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# Blood Vessel Segmentation in Breast MRI: Comprehensive Review of Techniques and Challenges

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Angiogenesis is the ongoing formation of new blood vessels from existing ones, occurring throughout life in both healthy and diseased states. Furthermore, it plays a crucial role in the development and progression of breast cancer. Magnetic Resonance Imaging (MRI) is a sensitive, non-invasive technique for monitoring and identifying lesions, establishing it as standard clinical practice. However, its effectiveness in visualizing blood vessels in breast tissue requires further investigation. Blood vessel analysis provides valuable insights into tumor progression and information that can be correlated with the underlying tumor biology. This paper presents a comprehensive review of techniques and methodologies. A key contribution of this work is the proposal of a consolidated workflow that synthesizes the strengths of the various approaches reviewed, offering a more integrated solution to blood vessel segmentation in breast MRI. The paper also examines the challenges and limitations in this field, including image quality, algorithmic constraints, anatomical complexities, and data scarcity. Our study identifies ongoing issues, particularly the need for robust evaluation metrics and standardized datasets. Addressing these issues is essential for driving future advancements in breast MRI vessel segmentation and improving clinical outcomes.

**Keywords:** *breast MRI; breast cancer; blood vessel segmentation; angiogenesis.*

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## 1. Introduction

Breast cancer is the leading cause of cancer-related death among women worldwide. In 2022, 2.3 million women were diagnosed with breast cancer, resulting in 670 000 global deaths [1]. Addressing late-stage breast cancer diagnosis is critical for improving outcomes [2]. The World Health Organization (WHO) recommends two strategies: early diagnosis to identify symptomatic cancer sooner and screening to detect asymptomatic disease in targeted populations, enhancing early cancer detection [3, 4].

### 1.1. Angiogenesis and progression of breast cancer

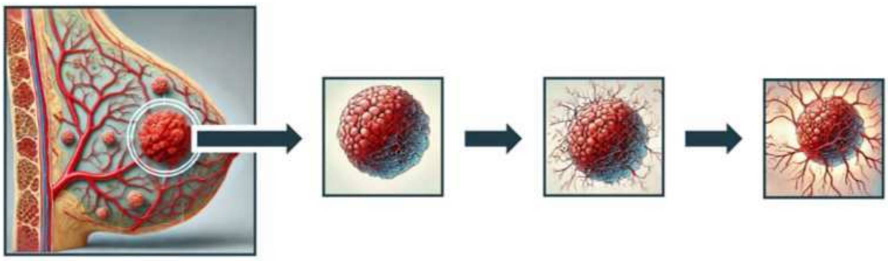

Fig. 1. A simplified illustration of angiogenesis in a breast tumor.

Angiogenesis, the formation of new blood vessels from existing ones, is a continuous process occurring throughout life, from fetal development to old age, in both healthy and diseased states [5]. Nearly all metabolically active tissues in the body are within a few hundred micrometers of a blood capillary, which forms through angiogenesis and is essential for exchanging nutrients and waste products [6]. Angiogenesis plays a crucial role in the development and progression of breast cancer. While breast cancer was initially believed to be driven mainly by genetic mutations in ductal epithelial cells, it is now understood that tumor growth and metastasis also rely heavily on microenvironmental factors [7]. As a result, the tumor activates an angiogenic switch, transitioning irreversibly into an active angiogenic state (see Figure 1). This change allows the tumor to recruit new blood vessels, restoring oxygen and nutrient supply to both angiogenic and adjacent non-angiogenic cells, thereby accelerating tumor growth [8].

### 1.2. Medical imaging and blood vessel segmentation

Key imaging modalities such as mammography, ultrasound, magnetic resonance imaging (MRI), and positron emission tomography (PET) play a crucial role in the auxiliary diagnosis of breast cancer [9]. Extracting information from medical images regarding blood vessels' location, size, and shape can provide valuable insights for clinicians, particularly before surgery and during neoadjuvant therapy [10]. Beforehand, this requires a segmentation process to be carried out.

Manual segmentation of blood vessels is a time-consuming and costly process with limited consistency and reproducibility between operators. In contrast, semi-automatic and automatic vessel segmentation methods still rely on expert clinicians to either perform initial segmentation or validate the results [11]. Moreover, the advancement and assessment of these algorithms are hindered by the high cost of expert annotations and the scarcity of publicly available image datasets with Gold Standard segmentations, which are currently restricted to specific anatomical areas like the retina [12]. Nonetheless, automatic or semi-automatic blood vessel segmentation holds the potential to support clinicians, making it a significant area of interest in medical research [13].

The benefits of MRI as a sensitive and non-invasive technique for monitoring and identifying lesions and diagnosis have established it as a standard clinical practice [14]. Because of MRI's crucial role in medical care, it is unlikely to be rapidly replaced by another imaging technique as the clinical standard. Therefore, it is important to develop effective methods for assessing blood vessel density and structure in MRI images [15].

### 1.3. Research methodology

This study aims to identify existing methods for blood vessel segmentation in breast MRI. Additionally, the study discusses the challenges and limitations in accurately delineating vascular structures. To achieve our goal, we have formulated the following research questions: "What are the existing approaches for blood vessel segmentation in breast MRI?", "What are the limitations of these approaches?", and "What are the challenges in this field?". To address these questions, we conducted a comprehensive literature review for studies focusing on blood vessel segmentation using breast MRI imaging in Scopus, Web of Science, Google Scholar, and PubMed (see Figure 2). After search processing, 118 studies were identified. After screening and applying inclusion and exclusion criteria (see Table 1), our search yielded only 7 studies that met our criteria, all published between 2009 and 2024. In addition to the literature review results, the paper proposes a consolidated workflow for the blood vessel segmentation process that synthesizes the existing methods included in this review.

**Table 1.** Inclusion and exclusion criteria applied for the selection of studies.

| Inclusion criteria | Exclusion criteria |
|---|---|
| Use of English as a language | Focusing on organs other than the breast |
| Being a conference or journal paper | Utilizing imaging modalities other than MRI |
| Focus on blood vessel segmentation within breast MRI images | Involving tasks other than segmentation |
| Studies that specifically examine breast | Not open access or no full text available |
| Use Magnetic Resonance Imaging (MRI) as imaging modality | Involving segmentation types other than blood vessel segmentation |

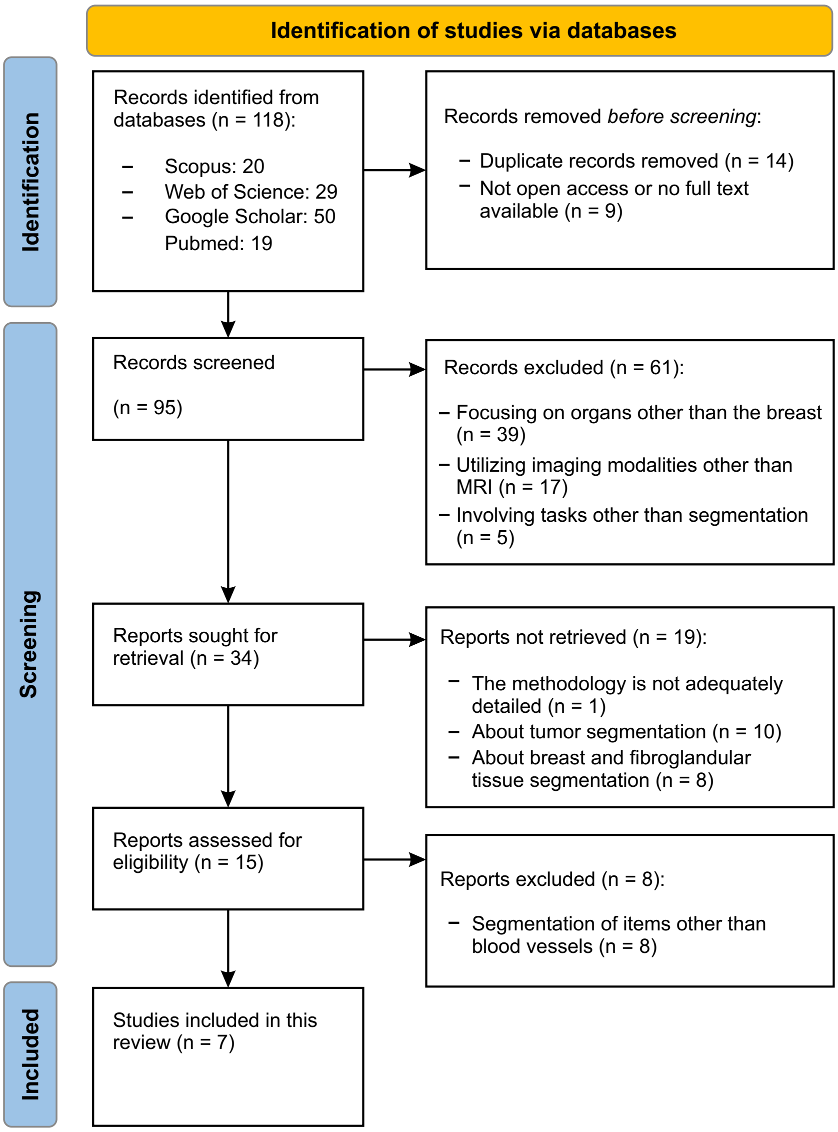


**Fig. 2.** PRISMA Flowchart: The initial database search (Scopus, Web of Science, Google Scholar, and PubMed) identified 118 studies. In the end, 7 studies were included in the review.

## 1.4. Contributions

While significant advancements have been made in medical image analysis, particularly in the segmentation of various anatomical structures such as the brain, liver, kidneys, coronary vessels, and retina, and across different imaging modalities such as CT, PET, and ultrasound, a dedicated and in-depth review specifically focused on blood vessel segmentation in breast MRI remains absent from the literature [16–19].

Through this study, we present several key contributions to the field of blood vessel segmentation in breast MRI:

- We provide an extensive analysis of existing segmentation techniques, including traditional, machine learning, and deep learning approaches.
- We highlight the challenges and limitations of current methods, such as image quality issues and algorithmic constraints.
- We propose a consolidated workflow that combines the strengths of various methods into a comprehensive roadmap, offering a clear and structured approach to guide future research and clinical applications in blood vessel segmentation in breast MRI.

## 2. Blood vessel segmentation on breast MRI

### 2.1. Breast MRI

Magnetic resonance imaging is a complex technique that utilizes magnetic fields and electromagnetic energy to produce high-resolution images of internal structures, even at the microscopic level. This advanced technology relies on the interaction between the magnetic fields and the body's protons, generating detailed visual information [20]. MRI encompasses a variety of imaging techniques, each designed to cater to specific diagnostic needs. These include, but are not limited to, standard MRI, functional MRI, diffusion-weighted MRI, and dynamic contrast-enhanced MRI, among others. Breast MRI has a wide range of clinical applications, including the screening of individuals at high risk for breast cancer, the diagnostic evaluation of suspicious breast lesions, the assessment of treatment response, and the guidance of interventional procedures [21].

The efficiency of Breast MRI in visualizing and detecting blood vessels within breast tissue should be investigated due to its ability to generate high-contrast images and detect changes in blood flow. Dynamic contrast-enhanced MRI, which uses a contrast agent, enables the assessment of tumor angiogenesis, a hallmark of malignant breast lesions [22]. Tumors often trigger new blood vessel growth, which can be detected by MRI scans, particularly T1-weighted imaging. Diagnostic assessments can utilize time-intensity curves are categorized into three types, providing insights into the likelihood of malignancy based on signal intensity changes over time. Type 1 indicates benign lesions, type 2 indicates indeterminate lesions, and type 3 indicates likely malignant lesions [23].

### 2.2. Exiting Methods of blood vessel segmentation on breast MRI

The literature reveals limited studies on the topic of blood vessel segmentation, partly due to the challenges posed by the limitations of MRI in directly visualizing biological structures and the inherent heterogeneity of the human breast, both within and across individuals. We have identified seven relevant studies addressing this research area (see Table 2). Gierlinger et al. introduced the multi-seed region growing algorithm, which builds upon the seed region growing (SRG) algorithm. The MSRG algorithm aims to enhance breast MRI by extracting vessel-like structures, using multiple seeds to efficiently grow regions based on pixel connectivity. Despite certain limitations, the MSRG algorithm provides valuable insights for refining the segmentation process [24]. In related research, Glotsos et al. proposed a modified Seeded Region Growing algorithm for vessel segmentation in breast MRI. This method classifies pixels into seed, background, and weak candidate regions, achieving approximately 94.4% accuracy in lesion characterization. However, the approach may be susceptible to noise and requires precise seed selection for optimal performance [25].

In the context of blood vessel segmentation in 3D breast MRIs, Kahala et al. introduced an algorithm that leverages Hessian-based techniques to generate a 3D model and enhance textural characteristics. This algorithm accomplishes vessel completion by tracing the centerlines of endpoints identified through skeletonization. Benchmarking the algorithm against manual segmentation, the researchers reported a sensitivity of 86% and a specificity of 88.3%, suggesting its efficacy in tumor detection [26]. However, the algorithm's reliance on tracking methods may not be as effective for curved blood vessels near suspicious masses, potentially impacting accurate detection. Addressing 3D breast MRI, Vignati et al. proposed a fully automated 3D Hessian-based algorithm for detecting blood vessels in breast DCE-MRI. The algorithm identifies linear structures and filters out non-vessel enhancements based on morphology. It achieves a correct detection rate of 89.1%, a missed detection rate of 10.9%, and an incorrect detection rate of 27.1%. Compared to the Computer Aided Diagnosis (CAD) system, the algorithm reduces vessel false positives by 68.4%, enhancing diagnostic accuracy. Yet, the algorithm has key limitations: it overlooks vessel length, often misses branching points, and relies on an empirically set threshold for the covariance eigenvalue ratio, which can impact segmentation accuracy and consistency [27].

To improve the accuracy of hot-spot labeling in CAD systems for breast MRI, Lin et al. implemented a vessel exclusion process using a connectivity-based approach. The goal of this approach is to identify and eliminate potentially mislabeled blood vessel enhancements in 2D MIP images and extend this analysis to adjacent 3D slices. When validated against radiologist annotations, this method significantly reduced false positives. The detection rates showed 85.6% correctness and a 19.2% missed detection rate [28]. To further improve blood vessel detection, Zaman et al. developed an algorithm leveraging morphological operators and gradient features. This algorithm incorporates steps such as gradient magnitude operations for edge detection, histogram equalization, and adaptive thresholding. These steps serve to enhance the visibility and accuracy of vessel identification, particularly in environments with high noise levels. Together, these techniques strive to enhance the reliability and precision of breast MRI analyses by effectively mitigating incorrect vessel labeling and bolstering detection capabilities [29].

In [30], Lew et al. developed a convolutional neural network algorithm to segment breast tissue, fibroglandular tissue, and blood vessels in MRI scans, using a dataset of 100 annotated studies. The algorithm demonstrated high Dice scores, indicating accurate segmentation, with 0.92 for breast tissue, 0.86 for fibroglandular tissue, and 0.65 for blood vessels. Furthermore, the algorithm's segmentation outputs highly correlated (0.95) with manually created masks, suggesting its efficacy. However, the limited size and potential variability in the training dataset may constrain the algorithm's general applicability and data quality. Additionally, a lower correlation (0.75) with radiologist evaluations implies some discrepancies between the model's predictions and expert assessments.

**Table 2.** Summary of vessel segmentation techniques in breast MRI.

| Ref. | Year | Dataset Size | Image Dim. | Technique | Pre-/Post-processing Techniques |
|---|---|---|---|---|---|
| [30] | 2024 | 100 | 2D/3D | U-Net based approach | – Resizing<br>– Capping Extreme Values<br>– Normalization |
| [24] | 2021 | 36 | 3D | Seeded Region Growing | – Quality enhancement<br>– Thresholding |
| [29] | 2021 | N/A | 2D | Thresholding | – Contrast Adjustment<br>– Dilation<br>– Erosion<br>– Gradient Magnitude Calculation |
| [26] | 2017 | 24 | 3D | Hessian based method | – Texture enhancement<br>– Centerline tracking<br>– Skeletonizing |
| [25] | 2014 | 20 | 2D | Seeded Region Growing | – Background removal<br>– Median filtering |
| [27] | 2012 | 28 | 3D | Hessian-based algorithm | – Multiscale analysis<br>– Skeletonizing |
| [28] | 2009 | 34 | 2D | Hessian based approach | – Filter bank enhancement<br>– MIP application<br>– Centerline tracking<br>– 3D skeletonizing |

## 3. Consolidated workflow for blood vessel segmentation in breast MRI

Adopting a standardized workflow that incorporates best practices and methodologies from the literature is essential to improve process efficiency and outcome reliability. This section introduces a consolidated workflow for blood vessel segmentation, synthesized from various approaches previously discussed. The proposed workflow includes the sequential steps involved in the segmentation of blood vessels process from image data, including preprocessing, feature extraction, morphological operations, and various post-processing techniques. The decision nodes guide the process based on the evaluation of results, highlighting when additional enhancements or 3D processing might be necessary to achieve satisfactory outcomes.

### 3.1. Step 1: Image preprocessing

Image preprocessing techniques play a crucial role in enhancing blood vessel segmentation in MRI. Various methods have been used in the previously cited studies to improve blood vessel segmentation accuracy by addressing challenges such as low contrast and noise.

**Grayscale conversion and contrast enhancement.** The first step in the preprocessing pipeline of Breast MRI is to convert the original breast MRI images to grayscale if necessary. This simplifies the image representation and reduces the computational complexity of subsequent processing steps. Then, the contrast of images should be enhanced. Three different techniques were employed in the included studies: gamma correction, contrast-limited adaptive histogram equalization, and homomorphic filtering:

- **Gamma correction** [31] is a nonlinear transformation that adjusts the image's brightness and contrast by raising the pixel values to a power, known as the gamma value.
- **Contrast-limited adaptive histogram equalization (CLAHE)** [32] is a modification of the standard histogram equalization algorithm, which adaptively enhances the contrast of local regions within the image, rather than applying a global transformation (see Figure 3).
- **Homomorphic filtering** [33] is a technique that separates an image's illumination and reflectance components, allowing for the selective enhancement of the reflectance component, which typically contains the high-frequency details of the image.

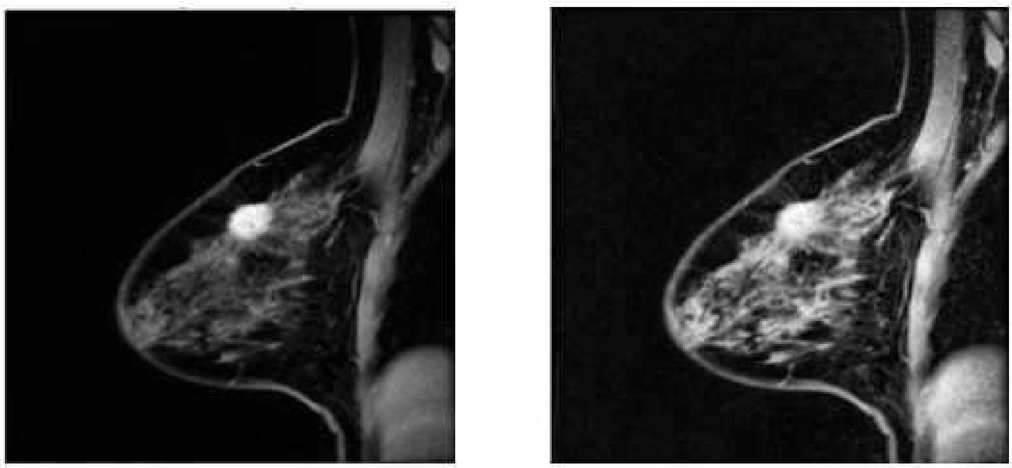

**Fig. 3.** Comparison of Breast MRI Scans Before and After CLAHE Enhancement: The left image presents the original scan, while the right image illustrates enhanced contrast and improved visibility of internal structures following the application of CLAHE.

**Noise reduction.** Several image processing techniques have been employed in the reviewed studies to reduce noise and preserve important image features:

- **Median filtering** [34]: Replaces each pixel value with the median of neighboring pixel values, effectively removing noise while preserving edges.
- **Gaussian filtering** [35]: Uses a Gaussian kernel to smooth the image and reduce noise but can lead to blurring of sharp edges.
- **Bilateral filtering** [36]: Combines spatial and intensity information to preserve edges while reducing noise.

**Image enhancement.** Medical imaging, such as breast MRI, can often suffer from quality issues that hinder the visualization and detection of important anatomical structures like blood vessels. In these cases, a variety of image enhancement techniques can be employed to improve the detection and analysis of these critical components:

- **Joint Histogram Equalization** [37]: This method combines histogram equalization with a joint optimization approach to enhance both global and local contrast of the image.
- **2D Gabor Filter** [38]: A linear filter that enhances specific spatial frequencies and orientations within the image, potentially highlighting blood vessel structures.
- **Unsharp Masking Filter** [39]: Enhances high-frequency details by subtracting a blurred version of the image from the original, improving edge sharpness.
- **Adaptive Unsharp Masking Filter** [40]: An advanced sharpening technique that dynamically adjusts the amount of sharpening based on local image characteristics, effectively enhancing the contrast of fine details.
- **PSO-based Unsharp Masking Filter** [41]: This method uses a particle swarm optimization algorithm to fine-tune the parameters of the unsharp masking filter, further improving the enhancement of blood vessel structures.

**Morphological operations.** A set of morphological operations was also applied to the enhanced breast MRI images further to refine the segmentation of the blood vessel structures:

- **Dilation** [42]: A morphological operation that enlarges the boundaries of regions, potentially connecting discontinuous blood vessel segments.
- **Erosion** [43]: A complementary operation to dilation, which shrinks the boundaries of regions, potentially removing small noise artifacts.
- **Morphological cleaning**: This operation combines dilation and erosion to remove small, isolated regions, effectively cleaning up the segmented blood vessel structures.

### 3.2. Step 2: Feature extraction

One of the key challenges in vessel segmentation is the extraction of relevant features from the MRI data. Three main techniques have been explored in the literature for blood vessel segmentation in Breast MRI.

- **Gradient magnitude calculation**: Identifies areas with significant intensity changes, often corresponding to vessel boundaries.
- **Statistical analysis**: Includes metrics such as mean, standard deviation, and higher-order moments, which provide insights into tissue properties and help differentiate vessels from surrounding tissues.
- **Textural feature extraction**: Analyzes spatial patterns and relationships within the image, offering valuable cues for vessel segmentation.

### 3.3. Step 3: Blood vessel segmentation

Various techniques for blood vessel segmentation have been identified in the literature. The following schema provides a synthesized overview of these methods, categorizing them into distinct groups based on their underlying approaches (see Figure 4). The blood vessel segmentation techniques are categorized into 3 main groups: Traditional Methods, Machine Learning Approaches, and Deep Learning Approaches.

**Traditional methods.** Traditional blood vessel segmentation methods typically rely on a combination of image processing techniques, such as hysteresis thresholding, thinning, pruning, and seed region growing.

Hysteresis thresholding [44] is a technique that involves setting two threshold values – a high and a low – to identify pixels belonging to blood vessels. Additionally, thinning and pruning are applied to refine the segmented vessels by removing spurious connections and ensuring the continuity of the vascular structure. Another approach, seed region growing (SRG) [45], starts from user-specified seed points and iteratively expands the regions by including neighboring pixels that meet specific similarity criteria. These methods have been widely used in the past and have demonstrated reasonable performance. However, they are often sensitive to image noise, contrast variations, and vessel complexity, which can lead to suboptimal segmentation results.

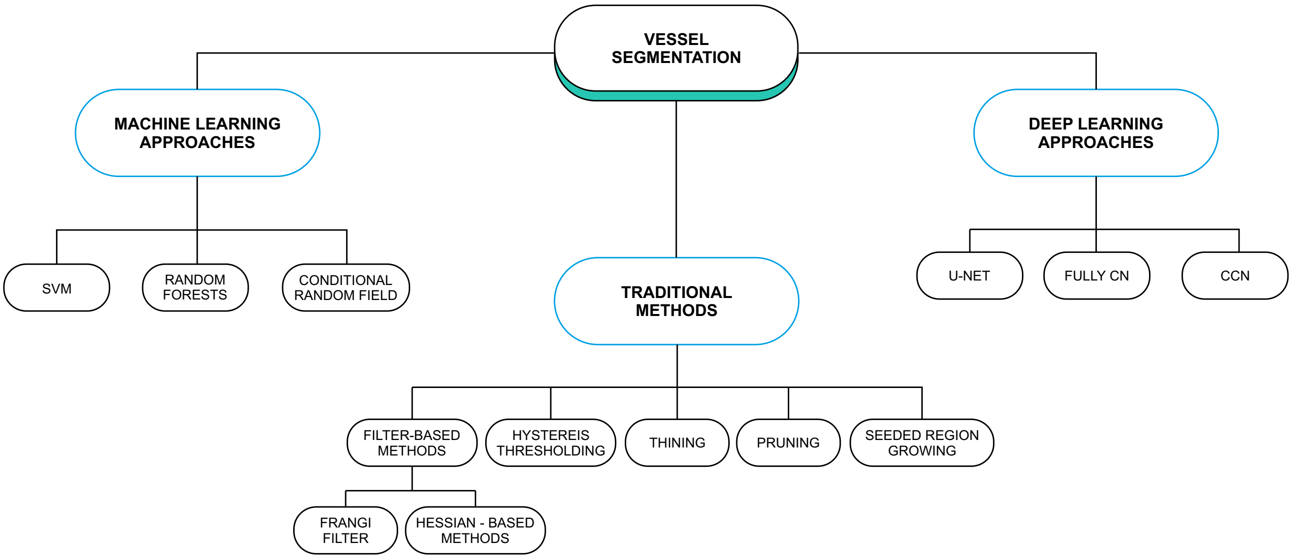


**Fig. 4.** Classification of blood vessel segmentation techniques, categorized into traditional, machine learning, and deep learning approaches, highlighting techniques commonly used in existing literature.

To address the limitations of previous blood vessel segmentation methods, researchers have turned to filter-based approaches. One notable example is the Frangi filter [41], which relies on the analysis of the Hessian matrix to capture the local second-order structure of the image (see Figure 5). This filter is specifically designed to enhance tubular structures, such as blood vessels, by identifying regions with high vesselness values. Furthermore, other Hessian-matrix-based filters [42] have also been utilized, effectively capturing the elongated and tubular nature of blood vessels.

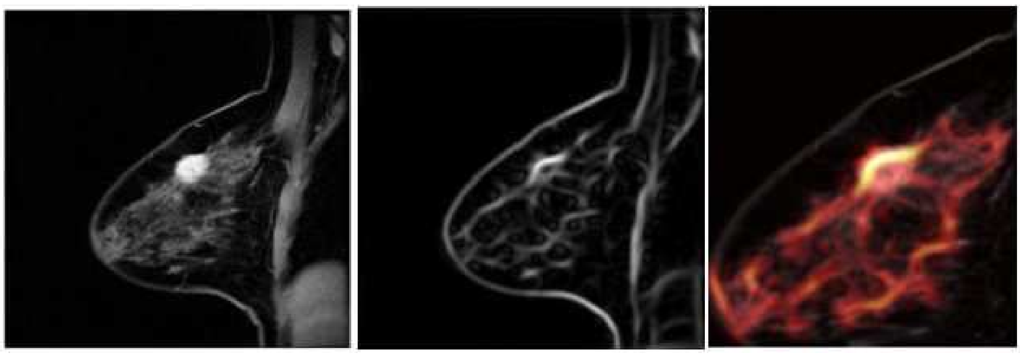

**Fig. 5.** Visualization of pre-processing techniques applied to breast MRI images. The figure shows the impact of Frangi and Hessian filters, as well as CLAHE and MIP enhancement techniques.

These filter-based approaches have shown improved performance over earlier methods by reducing noise and enhancing vessel contrast (see Figure 5). However, they still encounter difficulties when faced with complex vessel networks, particularly in the presence of pathological changes or imaging artifacts. This issue is made more challenging by the dense fibroglandular tissue in the breast, which can obscure the distinction between blood vessels and surrounding structures, ultimately reducing segmentation accuracy.

**Machine learning-based approaches.** Machine learning techniques have been explored to overcome the limitations of traditional and filter-based blood vessel segmentation methods. These approaches leverage machine learning algorithms to learn discriminative features from data, enabling more robust and accurate segmentation. Common techniques include random forests, support vector machines, and Conditional Random Fields, which can capture complex relationships, classify pixels, and model spatial dependencies for coherent results [46]. While machine learning techniques have shown promise in overcoming the limitations of traditional and filter-based blood vessel segmentation methods, these approaches also face their own set of challenges. The reliance on large, labeled datasets for training can be a significant barrier, as the acquisition of high-quality, annotated medical images is often a labor-intensive and time-consuming process [47]. Additionally, the interpretability and explainability of machine learning models can be a concern, as the internal decision-making processes may not be easily understood by domain experts. Furthermore, the generalization of these models to new or unseen data, particularly in the presence of diverse imaging conditions and anatomical variations, remains an area that requires further investigation and improvement.

**Deep learning-based approaches.** Deep learning models, such as convolutional neural networks, have demonstrated remarkable success in medical image analysis tasks, including the segmentation of blood vessels [48]. The U-Net architecture, a prominent deep learning model, has proven to be highly effective in this domain. U-Net combines low-level and high-level features extracted from the input images, enabling it to produce detailed and precise segmentation maps of the vascular structures. However, the application of U-Net and other deep learning models for blood vessel segmentation in breast MRI has been limited by the scarce availability of large, annotated training datasets in this specific field. Breast MRI presents unique challenges, such as the complex and heterogeneous nature of the breast tissue, the presence of various anatomical structures, and the potential impact of imaging artifacts and variations. The lack of comprehensive training data in this domain has hindered the development and deployment of deep learning-based vessel segmentation techniques for breast MRI, constraining their widespread adoption in clinical practice.

### 3.4. Step 4: Post-processing

Post-processing techniques are commonly employed to refine and enhance the results of blood vessel segmentation from deep learning models. These post-processing steps often include morphological cleaning to remove artifacts and smooth the boundaries of the detected vessels. Additionally, skeletonization and centerline tracking algorithms are used to extract the medial axes of the vessels, which can facilitate further analysis. Finally, additional filtering or optimization techniques may be applied to address any remaining inaccuracies or issues in the segmented vascular structures. These post-processing methods play a crucial role in improving the overall quality, accuracy, and clinical relevance of the final blood vessel segmentation maps.

### 3.5. Step 5: Evaluation

Evaluating the performance of blood vessel segmentation models is essential for ensuring their reliability and applicability in real-world scenarios. A comprehensive evaluation includes statistical analysis, predictive modeling, and performance metrics. Statistical analysis – such as hypothesis testing, confidence intervals, and analysis of variance – helps assess the significance and robustness of the results. Predictive modeling techniques, including cross-validation and holdout testing, estimate the model's performance on new data, thereby ensuring its generalizability. Furthermore, metrics like the Dice coefficient, Jaccard index, precision, recall, and F1-score offer a thorough assessment of segmentation accuracy [49].

After the evaluation step, the process enters a decision-making phase where the results are assessed for their quality and accuracy. If the results are deemed unsatisfactory, the workflow proceeds to determine whether significant modifications are required. If such modifications are needed, the process moves to an additional enhancement phase, which involves advanced techniques like residual connections, Kalman filters, convolutional block attention modules, or particle filters to refine the output. Following these enhancements, the workflow loops back to the pre-processing stage for further adjustments and reevaluation. Once the results meet the desired standards, the workflow concludes, ensuring a robust and precise segmentation outcome through this iterative and meticulous approach.

### 3.6. 3D-processing for visualization

Medical imaging techniques for 3D visualization of blood vessels involve a multi-step process [50]. First, a two-step registration approach is used to align the images properly. Next, 3D interpolation techniques are employed to reconstruct a continuous 3D representation, enabling comprehensive analysis and visualization of the vascular structure. Additionally, maximum intensity projection (MIP) techniques can be used to enhance the 3D visualization by selectively highlighting the high-intensity voxels, such as those corresponding to blood vessels, within the reconstructed 3D volume (see Figure 6).

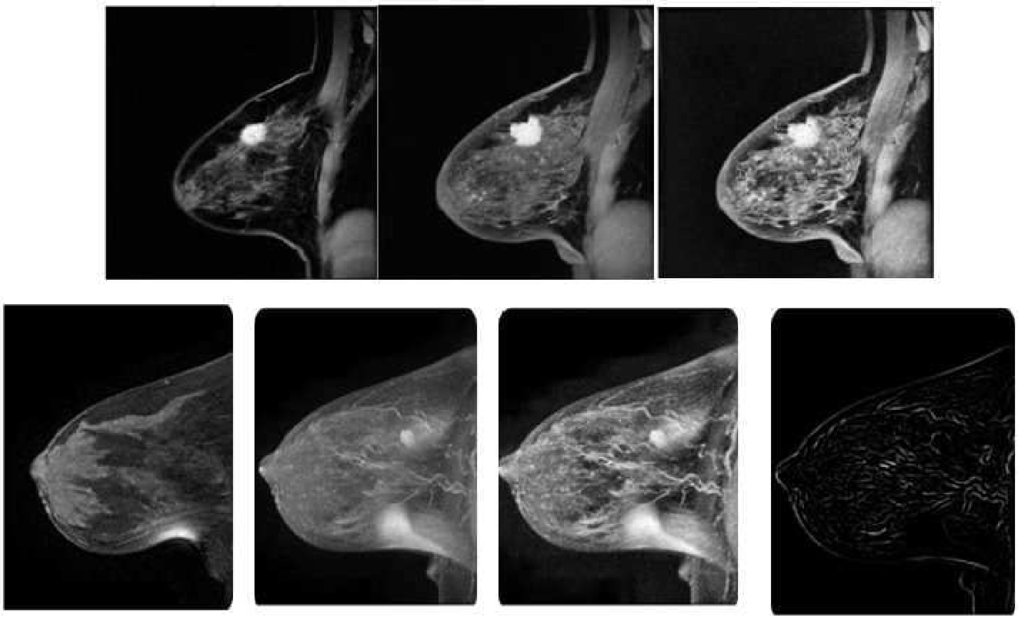

**Fig. 6.** Enhancement of breast MRI imaging: Original scan (left), after applying Maximum Intensity Projection (center), and subsequent enhancement with CLAHE on the MIP image (right).

Finally, advanced 3D volume rendering techniques are utilized. These generate high-quality, interactive visualizations to explore complex 3D blood vessel anatomy and surrounding tissues in-depth.

## 4. Challenges and limitations in breast MRI vessel segmentation

In this section, we will delve into the difficulties and constraints that researchers encounter when segmenting blood vessels in breast MRI images. These challenges, which have been identified through a comprehensive literature review, emphasize the complexities and gaps in this field, indicating the necessity for further progress.

**Image quality and resolution.** The accurate segmentation of vessels from surrounding tissue is complex and can be influenced by noise and variations in image quality. Challenges arise due to noise and low-resolution obscuring vessel-like structures, as well as the low resolution of MRI which complicates accurate blood vessel detection. Additionally, the low contrast between blood vessels and surrounding tissues hinders accurate segmentation.

**Algorithmic and methodological limitations.** The accuracy of blood vessel segmentation in breast MRI is significantly affected by algorithmic and methodological limitations. Challenges include under-segmentation, where algorithms may miss important vascular structures, and the need for precise seed point selection to avoid suboptimal results. Detection issues can occur with very faint or nonlinear vascular enhancements, especially at junctions or branching points, and methods often struggle with low-intensity detection and diffused vessel boundaries.

**Anatomical and physiological challenges.** The process of identifying and isolating blood vessels in breast MRI is significantly affected by anatomical and physiological obstacles. The discomfort experienced by patients during imaging can result in lower image quality, which can then impact the accuracy of diagnoses. Moreover, the presence of noise and fatty tissues can make it difficult to distinguish blood vessels from other structures. The intricate anatomy of the breast, including connective and fibroglandular tissues that resemble blood vessels, as well as the natural variation in blood vessel shapes and sizes, pose further challenges to achieving consistent and precise segmentation.

**Data and evaluation.** Data and evaluation challenges significantly hinder progress in blood vessel segmentation in breast MRI. The lack of large-scale, publicly available annotated datasets delays model development. Ambiguity in annotations due to limited anatomical landmarks complicates tissue boundary definitions. The use of private datasets restricts reproducibility and generalizability, while variability in MRI sequences and parameters affects consistency. Reliance on radiologist annotations introduces subjectivity and variability, and the absence of standardized evaluation methods limits the effectiveness of comparative studies and clinical applications.

## 5. Conclusion

Through this study, we analyzed various techniques, including traditional methods as well as machine learning and deep learning approaches. Additionally, we identified the challenges and limitations of existing methods, particularly regarding image quality and algorithmic constraints. We also proposed a consolidated workflow that integrates the strengths of different techniques, creating a structured roadmap for future research and clinical applications. From the review, we found that most existing techniques primarily focus on filter-based methods. Machine learning is less often used to segment blood vessels and is more focused on learning discriminative features from data, capturing complex relationships, classifying pixels, and modeling spatial dependencies to achieve coherent results. Deep learning, particularly the U-Net architecture, was applied in a single study. However, the use of U-Net and other deep learning models for blood vessel segmentation in breast MRI is limited by the scarcity of large, annotated training datasets in this specific field. Additionally, these advancements encounter challenges such as image quality issues and anatomical complexities.

Future research should prioritize overcoming the current limitations in blood vessel segmentation. Developing algorithms that are more robust to variations in patient motion, image quality, and vessel morphology is critical. These factors, such as motion artifacts or changes in vessel structure, often degrade segmentation accuracy. Additionally, creating publicly accessible, standardized datasets with high-quality annotations will be essential for training and benchmarking new models. Such datasets would enable more effective cross-comparisons between different approaches. Lastly, the establishment of standardized evaluation metrics is necessary to ensure consistent performance comparisons across studies. Addressing these challenges will ultimately lead to improved diagnostic accuracy, better treatment planning, and enhanced patient outcomes in breast MRI blood vessel analysis.


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# Сегментація кровоносних судин при МРТ молочної залози: комплексний огляд методик та проблем

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Ангіогенез — це безперервне утворення нових кровоносних судин з існуючих, яке відбувається протягом життя як у здорових, так і в хворих станах. Крім того, він відіграє вирішальну роль у розвитку та прогресуванні раку молочної залози. Магнітно-резонансна томографія (МРТ) — це чутливий, неінвазивний метод моніторингу та виявлення уражень, що робить його стандартною клінічною практикою. Однак її ефективність у візуалізації кровоносних судин у тканинах молочної залози потребує подальшого дослідження. Аналіз кровоносних судин надає цінну інформацію про прогресування пухлини та інформацію, яку можна співвіднести з основною біологією пухлини. У цій статті представлено всебічний огляд методологій та методик. Ключовим внеском цієї роботи є пропозиція консолідованого робочого процесу, який об'єднує сильні сторони різних розглянутих підходів, пропонуючи більш комплексне рішення для сегментації кровоносних судин при МРТ молочної залози. У статті також розглядаються проблеми та обмеження в цій галузі, включаючи якість зображення, алгоритмічні обмеження, анатомічні складності та дефіцит даних. Наше дослідження визначає поточні проблеми, зокрема потребу в надійних показниках оцінки та стандартизованих наборах даних. Вирішення цих питань є важливим для сприяння майбутньому прогресу в сегментації судин молочної залози за допомогою МРТ та покращення клінічних результатів.

**Ключові слова:** *МРТ молочної залози; рак молочної залози; сегментація кровоносних судин; ангіогенез.*