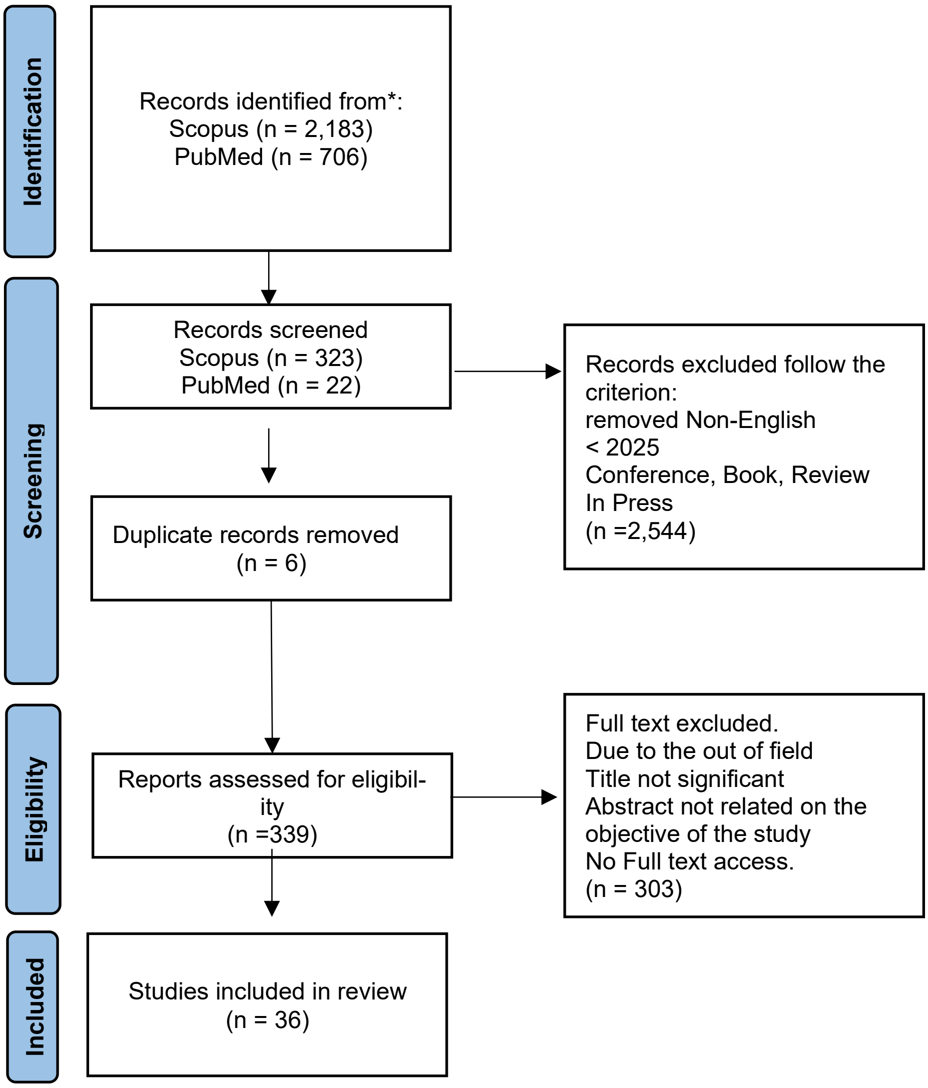

Fig. 2: Flow Diagram of the Proposed Searching Study.

4. Results and Discussion

Based on the quality assessment results presented in Table 4, the overall methodological rigor of the 36 selected primary studies demonstrates a consistently high standard of research quality within the field of Artificial Intelligence (AI) and Radiomics in Contrast-Enhanced Mammography (CEM). The majority of studies scored between 75% and 83%, reflecting strong adherence to essential quality indicators such as research design clarity, data integrity, and analytical robustness. To provide continuity with the broader evolution of the field, the findings of this 2025-focused review should be interpreted in the context of established foundational and late-2024 studies on AI and radiomics in contrast-enhanced mammography (CEM). Earlier landmark investigations laid the methodological groundwork for feature extraction, lesion segmentation, and model validation, particularly demonstrating the feasibility of radiomics-based risk stratification and the added diagnostic value of contrast enhancement. Late-2024 studies further advanced this foundation by introducing multicenter datasets, hybrid deep learning–radiomics pipelines, and early efforts toward explainable AI and standardized reporting frameworks. The studies published in 2025, which form the core of this review, largely build upon these prior contributions by refining model architectures, improving generalizability through ensemble and transformer-based approaches, and expanding prognostic and molecular subtype prediction capabilities. By situating recent evidence within this established trajectory, the review clarifies that current advances represent methodological maturation and optimization rather than isolated innovation, thereby strengthening the coherence and interpretability of the synthesized findings while maintaining the predefined inclusion criteria.

Notably, one study (PS12) achieved the highest rating of 92%, signifying exceptional methodological quality and comprehensive reporting. In contrast, a small number of studies (PS4, PS9, and PS16) attained lower scores, ranging from 58% to 67%, suggesting partial fulfillment of evaluation criteria and potential limitations in study design or data validation processes. The consistent performance across the majority of studies highlights the growing maturity and methodological soundness in AI-driven imaging research, particularly regarding reproducibility, feature extraction, and model performance evaluation.

These findings further indicate that research in AI and radiomics applied to CEM has reached a stable level of methodological reliability, enabling stronger clinical translation and evidence-based integration into diagnostic workflows. However, the lower-performing studies underline the continued need for standardized validation frameworks, larger datasets, and transparent reporting practices to strengthen credibility and generalizability. The predominance of high-quality studies enhances confidence in the synthesized evidence derived from this structured review, ensuring that the conclusions drawn are both reliable and representative of the field's current state. Overall, the quality assessment underscores that the selected studies collectively provide a robust foundation for understanding the diagnostic and predictive applications of AI and radiomics in enhancing breast cancer detection through contrast-enhanced mammography.

Table 4: Quality Assessment Results of Selected Primary Studies

PS	QA1	QA2	QA3	QA4	QA5	QA6	Total Mark	%
PS1	Y	Y	P	Y	Y	N	4.5	75%
PS2	Y	Y	Y	Y	Y	N	5.0	83%
PS3	Y	Y	Y	P	Y	N	4.5	75%
PS4	Y	Y	P	P	P	N	3.5	58%
PS5	Y	Y	Y	P	Y	N	4.5	75%
PS6	Y	Y	Y	P	Y	N	4.5	75%
PS7	Y	Y	Y	P	Y	N	4.5	75%
PS8	Y	Y	Y	Y	Y	N	5.0	83%
PS9	Y	Y	P	P	P	N	3.5	58%
PS10	Y	Y	Y	P	Y	N	4.5	75%
PS11	Y	Y	Y	Y	Y	N	5.0	83%
PS12	Y	Y	Y	Y	Y	P	5.5	92%
PS13	Y	Y	Y	Y	Y	N	5.0	83%
PS14	Y	Y	Y	Y	P	N	4.5	75%
PS15	Y	Y	Y	Y	Y	N	5.0	83%
PS16	Y	Y	P	P	P	Y	4.0	67%
PS17	Y	Y	Y	Y	Y	N	5.0	83%
PS18	Y	Y	Y	Y	Y	N	5.0	83%
PS19	Y	Y	Y	Y	Y	N	5.0	83%
PS20	Y	Y	Y	Y	Y	N	5.0	83%
PS21	Y	Y	Y	Y	Y	N	5.0	83%
PS22	Y	Y	Y	Y	Y	N	5.0	83%
PS23	Y	Y	Y	Y	Y	N	5.0	83%
PS24	Y	Y	Y	Y	Y	N	5.0	83%
PS25	Y	Y	Y	Y	Y	N	5.0	83%
PS26	Y	Y	Y	Y	Y	N	5.0	83%
PS27	Y	Y	Y	Y	Y	N	5.0	83%
PS28	Y	Y	Y	Y	Y	N	5.0	83%
PS29	Y	Y	Y	Y	Y	N	5.0	83%
PS30	Y	Y	Y	Y	Y	N	5.0	83%
PS31	Y	Y	Y	Y	Y	N	5.0	83%
PS32	Y	Y	Y	Y	Y	N	5.0	83%
PS33	Y	Y	Y	Y	Y	N	5.0	83%
PS34	Y	Y	Y	Y	Y	N	5.0	83%
PS35	Y	Y	Y	Y	Y	N	5.0	83%
PS36	Y	Y	Y	Y	Y	N	5.0	83%

4.1. AI architectures & classification/detection models

Recent advances in artificial intelligence (AI) and deep learning (DL) have transformed mammographic image analysis, enabling enhanced diagnostic accuracy through novel classification and feature extraction frameworks. Among these developments, ensemble architectures and hybrid models have emerged as leading strategies for improving model generalization and clinical interpretability. Ergün, Çoban, and Kayadibi (2025) introduced the Breast Cancer Ensemble Convolutional Neural Network (BCECNN), integrating multiple convolutional neural network (CNN) architectures such as AlexNet, VGG16, and EfficientNetB0 using a voting mechanism. This model achieved a high diagnostic accuracy of 98.75%, demonstrating the robustness of ensemble learning, even with limited datasets. The inclusion of explainable artificial intelligence (XAI) methods, including Grad-CAM and LIME, further improved transparency and interpretability in clinical validation. Similarly, Varshney, Verma, Kaur, and Puri (2025) proposed a hybrid system combining radiomic and DL-derived features, where Recursive Feature Elimination improved feature selection efficiency. Their ensemble classifier reached 98.43% accuracy and 0.99 ROC-AUC, showing superior diagnostic precision. The integration of ensemble and hybrid learning principles across these studies suggests that combining multiple architectures can mitigate data scarcity challenges while offering better interpretability and model reliability for breast cancer diagnosis.

Deep learning-based hybrid frameworks have also been shown to address the limitations of traditional single-modality diagnostic models. Pacal and Attallah (2025) developed the InceptionNeXt-Transformer, a multi-scale architecture combining CNNs and Vision Transformers for multimodal breast cancer analysis. This model achieved accuracy rates approaching 100% across datasets including histopathology, mammography, and ultrasound, demonstrating strong generalization capability and computational efficiency. Similarly, Chen and Martel (2025) designed a hybrid Swin Transformer–CNN model, termed HybMNet, which incorporated self-supervised learning (SSL) to overcome the scarcity of labeled mammographic data. Their model improved classification on the INbreast and CMMD datasets, achieving AUCs of 0.889 and 0.864, respectively. The use of SSL pretraining enabled effective feature extraction despite limited supervision, improving lesion detection in mammograms. These studies collectively highlight the potential of transformer-based hybrid architectures to combine local and global context features efficiently, offering reliable and scalable solutions for diverse imaging modalities.

Attention mechanisms and local context modules have also been effectively integrated to enhance feature discrimination in complex mammographic data. Abdelhalim et al. (2025) designed a deep learning model employing a Local Context Attention Module (LCAM) to classify mammographic masses based on BI-RADS categories. Their model achieved 82.46% sensitivity and 91.42% specificity across 3,020 patients, demonstrating improved accuracy through spatial-channel attention refinement. Likewise, Krishna, Stancilas, Srinivasan, and Vijayakumar (2025) utilized an Attention Branch Network (ABN) to interpret thermographic images for breast abnormality detection, achieving an impressive 98.15% accuracy. The integration of attention modules in both studies enabled models to focus on salient regions, improving lesion localization and interpretability. Panambur et al. (2025) extended this concept through attention-guided erasing (AGE), a novel data augmentation approach enhancing feature generalization during transfer learning. The model demonstrated notable F1-score improvements, particularly in breast density and malignancy classification tasks, underscoring how attention-driven mechanisms can refine transfer learning outcomes across datasets. Collectively, attention-based networks represent a pivotal trend in modern AI-driven mammographic systems by amplifying diagnostic precision while maintaining model explainability.

Hybrid and ensemble deep learning architectures have further evolved through multi-task and topology-guided approaches to capture complex mammographic patterns. Li et al. (2025) proposed an explainable BI-RADS-assisted diagnostic pipeline incorporating multi-scale feature fusion and spatial attention (MFFSA), achieving AUCs above 91% across multiple datasets. The combination of BI-RADS-based classification with explainability modules connected radiological indicators to deep features, advancing the interpretability of automated assessments. In another approach, Niranjana, Ravi, and Sivadasan (2025) developed IEU Net++, a hybrid deep learning model combining InceptionResNetV2 and EfficientNetB7 architectures for multiclass classification of mammographic images. Their framework achieved up to 99.87% accuracy and 0.972 Dice scores across INBreast and MIAS datasets, showing outstanding performance in differentiating between benign and malignant lesions. These findings emphasize the growing trend of multi-scale, hybrid networks that integrate both local and high-level spatial representations for superior accuracy and generalization in breast cancer detection.

Further enhancements in model adaptability and robustness have been achieved through similarity learning and AI-assisted 2D mammography approaches. Vijetha, Jude, and KanthiThilaka (2025) proposed the Sisters Similarity Neural Network (SSNN), which utilized patch-based preprocessing and discriminative similarity learning to handle data variability and noise in mammograms. This model achieved 92.3% accuracy and an AUC of 0.936, highlighting improved lesion detection consistency even under data heterogeneity. Complementing this work, Ciurescu et al. (2025) applied AI-driven CNN models for 2D mammography screening, reaching 88.5% accuracy and an AUC of 0.93. The system notably improved lesion classification accuracy while reducing false positives, though optimization was still needed to minimize false negatives. Both studies reveal the significance of designing adaptable frameworks that address real-world image quality variations and radiological inconsistencies to enhance screening reliability in clinical applications.

Lastly, traditional machine learning methods continue to complement deep learning innovations by providing interpretable and computationally efficient alternatives for preliminary diagnosis. La Moglia and Almustafa (2025) compared eight classical classifiers and found Logistic Regression achieved the highest testing accuracy of 91.67%, with notable improvement after feature selection using the LGBM model. These results reaffirm that, while deep learning dominates current research, optimized classical algorithms still play a meaningful role in low-resource or early-screening environments. Combined with advanced CNN and transformer-based architectures, these approaches collectively form a spectrum of AI methodologies that progressively strengthen diagnostic decision-making in mammography.

In summary, the reviewed studies converge on several key advancements in breast cancer detection using AI-based architectures: ensemble learning for accuracy improvement (Ergün et al., 2025; Varshney et al., 2025), hybrid transformer-CNN models for multimodal generalization (Pacal & Attallah, 2025; Chen & Martel, 2025), attention mechanisms for interpretability (Abdelhalim et al., 2025; Krishna et al., 2025; Panambur et al., 2025), and multi-scale or similarity-based frameworks for robustness (Li et al., 2025; Vijetha et al., 2025). Collectively, these studies illustrate that future diagnostic models in mammography will increasingly depend on multi-level integration of radiomic, attention-guided, and self-supervised learning strategies to achieve precision, transparency, and adaptability across diverse clinical contexts.

4.2. Radiomics & multi-modality predictive / prognostic models

The integration of artificial intelligence (AI) and radiomics in breast imaging has led to a paradigm shift in predictive and prognostic modeling, particularly in contrast-enhanced mammography (CEM). A growing body of research demonstrates the capacity of radiomics-based approaches to extract quantifiable imaging biomarkers that enhance diagnostic precision, risk stratification, and outcome prediction. Radiomics models, as evidenced by studies such as those by Wang et al. (2025), Lafcı et al. (2025), and Zhang et al. (2025), have shown significant improvements in identifying subtle imaging patterns associated with malignancy, outperforming conventional diagnostic methods. These approaches bridge the gap between image interpretation and individualized patient management by capturing minute heterogeneities invisible to the human eye. Notably, Wang et al. (2025) introduced a Multi-Time Point Breast Cancer Risk Model (MTP-BCR) that integrates longitudinal mammographic data to predict breast cancer risk over a ten-year period with an AUC of 0.80, underscoring the power of temporal imaging data. Similarly, Lafcı et al. (2025) demonstrated that radiomics features extracted from craniocaudal and mediolateral oblique projections could improve the differentiation between benign and malignant lesions, achieving AUC values comparable to experienced radiologists. Complementing these findings, Zhang et al. (2025) confirmed that deep learning integration with full-breast mammograms enhances the predictive capability for lymph node metastasis, providing a foundation for improved surgical decision-making.

Advancements in multi-modality imaging and AI-based integration have significantly improved diagnostic modeling for breast cancer. Wu et al. (2025) and Wang Q. et al. (2025) developed multi-modality radiomics frameworks combining MRI, ultrasound, and mammography, achieving superior diagnostic accuracy compared to single-modality models. Wu et al. (2025) demonstrated that a logistic regression model integrating peritumoral features across modalities reached an AUC of 0.905, emphasizing the benefit of including spatial information beyond the lesion boundary. Likewise, Wang Q. et al. (2025) established a Dual-Modality Virtual Biopsy System (DM-VBS) integrating MRI and mammography radiomics for HER2 prediction, attaining over 85% classification accuracy in validation cohorts. The inclusion of both radiomic and deep learning-derived features enhanced the system's ability to distinguish HER2-positive from HER2-negative cases, suggesting that noninvasive imaging biomarkers could serve as surrogates for molecular profiling. The consistent diagnostic gains across modalities illustrate how multi-source image integration, coupled with radiomics, may provide a more comprehensive view of tumor biology and improve personalized care pathways.

Machine learning models built on radiomic features have further contributed to refining diagnostic workflows and enhancing clinical decision-making. Studies such as Ma et al. (2025), Ismail et al. (2025), and Liu et al. (2025) explored distinct algorithmic approaches for breast cancer subtype classification, lesion differentiation, and biopsy outcome prediction. Ma et al. (2025) constructed an interpretable machine learning model based on CEM features for molecular subtype prediction, achieving an AUC of 0.798 for luminal versus non-luminal subtypes. Their use of the SHAP algorithm provided transparency in feature importance, a critical step toward clinical acceptability. In another approach, Ismail et al. (2025) applied an Auto-Sklearn ensemble framework that automated model selection and tuning for radiomic classification tasks, demonstrating improved accuracy and efficiency compared to manual model optimization. Meanwhile, Liu et al. (2025) combined radiomics and radiologist-assessed clinical descriptors in a logistic regression model that predicted breast biopsy outcomes for BI-RADS 4A–5 lesions, achieving an AUC of 0.90. These studies collectively highlight how machine learning can transform traditional diagnostic interpretation into quantitative, reproducible assessments, thereby reducing inter-observer variability and enhancing diagnostic confidence.

Beyond diagnosis, recent investigations have expanded the application of radiomics in CEM toward prognostic modeling and survival prediction. Nicosia et al. (2025) presented a radiomics-based prognostic model derived from CEM that successfully predicted disease-free and overall survival in breast cancer patients. By employing a Cox-LASSO regression model, they established a significant correlation between radiomic scores and long-term survival outcomes, with C-index values reaching 0.84 when combined with clinical data. This advancement underscores the potential of CEM-derived radiomics as a noninvasive prognostic marker. Similarly, Wang X. et al. (2025) and Zhang et al. (2025) reinforced the value of integrating longitudinal and morphological features for risk stratification and metastasis prediction, respectively. Such prognostic models not only assist in early disease detection but also enable risk-adaptive follow-up and therapy planning, marking a shift toward more individualized breast cancer management strategies.

Emerging technologies have also focused on enhancing radiomics capabilities through integration with advanced computational frameworks. Ra et al. (2025) proposed an innovative method that leveraged large language models (LLMs) to augment radiomic feature representation. By embedding LLM-learned clinical knowledge into radiomic feature analysis, their approach achieved superior accuracy compared to conventional models, particularly in cross-dataset generalization. Similarly, Pacal and Attallah (2025) introduced the Inception-NeXt-Transformer architecture, merging convolutional networks with vision transformers for multimodal image analysis. This model achieved nearly perfect accuracy across several breast imaging datasets, demonstrating strong generalization and computational efficiency. The integration of transformer-based architectures and LLMs represents a promising evolution in radiomics, allowing models to synthesize multimodal and contextual information more effectively than traditional convolutional frameworks.

Overall, the convergence of radiomics, deep learning, and multi-modality imaging in CEM has yielded significant advancements in diagnostic accuracy, prognostic prediction, and clinical decision support. The collective findings from studies by Wu et al. (2025), Ma et al. (2025), Liu et al. (2025), Nicosia et al. (2025), and Wang Q. et al. (2025) emphasize the emerging role of radiomics-based predictive models in enabling precision breast cancer care. These developments highlight the necessity of larger, multicentric validation studies and standardized radiomic pipelines to ensure reproducibility and clinical integration. Furthermore, the growing incorporation of interpretable AI models enhances the transparency and trustworthiness of CEM-based radiomics systems, paving the way toward broader adoption in routine breast cancer diagnosis and prognosis.

4.3. Segmentation, microcalcification & data-tooling for detection

Recent investigations emphasize data augmentation, automated segmentation, and specialized tooling as central to improving lesion detection in contrast-enhanced mammography (CEM) and related mammographic modalities. Camp et al. (2025) examined the role of synthetic microcalcification insertion and showed that synthetic examples can increase detection sensitivity for malignant lesions when combined with limited real data, although gains in precision were not uniform. Panambur et al. (2025) demonstrated that attention-guided erasing (AGE) derived from self-supervised attention maps provides modest but consistent F1-score improvements across several classification tasks, including patch-level calcification detection. Mansour et al. (2024) reported that AI overlays on prior negative mammograms flagged substantial proportions of missed carcinomas, with particularly strong performance on distortion and grouped microcalcifications; this result supports the hypothesis that automated preprocessing and visualization can uncover subtle early markers otherwise overlooked in routine screening.

Augmentation strategies and synthetic augmentation interact with model design choices and validation schemes in nontrivial ways. Camp et al. (2025) observed a performance plateau in detection sensitivity when synthetic data dominated training, and found that ensembles combining DL and handcrafted radiomics sometimes reduced generalization on external sets due to spurious region proposals. Panambur et al. (2025) stressed that attention-based erasing improved downstream transfer learning most for tasks where background noise obscures salient patches, while yielding negligible benefit when erased regions masked critical mass features. Mansour et al. (2025, British Journal of Radiology) additionally revealed that AI assistance increased sensitivity for grouped microcalcifications but required human expert specification to achieve acceptable positive predictive value. Together, these findings indicate that augmentation must be task-aware and validated across internal and external cohorts to avoid overfitting to synthetic artefacts.

Automated segmentation of anatomical landmarks and conversion to three-dimensional representations show promise for downstream detection and quality assurance. Sierra-Franco et al. (2025) developed a large annotated dataset for nipple, pectoral muscle, fibroglandular and fatty tissue segmentation and compared multiple semantic segmentation architectures, reporting robust performance and several clinical applications such as automated multi-view registration and breast density estimation. Idress et al. (2024) proposed a hybrid pipeline using advanced preprocessing, DENSE SE-Net segmentation, and conversion to digital breast tomosynthesis (DBT) 3D images followed by YOLOv7 detection and semi-supervised CNN classification; simulation results indicated improvements in accuracy and ROC metrics relative to prior methods. The combination of reliable anatomical segmentation (Sierra-Franco et al.) and DBT-based 3D reconstruction (Idress et al.) suggests a practical route to reduce false positives and improve lesion localization in dense breasts.

Specialized toolboxes and similarity-guided learning address the microcalcification modelling and generalization challenges. Mansour et al. (2025, British Journal of Radiology) produced an automated toolbox for microcalcification cluster modelling, showing high correlation between AI heatmap scores and histopathologically confirmed malignant calcifications; sensitivity for grouped calcifications was reported near 94.7%. Camp et al. (2025) corroborated the utility of simulated calcification data to fill gaps where real annotated examples are scarce, but emphasized careful calibration of simulated appearance and texture. Panambur et al. (2025) further observed that self-supervised attention maps can be repurposed for targeted erasing or augmentation to improve the model's robustness to imaging variations. These studies together indicate that targeted tool development — combining synthetic data, explicit cluster modelling, and attention-based augmentation — can enhance detection and characterization of microcalcifications when validated on varied cohorts.

Operational considerations and remaining limitations require careful attention before clinical deployment. Camp et al. (2025) showed that blending synthetic and real data demands distributional alignment to avoid precision loss, and that ensemble stacking without careful error analysis may degrade external performance. Sierra-Franco et al. (2025) noted that segmentation models require large, diverse annotated sets to maintain robustness across acquisition devices and patient morphologies. Mansour et al. (2024, European Journal of Radiology Open) highlighted that AI flagging increases detection but may not predict specific pathology types; thus, AI should be used to augment triage rather than replace confirmatory imaging or biopsy. Idress et al. (2024) reported promising simulation metrics for DBT-based 3D systems, but translation into clinical practice needs prospective validation and assessment of workflow impact. Collectively, the literature recommends task-specific augmentation, multimodal segmentation pipelines, and rigorous external validation as prerequisites for trustworthy CEM-based detection systems.

Despite promising diagnostic and prognostic performance, several factors must be addressed before AI- and radiomics-enhanced contrast-enhanced mammography (CEM) can be routinely adopted in clinical practice. From a regulatory perspective, most existing models remain at an investigational stage and require rigorous external and prospective validation to meet approval standards set by regulatory authorities. Transparent reporting, explainable AI mechanisms, and compliance with emerging medical AI governance frameworks are essential to support regulatory readiness. In terms of clinical workflow integration, successful implementation depends on seamless interoperability with picture archiving and communication systems (PACS), minimal disruption to radiologists' reading time, and clear human–AI interaction pathways that support, rather than replace, clinical judgment. Cost-effectiveness is another critical consideration, as AI deployment involves expenses related to software acquisition, infrastructure, data management, and ongoing model maintenance, which must be justified by measurable improvements in diagnostic efficiency or patient outcomes. Furthermore, real-world implementation is challenged by data heterogeneity, institutional variability, and clinician trust, underscoring the need for multicenter trials, standardized pipelines, and user-centered design to facilitate safe and sustainable clinical adoption.

Overall, the field shows a convergent trend: augmentation (synthetic or attention-guided), robust anatomical segmentation, and specialized microcalcification toolboxes jointly improve sensitivity and localization, while generalizability and precision hinge on suitable validation strategies and human-in-the-loop interpretation. Future work should prioritize multicenter external testing, standardization of synthetic data generation, and integrated pipelines that combine segmentation, detection, and explainable outputs to support clinical decision pathways.

5. Conclusion

This systematic literature review aimed to evaluate the recent developments in the application of artificial intelligence (AI) and radiomics in contrast-enhanced mammography (CEM), focusing on their diagnostic, predictive, and prognostic capabilities for breast cancer detection and characterization. The review synthesized evidence from studies published within the 2025 timeframe, selected from Scopus and PubMed databases using strict inclusion criteria that prioritized peer-reviewed, English-language, and final-stage journal articles. This review is subject to several limitations that should be acknowledged. First, the literature search was restricted to the Scopus and PubMed databases, which, while comprehensive and widely recognized, may not capture all relevant engineering- and computer science–focused studies in artificial intelligence. Although Scopus provides partial coverage of technical and AI-related journals, some specialized contributions indexed in databases such as IEEE Xplore may have been missed. This database selection may therefore have led to the exclusion of certain methodological innovations originating from the engineering and informatics communities. Future systematic reviews are encouraged to incorporate additional databases, including IEEE Xplore and similar technical repositories, to ensure broader coverage and a more exhaustive synthesis of AI-driven breast imaging research.

The analysis was structured according to the PRISMA approach and guided by research questions framed under the PICo model, which explored how advanced AI architectures, multi-modality radiomics, and microcalcification detection frameworks enhance diagnostic precision and clinical interpretability in CEM. The overarching purpose was to consolidate fragmented findings across domains of AI-driven imaging, identify methodological strengths and weaknesses, and highlight the potential for integrated computational models to improve breast cancer management.

The review identified three dominant research themes: AI architectures and classification models, radiomics-based multi-modality predictive frameworks, and segmentation or data-tooling for microcalcification detection. Across these domains, consistent evidence demonstrated that ensemble and hybrid deep learning models combining convolutional neural networks (CNNs), transformers, and attention mechanisms achieved superior performance in differentiating benign and malignant lesions, as well as predicting molecular subtypes. Radiomics analyses showed strong potential in prognostic modeling, risk prediction, and feature-based survival estimation, especially when combined with clinical and imaging data from modalities such as MRI and ultrasound. Additionally, studies integrating synthetic data generation, attention-guided augmentation, and automated segmentation techniques improved model robustness and lesion localization accuracy. The findings collectively reveal that the fusion of AI and radiomics with CEM enhances both diagnostic accuracy and interpretability, bridging the gap between imaging data and personalized decision-making. Despite methodological variations, most included studies achieved high-quality assessment scores, indicating methodological maturity and increasing readiness for clinical translation.

The synthesis contributes to the field by offering a comprehensive framework that integrates AI architectures, radiomics modeling, and segmentation strategies into a unified perspective on intelligent breast imaging. This review highlights how the convergence of these approaches can reduce diagnostic variability, optimize detection workflows, and support precision medicine initiatives. In practical terms, the results underscore the potential of AI-enhanced CEM to assist radiologists in early cancer detection, improve risk stratification, and reduce unnecessary biopsies through more accurate lesion characterization. However, several limitations were noted, including a narrow publication timeframe, the use of only two databases, and language restrictions, which may have excluded relevant research. Furthermore, most included studies relied on retrospective datasets with limited population diversity, suggesting the need for large-scale, multicenter validation to ensure generalizability. Future investigations should focus on standardizing image acquisition protocols, developing explainable AI frameworks, and assessing real-world clinical integration to ensure safe and effective deployment. Overall, this review reinforces the importance of evidence-based synthesis for advancing the field of AI-driven radiology. Systematic reviews such as this not only clarify the evolving research landscape but also provide critical direction for future innovation, ensuring that emerging technologies in CEM continue to align with clinical accuracy, ethical transparency, and patient-centered care.

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Conflicts of Interest

The authors declare that there are no conflicts of interest related to this study.

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