

Review

Advances in Medical Image Processing for Early Breast Cancer Detection: Classical Techniques and Deep Learning Perspectives

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Abstract

Breast cancer is the most common malignancy among women and a leading cause of cancer-related mortality, making early and accurate detection essential. This review summarises advances in breast imaging and computational diagnostics across mammography, ultrasound, and magnetic resonance imaging (MRI), highlighting challenges in differentiating benign from malignant lesions and identifying rarer tumour types. Key preprocessing steps—denoising, deblurring, and contrast enhancement—are reviewed as they improve image quality prior to analysis. Classical methods (e.g., thresholding, edge detection, and region growing) are compared with deep learning approaches for segmentation and classification. CNNs, RNNs, and emerging transformer-based models consistently outperform handcrafted pipelines, with representative studies reporting 5–15% gains in AUC/accuracy and deep models achieving AUC > 0.85–0.95 on several benchmarks. The review also discusses dataset constraints, common evaluation metrics (AUC, Dice, sensitivity, specificity), and clinical translation barriers such as interpretability and domain shift. Overall, AI-driven methods show strong potential to enhance early detection and support improved breast cancer outcomes.

Keywords: breast cancer detection; medical imaging; MRI; ultrasound; mammography; image processing; deep learning; convolutional neural networks; recurrent neural networks; tumour segmentation



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1. Introduction

Breast cancer continues to be a major global health challenge for women, accounting for approximately 2.3 million new cases and 666,103 deaths annually worldwide [1]. Despite significant advances in screening and treatment, early and accurate detection remains critical to improving survival rates and reducing mortality. Medical imaging plays a central role in this process, with modalities such as magnetic resonance imaging (MRI), ultrasound, and mammography serving as indispensable tools for tumour detection and characterisation [2]. Each modality, however, presents distinct advantages and limitations that affect diagnostic accuracy and clinical applicability.

Mammography remains the most widely used screening tool, offering high sensitivity for micro-calcifications and architectural distortions, but suffers from reduced effectiveness in women with dense breast tissue [3]. Ultrasound provides real-time lesion assessment and improved performance in dense breasts, yet its operator dependency and higher false-positive rates limit reliability [4]. Dynamic contrast-enhanced MRI (DCE-MRI) achieves

sensitivity levels approaching 90–95%, but its high cost, long acquisition time, and susceptibility to false positives often lead to unnecessary biopsies [5]. These challenges highlight the need for advanced computational approaches to augment human interpretation, enhance diagnostic precision, and reduce inter-observer variability.

Traditional computer-aided detection (CAD) systems relied on classical image processing methods such as thresholding, region growing, and active contour models for tumour segmentation [6]. While these approaches demonstrated value, their dependence on hand-crafted features and vulnerability to noise and artefacts limited their scalability in complex clinical settings. Recent breakthroughs in artificial intelligence (AI), particularly deep learning (DL), have revolutionised breast imaging by enabling automated feature extraction and significantly improving diagnostic accuracy [7]. Convolutional neural networks (CNNs) have achieved notable success in segmentation and classification tasks, with architectures such as U-Net [8] and ResNet [9] achieving area under the curve (AUC) values exceeding 0.95 in distinguishing benign from malignant lesions [10]. Recurrent neural networks (RNNs) and hybrid CNN–RNN models have further improved diagnostic performance by capturing temporal patterns in DCE-MRI and sequential ultrasound imaging [11].

Despite these advances, several challenges remain. Many studies are constrained by limited dataset size and diversity, which restricts generalisability across patient populations and imaging platforms [12]. Moreover, the “black-box” nature of deep learning models raises concerns regarding transparency, interpretability, and clinical adoption [13]. Addressing these challenges requires the development of explainable and robust AI frameworks, integration of multimodal imaging data, and careful consideration of ethical and regulatory factors.

This review is structured as follows: Section 2 presents breast tumour characteristics across imaging modalities. Section 3 discusses image preprocessing techniques for quality enhancement. Section 4 reviews classical image processing methods, while Section 5 examines deep learning approaches. Section 6 discussed challenges, opportunities, and future directions in breast cancer detection. By critically evaluating existing literature, this paper highlights the transformative potential of AI in breast imaging while identifying key areas for future research. To better clarify the structure, Figure 1 presents the flow of this review.

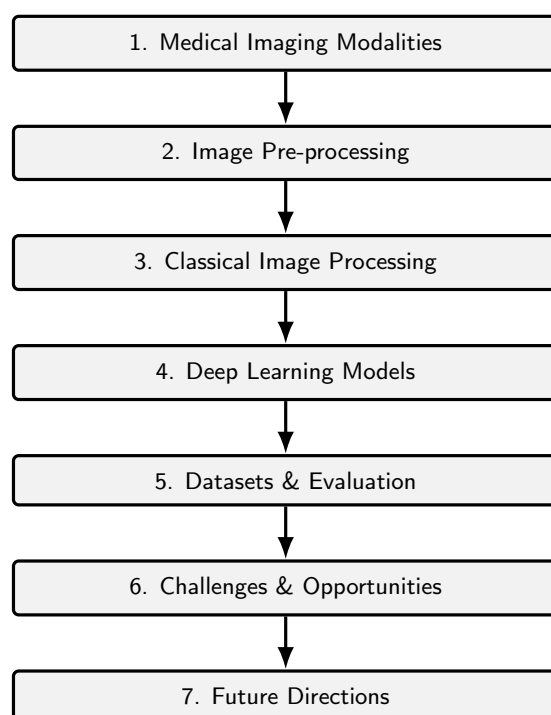


Figure 1. Paper structure.

2. Breast Tumour Characteristics in Medical Images

Classical pathology divides breast tumours into several categories based on their overall morphology and architectural organisation. Invasive ductal carcinoma, not otherwise specified, (IDC NOS) is the most common type observed and reported, which consists of about 75% of cases; then invasive lobular carcinoma (ILC) represents about 10% of cases, the next most frequent histologic type of breast cancer. Together, the two categories make up the majority of breast cancer [14]. Whilst most tumours in breast cancer are oestrogen receptor (ER) positive (86%), well or moderately differentiated (73%), small ≤ 20 mm (74%) and stage I/II (91%) [15]. However, rare breast cancer is associated with a higher risk of mortality due to its tumour being characterised by poor clinical and pathologic characteristics, especially regarding inflammatory carcinomas [16]. Thus, despite the fact that the typical image features of IDC-NOS and ILC are well known, the appearance of unusual tumours is not well-established. Unusual breast tumours are the subtypes of IDC, including mucinous, tubular, medullary, and papillary carcinomas, which account for 10% of invasive breast tumours. Other very rare malignant breast lesions include lymphoid and hematopoietic malignancies, mesenchymal stromal tumours (such as malignant phyllodes tumours and sarcomas), and metastatic tumours.

2.1. MRI

Breast magnetic resonance imaging (MRI) is a highly sensitive imaging modality that provides excellent soft-tissue contrast and enables detailed evaluation of breast morphology and enhancement patterns. Unlike mammography and ultrasound, MRI can capture dynamic vascular information through contrast-enhanced sequences, making it particularly valuable for detecting small lesions, assessing tumour extent, and identifying multifocal or multicentric disease. It is widely used in high-risk screening, pre-operative staging, and treatment response monitoring, especially in women with dense breast tissue. However, most of these tumours lack morphologic and/or dynamic signs that typically predict malignancy; therefore, it causes the difficulty of differential diagnosis from benign breast masses [17]. In addition, characteristically benign kinetics can be present in malignant lesions. As invasive breast cancers approach 1 cm, the features on MRI become increasingly typical of malignancy, but those ≤ 5 mm cancers are difficult to distinguish from more common benign lesions, which have similar features. As a result, this makes the diagnosis more difficult [18]. The typical breast MRI appearance of invasive ductal carcinoma can be a focal mass with an irregular shape, plateau curve (type III) or washout curve (type IV) with strong enhancement in the early phase. A tumour with well-defined margins and a rounded shape with smooth borders is less often seen in breast mammography, but they may make up to one-third of IDC cases, supported by the research data. In the MRI image case of ductal carcinoma in situ (DCIS), a non-invasive early stage breast cancer type, demonstrates a non-mass enhancement, which usually appears as areas of an increased signal without a clear border or mass-like shape [19]. Different to the IDC NOS, medullary invasive cancers usually demonstrated a roundish configuration with pushing margins and no evidence of infiltrating disease in both imaging studies and gross pathology [20,21]. Lobular invasive breast cancer, due to its growth pattern, on MRI, the majority of cancers are present as very irregular masses, and in 20% of cases, instead of an actual mass, diffuse infiltration of the parenchyma manifests itself as diffuse asymmetric enhancement [22]. Figure 2 is an MRI image for the preoperative work-up for breast cancer in the upper right quadrant. As shown in the pre- and post-treatment MRI (Figure 3), the patient's invasive lobular carcinoma lesion significantly shrank following neoadjuvant chemotherapy, though areas of irregular enhancement persisted. For those other unusual tumours, Table 1 summarises their characteristics in the MRI images.

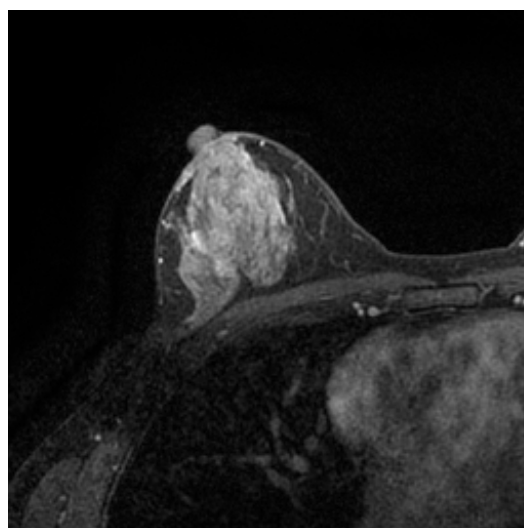


Figure 2. Invasive ductal carcinoma, 2 cm in diameter, with a small satellite nodule at the inferior tumor margin, in a 45-year-old woman [23].

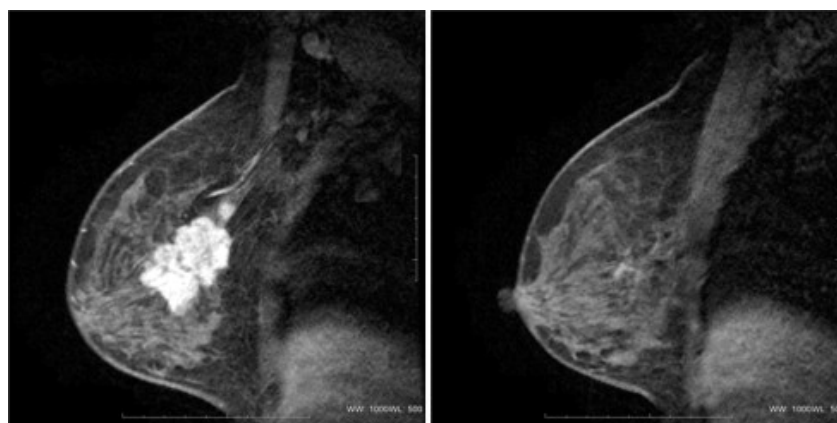


Figure 3. A 53-year-old female patient with invasive lobular carcinoma, MRI before (left) and after treatment (right). The MRI showed that the lesion had significantly shrunk after treatment, and there were still irregular enhancement areas after neoadjuvant chemotherapy [24].

Table 1. MRI features of unusual breast tumours.

	Mucinous	Medullary	Tubular	Papillary Intraductal
Shape	Lobulated, oval, round	Lobulated, oval, round	Spiculated	Non-mass-like enhancement with a segmental distribution
Margins	Smooth	Smooth	III-defined	
Kinetic curve	Type I	Type II or III	Type I	Type I
	Inflammatory	Papillary Intracystic	Papillary Invasive	
Shape	Irregular	Round, oval	Round, oval	
Margins	Irregular, spiculated	Smooth	Smooth	
Kinetic curve	Type III or II	Type III	Type III	

2.2. Ultrasound

For ultrasound images, research finds that invasive cancers are more common in breast cancers with irregular shapes, non-parallel orientations and hypoechoic or complex echo patterns, which are the typical malignant features of solid breast masses, than in cases of ductal carcinoma in situ (DCIS) cases [25]. A previous study described that high-grade invasive cancers were more likely to demonstrate posterior acoustic enhancement and

a well-defined margin on ultrasound [26]. The majority of ultrasound-detected breast cancers occur in women with dense breast tissue (BI-RADS grade 3 or 4). Compared to mammography-detected cancers, ultrasound-detected cancers were more frequently categorised as BI-RADS category 4 and less likely to be classified as category 5. The tumours are generally smaller, with a mean size of 1.32 cm, and 41.5% of them are ≤ 1 cm in size; they are more likely to be invasive, node-negative, and well or moderately differentiated [27]. As shown in Figure 4, an IDC tumour typically presents as a hypoechoic mass with an indistinct margin and irregular border. The nodule appears markedly hypoechoic, has a taller-than-wide shape, and casts a strong acoustic shadow. Furthermore, studies indicate that margin characteristics correlate with tumour grade. Tumours with spiculated or angular margins are commonly low-grade (Grade I or II), while those with well-defined or lobulated margins are typically high-grade (Grade III). The data shows that posterior shadowing is highly indicative of ER-positive tumours (97% likelihood) and is more frequently observed in low-grade tumours (92%), suggesting a less aggressive nature with a better prognosis. In contrast, posterior enhancement is strongly linked to ER-negative, PR-negative (triple-negative) tumours, commonly found in high-grade (Grade III) cases (76.4%), indicating a more aggressive tumour with a poorer prognosis [28]. Figure 5 is an estrogen receptor-positive/progesterone receptor-positive breast cancer case found in a 41-year-old woman. Ultrasound is a valuable tool for distinguishing malignant lesions, which are typically hypoechoic with poorly defined margins. Table 2 summarises the key ultrasound characteristics of malignant breast tissues [29]. Rare cancer types like triple-negatives have different tumour characteristics in ultrasound images. Figure 6 illustrates the triple negative breast tumours with regular shape and circumscribed margins: (A) invasive ductal carcinoma in a 35-year-old female patient (BI-RADS: 4A, grade III, Ki67 30%); (B) invasive ductal carcinoma in a 55-year-old female patient (BI-RADS: 4A, grade III, Ki67 30%); (C) invasive ductal carcinoma in a 33-year-old female patient (BI-RADS: 4A, grade III, Ki67 80%); (D) invasive ductal carcinoma in a 48-year-old female patient (BI-RADS: 5, grade III, Ki67 80%).

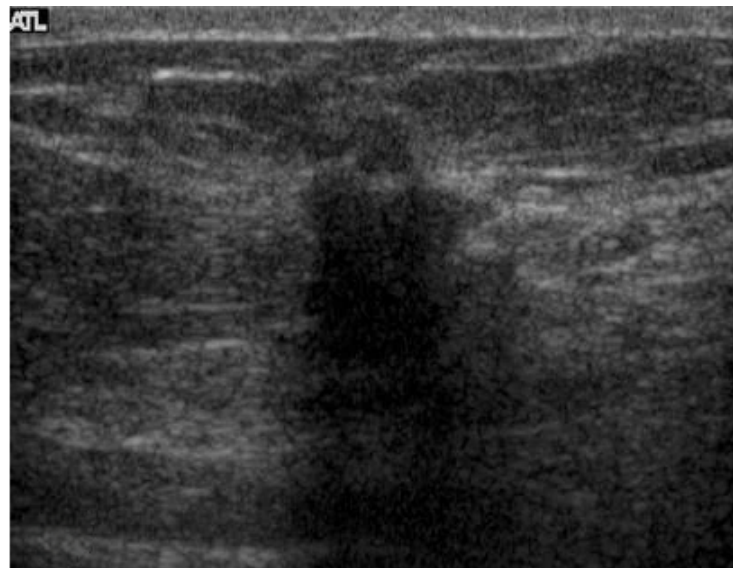


Figure 4. The infiltrating ductal carcinoma on the left has an indistinct margin with an irregular border. The nodule is markedly hypoechoic, taller than wide, and casts a strong shadow [30].

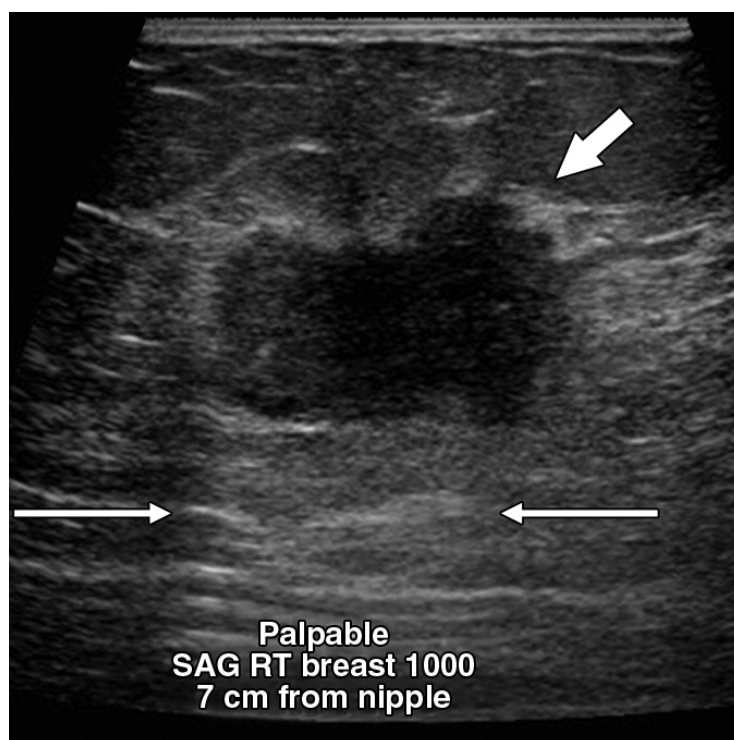


Figure 5. In the left breast of a 41-year-old woman with estrogen receptor-positive/progesterone receptor-positive breast cancer, the ultrasound image shows a slightly hypoechoic mass (callipers) with relatively circumscribed margins. The predominant feature posterior to the mass is no acoustic change [28].

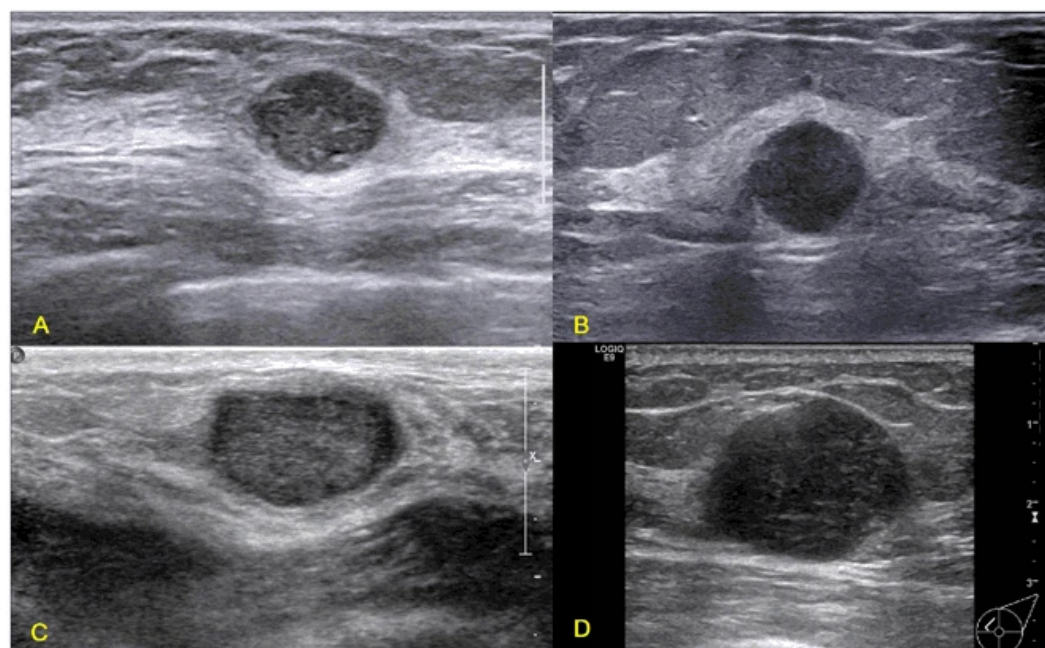


Figure 6. Ultrasound images for triple-negative breast cancer with a regular shape, a circumscribed margin, and posterior acoustic enhancement. (A) Invasive ductal carcinoma in a 35-year-old female patient; (B) Invasive ductal carcinoma in a 55-year-old female patient; (C) Invasive ductal carcinoma in a 33-year-old female patient; (D) Invasive ductal carcinoma in a 48-year-old female patient [31].

Table 2. Suspicious malignant lesions on ultrasound.

Solid Nodule Characteristics	Positive Predictive Value
Speculation	91.8
Taller than wide	81.2
Angular margins	67.5
Shadowing	64.9
Branching pattern	64.0
Hypo echogenicity	60.1
Calcifications	59.6
Duct extension	50.8
Micro lobulations	48.2

2.3. Mammography

Sickles provides insights into both conventional and subtle indirect signs that indicate malignancy when discussing mammographic findings in breast tumour detection. A common early sign of breast cancer is clustered calcifications, which are often seen as small (≤ 0.5 mm) calcifications. Malignant calcifications tend to have thin linear, curvilinear, or branching shapes, whereas round or oval shapes are more likely benign. Another conventional mammographic sign of breast cancer is a poorly defined mass; those irregular, ill-defined masses are indicative of malignancy, especially spiculated or multinodular (knobby) margins, which strongly suggest cancer. However, many early cancers appear as non-spiculated masses with poorly defined borders, making them hard to distinguish from benign lesions. Moreover, there are several indirect (subtle) mammographic signs of breast cancer, including single duct, architectural distortion, asymmetry, and developing density [32]. Most masses, those with calcification and architectural distortion, are caused by invasive cancer, and the most common malignancy appearance in mammography of DCIS is calcification [33]. Different from common breast cancer, a study focused on the mammographic characteristics of tubular carcinoma of the breast, a rare and less aggressive subtype of breast cancer, stated that most tubular carcinomas are small and spiculated [34]. Figure 7 provides three different types of breast tumour appearances in mammogram images: palpable, spiculated, and calcified in various situations of breast density. And Figure 8 gives another clear visualisation of the mammography image of an IDC case, a large mass with irregular and spiculated margins can be easily seen in the image.

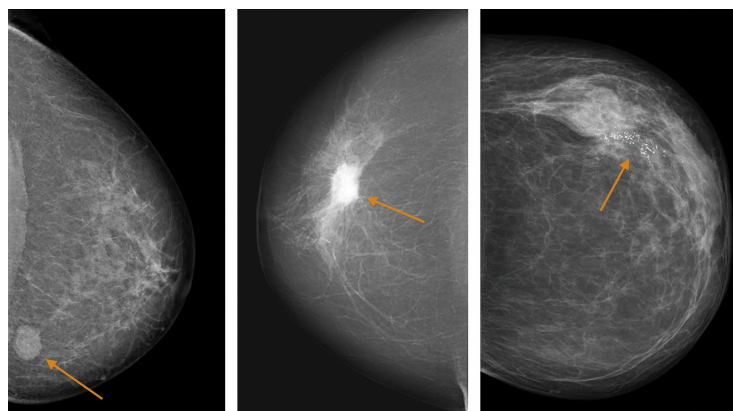


Figure 7. Mammographic breast tumour appearances. From **left to right**: A palpable mass in the left breast of an 80-year-old woman with moderate breast density. A spiculated mass in the right breast of a 79-year-old woman with fatty degeneration of the breast. Calcifications in the left breast of a 77-year-old woman with moderate breast density. All images were acquired in the cephalopod projection [35].

In Table 3, we summarised the different characteristics of three medical image modalities that are used most frequently in breast cancer diagnostics. Also, we compared three modalities and came up with the advantages and disadvantages of each. Nevertheless, there are other medical image modalities that we have not discussed in this section, which are also useful and popular in breast cancer diagnostics. For example, PET-CT combines a positron emission tomography (PET) scan and a computed tomography (CT) scan to provide detailed, 3D images of the body's structure and function; histopathology involves the microscopic examination of breast tissue to diagnose and characterise breast diseases, most commonly breast cancer.

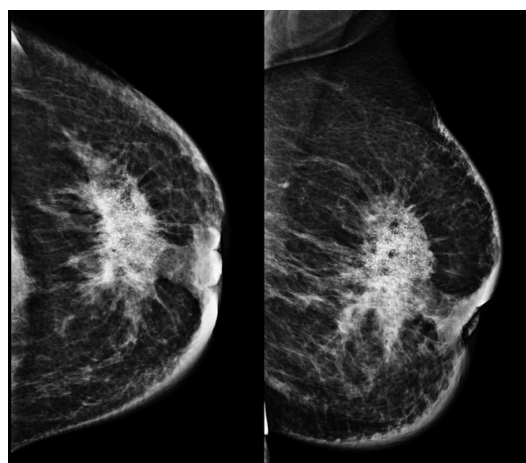


Figure 8. A large mass with irregular and spiculated margin, internal microcalcifications, surrounding parenchymal distortion, and adjacent skin thickening and retraction is noted at the central portion of the left breast in both bilateral craniocaudal (CC) and mediolateral oblique (MLO) views, was found in a 55 years woman who has been confirmed to have invasive ductal carcinoma [36].

Table 3. Comparison of imaging modalities for breast cancer diagnosis.

Aspect	MRI	Mammogram	Ultrasound
Methods	Uses radio waves and a strong magnetic field to create detailed images	Uses specialised X-ray imaging to capture breast tissue for cancer detection	Uses high-frequency sound waves to create images of breast tissue
Resolution	High	High	Low
Cost	High	Low	Low
Clinical use	High-risk screening, investigating abnormalities	Routine screening for breast cancer in asymptomatic individuals	Used to investigate symptoms and characterise palpable lumps
Advantages	High sensitivity, no radiation exposure	Low cost, effective for early detection	Effective in dense breast tissue, no radiation exposure
Disadvantages	High cost, noisy environment, longer scan time	Discomfort during compression, radiation exposure, increased false positives in dense tissue	Operator-dependent, limited coverage of the whole breast

3. Image Preprocessing for Medical Images

The very first steps of image processing include several different operations that are known as image preprocessing, such as non-linear characteristics corrections, adjusting brightness and/or contrast, radiometric and geometric corrections, etc. Image preprocess-

ing is always a crucial procedure to improve the performance and accuracy of further analysis. It can include image enhancement (deblurring, denoising, etc.), cropping, and re-sizing. Medical images have features of low contrast and high noise. One should pay attention to which image system is used to apply image enhancement techniques to medical images. Figure 9 introduces the pipeline for the image preprocessing procedure and lists both mandatory and optional actions that can be taken in the process.

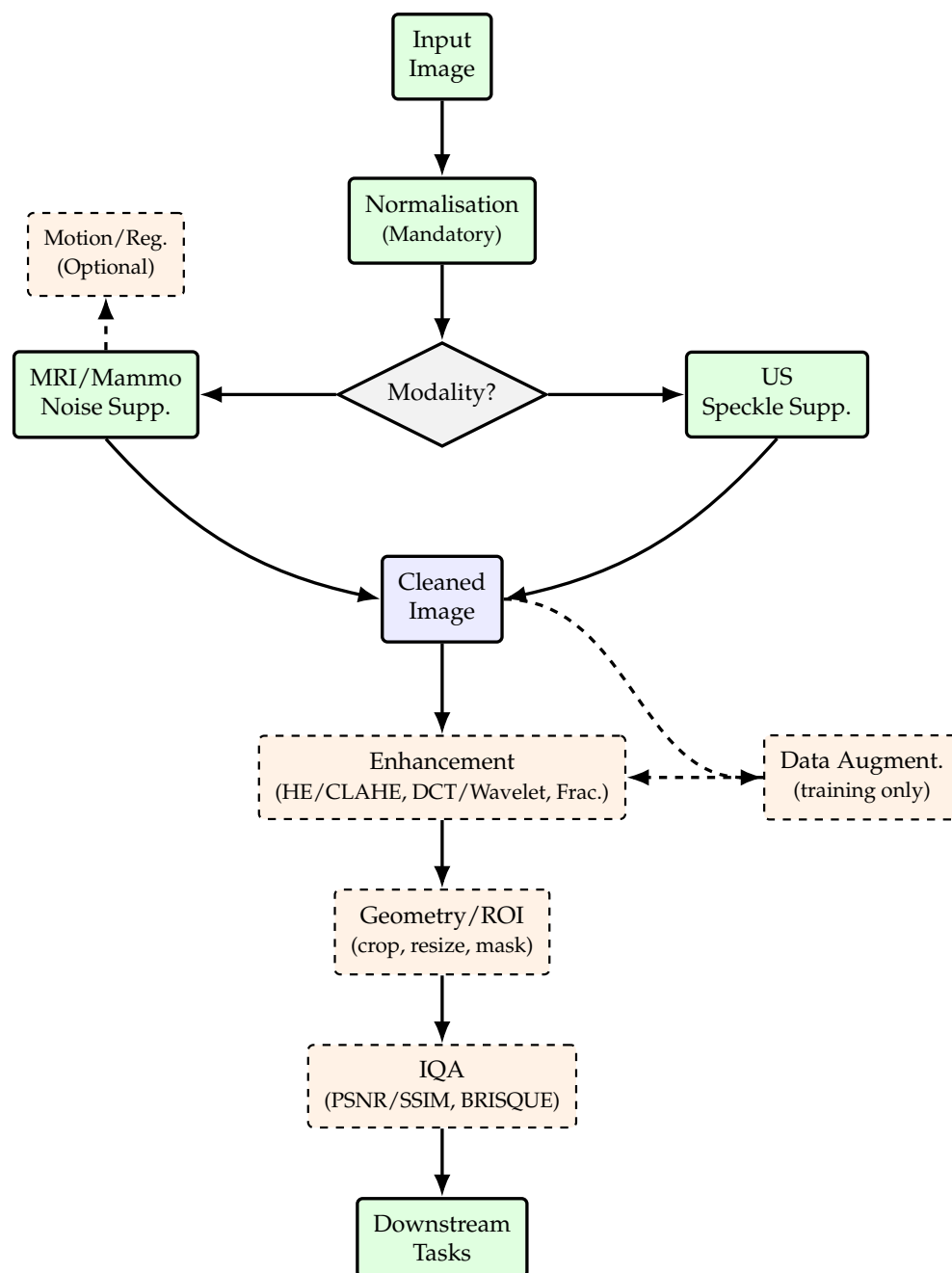


Figure 9. Preprocessing pipeline. Legend: **Green** = Mandatory processing steps; **Orange dashed** = Optional steps; **Blue** = Merge/decision point; **Solid arrows** = Primary workflow; **Dashed arrows** = Optional/alternative paths. Abbreviations: HE (Histogram Equalisation), CLAHE (Contrast-Limited Adaptive Histogram Equalisation), DCT (Discrete Cosine Transform), IQA (Image Quality Assessment), PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator), ROI (Region of Interest), REG (Registration).

3.1. Denoising and Deblurring

Denoising and/or deblurring processing is often applied to MRI and ultrasound images. A unified Bayesian framework was proposed to reduce noise in medical images, particularly for both additive noise like Gaussian and multiplicative noise like Poisson or Rayleigh. By expressing the Maximum a Posteriori (MAP) estimate as a solution to the Sylvester–Lyapunov equation $AX + XB = C$, enabling robust and computationally efficient noise reduction while preserving image features such as edges, the method outperformed traditional filters in better maintaining edge details in both synthetic and real datasets. The detailed methods are shown below to estimate the clean image $\mathbf{X}$ from a noisy observation $\mathbf{Y}$ using a Maximum a Posteriori (MAP) estimation framework. The MAP estimator minimises the negative log-posterior, given by

$$\mathbf{X}^* = \arg \min_{\mathbf{X}} [-\log P(\mathbf{Y} | \mathbf{X}) - \log P(\mathbf{X})]. \quad (1)$$

This leads to the energy functional

$$E(\mathbf{X}) = E_d(\mathbf{X}, \mathbf{Y}) + \lambda E_p(\mathbf{X}), \quad (2)$$

where $E_d(X, Y)$ is the data fidelity term, $E_p(X)$ is the regularisation term (prior), and λ is the regularisation parameter.

In the case of additive white Gaussian noise, the data fidelity term takes the form

$$E_d(\mathbf{X}, \mathbf{Y}) = \frac{1}{2\sigma^2} \|\mathbf{X} - \mathbf{Y}\|^2. \quad (3)$$

When dealing with other noise models, such as Poisson or Rayleigh noise, surrogate approximations are typically used to adapt the MAP framework.

Several priors are considered to enforce image regularity. A common choice is the Gaussian (L2) prior:

$$E_p(\mathbf{X}) = \sum_{i,j} \left((\partial_x X_{i,j})^2 + (\partial_y X_{i,j})^2 \right). \quad (4)$$

To better preserve edges, the total variation (TV) prior is used:

$$E_p(\mathbf{X}) = \sum_{i,j} \sqrt{(\partial_x X_{i,j})^2 + (\partial_y X_{i,j})^2}. \quad (5)$$

An alternative is the Benford prior, which applies a logarithmic penalty on gradients:

$$E_p(\mathbf{X}) = \sum_{i,j} \log(1 + \|\nabla X_{i,j}\|). \quad (6)$$

Under the assumption of Gaussian noise and a Gaussian prior, the MAP estimation leads to an Euler–Lagrange equation:

$$\nabla E(\mathbf{X}) = \frac{1}{\sigma^2} (\mathbf{X} - \mathbf{Y}) + \lambda \mathbf{LX} = 0. \quad (7)$$

which results in a Sylvester–Lyapunov equation of the form

$$A\mathbf{X} + \mathbf{X}B = C, \quad (8)$$

where $A = I + \lambda D_x$, $B = \lambda D_y$, and $C = \mathbf{Y}$. Here, D_x and D_y represent discrete derivative operators in horizontal and vertical directions, respectively.

For nonlinear priors like TV and Benford, the optimisation becomes non-quadratic. A Majorise–Minimise (MM) approach is employed, using a quadratic surrogate energy at each iteration. The update rule at iteration k is given by

$$A^{(k)}X^{(k+1)} + X^{(k+1)}B^{(k)} = C^{(k)}, \quad (9)$$

which is again solved using Sylvester solvers [37].

For the ultrasound images denosing process, some traditional homomorphic techniques usually convert the multiplicative speckle noise into additive noise using a logarithmic transformation and then filters (e.g., wavelet denoising) are applied based on the assumption that the resulting noise is white Gaussian noise (WGN). However, this assumption has been proven invalid; the log-transformed noise is non-Gaussian, often following a Fisher–Tippett distribution with a spiky, heavy-tailed nature. Thus, a two-stage preprocessing pipeline is introduced to overcome the problem. Spectral Equalisation: A decorrelation filter flattens the power spectral density of the image to reduce spatial correlation. Assuming a convolutional image formation model:

$$g(n, m) = f(n, m) * h(n, m) + u(n, m), \quad (10)$$

where g is the RF image, f the tissue reflectivity, h the point spread function (PSF), and u additive noise, the power spectral density is

$$P_g(\omega_1, \omega_2) = \sigma_f^2 |H(\omega_1, \omega_2)|^2 + \sigma_u^2, \quad (11)$$

with σ_f^2 and σ_u^2 denoting variances of the reflectivity and noise, respectively.

The spectral equalisation filter is defined by

$$L(\omega_1, \omega_2) = \left(|H(\omega_1, \omega_2)|^2 + \varepsilon \right)^{-1/2}, \quad (12)$$

where $\varepsilon = \sigma_u^2 / \sigma_f^2$ is a tunable parameter controlling high-frequency amplification. Applying this filter flattens the power spectrum and reduces spatial correlation. Then, Outlier Shrinkage is the nonlinear suppression of spiky noise components using robust residuals from median-filtered images. After log-transforming the decorrelated envelope image $G(n, m)$, the spiky noise component is suppressed using robust residuals:

$$R(n, m) = \text{sign}(\Delta G(n, m)) \cdot (|\Delta G(n, m)| - \lambda)_+, \quad (13)$$

where $\Delta G(n, m) = G(n, m) - \text{MedianFilter}(G)(n, m)$, λ is a threshold (typically covering 93–95% of values), and

$$(x)_+ = \begin{cases} x, & x > 0, \\ 0, & \text{otherwise.} \end{cases}$$

The preprocessed image is then:

$$G'(n, m) = G(n, m) - R(n, m), \quad (14)$$

which approximates white Gaussian noise (WGN) behaviour, allowing optimal performance of standard denoising filters [38].

A wavelet-domain denoising method using a Bivariate Laplacian Mixture Model (BLMM) in the dual-tree complex wavelet domain effectively captures interscale and

intrascale wavelet coefficient dependencies. The clean wavelet coefficient vector is modelled as a local mixture of bivariate Laplacian distributions:

$$p(\mathbf{w}_k) = \sum_{i=1}^I a_{i,k} \cdot p_i(\mathbf{w}_k), \quad (15)$$

where each component $p_i(\mathbf{w}_k)$ is defined as

$$p_i(\mathbf{w}_k) = \frac{1}{2\sigma_{i,w}\sigma_{i,p}} \exp\left(-\sqrt{2}\left(\frac{|w_k|}{\sigma_{i,w}} + \frac{|w_{p,k}|}{\sigma_{i,p}}\right)\right), \quad (16)$$

with $\mathbf{w}_k = (w_k, w_{p,k})$ representing a wavelet coefficient and its parent.

With EM-based estimation of weights and variances. Closed-form MAP and MMSE estimators are derived for Gaussian and Rayleigh noise, enabling spatially adaptive and statistically grounded shrinkage. The method shows strong performance on MR, CT and ultrasound imaging, preserving structural features while reducing noise [39].

3.2. Image Quality Enhancement

Medical images usually show limited contrast and quality, which can affect the accuracy of diagnostic results. Many studies have worked on methods to improve image quality using filters or histograms. To enhance medical images, an adaptive fractional-order differential (AFDA) operator is developed that intelligently balances between sharpening edges, preserving textures, and maintaining smooth areas. The core mathematical theory behind the AFDA relies primarily on fractional calculus. Fractional derivatives generalise integer-order derivatives to non-integer (fractional) orders, defined by the Grünwald–Letnikov fractional derivative [40]:

$${}_a D_b^v f(t) = \lim_{h \rightarrow 0} h^{-v} \sum_{j=0}^{\lfloor (b-a)/h \rfloor} (-1)^j \binom{v}{j} f(t - jh),$$

In the frequency domain, fractional derivatives behave as power-law filters, emphasising high-frequency features based on fractional order v :

$$\mathcal{F}\{D^v s\}(\omega) = (i\omega)^v S(\omega) = |\omega|^v e^{i \operatorname{sgn}(\omega) \frac{\pi v}{2}} S(\omega).$$

To make the operator adaptive, the fractional order $v(i, j)$ at each pixel position (i, j) is computed by using local gradient magnitude $M(i, j)$ and a threshold t :

$$v(i, j) = \begin{cases} \frac{M(i, j) - t}{M(i, j)}, & M(i, j) \geq t \text{ and } \frac{M(i, j) - t}{M(i, j)} \geq v_1, \\ v_1, & M(i, j) \geq t \text{ and } \frac{M(i, j) - t}{M(i, j)} < v_1, \\ v_2, & 2 < M(i, j) < t \text{ and } \frac{M(i, j)}{t} \geq v_2, \\ \frac{M(i, j)}{t}, & 2 < M(i, j) < t \text{ and } \frac{M(i, j)}{t} < v_2, \\ 0, & M(i, j) \leq 2, \end{cases}$$

where thresholds v_1 and v_2 are defined using global mean gradient Q and local means of edge and texture gradients $\overline{M_{\text{edge}}}$ and $\overline{M_{\text{tex}}}$:

$$v_1 = \frac{\overline{M_{\text{edge}}} - Q}{\overline{M_{\text{edge}}}}, \quad v_2 = \frac{Q - \overline{M_{\text{tex}}}}{Q}.$$

An improved Otsu threshold based on gradient histograms is used to achieve effective segmentation to determine these thresholds. For a given gradient histogram $p(k)$, the Otsu thresholds optimise the variance between classes:

$$\sigma_B^2(t) = w_1(\mu_1 - \mu)^2 + w_2(\mu_2 - \mu)^2, \quad \text{where} \quad \mu = w_1\mu_1 + w_2\mu_2,$$

with class weights w_1, w_2 and class means μ_1, μ_2 calculated from the histogram:

$$w_1(t) = \sum_{i=0}^t p(i), \quad w_2(t) = \sum_{i=t+1}^{N_{\max}} p(i), \quad \mu_1 = \frac{1}{w_1} \sum_{i=0}^t i p(i), \quad \mu_2 = \frac{1}{w_2} \sum_{i=t+1}^{N_{\max}} i p(i).$$

A histogram equalisation is a classical method in digital image processing, which can be done globally in medical images to improve contrast. Shams explores various histogram-based algorithms aimed at improving the contrast and visual quality of medical images, crucial for accurate medical diagnoses. The study specifically evaluates and compares four main histogram-based enhancement techniques. Histogram-based enhancement methods are based primarily on the distribution of pixel intensity levels. For a digital image, the histogram and its normalised form are defined as

$$h(r_k) = n_k, \quad p(r_k) = \frac{n_k}{MN}, \quad k = 0, 1, \dots, L-1 \quad (17)$$

where n_k is the count of pixels at intensity level r_k , and MN is the total pixel count.

The Histogram Equalisation (HE) algorithm transforms the intensity using the cumulative distribution function (CDF):

$$\text{cdf}(k) = \sum_{i=0}^k p(r_i), \quad s_k = T(r_k) = \text{floor}[(L-1) \cdot \text{cdf}(k)] \quad (18)$$

Cumulative Histogram Equalisation (CHE) uses the general formula:

$$eh(k) = \text{round} \left((L-1) \frac{\text{cdf}(k) - \text{cdf}_{\min}}{MN - \text{cdf}_{\min}} \right) \quad (19)$$

Quadrant Dynamic Histogram Equalisation (QDHE) partitions histograms dynamically using medians as follows:

$$m_1 = I_{\text{width} \times \text{height}} \times 0.25, \quad m_2 = I_{\text{width} \times \text{height}} \times 0.50, \quad m_3 = I_{\text{width} \times \text{height}} \times 0.75 \quad (20)$$

It clips histogram intensities exceeding a threshold T_c , computed as:

$$T_c = \text{average intensity of the image} \quad (21)$$

The dynamic intensity redistribution is performed by

$$\text{range}_i = (L-1) \frac{\text{span}_i}{\sum_{k=1}^4 \text{span}_k} \quad (22)$$

Contrast Limited Adaptive Histogram Equalisation (CLAHE) applies local enhancements controlled by a clip limit β :

$$\beta = \frac{M}{N} \left(1 + \frac{\alpha}{100} (S_{\max} - 1) \right) \quad (23)$$

Performance evaluation metrics for these enhancement algorithms include Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Standard Deviation (SD):

$$\text{MSE} = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N [I'(i,j) - I(i,j)]^2, \quad \text{PSNR} = 10 \log_{10} \frac{(L-1)^2}{\text{MSE}} \quad (24)$$

$$\text{SD} = \sqrt{\frac{1}{n-1} \sum_{k=1}^n (f(i,j) - X)^2} \quad (25)$$

Compared experimental results via different metrics, including PSNR, MSE, and SD, QDHE generally outperformed other methods, providing the best overall contrast enhancement and preserving image brightness effectively; however, CLAHE was particularly effective on images with non-uniform intensity distributions [41].

Apart from the four methods compared in the above study, there are other histogram-based methods, including bi-histogram equalisation (BHE), brightness-preserving bi-histogram fuzzy equalisation (BPFHE), recursive mean-separate histogram equalisation (RMSHE), adaptive histogram equalisation (AHE), dualistic sub-image histogram equalisation (DSIHE), and recursive sub-image histogram equalisation (RSIHE). BHE uses the greyscale average to divide the histogram into two sub-histograms and equalises the separated histograms to enhance contrast. Meanwhile, RMSHE is a modified form of BHE where the histogram is recursively divided into multiple sub-histograms based on the average brightness [42]. BPFHE has two stages. First, the fuzzy histogram is calculated based on fuzzy set theory, which can handle the inaccuracy of greyscale values better than the classical sharp histogram. Two well-known parameters, such as entropy or average information content (AIC) and feature similarity index matrix (FSIM), are used to evaluate the proposed BPFHE algorithm for different greyscale images [43]. AHE is a technique that operates on smaller areas or tiles of an image rather than the entire area, and each tile is processed to enhance contrast [44]. DSIHE and RSIHE both decompose the image, but using different variable median values and the cumulative density function [45]. Figure 10 presents the results of images that are enhanced by different histogram techniques.

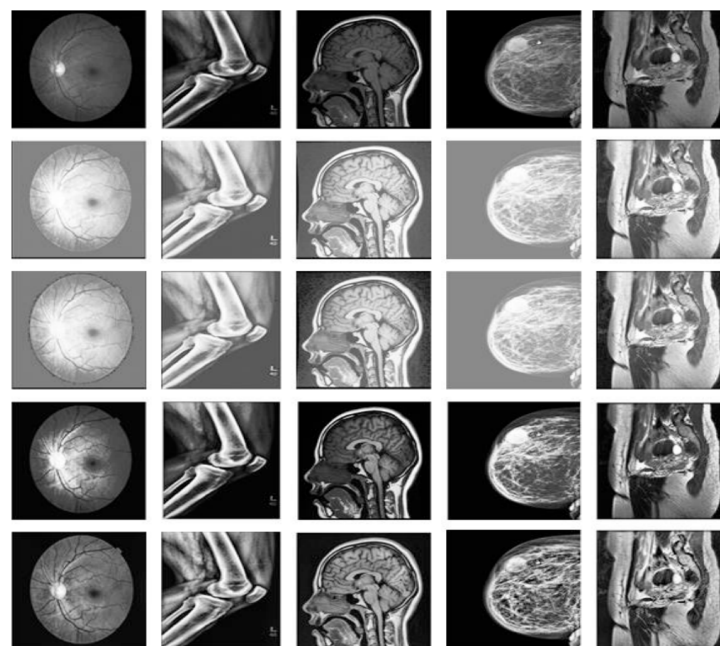


Figure 10. The 1st (top) row displays the five original medical images, the following rows display the enhanced images by the techniques HE, CHE, QDHE and CLAHE, in sequence [41].

3.3. Frequency Domain Enhancement

Beyond histogram-based methods for medical image enhancement, frequency domain techniques offer powerful alternatives by transforming images into frequency representations, where specific components can be selectively enhanced or suppressed. These methods include widely adopted transforms such as the Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), Hartley Transform, Haar Transform, Slant Transform, Wavelet Transform, Curvelet Transform, and Contourlet Transform. Each transform is tailored to extract different types of features: FFT efficiently converts spatial data into frequency components, DCT emphasises energy compaction for compression, and the Hartley Transform retains real-valued computations for speed and efficiency. The Haar and Slant transforms emphasise abrupt and smooth transitions, respectively, while Wavelet-based approaches excel at multi-resolution analysis and local adaptation. In the reviewed literature, Tang et al. [46] proposed a DCT-based method that enhances contrast by grouping and adjusting coefficients across frequency bands, enabling block-wise contrast adaptation. Jin et al. [47] advanced this concept by applying Local Adaptive Histogram Equalisation (LAHE) within wavelet sub-bands, effectively improving local contrast in medical images. Toet [48] introduced an adaptive multi-scale enhancement framework based on pyramid recombination, facilitating scale-specific detail amplification, while Mukhopadhyay and Chanda [49,50] used morphological top-hat transforms to isolate and enhance local features. More recently, Iqbal et al. [51] developed a Dual-Tree Complex Wavelet Transform with Nonlocal Means (DT-CWT-NLM) enhancement method that combines spatial and frequency information to boost edge detail while minimising noise. Supporting these findings, Singh and Mittal [52] emphasised the capability of frequency-based transforms such as DCT, DFT, and wavelets to enhance edges, suppress periodic noise, and preserve structure through transform coefficient manipulation. Collectively, these frequency domain techniques provide a rich and flexible framework for medical image enhancement, offering substantial improvements in contrast, detail preservation, and noise resilience compared to traditional spatial-domain approaches [53]. Figure 11 demonstrates the pipeline of how the frequency domain enhancement works in image processing. And Figure 12 is a set of result images that used frequency-domain methods, including chest X-ray, fast MRI and a dataset from NYU.



Figure 11. Filtering technique in the frequency domain.

3.4. Image Quality Assessment

Image quality assessment (IQA) in medical imaging can be divided into full-reference (FR) methods, which require a pristine ‘ground-truth’ image, and no-reference (NR) or blind methods, which predict perceptual quality without any reference. FR metrics quantify the fidelity of a test image by comparing it directly to a high-quality reference. Classical pixel error measures, like the peak signal-to-noise ratio (PSNR) and mean squared error, correlate poorly with human perception in medical scans, motivating more sophisticated approaches. The Structural Similarity Index (SSIM) models image degradation via three components: luminance, contrast, and structure computed over local windows and then averaged to yield a global similarity score. Extensions include Multiscale SSIM (MS-SSIM), which evaluates SSIM at multiple resolutions, and Information Weighted SSIM (IW-SSIM), which weights local SSIM scores by the information content of each region, both of which improve agreement with subjective ratings in MR images [55]. Feature similarity measures such as FSIM and its Riesz-transform variant (RFSIM) exploit phase congruency and gradient

magnitude to emphasise edge-related distortions, achieving top performance across general and medical image datasets. Information-theoretic criteria such as the Information Fidelity Criterion (IFC) and its visual extension (VIF) treat the reference–test pair as input and output of a communication channel, estimating the mutual information preserved and producing perceptually meaningful scores, albeit at a higher computational cost [56].

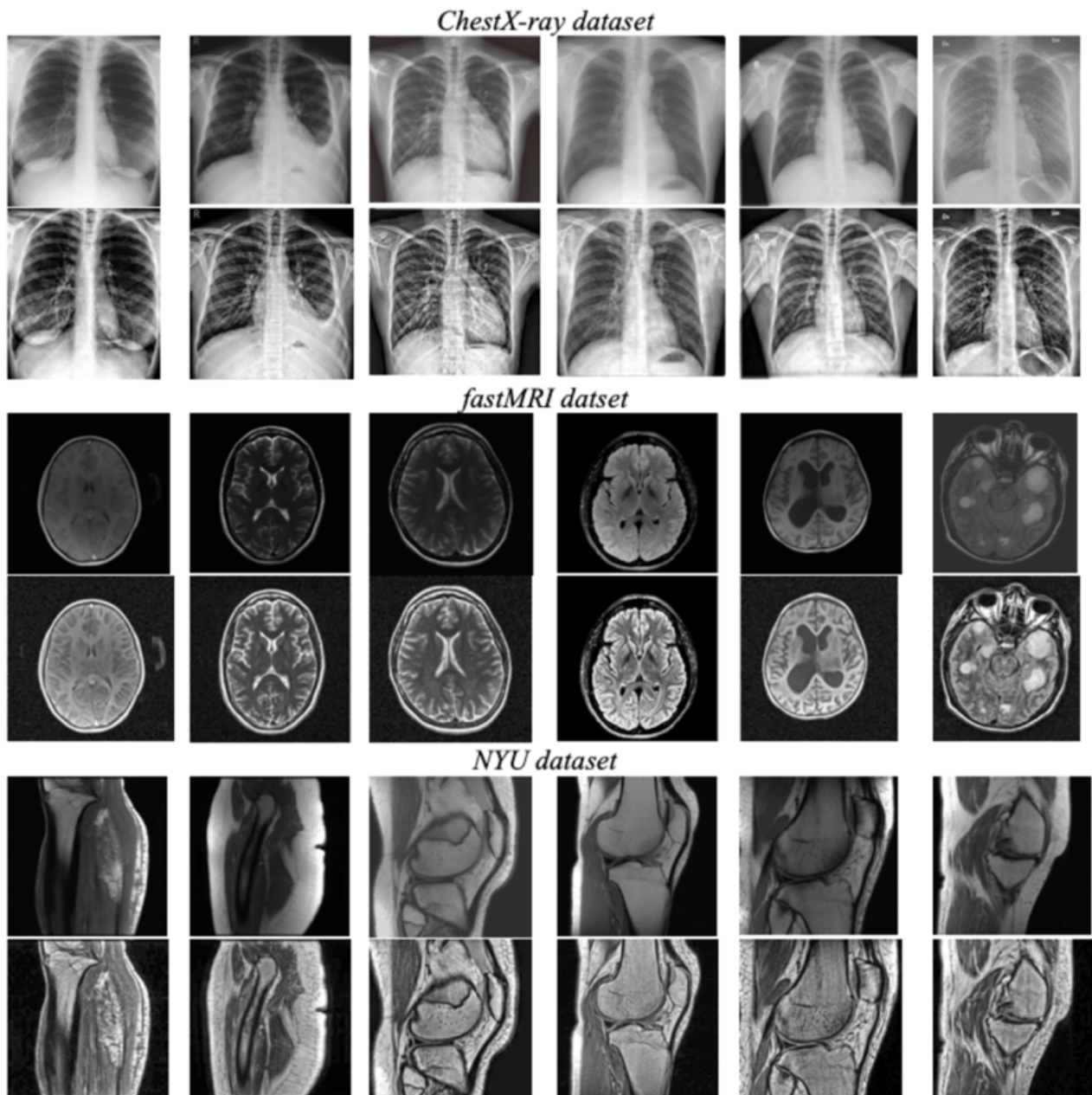


Figure 12. Result images using frequency domain enhancement [54].

In routine clinical MRI, there is rarely a true reference, which requires NR IQA. Natural-scene statistics (NSS)-based indices model undistorted images by fitting statistical distributions to transform or spatial-domain coefficients, then quantify how distortions perturb these statistics. BRISQUE, a popular spatial-domain NSS model, applies mean-subtracted contrast normalisation (MSCN) and fits the resulting coefficients to a generalised Gaussian distribution, with deviations from the learned model indicating quality loss [57]. Wavelet domain NSS methods (e.g., DIIVINE) first identify the distortion type, then apply distortion-specific wavelet-based features, while DCT-based schemes like BLIINDS-II employ Bayesian modelling of transform coefficient statistics to predict quality from a compact

feature set [58]. Transform-free spatial domain models exploit local image features such as gradients: gradient similarity measures compute pixel-wise comparison of gradient magnitude or orientation between distorted images and an implicit edge model to capture contrast and structural changes, providing fast, real-time blind IQA [59]. Learning-based NR methods further integrate handcrafted features (e.g., high-boost-filtered local descriptors) into regression models, such as support vector regression, to predict quality scores closely matching radiologist opinions. Table 4 summarises the IQA methods of both FR and NR reviewed in this section.

Table 4. Comparison of full-reference and no-reference image quality assessment methods.

Full-Reference (FR) Methods	No-Reference (NR) Methods
PSNR Peak Signal-to-Noise Ratio; measures pixel-wise fidelity via log-scaled MSE.	BRISQUE Blind/Referenceless Image Spatial Quality Evaluator; models deviations from natural scene statistics in the spatial domain.
SSIM Structural Similarity Index; compares luminance, contrast and structure between test and reference.	DIIVINE Distortion Identification-based Image Verity and Integrity Evaluation; wavelet-domain NSS with distortion classification.
MS-SSIM Multiscale SSIM evaluates SSIM over multiple resolutions for scale-aware quality assessment.	BLIINDS-II Blind Image Integrity Notator using DCT Statistics; Bayesian modelling of DCT coefficient distributions.
IW-SSIM Information-Weighted SSIM: weights local SSIM scores by regional information content.	Gradient Similarity Compares gradient magnitude/orientation to an implicit edge model to detect blur and structural distortions.
FSIM/RFSIM Feature SIMilarity index; uses phase congruency and gradient features (Riesz-transform variant in RFSIM) to emphasise edge fidelity.	Feature-Based NR Extracts artefact-sensitive features (e.g., blockiness, noise, ringing) and uses regression to predict perceptual quality.
IFC/VIF Information Fidelity Criterion/Visual Information Fidelity; treats IQA as mutual-information preservation in a communication channel.	Task-Based Observer Models Models diagnostic detectability (e.g., Channelised Hotelling Observer) to assess quality based on task performance.

3.5. Evaluation Metrics

To comprehensively assess processing performance, a suite of evaluation metrics has been established to quantify results across multiple dimensions. Table 5 summarises the most commonly used metrics for medical image segmentation quality assessment. These metrics, along with recommendations for their appropriate application and notes on possible interpretation biases, are drawn from the standardised framework proposed by Müller et al. [60].

Table 5. Evaluation metrics in medical image processing.

Metric	Formula	Description
Dice Similarity Coefficient (DSC)	$DSC(A, B) = \frac{2 A \cap B }{ A + B }$	Measures overlap between the prediction and the ground truth.
Intersection-over-Union (IoU)	$IoU = \frac{TP}{TP + FP + FN}$	Ratio of intersection to union of predicted and true regions.
Sensitivity (Recall)	$Sens = \frac{TP}{TP + FN}$	Proportion of actual positives correctly identified.
Specificity	$Spec = \frac{TN}{TN + FP}$	Proportion of actual negatives correctly identified.
Accuracy	$Acc = \frac{TP + TN}{TP + TN + FP + FN}$	Overall proportion of correctly classified pixels.
Area Under ROC Curve (AUC)	$AUC = 1 - \frac{1}{2} \left(\frac{FP}{FP + TN} + \frac{FN}{FN + TP} \right)$	Measure of separability between positive and negative classes.
Cohen's Kappa (κ)	$\kappa = \frac{(TP + TN) - f_c}{(TP + TN + FP + FN) - f_c}$ $f_c = \frac{(TN + FN)(TN + FP) + (FP + TP)(FN + TP)}{TP + TN + FP + FN}$	Agreement between prediction and ground truth beyond chance.
Average Hausdorff Distance (AHD)	$AHD = \max(d(A, B), d(B, A)),$ $d(A, B) = \frac{1}{ A } \sum_{a \in A} \min_{b \in B} \ a - b\ $	Measures the boundary discrepancy between two contours.

Notes: TP = true positives; FP = false positives; FN = false negatives; TN = true negatives; A = set of predicted boundary points; B = set of ground truth boundary points.

4. Medical Image Processing Using Classical Methods

Petrou and Kamata stated in their book that image processing attempts to solve three main problems related to texture: Classification, which involves analysing the texture in a sample image of the surface to identify what a surface represents; Segmentation, which involves dividing an image into regions of different textures; and Defect detection, which consists in determining whether the texture is as expected or contains defects. They also identified that texture has two important properties: texture is scale-dependent, and image texture depends on the imaging geometry [61]. Furthermore, image processing is not a one-step process; it requires distinguishing several steps that must be performed sequentially to extract the data of interest from the observed scene. Since the 21st century, many methods have been developed for the early detection of breast cancer. These methods include threshold segmentation, active contour model, region growth, watershed, template matching, level set, and marker-controlled watershed methods.

4.1. MRI Analysis

MRI is a common diagnostic tool for breast cancer, providing clear cross-sectional images with high resolution [62]. CAD (computer-aided diagnosis) applications with image processing tools that include classification and segmentation help improve the efficiency and precision of breast cancer detection. A study conducted a texture analysis using co-occurrence matrix (COM) features, which quantify the heterogeneity of pixel intensity distributions in 200 cases. Classification was performed using a cross-validated k-nearest neighbour ($k = 3$) model on retrospective training data and prospectively applied to a test set. Significant differences in entropy characteristics were observed between invasive lobular and ductal cancers, suggesting distinct internal heterogeneity patterns and demonstrating that the textural features can reflect the aggressiveness of the tumours, achieving up to 75% accuracy [63]. Yao et al. emphasise texture analysis and wavelet trans-

form, demonstrating high accuracy in classification by applying advanced texture features combined with wavelet transforms, using an SVM committee for robust classification [64]. While Levman et al. systematically explore various feature extraction strategies and kernel functions in SVMs, demonstrating the flexibility and robustness of SVM-based methods, using principal component visualisation for better interpretability [65]. In the context of rapid T2*-weighted imaging, Torheim et al. evaluate several classifiers. Their primary finding is the effectiveness of the minimum enhancement threshold method. Then, noise reduction methods were incorporated, which slightly improved their results [66]. The straightforward yet effective 2D image processing techniques, including Otsu's thresholding, median filtering, and morphological operations, can achieve high accuracy (97.33%) with minimal human intervention. This method prioritises simplicity, speed, and practical usability, though it may be less robust for complex cases [67]. A sophisticated and fully automated 3D segmentation framework that utilises a probabilistic atlas and statistical (Expectation Maximisation) modelling achieved a high segmentation accuracy (Dice Similarity Coefficient of up to 0.94), which is robust and suitable for clinical assessments and potential use in large-scale studies [68]. A study combined structural segmentation techniques and K-means clustering for precise tumour identification, alongside effective 3D reconstruction (Marching Cubes and Maximum Intensity Projection) for enhanced visualisation. This approach is particularly valuable for detailed clinical visualisation and diagnosis, but lacks a rigorous quantitative evaluation for further application [69].

4.2. Mammogram Analysis

Mammogram segmentation based on classical methods can be divided into three categories: region-based segmentation, edge-based segmentation, and threshold-based segmentation. Classical segmentation divides the image into non-overlapping regions with specific properties. Discussing the region-based methods (RM), Senthilkumar et al. proposed a region growing segmentation algorithm for breast cancer detection, which applied a median filter to remove noise from the target mammogram image and then enhanced the image through contrast-limited adaptive histogram equalisation (CLAHE) to improve the segmentation accuracy. In this method, the researchers used the Harris region point detector to obtain the growing seeds and used CG-1 to extract the qualitative concept of the selected window for calculating E_x , E_n , and H_e of the window. The methods achieved a segmentation accuracy of 93% [70]. Berber et al. introduced a breast mass contour segmentation method (BMCS) for digital mammograms based on classical seeded region growth, which enhances traditional seeded region-growing methods by incorporating an adaptive thresholding strategy. BMCS is specifically designed to improve segmentation accuracy in digital mammograms by dynamically adjusting threshold values to prevent common issues like under- and over-segmentation [71]. Petrick presented an effective approach to breast mass segmentation that integrates density-weighted contrast enhancement (DWCE) and an adaptive region-growing algorithm for digitised mammograms. The DWCE firstly applies an adaptive filtering to enhance local contrast, accentuating mammographic structures while suppressing background noise and subtle intensity variations. Then, Laplacian–Gaussian edge detection is applied, yielding initial regions that highlight potential breast masses. This preprocessing efficiently identifies mass candidates, but typically results in undersegmented structures. To refine segmentation, region-growing is applied based on greyscale and gradient information, utilising gradient-based thresholds that are adaptively updated during iterative expansions. The technique begins by identifying seed regions from local intensity maxima within areas highlighted by DWCE. As a result, it prevents over- and under-segmentation and significantly improves the precision of the mass contour [72]. An automated approach to segment and classify breast masses from mammograms is

proposed by combining optimised region growth and Dragon Fly Optimisation (DFO). The initial seed selection and optimal thresholds are adaptively determined using the DFO, a swarm-based optimisation technique. The method maximises Rényi's entropy to select the optimal segmentation parameters, significantly enhancing segmentation accuracy and robustness against intensity variations in mammograms. Using Grey Level Co-occurrence Matrix (GLCM) and Grey Level Run Length Matrix (GLRLM) to extract texture features from the segmented region, and feed the features into a Feed Forward Neural Network (FFNN) classifier trained via back-propagation (Levenberg–Marquardt algorithm), so the classifier is able to differentiate between benign and malignant breast masses based on extracted texture features [73]. Figure 13 demonstrates the architecture of the optimised region growing system.

Seed selection is very crucial for seed-based region growing segmentation. An automated approach for selecting the initial seed point is presented to detect microcalcifications in mammogram images. The method involves regional maxima identification to extract candidate regions where microcalcifications typically appear; eliminating plateau pixels to ensure accurate seed points by refining local maxima through morphological techniques; and determination of optimal local maxima, where the average position of these maxima is selected as the initial seed. By utilising mathematical morphology, specifically morphological operations (dilation, erosion, opening, closing, and regional maxima), optimal initial seed points can be automatically determined without human intervention [74]. Isa and Siong proposed an automated method for segmenting breast microcalcifications in mammograms using a seeded region-growing algorithm with morphologically based automatic seed selection. The technique involves preprocessing to enhance contrast, automatic seed identification through morphological operations, and adaptive region-growing based on intensity similarity. The method achieves robust, accurate segmentation with high consistency compared to expert radiologist annotations, highlighting its effectiveness for early detection of breast cancer [75]. Pereira et al. introduced a computational framework combining wavelet multiresolution analysis and a genetic algorithm (GA) for automated segmentation and detection of breast cancer in mammograms. Initially, artefacts are removed from mammographic images using morphological operations. Subsequently, image enhancement is performed through wavelet decomposition and adaptive Wiener filtering to improve contrast and reduce noise. For segmentation, a multilevel thresholding approach is implemented, where optimal thresholds are determined using a genetic algorithm (GA) applied to wavelet-reduced histograms. The genetic algorithm efficiently selects the optimal number and values of thresholds, thereby accurately delineating suspicious regions. Post-processing further reduces false positives by comparing suspicious areas across cranio-caudal (CC) and mediolateral oblique (MLO) views [76]. Table 6 summarises the three main categories of segmentation using classical methods for mammogram images, listing both advantages and disadvantages for each category. Furthermore, Tables 7–9 summarise various works on classical segmentation methods applied to breast mammogram images in recent decades, presenting a timeline of the development of these techniques.

Table 6. Comparison of classical segmentation methods: merits and demerits [77].

Category	Merits	Demerits
Edge-based segmentation methods	Works well when the edge is prominent Easy to find the local edge orientation	Sensitive to noise Reduce overall contrast in mammograms Produce unsatisfactory results when it detects the fake and weak edges in mammograms Not suitable for mammogram images having smooth edges
Threshold-based segmentation methods	Simple and easy to implement Faster Inexpensive	It is not applicable if the tumour area ratio is unknown Sensitive to noise in mammograms Gives poor results when mammograms have low contrast Difficulties in fixing the threshold value if the number of regions increases Not easy to process the mammogram whose histograms are nearly unimodal
Region-based segmentation methods	Connected regions are guaranteed Multiple criteria and give good results with less noise	Causes over-segmentation if mammograms are noisy Cannot distinguish the shading of the real mammograms Time-consuming due to the high resolution of mammograms Not suitable for noisy mammograms Seed points must be selected

Table 7. Summary of reviewed works related to classical segmentation in mammogram images: region-growth based methods.

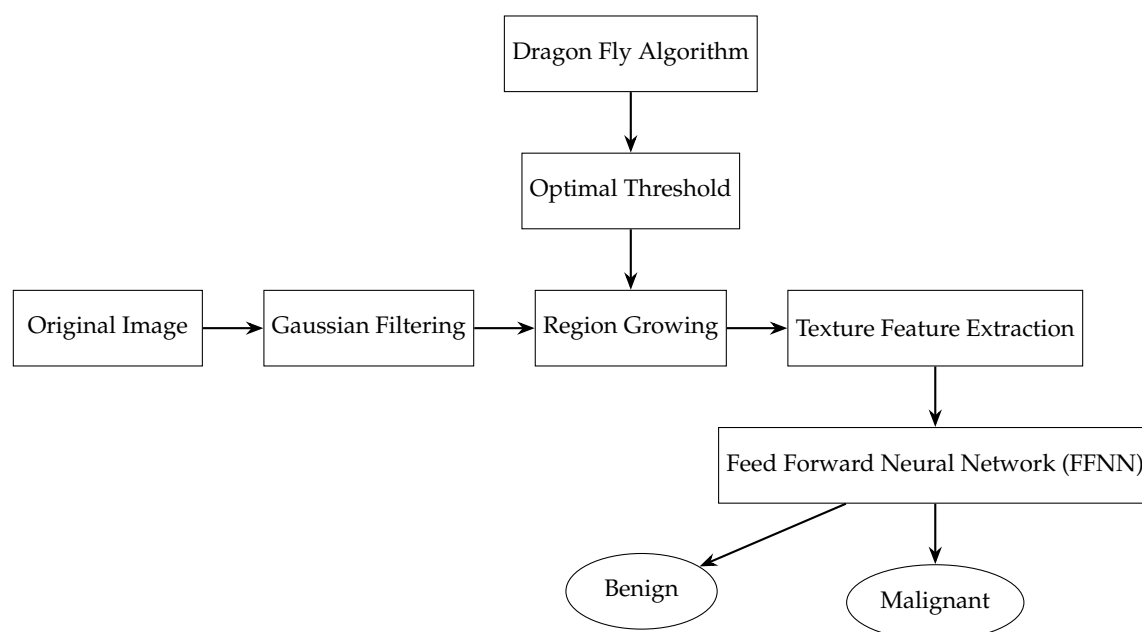
Ref.	Year	Technique	Filter	Database	Evaluation Metric
[72]	1999	Adaptive and region growing	Gaussian	UMH	98.0% accuracy
[78]	2001	Region growing	Kalman	DDSM	ROC: 93.0%, without adaptive: 86.0%
[79]	2001	Partial loss of region	Sobel	Japanese	97.0% true positive
[80]	2004	Region growing	–	MIAS	90.0% TPR, 1.3 FTR/image
[81]	2006	Contour searching	–	MAGIC-5	ROC: 85.6 ± 0.8%
[82]	2006	Morphological algorithm	Median	MIAS	95.0% detection rate
[83]	2010	Watershed	Morphological	DDSM	Mean ± SD = 0.93 ± 0.03 94.59% sensitivity, 3.90% false positive
[75]	2012	Region growing	Contrast	MIAS	95.0% detection rate
[84]	2012	Morphological	Median	MIAS	97.2% sensitivity, 1.83% false positive
[85]	2012	Region growing	Adaptive	DDSM	98.0% accuracy
[74]	2012	Seed point selection	Math. Morphology	NCSM	MIAS: 95.3%, NMR: 94.0%
[86]	2013	Morphological gradient watershed	Adaptive median	MIAS & NMR	95.06% accuracy
[71]	2013	Otsu	Morphological	DEMS	90.83% detection, ROC: 91.3%
[86]	2014	Marker-controlled watershed	Sobel	MIAS	79.2 ± 8% (mean ± SD)
[76]	2014	Wavelet + GA	Wiener	MIAS & DDSM	Sensitivity: 90.47%, Specificity: 75.0%, Accuracy: 84.85%
[87]	2014	Watershed transformation	–	MSKE	96.18% accuracy
[88]	2015	Watershed	Median	Mini-MIAS	

Table 8. Summary of reviewed works related to classical segmentation in mammogram images: threshold-based segmentation methods.

Ref.	Year	Technique	Filter	Database	Evaluation Metric
[89]	2001	Histogram thresholding	Morphological	DDSM	96.0% detection rate, 90.0% accuracy
[90]	2001	Kittler's optimal thresholding	–	BCCCF	92.0–95.0% Spearman, 6.9% avg. density
[91]	2009	Otsu + K-means clustering	CLAHE	MIAS	85.0% accuracy, 70.0% sensitivity
[92]	2011	Adaptive global + local threshold	Meteorological	MIAS	91.3% sensitivity, 0.71% false positive
[93]	2012	Otsu thresholding	Morphological	MIAS	ME1: 1.7188, ME2: 0.0083, MHD: 0.8702
[94]	2012	Histogram + edge detection	Gaussian	MIAS & EPIC	MIAS: 98.8%, EPIC: 91.5%
[95]	2013	Otsu	Median	MIAS	–
[96]	2014	Otsu	Median	MIAS	92.86% accuracy, 4.97% error rate
[97]	2015	Threshold + evolutionary	Average	DDSM	95.2% accuracy
[98]	2016	Otsu	Median	MIAS	96.55% accuracy, 96.97% sensitivity, 96.29% specificity
[99]	2016	Morphological threshold	Median	MIAS	94.54% accuracy, 5.45% false ID

Table 9. Summary of reviewed works related to classical segmentation in mammogram images: edge-based segmentation methods.

Ref.	Year	Technique	Filter	Database	Evaluation Metric
[100]	2004	Edge detection	Median	MIAS	83.9% accuracy
[101]	2011	Active contour	Binary homogeneity	MIAS	99.6% CM, 98.7% CR, 98.3% quality
[102]	2012	Sobel, Prewitt, Laplacian	Adobe Photoshop	NCSM	79.0% (Sobel), 72.0% (Prewitt), 71.0% (Laplacian)
[103]	2014	Energy minimization + contour	–	MIAS	90.0% accuracy, 92.27% precision
[104]	2015	Dynamic graph cut	–	MIAS + DDSM	98.88% sens., 98.89% spec., 93.0% (neg. values)
[105]	2016	Edge detection	2-D	MIAS	92.5% accuracy, 93.0% sensitivity, 85.0% specificity

**Figure 13.** Architecture of the system using optimised region growing.

4.3. Ultrasound Analysis

Traditional segmentation methods for breast ultrasound (BUS) images—namely thresholding, region growing, and watershed algorithms—have formed the foundation of early computer-aided diagnostic approaches, offering interpretable and computationally efficient solutions. Maolood et al. [106] introduced a two-stage fuzzy entropy thresholding

integrated with a level-set algorithm, which enhanced boundary precision under noisy conditions but required sensitive parameter tuning. Similarly, Gómez-Flores et al. [107] proposed a fully automated segmentation framework using iterative thresholding combined with texture-based preprocessing and radial derivative enhancement, achieving robust results across a large dataset, though its effectiveness declined with low-contrast lesions. Region-growing techniques, as applied by Massich et al. [108], offered a simple strategy to define lesion boundaries by combining Gaussian-based preprocessing with seeded region expansion; however, performance heavily depended on accurate initialisation. For boundary-focused approaches, Gomez et al. [109] employed marker-controlled watershed segmentation, leveraging anisotropic diffusion and contrast-limited adaptive histogram equalisation (CLAHE) to guide contour extraction, which improved localisation accuracy but at the cost of computational complexity. Extending this line of work, Gu et al. [110] incorporated Sobel gradient magnitude and morphological reconstruction within a 3D BUS segmentation pipeline, enabling multi-slice tissue classification with moderate success, although its sensitivity to small lesion detection remained a limitation. Together, these methods laid the foundation for BUS segmentation, emphasising the balance between algorithmic simplicity, boundary accuracy, and robustness to noise and image variability.

Several early studies on breast ultrasound (BUS) image classification employed traditional, non-learning-based approaches that relied on rule-based heuristics, expert-defined thresholds, and statistical decision logic. Bartolotta et al. [111] exemplify classification schemes grounded in radiological descriptors and BI-RADS-based feature mapping, the latter integrating the S-Detect system for structured lesion characterisation without involving any learning algorithm. Similarly, Pesce et al. [112] used fixed threshold values derived from shear wave elastography (SWE) metrics to differentiate malignant from benign lesions, offering quantitative but non-adaptive decision support. Moon et al. [113] introduced fuzzy clustering for elastography analysis, where classification relied on membership functions rather than trained models, providing flexibility in handling ambiguous cases but limited by its sensitivity to cluster initialisation. Ding et al. [114] applied a citation-kNN method. This memory-based logic system used local distance metrics and neighbourhood influence for classification, albeit lacking generalisation capability due to its reliance on stored instances. Thus, these classical methods offer interpretability and simplicity, making them clinically appealing in early CAD systems, but rigid decision rules and limited adaptability to complex imaging variations constrain their performance. Table 10 summarises some more related work in classical segmentation for ultrasound images.

Table 10. Summary of reviewed works related to classical segmentation in ultrasound images.

Ref.	Year	Technique	Filter	Database	Evaluation Metric
[115]	2014	Geodesic Active Contours (GAC)	SRAD	–	–
[116]	2015	Frequency-domain	Gaussian 2-D + Adaptive Z-shaped function	184 BUS images	APR: 99.39%, ARR: 29.29%
[117]	2015	Robust Graph-Based (RGB) + Active Contour Model (ACM)	Total Variation (TV)	46 BUS images	Sensitivity: 94.50%, Accuracy: 95.42%
[118]	2015	Support Vector Machine (SVM) + AdaBoost	Bandpass + non-linear	–	Precision rate 89.3%
[110]	2016	Watershed	Morphological + 3D Sobel	21 cases of whole breast ultrasound	Accuracy: 85.7%
[119]	2018	Exploding Seeds Method (ESM) + Distance Regularized Level Set Evolution (DRLSE)	Gaussian	180 BUS images	Accuracy: 99.10%, Sensitivity: 95.76%
[120]	2019	GLCM + Morphological + Histogram	Median	250 BUS images	–
[121]	2020	Walking Particle	Canny Edge + Histogram	400 BUS images	Accuracy: 97.12%, Sensitivity: 96.30%

Table 10. Cont.

Ref.	Year	Technique	Filter	Database	Evaluation Metric
[122]	2020	Superpixel-based Graph Cut + Fuzzy C-Means	Anisotropic Diffusion	110 BUS images	Accuracy: 98%
[123]	2020	Simple Linear Iterative Clustering (SLIC)	Histogram + Bilateral + Pyramid mean shift	320 BUS images	F1-score: $89.87 \pm 4.05\%$

5. Medical Image Processing Using Deep Learning Methods

With recent advances in artificial intelligence, deep learning has emerged as a powerful tool for breast cancer detection, enabling earlier diagnoses and improving patient survival rates. Unlike traditional machine learning methods, deep networks can automatically learn rich hierarchical features from imaging data, reducing the need for manual intervention in feature extraction. The most popular methods applied in the diagnosis and detection of breast cancer are the convolutional neural network (CNN) and the recurrent neural network (RNN). Figure 14 shows the architecture of a CNN for the classification of medical images, and Figure 15 gives a basic architecture of an RNN.

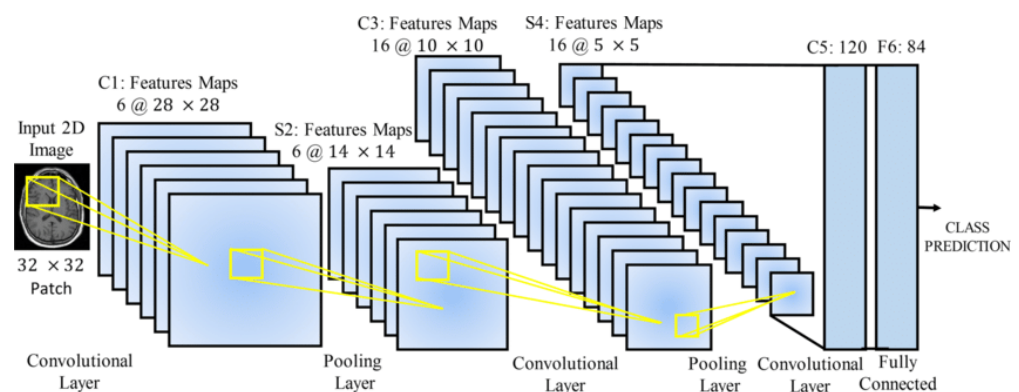


Figure 14. A typical convolutional neural network (CNN) architecture for medical image classification. The diagram shows successive convolutional, pooling, and fully connected layers. Yellow boxes and connecting lines indicate the progressive receptive field mapping from the input image to deeper feature representations [124].

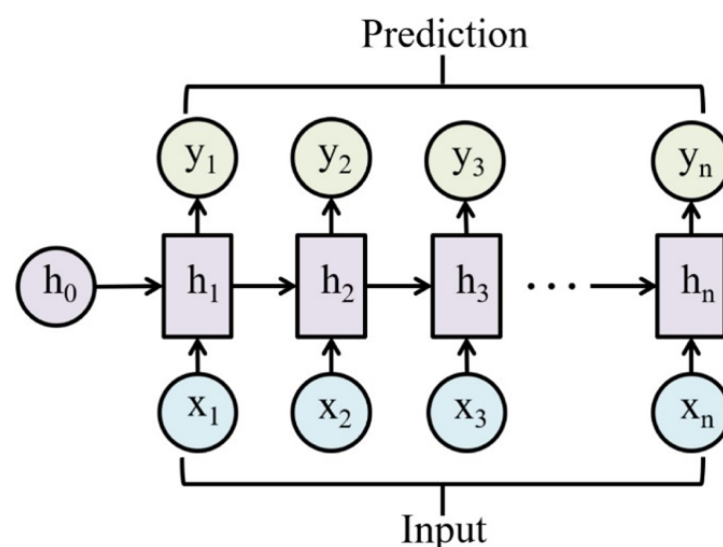


Figure 15. A basic recurrent neural network (RNN) architecture. At each time step t , the input x_t is processed together with the previous hidden state h_{t-1} to produce the current hidden state h_t and the corresponding output y_t . Different node colours distinguish inputs, hidden states, and outputs, while arrows indicate temporal information flow across time steps [125].

5.1. Convolutional Neural Network (CNN)

Convolutional neural networks (CNNs) have become a cornerstone of medical image analysis, particularly for segmentation and classification, because their hierarchical representations capture complex patterns in high-dimensional imaging data. Among CNN-based segmentation models, U-Net remains one of the most influential architectures. Originally developed for biomedical image segmentation, U-Net employs an encoder–decoder design with skip connections that preserve fine-grained spatial information during reconstruction. Numerous extensions, including 3D U-Net for volumetric imaging and attention U-Net for selectively emphasising salient regions, have further improved performance in clinically realistic settings [126]. Suzuki [127] provides a detailed comparison between classical machine learning pipelines and deep CNNs, highlighting CNNs' key advantage in end-to-end learning directly from raw pixel intensities without dependence on handcrafted features or prior segmentation. Relative to Massive-Training Artificial Neural Networks (MTANNs), CNNs offer greater architectural flexibility and scalability, though they typically require larger annotated datasets to realise their full potential. Nevertheless, CNNs have become widely adopted due to their ability to reduce false positives in lesion detection while improving sensitivity in classification tasks such as malignancy prediction. Lundervold [128] further summarise CNN integration across the MRI workflow, spanning reconstruction, denoising, and downstream disease detection, and report the strong performance of architectures such as U-Net and V-Net for tissue segmentation and pathology localisation in applications including brain and prostate imaging. More broadly, CNNs outperform traditional image processing approaches by learning task-specific features from data, enabling state-of-the-art performance in tumour segmentation, anomaly detection, and super-resolution MRI reconstruction. Importantly, CNNs have also been extended to quantitative imaging problems such as MR fingerprinting and quantitative susceptibility mapping (QSM), demonstrating their capacity to approximate complex inverse mappings in imaging physics. For example, QSMnet, a 3D U-Net-style CNN, enables robust susceptibility estimation from single-orientation measurements, supporting more efficient clinical workflows. Ravi et al. also emphasise CNN effectiveness across modalities, including CT, X-ray, and MRI, noting that GPU-accelerated optimisation and transfer learning have reduced reliance on domain-specific feature engineering and made high-performance classification more accessible across institutions. Raghu et al. [129] critically examine transfer learning in medical imaging and show that although pre-trained backbones (e.g., ResNet and VGG) can accelerate convergence and improve performance when labels are scarce, careful fine-tuning remains essential to mitigate domain shift between natural images and medical data. In breast imaging, Wang et al. [130] demonstrate that CNNs outperform conventional models for mammography and ultrasound classification, with fine-tuned ResNet-50 and InceptionV3 achieving strong sensitivity and specificity in distinguishing malignant lesions. In breast MRI, CNN-based pipelines are also widely employed for lesion segmentation, exploiting both spatial texture and temporal kinetics (e.g., from DCE-MRI). Although earlier studies combined wavelet-transformed features with classifiers such as SVMs, modern CNN models increasingly provide automated, robust segmentation and improved generalisation under limited annotation regimes [131]. Figure 16, as shown, is a comparative study of different state-of-the-art methods that use CNN models.

Across dynamic contrast-enhanced MRI (DCE-MRI), ultrasound, mammography, thermography, and histopathology, a consistent pattern emerges: explicitly incorporating lesion localisation and richer feature representations into learning pipelines improves diagnostic performance across modalities. Recent CNN-based frameworks for breast cancer diagnosis increasingly integrate segmentation, attention, and lesion-guided learning to enhance accuracy and interpretability. In ultrasound, Hossain et al. propose RKO-UNet, which intro-

duces spatial and channel self-attention for precise tumour segmentation and subsequently feeds segmented regions into a fine-tuned CNN, achieving 98.41% accuracy [132]. Similarly, Chiao et al. demonstrate that Mask R-CNN can perform joint detection, pixel-level segmentation, and benign/malignant classification on sonograms, reporting $mAP \approx 0.75$ and 85% accuracy [133]. In mammography, Salama and Aly combine a modified U-Net with InceptionV3 in an end-to-end framework, reaching 98.87% accuracy with $AUC \approx 0.988$ on DDSM [134]. Complementing mask-driven pipelines, Singh et al. employ a conditional GAN to generate high-fidelity mass masks that inform a shape-aware CNN, achieving Dice = 0.94, $IoU = 0.87$, and 80% accuracy for shape classification [135]; Figure 17 illustrates the workflow of this approach. For DCE-MRI segmentation, El Adoui et al. report that U-Net outperforms SegNet (mean IoU 76.14% vs. 68.88%) [136]. Earlier hybrid pipelines, such as Rouhi et al. [137], coupled region-growing and cellular neural network segmentation with genetic algorithm feature selection, achieving 96.47% accuracy on mammograms and foreshadowing today's lesion-guided learning strategies. Beyond X-ray imaging, thermal CAD has also benefited from CNNs, with a custom architecture reaching 92% accuracy through aggressive augmentation [138]. Meanwhile, U-Net has shown strong performance for automated mammographic mass segmentation (Dice = 0.951, $IoU = 0.909$) [139]. In histopathology, subtype classification has likewise been strengthened by transfer learning, where a fine-tuned DenseNet achieved 95.4% accuracy across multiple tumour categories [140].

More recent developments further strengthen the evidence that segmentation-informed supervision improves classification. Tsochatzidis et al. enhance ResNet-50 by concatenating segmentation masks at each layer and optimising a spatially aware loss, increasing mass-classification AUC from approximately 0.84 to 0.90 on DDSM and CBIS-DDSM [141]. Heenaye-Mamode Khan et al. introduce an adaptive learning-rate strategy within ResNet-50 to improve four-way abnormality classification (masses, calcifications, carcinomas, and asymmetry), raising accuracy from 81.5% to 88% [142]. Aumente-Maestro et al. propose a multi-task framework that jointly learns segmentation and classification, demonstrating that shared representations can improve both interpretability and diagnostic prediction while cautioning that dataset integrity issues (e.g., duplication in BUSI) may inflate reported performance [143]. In a modular workflow closer to clinical deployment, Islam et al. combine U-Net segmentation with an ensemble CNN classifier (MobileNet and Xception), reinforcing the value of lesion-focused refinement while enabling visual explanation via Grad-CAM [144]. UCapsNet extends this two-stage paradigm by integrating an enhanced U-Net for lesion delineation with a capsule-based classifier, aiming to preserve spatial hierarchies and reduce information loss associated with pooling-based CNNs [145]. Beyond architectural refinements, CNN-centric pipelines are increasingly strengthened through training strategies that address limited labels and distribution shift. For example, self-supervised learning for breast tumour segmentation in DCE-MRI incorporates pretext tasks such as global content perception and peritumoral restoration to improve representation quality under scarce supervision. Likewise, contrastive learning has been explored as an effective domain adaptation mechanism for 2D mammography classification, where supervised contrastive objectives improve cross-domain feature alignment. Relatedly, Self-AdaptNet formalises a CNN-centred self-supervised adversarial adaptation framework that combines contrastive representation learning (e.g., SimCLR/BYOL-style pretraining) with adversarial domain alignment to improve generalisation in breast cancer detection. Table 11 has summarised the key takeaways for the studies reviewed in this section. Collectively, these studies indicate that contemporary gains in CNN-based breast imaging arise not solely from deeper backbones, but from lesion-aware supervision, multi-task optimisation, ensemble learning, contrastive representation learning, and domain adapta-

tion—reinforcing review findings that position CNNs as dominant while also reflecting a clear shift toward hybrid and self-supervised systems in modern breast cancer diagnosis.

(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)
Image	Original MG image	GTM	FCN (with Aug.)	Dilated-Net (with Aug.)	SegNet (with Aug.)	RG	U-Net (with Aug.)	Proposed Vanilla U-Net (no Aug.)	Proposed Vanilla U-Net (with Aug.)	Faster R-CNN (with Aug.)
1										
			DI=0.830 IOU=0.711	DI=0.826 IOU=0.703	DI=0.831 IOU=0.710	DI=0.328 IOU=0.196	DI=0.838 IOU=0.722	DI=0.851 IOU=0.740	DI=0.931 IOU=0.871	IOU=0.732
			DI=0.812 IOU=0.684	DI=0.073 IOU=0.038	DI=0.828 IOU=0.706	DI=0.355 IOU=0.215	DI=0.833 IOU=0.714	DI=0.838 IOU=0.722	DI=0.933 IOU=0.871	IOU=0.425
2										
			DI=0.925 IOU=0.860	DI=0.881 IOU=0.787	DI=0.932 IOU=0.873	DI=0.675 IOU=0.510	DI=0.938 IOU=0.883	DI=0.939 IOU=0.884	DI=0.960 IOU=0.923	IOU=0.756
			DI=0.921 IOU=0.853	DI=0.900 IOU=0.817	DI=0.945 IOU=0.896	DI=0.575 IOU=0.403	DI=0.951 IOU=0.906	DI=0.951 IOU=0.907	DI=0.962 IOU=0.927	IOU=0.768
3										
			DI=0.784 IOU=0.644	DI=0.562 IOU=0.391	DI=0.788 IOU=0.651	DI=0.214 IOU=0.120	DI=0.790 IOU=0.653	DI=0.805 IOU=0.674	DI=0.830 IOU=0.709	IOU=0.485
			DI=0.787 IOU=0.649	DI=0.754 IOU=0.606	DI=0.754 IOU=0.605	DI=0.131 IOU=0.070	DI=0.762 IOU=0.615	DI=0.787 IOU=0.689	DI=0.789 IOU=0.651	IOU=0.276
4										
			DI=0.883 IOU=0.790	DI=0.856 IOU=0.748	DI=0.911 IOU=0.836	DI=0.590 IOU=0.418	DI=0.907 IOU=0.830	DI=0.912 IOU=0.838	DI=0.963 IOU=0.929	IOU=0.561
			DI=0.905 IOU=0.827	DI=0.516 IOU=0.347	DI=0.820 IOU=0.695	DI=0.460 IOU=0.298	DI=0.909 IOU=0.834	DI=0.911 IOU=0.836	DI=0.949 IOU=0.903	IOU=0.655

Figure 16. Comparison study of different state-of-the-art methods. (a) Image index, (b) the original FFDM MG images from the INbreast database (the red rectangles show the location of the BBs of the ground truth lesions), (c) the GTMs given by radiologists, (d) the FCN model, (e) the Dilated-Net model, (f) the SegNet model, (g) the RG method, (h) U-Net model trained with the augmented dataset, (i) the proposed Vanilla U-Net model without augmentation, (j) the proposed Vanilla U-Net model trained with the augmented dataset, and finally (k) the Faster R-CNN model trained with the augmented dataset [139].

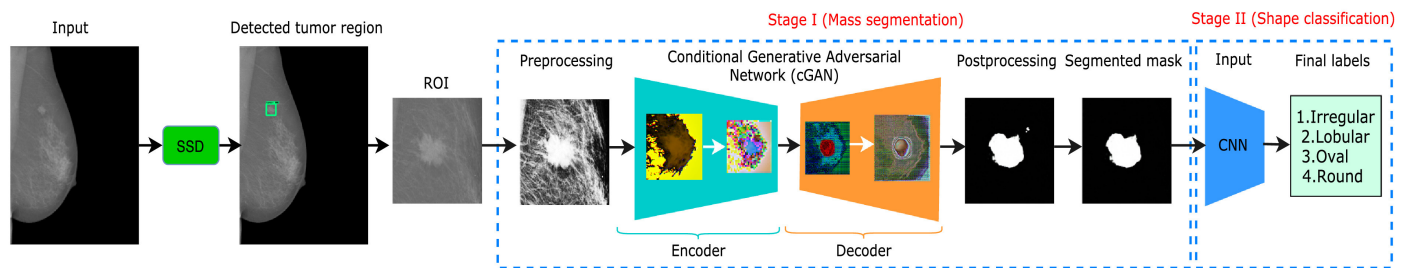


Figure 17. Automatic Automatic workflow for breast tumour segmentation and shape classification using a conditional generative adversarial network (cGAN) and a convolutional neural network (CNN). Stage I performs mass segmentation, including preprocessing, cGAN-based encoder–decoder segmentation, and postprocessing to obtain a binary tumour mask. Stage II performs shape classification based on the segmented tumour. Different colours denote functional modules in the pipeline, while the green box lists the final tumour shape categories (irregular, lobular, oval, and round) predicted by the CNN [135].

Table 11. Summary of CNN-based literature reviewed.

Study	Year	Modality	Model/Framework	Key Results
Castiglioni et al. [126]	2021	Multi-modal	U-Net family (U-Net, 3D U-Net, Attention U-Net)	-
Suzuki [127]	2017	Multi-modal	Deep CNNs vs. classical ML/MTANN comparison	-
Lundervold [128]	2019	MRI	CNN variants (U-Net, V-Net, QSMnet) across workflow	-
Raghu et al. [129]	2020	Medical imaging (general)	Transfer learning analysis (e.g., ResNet, VGG)	-
Wang et al. [130]	2021	Mammography, Ultrasound, MRI	Fine-tuned ResNet-50, InceptionV3 for breast image classification	High sensitivity/specificity reported
Ben et al. [131]	2024	Breast MRI (DCE-MRI implied)	CNN-based automated lesion segmentation (vs. SVM+wavelets)	-
Rouhi et al. [137]	2015	Mammography	Region-growing + Cellular Neural Network + Genetic Algorithm feature selection	Accuracy = 96.47%
Chiao et al. [133]	2019	Ultrasound	Mask R-CNN (detection + segmentation + classification)	$mAP \approx 0.75$, Accuracy = 85%
Singh et al. [135]	2019	Mammography	cGAN-generated mass masks + shape-aware CNN	Dice = 0.94, IoU = 0.87, Shape accuracy = 80%
El Adoui et al. [136]	2019	DCE-MRI	U-Net vs. SegNet segmentation comparison	Mean IoU = 76.14% (U-Net) vs. 68.88% (SegNet)
Abdelhafiz et al. [139]	2020	Mammography	U-Net for automated mass segmentation	Dice = 0.951, IoU = 0.909
Nawaz et al. [140]	2018	Histopathology	Fine-tuned DenseNet for subtype classification	Accuracy = 95.4%
Zuluaga-Gomez et al. [138]	2021	Thermography	Custom CNN with aggressive augmentation	Accuracy = 92%
Salama & Aly [134]	2021	Mammography (DDSM)	Modified U-Net + InceptionV3 end-to-end pipeline	Accuracy = 98.87%, AUC $\approx$ 0.988
Hossain et al. [132]	2023	Ultrasound	RKO-UNet + spatial/channel self-attention + CNN classifier	Accuracy = 98.41%
Tsochatzidis et al. [141]	2021	Mammography (DDSM/CBIS-DDSM)	ResNet-50 + segmentation mask concatenation + spatially-aware loss	AUC $\approx$ 0.84 $\rightarrow$ $\approx$ 0.90
Heenaye-Mamode Khan et al. [142]	2021	Mammography	ResNet-50 + adaptive learning-rate strategy	Accuracy = 81.5% $\rightarrow$ 88%
Islam et al. [144]	2024	Ultrasound	U-Net + Ensemble CNN classifier (MobileNet + Xception) + Grad-CAM	-
Madhu et al. [145]	2024	Ultrasound (implied)	UCapsNet (Enhanced U-Net + Capsule classifier)	-
Aumente-Maestro et al. [143]	2025	Ultrasound (BUSI discussed)	Multi-task segmentation + classification + dataset integrity analysis	-

5.2. Recurrent Neural Network (RNN)

Several recent studies have demonstrated the efficacy of recurrent neural network (RNN) architectures—particularly LSTM and BiLSTM variants—when combined with convolutional and attention mechanisms for breast cancer imaging. Patil and Biradar [146] introduced a hybrid CNN–RNN model in which an RNN branch processes sequential GLCM/GLRM texture features alongside a CNN branch on segmented mammograms, with both components’ architectures jointly optimised via a firefly–chicken swarm algorithm, yielding marked accuracy gains on the MIAS dataset. Pan et al. [147] embedded a spatial–channel attention bidirectional LSTM module (SC-FCN-BLSTM) within a fully convolutional encoder–decoder for automated whole-breast ultrasound, capturing inter-slice context to achieve a Dice score of 0.8178. Figure 18 shows the whole architecture of this novel model. Tripathi et al. [148] proposed a context-based patch modelling approach in histopathology, ordering variable-size patches into sequences fed to a BiLSTM, an end-to-end scheme that reached 90% accuracy on microscopy images and 84% on whole-slide regions. Building on this, Srikantamurthy et al. [149] leveraged ImageNet-pretrained CNN features as inputs to an LSTM for multi-magnification subtype classification on BreakHis, achieving 99% binary and 92.5% four-class accuracy. Paul and Preethi [150] combined an LS-CED–based segmentation pipeline with a wildebeest herd–optimised RNN classifier (WHO-RNN), reporting 97.9% overall accuracy in their histopathology cohort. Zheng et al. [151] proposed a DLA-EABA pipeline that combined stacked sparse autoencoders, an LSTM layer, and an AdaBoost ensemble, achieving 97.2% precision in the Cancer Imaging Archive dataset. Aslan et al. [152] demonstrated that augmenting a CNN with a bidirectional LSTM increased the mammogram classification accuracy from 97.6% (CNN alone) to 98.56% in MIAS and INbreast. Saha and Chakraborty’s Her2Net incorporated trapezoidal LSTM blocks into a semantic-segmentation encoder–decoder for HER2-stained histopathology, yielding 98.3% accuracy and a 96.8% F1-score [153]. Yao et al. designed a parallel CNN–LSTM architecture with attention and switchable normalisation, surpassing IRRCNN benchmarks (e.g., >98.6% accuracy) on BACH2018 and Bioimaging2015 [154]. Finally, Malebary and Hashmi fused k-means segmentation, CNN feature extraction, and an LSTM-based ensemble classifier to achieve 96–98% accuracies and AUCs above 0.94 on DDSM and MIAS [155]. Duraisamy and Emperumal first applied Chan–Vese level-set segmentation to delineate fuzzy lesion boundaries and then refined these regions using a CNN augmented with LSTM modules for benign-vs-malignant discrimination [156]. Patil et al. introduced a holistically nested edge detector to generate attention maps, followed by region growing with adaptive fuzzy C-means—optimally tuned via a grasshopper-inspired metaheuristic—and an RNN classifier, yielding several points of improvement over traditional thresholding and neural baselines [157]. Ranjbarzadeh et al. leveraged U-Net++’s dense skip-connections for fine-grained ultrasound segmentation (and ported to mammograms), fusing multiple encoded feature maps through a cascade of lightweight CNNs for enhanced lesion delineation [158]. On the feature engineering front, Begum and Lakshmi extracted dominant wavelet-based textures and then selected them via an oppositional GSA before RNN-based binary classification, demonstrating the effectiveness of hand-crafted features in lightweight models [159]. Finally, Kaddes et al. achieved near-state-of-the-art results (around 99.9% accuracy) by combining CNN-derived spatial representations with an LSTM to model sequential patch dependencies across the mammogram, underscoring the power of hybrid CNN–LSTM architectures when large annotated datasets are available [160]. Across public benchmarks such as BUSI, MIAS, and DDSM, these pipelines report accuracy and AUC gains—often exceeding 95%—highlighting how attention-guided segmentation, meta-heuristic optimisation, and sequence modelling collectively push mammogram CAD toward clinical viability. Figure 19 lists the segmented results of breast

mammogram images that use a novel Grey-Level Co-occurrence Matrix (GLCM) model. Different to the CNN methods, RNN methods are often applied in combination with CNN or other deep learning models and specifically in breast diagnosis, RNN is more commonly applied for pathology image analysis.

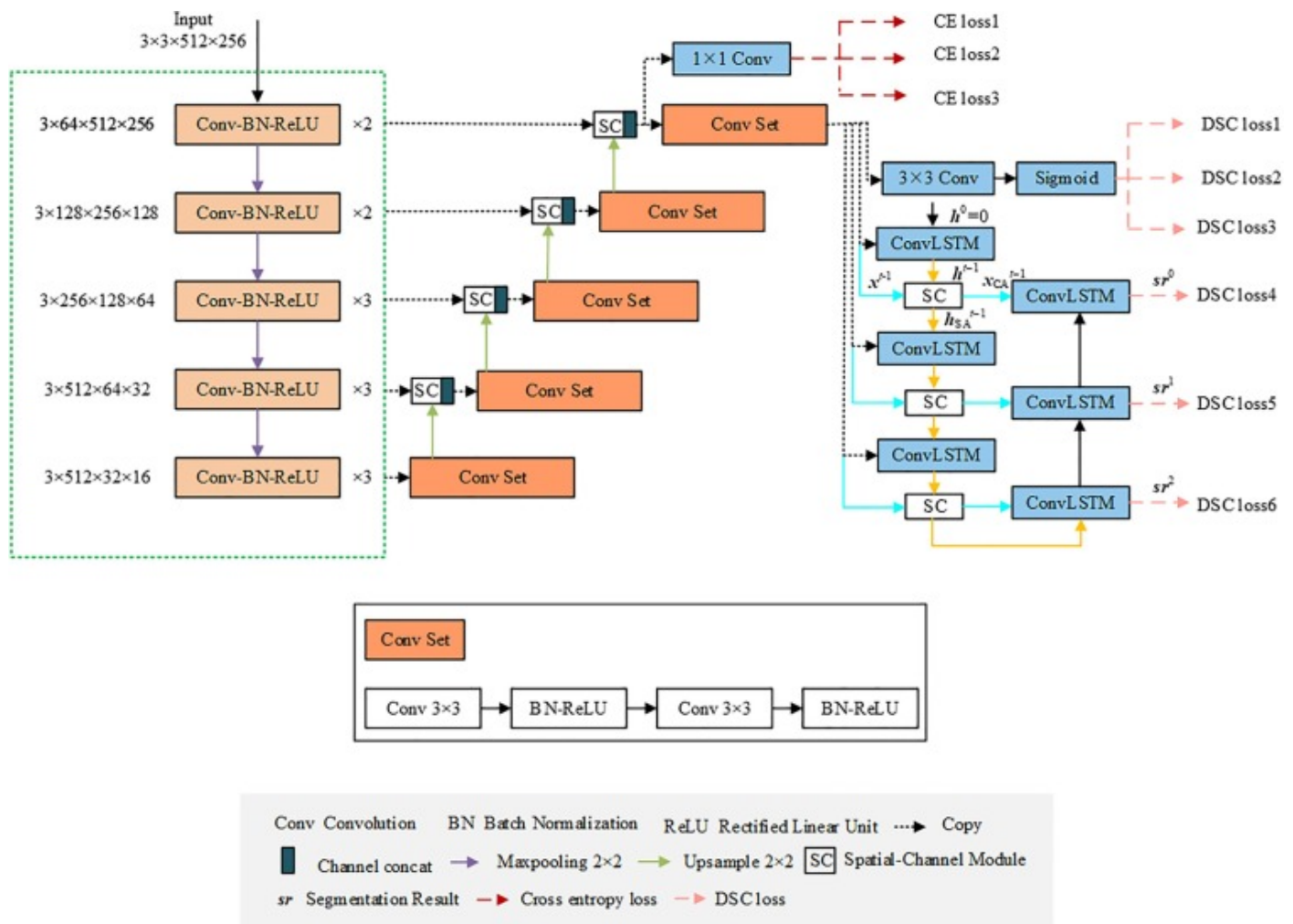


Figure 18. Architecture of SC-FCN-BLSTM [147].

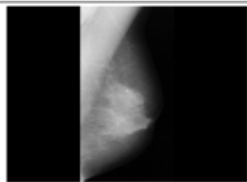
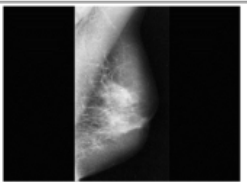
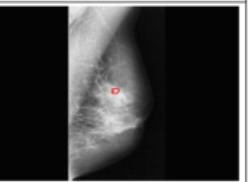
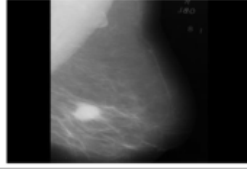
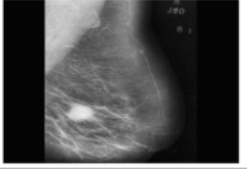
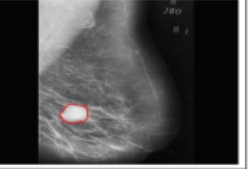
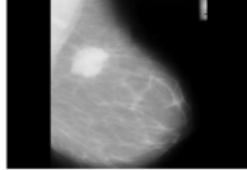
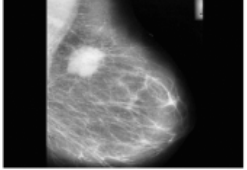
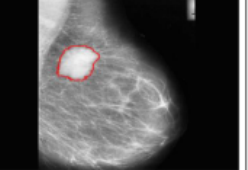
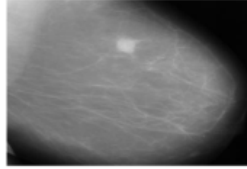
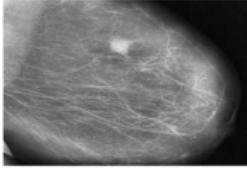
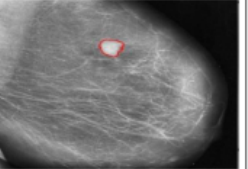
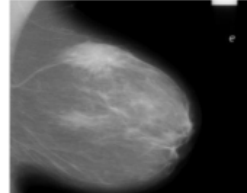
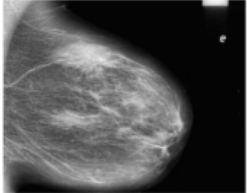
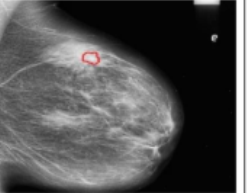
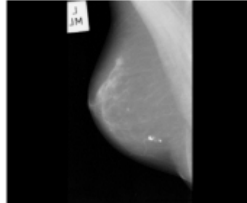
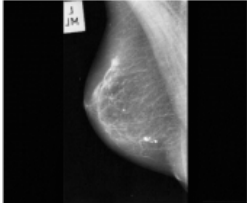
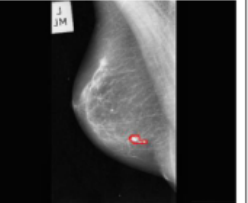
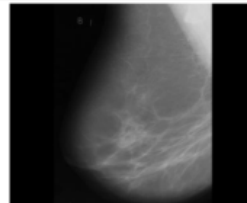
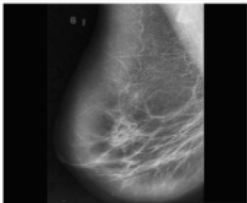
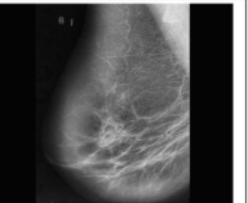
S. No	Abnormality	Input Image	Enhanced Image	Segmented image
1	Calcification (Benign (Normal))			
2	Well-defined/ circumscribed masses (Malignant)			
3	Speculated masses (Malignant)			
4	Other, ill- defined masses (Malignant)			
5	Architectural distortion (Benign (Normal))			
6	Asymmetry (Malignant)			
7	Normal			

Figure 19. Segmented results of breast mammogram by using RNN [161].

5.3. Transformers

Transformers, originally developed for natural language processing, have rapidly gained traction in medical imaging because of their ability to capture long-range dependencies and global contextual information that are often under-modelled by convolutional neural networks (CNNs). Figure 20 shows an example of input patches generation for the vision transformer. Using the standard Vision Transformer (ViT) architecture as an example, ViT first splits the input image into a sequence of fixed-size patches (e.g., $n \times 16 \times 16$). Each patch is then flattened and projected into a fixed-length embedding vector. A learnable class token is appended to the patch embeddings, after which positional embeddings are added to preserve spatial information across the sequence. And Figure 21 illustrates the

workflow of the transformer; multiple encoder blocks can be stacked sequentially, and the total number of stacked encoders is a key hyperparameter that largely determines the transformer's depth. Within the multi-head attention module, the number of attention heads is another crucial parameter, and together with the encoder depth, it defines the overall model capacity and scale of the transformer [162]. In breast cancer diagnostics, this capability has proven particularly valuable across imaging modalities, including mammography, thermography, digital breast tomosynthesis (DBT), histopathology, and MRI, where malignancy-related cues can be subtle, spatially distributed, and dependent on broader tissue structure rather than purely local texture patterns. Early work in mammography highlighted the limitations of CNN-centric approaches in learning global inter-view relationships, motivating transformer-based multi-view reasoning; for instance, Chen et al. [163] proposed a multi-view vision transformer (MVT) to process unregistered four-view mammograms jointly by combining local transformer blocks for intra-view dependencies with global blocks for inter-view dependency modelling, achieving an AUC of 0.818 and outperforming multi-view CNN baselines (AUC 0.784), thereby demonstrating the clinical relevance of attention-based contextual fusion for routine screening. In DBT, where volumetric imaging increases lesion visibility but complicates analysis due to the multi-slice structure, Kassis et al. [164] employed Swin Transformers for tumour detection using slice-level processing and cross-slice contextual reasoning, reporting an AUC of 0.934 at high resolution and outperforming both ResNet101 and vanilla ViT, while also showing that resolution scaling significantly enhances transformer performance and supports scalability for high-dimensional medical data. In parallel, hybrid Transformer–CNN paradigms have become increasingly prominent to balance CNNs' strong local inductive bias with transformers' global reasoning ability; Mahoro and Akhloufi [165] integrated TransUNet-based segmentation in breast thermography to remove irrelevant background before downstream classification, achieving accuracies above 97% for distinguishing healthy, sick, and uncertain cases, while Khan et al. [166] combined ViT-L16 attention representations with ResNet50 and EfficientNetB1 using a ProDense block and stack-ensemble strategy to reach 98.08% accuracy on the INbreast dataset. In mammography, PatchCascade-ViT proposes a self-supervised Vision Transformer pipeline combined with cascade learning for BI-RADS mammographic classification, reflecting an emerging trend where patch-level pretraining and staged decision refinement are used to improve diagnostic robustness and label efficiency [167]. Similarly, HybMNet presents a hybrid architecture that integrates Swin Transformer components with CNN feature extraction under a self-supervised pretraining strategy, illustrating how hierarchical Transformers (Swin-style window attention) can complement convolutional locality to support mammography classification [168]. This wider trend is consistent with transformer-centric evidence from the papers uploaded today, where transformer variants are empirically benchmarked for breast histopathology classification: a comparative evaluation of ViT and multiple transformer architectures (PiT, CvT, CrossFormer, CrossViT, NesT, MaxViT, and SepViT) demonstrated that hierarchical or structurally aware designs such as MaxViT, NesT, and CvT offer stronger and more reliable classification performance, while standard ViT-like models may exhibit weaker generalisation under certain training conditions [169].

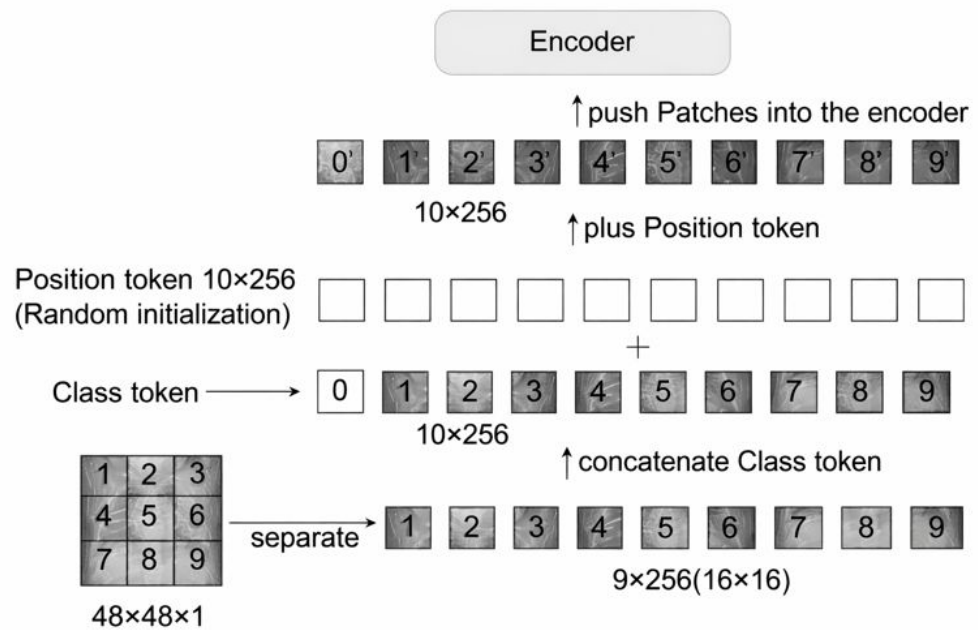


Figure 20. Example of input patches generation for Vision Transformer [162].

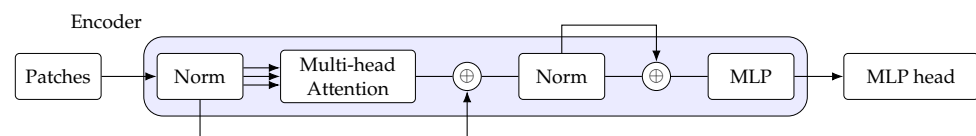


Figure 21. The Workflow of a Vision Transformer. Arrows indicate the forward flow of patch embeddings through layer normalisation, multi-head self-attention, and MLP blocks. The circled "+" symbols denote residual (skip) connections that add the block input to its output, facilitating stable optimisation.

Furthermore, narrative synthesis within recent state-of-the-art imaging reviews also emphasises the emergence of vision transformers as a major trend in breast imaging research, while noting persistent barriers to real-world deployment such as interpretability, limited prospective clinical validation, and variability across scanners and cohorts [170]. Beyond mammography and histopathology, transformer models are also beginning to extend into MRI-based breast cancer analysis, where emerging transformer architectures may provide a more effective mechanism for integrating spatiotemporal relationships in DCE-MRI compared to earlier CNN- and SVM-dominated feature learning. Table 12 summarises representative transformer-based breast cancer imaging studies reviewed in this section, including datasets, tasks, and reported performance. Collectively, these studies establish transformers as a powerful alternative or complement to CNNs in breast cancer diagnostics, primarily through: (1) modelling long-range and multi-view dependencies without explicit image registration, (2) adapting effectively to 2D, 3D, and sequential imaging settings, and (3) enabling hybrid or ensemble combinations that integrate global attention with local feature extraction; however, challenges remain in data scarcity, interpretability, and clinical generalisation, reinforcing the need for large-scale pretraining, domain-robust evaluation, and multi-centre validation.

Table 12. Summary of transformer-based literature reviewed for breast cancer imaging.

Study	Year	Model/Framework	Key Results
Chen et al. [163]	2022	Multi-view Vision Transformer (MVT) with local (intra-view) and global (inter-view) transformer blocks for four-view mammograms	AUC = 0.818; outperforming multi-view CNN baseline AUC = 0.784
Kassis et al. [164]	2024	Swin Transformer for DBT tumour detection with slice-level processing and cross-slice contextual reasoning	AUC = 0.934 (high-resolution setting); outperforming ResNet101 and vanilla ViT
Mahoro & Akhloufi [165]	2024	TransUNet-based segmentation + downstream classification pipeline for breast thermography (background removal prior to classification)	Accuracy > 97% (healthy vs. sick vs. uncertain classification)
Khan et al. [166]	2025	Hybrid/ensemble framework combining ViT-L16 attention representations with ResNet50 and EfficientNetB1 using ProDense block and stack-ensemble strategy	Accuracy = 98.08% on INbreast dataset
Chen et al. [167]	2025	PatchCascade-ViT: self-supervised Vision Transformer + cascade learning for BI-RADS mammography classification	-
Abdallah et al. [168]	2025	HybMNet: hybrid CNN + Swin Transformer components with self-supervised pretraining for mammography classification	-
Sriwastawa et al. [169]	2024	Comparative benchmarking of transformer architectures for breast histopathology classification (ViT, PiT, CvT, CrossFormer, CrossViT, NesT, MaxViT, SepViT)	-
Carriero et al. [170]	2024	Review synthesis of deep learning trends in breast imaging (emphasis on vision transformers, deployment barriers)	-

5.4. State-of-the-Art and Foundation Models

Recent evaluations of state-of-the-art (SOTA) deep learning and foundation models reveal a shift from narrowly optimised, task-specific performance toward robustness, label efficiency, and cross-domain generalisation. Conventional supervised architectures, including CNN- and U-Net-based models, continue to report strong Dice and AUC values on curated benchmarks, yet their evaluation typically remains confined to single-task, in-distribution testing. Frameworks such as nnU-Net demonstrate that automated configuration can yield consistently high segmentation accuracy across diverse datasets; however, these evaluations still rely on dataset-specific retraining, limiting insight into generalisability under domain shift [171]. Foundation models introduce broader evaluation criteria that emphasise cross-task robustness and reduced annotation dependence. Promptable models derived from SAM have been extensively evaluated on medical datasets, where out-of-the-box performance is inconsistent—particularly for low-contrast lesions and weak boundaries—highlighting that zero-shot capability alone is insufficient for clinical-grade deployment without domain adaptation [172]. In contrast, MedSAM, fine-tuned on more than 1.57 million medical image–mask pairs, demonstrates improved stability and accuracy across 86 internal and 60 external validation tasks, frequently matching or surpassing modality-specific specialist models. The scale and diversity of these evaluations provide stronger evidence of robustness than traditional single-dataset benchmarks [173].

More recent extensions, such as MedSAM-2 further broaden evaluation paradigms by incorporating minimal-prompt and cross-slice generalisation criteria. By reformulating 2D and 3D medical segmentation as a video-tracking problem, MedSAM-2 achieves new SOTA performance across multiple benchmarks while substantially reducing user interaction. Importantly, its evaluations include breast cancer datasets in both 2D and 3D settings, demon-

strating reliable tumour delineation from a single prompt across entire volumes, an operational advantage rarely captured in classical segmentation studies [174]. Self-supervised foundation models shift evaluation emphasis toward label efficiency and out-of-distribution performance. The 3DINO-ViT framework, pretrained on nearly 100,000 unlabeled CT and MRI volumes, consistently outperforms supervised and transfer-learning baselines across segmentation and classification tasks, particularly when trained with limited annotated data. Reported Dice improvements of up to 13–55% over random initialisation indicate that large-scale self-supervised pretraining provides measurable gains beyond architectural choice alone. Notably, 3DINO-ViT generalises effectively to 3D breast ultrasound tumour segmentation, supporting its suitability for breast imaging scenarios where annotations are scarce or costly [175].

Across breast cancer modalities—including mammography, ultrasound, and MRI—evaluation evidence suggests that foundation models are less distinguished by marginal gains in peak accuracy than by stable cross-modality performance, improved label efficiency, and reduced interaction cost. These properties directly address long-standing challenges in breast cancer imaging, such as heterogeneous acquisition protocols, rare tumour subtypes, and inter-institutional variability. Nevertheless, current evaluations remain largely retrospective, with limited prospective or multi-centre clinical validation. Consequently, recent reviews emphasise that foundation models should be regarded as complementary to task-specific models, with careful fine-tuning, validation, and governance required for safety-critical clinical deployment [176].

5.5. Datasets and Evaluation Metrics

Although deep learning studies in breast cancer imaging frequently report strong quantitative performance across diverse datasets and modalities, the clinical interpretation of these results requires careful consideration. In particular, breast cancer screening and diagnostic datasets are often highly imbalanced, meaning that accuracy can be misleading, as high values may simply reflect correct predictions on the dominant negative/benign class while masking poor malignant-case detection. For this reason, most studies additionally report sensitivity, specificity, and F1-score, alongside segmentation measures such as Dice and IoU and general discriminative indicators such as AUC. Among these, AUC remains one of the most commonly reported metrics because it provides a threshold-independent summary of performance and enables comparison across studies. However, AUC alone is not sufficient for clinical translation, as it does not reflect performance at a clinically relevant operating point and may remain high despite inadequate sensitivity in the low false-positive regions required for screening. Moreover, improvements in offline metrics do not necessarily imply real-world benefit, since deployment depends on whether an AI system enhances radiologist decision-making under realistic constraints. Consequently, evaluation frameworks increasingly emphasise reader studies and task-based observer performance models, which assess diagnostic performance with and without AI assistance, capturing inter-reader variability and the practical impact on workflow outcomes such as recall rates, reading time, and missed-cancer reduction. Additionally, the clinical usefulness of AI outputs depends not only on discrimination but also on probability calibration and threshold selection, as poorly calibrated models may produce overconfident malignancy risk estimates that distort decision-making. Therefore, clinically meaningful validation should include threshold-based reporting (e.g., at high-sensitivity operating points), calibration assessments, and external testing across multi-centre cohorts. These considerations highlight why strong performance on public benchmarks may not generalise to real-world populations, reinforcing the need for large-scale, diverse, and consistently annotated datasets, as summarised in Table 13.

Table 13. Summary of datasets and evaluation metrics in reviewed deep learning studies.

Modality	Common Datasets	Evaluation Metrics	Dataset Assessment
Mammography	DDSM, CBIS-DDSM, INbreast, MIAS	Accuracy, Sensitivity, Specificity, AUC, Dice, IoU	Public and widely used, enabling benchmarking; however, some are small (MIAS) and imbalanced.
Ultrasound	BUSI, institutional datasets	Accuracy, F1-score, Sensitivity, Specificity, Dice	Useful for lesion detection, but limited size and diversity; high variability across institutions.
MRI	Institutional DCE-MRI cohorts, small public sets	Dice, IoU, AHD, AUC	High-resolution data, but scarce public datasets; single-institution bias reduces generalisability.
Histopathology	BreakHis, BACH2018, Bioimaging2015	Accuracy, Precision, Recall, F1-score, AUC	Large number of images and magnifications; strong benchmarks, though annotation variability exists.
Other (Thermal, DBT)	Institutional thermal datasets, DBT cohorts	Accuracy, AUC, mAP	Emerging modalities; datasets are small and lack standardisation, limiting robustness.

6. Discussion

6.1. Classical and Deep Learning Methods: Performance and Trade-Offs

The comparative analysis of classical image processing and modern deep learning methods in breast cancer imaging highlights a series of important trade-offs between interpretability, accuracy, and clinical usability. Classical methods—including thresholding, texture analysis, and wavelet-based transforms—remain attractive due to their lower computational cost, robustness in smaller datasets, and clinician-friendly interpretability. These characteristics make them suitable as strong baselines in data-scarce or resource-constrained environments. However, their performance often saturates when faced with the heterogeneity of tumour appearance and complex background tissues, limiting their scalability in real-world clinical settings. Moreover, many classical pipelines rely on manually engineered descriptors and empirically selected hyperparameters, which may be sensitive to differences in image acquisition, scanner settings, and population characteristics, thereby reducing reproducibility across institutions.

Recent work in mammography further confirms the shift toward deep learning-based methods. Tsochatzidis et al. showed that convolutional neural networks (CNNs) consistently outperform handcrafted descriptors for lesion classification, particularly when fine-tuning pre-trained architectures on medical imaging datasets [141,177]. Their analysis indicates that fine-tuned backbones such as ResNet and VGG generally achieve higher AUCs than models trained from scratch, which is particularly important given the limited availability of large, fully annotated mammography cohorts. This dependence on transfer learning reflects both the flexibility and the data demands of deep learning, as strong performance typically requires either large-scale pre-training or carefully designed regularisation strategies to prevent overfitting. Nevertheless, transfer learning alone does not eliminate generalisation limitations, as pre-trained representations may still struggle with

subtle malignant patterns such as microcalcifications, architectural distortions, or lesions embedded in dense breast tissue.

A similar trend is observed in histopathological imaging. Sharma and Mehra compared handcrafted features (Hu moments, Haralick textures, and colour histograms) with transfer learning pipelines based on VGG16, VGG19, and ResNet50 [178]. Their results suggest that classical features combined with standard classifiers (e.g., SVM and Random Forest) can deliver competitive baseline accuracies (approximately 85–90%), while transfer learning approaches achieve consistently higher performance, exceeding 93% in patch-level classification. Although augmentation and balanced sampling help reduce overfitting and mitigate class imbalance, patch-level performance does not fully capture clinical diagnostic reasoning, which is inherently multi-scale and contextual, requiring integration of tissue architecture, cellular morphology, and tumour microenvironment cues.

Boumaraf et al. extended these comparisons by combining high-performing CNN classifiers with explainability mechanisms such as Grad-CAM visualisation [179]. While CNN-based approaches substantially outperform conventional machine learning models on datasets such as BreaKHis and KIMIA Path960 (up to 98% binary accuracy compared to 87–89% with classical classifiers), explainability methods introduce additional trade-offs. Visual saliency maps may support transparency and clinician engagement, yet they remain sensitive to perturbations and do not necessarily correspond to causal evidence, meaning that interpretability should be treated as supportive rather than definitive validation of clinical reliability.

6.2. Clinical Reality: Evaluation Gaps and Failure Modes

Despite steadily improving diagnostic and segmentation performance reported in the literature, clinical evidence indicates a substantial gap between algorithmic performance in retrospective studies and robust behaviour in real-world practice. Many deep learning models are evaluated on carefully curated datasets with balanced classes and homogeneous acquisition protocols, conditions that rarely reflect routine screening or diagnostic workflows. As a result, reported AUC or Dice scores may overestimate robustness when models are deployed across institutions.

Clinical reviews emphasise that overfitting to institutional data, class imbalance favouring malignant findings, and implicit biases in dataset composition frequently lead to reduced generalisation when models are applied across centres or populations [180,181]. In breast imaging, these limitations are amplified by variability in breast density, scanner vendors, compression techniques, and noise characteristics, which can result in unstable false-positive rates and reduced clinician trust despite high reported performance metrics [182].

Beyond algorithmic accuracy, robust clinical validation and regulatory readiness are critical for adoption. Many investigations remain retrospective and benchmark-focused, with limited external validation across scanner vendors, acquisition protocols, and patient demographics. Clinically deployable systems require multi-centre evaluation and prospective evidence demonstrating consistent benefit under realistic workflow conditions. These requirements are closely related to regulatory pathways for medical AI, including FDA clearance and CE marking, which increasingly emphasise transparency, robustness, calibration, and post-deployment monitoring to manage performance drift. In parallel, fairness considerations are increasingly important, as dataset composition can introduce hidden biases related to age, ethnicity, breast density distribution, and imaging vendor variation. Without systematic auditing and stratified evaluation, models risk reduced reliability in underrepresented subgroups, thereby amplifying disparities in diagnostic accuracy.

6.3. From Deep Learning to Foundation Models: Limitations and Future Directions

Taken together, the studies reviewed in this work indicate that classical methods, task-specific deep learning models, and emerging foundation models should be viewed as complementary rather than mutually exclusive. Classical approaches offer interpretability and stability but fail to scale to heterogeneous clinical data. Task-specific deep learning architectures represent the current state of the art in performance but remain sensitive to annotation availability, domain shift, and dataset bias. Foundation models promise improved generalisation and label efficiency, yet introduce new trade-offs, including increased computational cost, reduced transparency, and more complex deployment and governance requirements.

Several structural barriers continue to limit real-world translation. Data sharing restrictions and privacy concerns remain major obstacles to building sufficiently diverse training cohorts, and while federated learning offers a promising solution, its adoption in breast imaging remains relatively limited. Breast cancer diagnosis is inherently multimodal, yet many studies remain focused on single-modality inputs, underscoring the need for multimodal fusion strategies that integrate imaging with MRI multiparametric sequences, ultrasound correlation, pathology confirmation, radiology reports, and genetic risk factors. Furthermore, heavy reliance on fully supervised learning persists despite the scarcity of high-quality pixel-level or slide-level annotations, highlighting the importance of weakly supervised, semi-supervised, and self-supervised learning to improve scalability and reduce annotation burden. Uncertainty quantification also remains underexplored, even though uncertainty-aware modelling could support safer clinical decision-making by flagging ambiguous cases and reducing overconfident predictions.

Overall, the key challenge is not only to close the gap between performance and interpretability, but also to bridge the divide between retrospective benchmark success and clinically safe deployment. Future research should prioritise multi-centre data strategies, privacy-preserving learning, multimodal integration, annotation-efficient training, uncertainty-aware decision support, and fairness-aware validation. These advances will be essential for transforming computational breast cancer imaging methods from research prototypes into trustworthy clinical tools. Table 14 summarises the main differences between classical and deep learning image processing methods and the trade-offs between them.

Table 14. Comparison of classical image processing methods and deep learning methods in breast cancer detection

Aspect	Classical Methods	Deep Learning Methods	Trade-Off
Feature Basis	Handcrafted features (thresholds, edges, textures, wavelets)	Automatically learned features (CNNs, RNNs, Transformers)	Interpretability vs. automation
Segmentation	Thresholding, region growing, watershed, active contours	U-Net, Mask R-CNN, cGANs, CNN–Transformer hybrids	Simplicity vs. precision
Classification	k-NN, SVM, LDA trained on handcrafted features	CNNs (ResNet, Inception), CNN–RNN hybrids, Transformers	Low data needs vs. high accuracy
Performance	Accuracy: 75–93%, Dice $\leq$ 0.94	Accuracy: 95–99%, Dice $\geq$ 0.90, AUC up to 0.98	Moderate accuracy vs. state-of-the-art
Data Needs	Small datasets are sufficient for training	Require large annotated datasets	Resource-efficiency vs. scalability
Computational Cost	Low; feasible on basic hardware	High; requires GPUs and large memory	Feasibility vs. performance
Interpretability	Transparent and clinician-friendly	Black-box, difficult to explain	Trust vs. complexity
Generalisation	Limited cross-dataset transferability	Strong adaptability, but domain-shift sensitive	Stability vs. adaptability

7. Conclusions

This review examined medical image processing approaches for early breast cancer detection across mammography, ultrasound, and MRI, covering both classical image processing techniques and modern deep learning models. Classical methods remain clinically attractive due to their interpretability, low computational demand, and robustness in small or constrained datasets. However, their dependence on handcrafted features and manually tuned parameters limits scalability and performance in heterogeneous clinical settings.

Deep learning approaches, particularly convolutional neural networks and emerging transformer-based models, consistently demonstrate superior performance on benchmark datasets by enabling automated feature learning and improved contextual modelling. Despite these advances, high reported metrics such as AUC and Dice do not necessarily translate into reliable clinical deployment. Many studies remain retrospective and single-centre, with limited dataset diversity, making models vulnerable to overfitting, replication challenges, class imbalance bias, and performance degradation under domain shift. The lack of large-scale prospective validation and limited interpretability further constrain clinical adoption.

Bridging the gap between research performance and clinical utility requires a shift toward standardised evaluation, multi-centre validation, and greater emphasis on robustness and transparency. Future research is expected to focus on multimodal learning that integrates imaging with clinical data, federated learning frameworks that enable privacy-preserving collaboration, weakly supervised and self-supervised methods to reduce annotation burden, and fairness-aware model development to ensure equitable performance across populations.

In summary, AI-driven image processing has strong potential to enhance early breast cancer detection, but its clinical impact will depend on moving beyond benchmark optimisation toward robust, interpretable, and clinically validated systems.

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Abbreviations

The following abbreviations are used in this manuscript:

AHD	Average Hausdorff Distance
AHE	Adaptive Histogram Equalisation
AFDA	Adaptive Fractional-Order Differential Approach
AUC	Area Under the Curve
BHE	Bi-Histogram Equalisation
BI-RADS	Breast Imaging Reporting and Data System
BLIINDS-II	Blind Image Integrity Notator using DCT Statistics-II
BLMM	Bivariate Laplacian Mixture Model
BRISQUE	Blind/Referenceless Image Spatial Quality Evaluator
BUS	Breast Ultrasound
CAD	Computer-Aided Diagnosis
CC	Craniocaudal View

CHE	Cumulative Histogram Equalisation
CLAHE	Contrast-Limited Adaptive Histogram Equalisation
CNN	Convolutional Neural Network
COM	Co-occurrence Matrix
CT	Computed Tomography
DBT	Digital Breast Tomosynthesis
DCIS	Ductal Carcinoma In Situ
DCE-MRI	Dynamic Contrast-Enhanced Magnetic Resonance Imaging
DCT	Discrete Cosine Transform
DFT	Discrete Fourier Transform
DIIVINE	Distortion Identification-based Image Verity and Integrity Evaluation
DSC	Dice Similarity Coefficient
DT-CWT-NLM	Dual-Tree Complex Wavelet Transform with Nonlocal Means
DWCE	Density-Weighted Contrast Enhancement
EM	Expectation-Maximisation
ER	Estrogen Receptor
FFNN	Feed Forward Neural Network
FN	False Negative
FP	False Positive
FR	Full-Reference
FSIM	Feature SIMilarity Index
FFT	Fast Fourier Transform
GA	Genetic Algorithm
GLCM	Grey-Level Co-occurrence Matrix
GLRLM	Grey-Level Run Length Matrix
HE	Histogram Equalisation
IDC	Invasive Ductal Carcinoma
IDC NOS	Invasive Ductal Carcinoma, Not Otherwise Specified
IFC	Information Fidelity Criterion
ILC	Invasive Lobular Carcinoma
IoU	Intersection-over-Union
IQA	Image Quality Assessment
IW-SSIM	Information-Weighted Structural Similarity Index
LAHE	Local Adaptive Histogram Equalisation
MAP	Maximum a Posteriori
MM	Majorise–Minimise
MLO	Mediolateral Oblique View
mAP	mean Average Precision
MRI	Magnetic Resonance Imaging
MS-SSIM	Multiscale Structural Similarity Index
MSCN	Mean-Subtracted Contrast Normalised
MSE	Mean Squared Error
MVT	Multi-view Vision Transformer
NR	No-Reference
NSS	Natural Scene Statistics
PET	Positron Emission Tomography
PET-CT	Positron Emission Tomography–Computed Tomography
PR	Progesterone Receptor
PSF	Point Spread Function
PSNR	Peak Signal-to-Noise Ratio
QDHE	Quadrant Dynamic Histogram Equalisation
RF	Radio Frequency
RFSIM	Riesz Feature Similarity Index
RMSHE	Recursive Mean-Separate Histogram Equalisation

RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic
ROI	Region of Interest
RSIHE	Recursive Sub-Image Histogram Equalisation
SD	Standard Deviation
SSIM	Structural Similarity Index
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
TV	Total Variation
ViT	Vision Transformer
VIF	Visual Information Fidelity
WGN	White Gaussian Noise

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