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Microwave Imaging in Medical Diagnostics: A Systematic Review of Methods, Applications, and Future Directions

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ABSTRACT

Microwave imaging (MWI) has emerged as a promising non-invasive diagnostic technology in medical applications, offering significant advantages over conventional imaging modalities including reduced radiation exposure, cost-effectiveness, and enhanced patient comfort. This comprehensive survey presents a systematic review of MWI through a novel bifurcated taxonomy addressing both methodological aspects (imaging techniques, deep learning approaches, and antenna design) and application domains (breast imaging, brain imaging, and stroke diagnostics). The methodological analysis reveals substantial progress in reconstruction algorithms, with physics-assisted deep learning frameworks demonstrating superior performance in automated thresholding and bias reduction compared to traditional qualitative imaging methods. Advanced techniques like MDLI-Net and DL-MITAT have shown particular promise in handling sparse data scenarios. In antenna technologies, ultra-wideband antennas and miniaturized millimeter-wave sensors represent significant breakthroughs, with some systems capable of detecting malignancies as small as 1mm. Application-wise, brain imaging applications have achieved remarkable accuracy rates exceeding 94% using YOLOv5 models, while breast imaging systems demonstrate effective tumor detection in dense tissues where conventional mammography faces limitations. Despite these advancements in computational methods, particularly deep learning and sophisticated reconstruction algorithms, several challenges remain in translating MWI technology from experimental settings to widespread clinical adoption. Our contributions include structured analysis of recent advances in MWI techniques, critical insights into challenges across medical applications, and identification of research gaps and future directions. Key findings demonstrate that combining qualitative imaging with deep neural networks achieves reliable real-time reconstruction capabilities. While MWI shows considerable potential as a safe, cost-effective alternative to traditional imaging techniques, particularly for breast and brain imaging, further research in computational efficiency, clinical validation, and standardization protocols is necessary for successful clinical implementation across diverse healthcare settings.

Keywords: Microwave imaging; medical diagnostics; deep learning; breast cancer detection; brain imaging; stroke diagnostics; antenna design; reconstruction algorithms; non-invasive imaging; biomedical engineering

INTRODUCTION

Microwave imaging (MWI) has emerged as a promising non-invasive diagnostic technology in medical applications, offering significant advantages over conventional imaging modalities (Aldhaeebi et al. 2020), (Moloney et al. 2020). The growing interest in MWI stems from its potential to provide safe, cost-effective, and real-time imaging solutions while addressing limitations of traditional techniques such as X-ray mammography, magnetic resonance imaging (MRI), and ultrasound (Modiri et al. 2017),(Adachi et al. 2021). This technology leverages the interaction between electromagnetic waves and biological tissues, utilizing differences in dielectric properties to detect and characterize anatomical structures and anomalies (El Misilmani et al. 2020).

The evolution of MWI has been particularly significant in three key medical applications: breast cancer detection, brain imaging, and stroke diagnostics (Wang 2023), (Hossain et al. 2021), (Lai et al. 2023). In breast imaging, MWI offers a radiation-free alternative that shows promise in detecting tumors in dense breast tissue, where traditional mammography often faces limitations (AlSawaftah et al. 2022), (Janjic et al. 2021). For brain imaging and stroke diagnostics, MWI provides the potential for real-time monitoring and early detection capabilities that could significantly impact patient outcomes (Rodriguez-Duarte et al. 2021).

Recent advances in computational methods, particularly deep learning and sophisticated reconstruction algorithms, have substantially enhanced the capabilities of MWI systems (Bicer 2023), (Mojabi, Khoshdel, and Lovetri 2020). These developments, combined with innovations in antenna design and data acquisition techniques (Rafique et al. 2022), (Das, Chowdhury, and Jang 2022), have led to improved image quality, faster processing times, and more reliable diagnostic outcomes. However, despite these advancements, several challenges remain in translating MWI technology from experimental settings to widespread clinical adoption (El Misilmani et al. 2020), (Gopalakrishnan et al. 2023).

This comprehensive survey presents a systematic review of MWI in medical applications, structured around a novel bifurcated taxonomy that addresses both methodological aspects and application domains. The methodological dimension encompasses imaging techniques (Ruiz, Cavagnaro, and Crocco 2022), deep learning approaches (Hu et al. 2021), and antenna design technologies (Alibakhshikenari et al. 2020), while the application dimension focuses on specific medical uses including breast imaging, brain imaging, and stroke diagnostics (Alsaedi et al. 2021), (Hossain et al. 2023).

Our survey makes several key contributions to the field. First, it provides a structured analysis of recent advances in MWI techniques, including emerging deep learning applications (Yao, Jiang, and Wei 2020) and novel antenna designs (Singh et al. 2021). Second, it offers critical insights into the challenges and opportunities in various medical applications (Chishti et al. 2023). Finally, it identifies important research gaps and suggests future directions for advancing MWI technology in medical diagnostics (Reimer and Pistorius 2023).

Recent advances in antenna design for energy harvesting applications have shown promising developments in MEMS technology.(Sampe et al. 2023) demonstrated the design and performance evaluation of radio frequency micro energy harvesting MEMS antennas specifically optimized for low power electronic devices, achieving efficient energy conversion for wireless sensor applications. This work aligns with the miniaturization trends observed in medical imaging antenna systems

The remainder of this paper is organized as follows: Section 2 presents our taxonomy framework. Section 3 examines the methodological aspects of MWI, including imaging techniques, deep learning approaches, and antenna technologies. Section 4 explores the application aspects across different medical domains. Section 5 discusses current challenges and future directions, followed by conclusions in Section 6.

TAXONOMY

The taxonomy for microwave imaging in medical applications is strategically structured to methodically categorize and critically analyze the extant literature along two principal dimensions: methodological aspects and application aspects. This bifurcated classification scheme is crucial for facilitating a systematic exploration of both the technological advancements underpinning the field and the specific medical applications of microwave imaging, providing a comprehensive overview essential for an exhaustive survey article.

METHODOLOGICAL ASPECT

The Methodological Aspect of the taxonomy delves into the array of technical approaches and innovations foundational to microwave imaging. This aspect is further subdivided into three primary categories:

1. Imaging Techniques}: This category amalgamates all methods related to image reconstruction and the achievement of real-time imaging (Ruiz, Cavagnaro, and Crocco 2022), (Fang, Bakian-Dogaheh, and Moghaddam 2022) , (Bicer 2023), highlighting progress in enhancing image clarity and processing speed—crucial factors for effective medical diagnostics.

2. Deep Learning Approaches}: This category centralizes the application of advanced machine learning technologies in microwave imaging, including sophisticated algorithms for tumor detection and classification (Bicer 2023), (Reimer and Pistorius 2021a). It showcases how the integration of deep learning is pivotal to improving diagnostic accuracy and operational efficiency.
3. Antenna Design and Technologies}: This category encompasses specific designs and technological advancements in antennas tailored for microwave imaging applications (El Misilmani et al. 2020),(Singh et al. 2021) ,(Alibakhshikenari et al. 2020). It covers both antenna designs particular to specific medical applications and the development of advanced antenna technologies that elevate imaging precision and adaptability to diverse diagnostic contexts.

APPLICATION ASPECT

The Application Aspect of the taxonomy focuses on the practical deployment of microwave imaging technologies across healthcare settings, segmented into three categories:

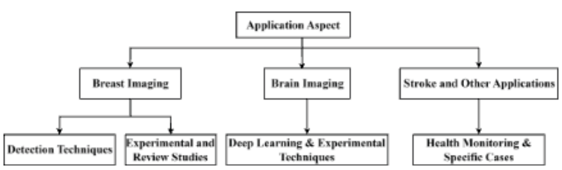

FIGURE 1 Application Aspect

1. Breast Imaging}: This category is dedicated to studies and technologies specifically aimed at enhancing breast cancer detection. It includes a variety of detection techniques and a comprehensive review of experimental studies (Wang 2023),(Modiri et al. 2017), (Chishti et al. 2023), underscoring the significant emphasis on this major application area of microwave imaging.
2. Brain Imaging}: This category comprises methodologies and studies focused on leveraging microwave imaging technologies for the detection and diagnosis of brain tumors (Hossain et al. 2021), (Lu et al. 2022). It highlights the adaptability of microwave imaging techniques to various complex medical scenarios, reflecting the technology's broad utility spectrum.
3. Stroke and Other Applications}: This category captures the utilization of microwave imaging in diagnosing strokes and other medical conditions, as well as its application in general health monitoring. It illustrates the versatility of microwave imaging technologies, extending well beyond traditional cancer detection applications to encompass a wide range of diagnostic uses.

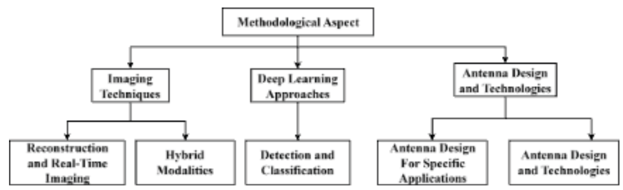

FIGURE 2 Methodological Aspect

RESEARCH GAP

To clarify the novelty of our proposed bifurcated taxonomy, it is essential to distinguish between the general concept of dual-dimensional classification and its domain-specific implementation in microwave medical imaging. While methodology-application frameworks are indeed established in mature survey domains such as computer science, materials engineering, and general medical imaging, the microwave medical imaging field represents a unique interdisciplinary convergence that has not previously benefited from such systematic organization. The complexity of this field, which requires simultaneous consideration of electromagnetic theory, signal processing algorithms, antenna engineering, deep learning methodologies, and diverse medical applications, has resulted in a fragmented literature landscape where technological advances and clinical implementations are often discussed in isolation. Our bifurcated taxonomy addresses this specific organizational gap by providing the first systematic framework that enables coherent navigation of both the rapidly evolving technological methodologies and the diverse medical application domains within microwave imaging. This domain-specific implementation is particularly crucial given the field's interdisciplinary nature, where advances in one methodological area often have implications across multiple medical applications, and conversely, clinical requirements in specific applications drive methodological innovations that benefit the entire field.

The existing surveys on microwave imaging in medical applications exhibit a significant gap in coverage and comprehensiveness, particularly when compared to the proposed comprehensive survey. Most existing literature primarily focuses on a single application domain, predominantly breast cancer detection. For instance, surveys such as those by (AlSawaftah et al. 2022), (El Misilmani et al. 2020), (Benny, Anjit, and Mythili 2020) delve into breast imaging but do not extend their analysis to other critical medical applications like brain imaging or stroke detection. Moreover, these surveys tend to emphasize specific methodological advancements, such as microwave tomography and radar-based imaging, without integrating a broader spectrum of techniques or the latest innovations in deep learning and antenna design.

Furthermore, surveys such as (Ahmed 2021) focus on security applications of microwave imaging, which, while valuable, do not address the diverse medical applications where microwave imaging could have significant impacts. Similarly, (Reimer and Pistorius 2021a) evaluates image quality and machine learning approaches specifically for breast microwave sensing, yet it lacks a comprehensive methodological and application perspective. The survey (Anitha, Beohar, and Nella 2023) discusses THz imaging but does not encompass the full range of microwave imaging technologies and their medical applications.

In contrast, the proposed survey uniquely fills these gaps by offering a bifurcated taxonomy that systematically explores both methodological aspects—comprising imaging techniques, deep learning approaches, and antenna design and technologies—and application aspects, covering a wide array of medical applications such as breast imaging, brain imaging, and stroke diagnostics. This comprehensive approach not only organizes the extensive existing research but also highlights the intricate interplay between technological innovations and practical healthcare solutions, ultimately emphasizing the pivotal role of microwave imaging in advancing medical diagnostics and improving patient outcomes. This dual focus on both methodological and application dimensions sets the proposed survey apart, providing a much-needed comprehensive overview that is currently missing in the literature.

METHODOLOGICAL ASPECT OF MICROWAVE IMAGING

IMAGING TECHNIQUES

Advancements in imaging techniques have significantly enhanced the capabilities of microwave imaging in medical diagnostics. A physics-assisted deep learning framework, proposed by (Ruiz, Cavagnaro, and Crocco 2022), combines qualitative imaging with deep neural networks to achieve reliable and user-independent shape reconstruction of unknown targets in real-time. This approach addresses the limitations of traditional qualitative imaging methods by automating the thresholding process, thereby reducing user bias.

The integration of advanced materials in microwave frequency applications has gained significant attention in recent years.(Cheah et al. 2024) provided a comprehensive review of graphene-based materials for energy harvesting at microwave frequencies, highlighting the potential of these materials to replace conventional copper-based components in antenna systems.

Building on this, (Bicer 2023) introduced neurocomputational models using deep neural networks and convolutional neural networks for radar-based microwave imaging of breast tumors, demonstrating high accuracy in image generation. In a different approach, (Alsaedi et al. 2021) proposed a hybrid technique combining microwave radiation and infrared thermography, supported by a Convolutional Neural Network, for enhanced breast cancer detection. This method exploits the differences in electromagnetic power transmission between healthy and cancerous tissues, showing promise in tumor detection and localization.

Further advancing the field, (Zhang et al. 2019) developed a CNN-based ultrasound imaging technique for detecting and monitoring thermal lesions induced by microwave ablation in porcine livers, outperforming traditional B-mode images in lesion detection and monitoring. These diverse approaches collectively demonstrate the evolving landscape of microwave imaging techniques, each contributing to improved accuracy, real-time capabilities, and enhanced diagnostic potential in various medical applications.

TABLE 1. Comparative Analysis of Existing Surveys and the Proposed Comprehensive Survey on Microwave Imaging in Medical Applications

Reference	Medical Applications	Dualfocused Taxonomy	Imaging Techniques	Deep Learning Approaches	Antenna Design and Technologies	Overall Coverage
(AlSawaftah et al. 2022)	√ Breast Imaging Only	X	√ Microwave Tomography	X	X	Limited
(El Misilmani et al. 2020)	√ Breast Imaging Only	X	√ Microwave Tomography	X	√ Antenna Design	Limited
(Benny, Anjit, and Mythili 2020)	√ Breast Imaging Only	X		X	X	Limited
(Ahmed 2021)	√ Security Applications	X	√ SAR Imaging	X	√ Antenna Design	Limited
(Reimer and Pistorius 2023)	√ Breast Imaging Only	X	√ Image Quality Analysis	√ Machine Learning	X	Limited
(Anitha, Beohar, and Nella 2023)	X THz Imaging in Various Fields	X	√ Image Reconstruction	X	√ Antenna Design	Limited
Our Survey	√ Breast, Brain, Stroke & Other	√	√ Various Techniques	√ Deep Learning Approaches	√ Antenna Design & Technologies	Compre-hensive

TABLE 2. Comparative Analysis of Reconstruction Techniques in Microwave Imaging (MWI)

Method	Description	Advantages	Limitations	Applications	Performance
Traditional Qualitative Imaging (Ruiz, Cavagnaro, and Crocco 2022)	Identifies presence, position, and basic shape of targets	Quick and computationally light; Suitable for many practical applications	Lacks detailed morphological properties; Limited precision in structural details	General target detection	Accuracy up to 0.998, DSC up to 0.886, MCC up to 0.873 in experimental data
Advanced Reconstruction (Deep Learning) (Bicer 2023)	Improves reconstruction fidelity using automated classification	Reduces user bias; Enhances objectivity; Enables detailed characterization; Estimates EM properties	High computational cost; Depends on training data quality	Complex diagnostic scenarios	High accuracy in image generation; metrics vary by model
ISP Approaches (El Misilmani et al. 2020)	Recovers properties from scattered EM waves	Handles nonlinear problems; Wide applicability	Computationally complex; Requires sophisticated algorithms	Biomedical imaging, subsurface sensing	Promising results with deep learning integration (Yao, Jiang, and Wei 2020)
Real-time Qualitative Imaging (Gopalakrishnan et al. 2023)	Efficient shape recovery without approximations	Real-time capability; Computationally efficient	May sacrifice detail for speed	Rapid imaging applications	Real-time performance; metrics not specified
Morpholog-ical Information (El Misilmani et al. 2020)	Extracts detailed structural information	Enhanced accuracy; Detailed target info	Computationally intensive; Requires sophisticated hardware	Detailed diagnostic imaging	Improved structural accuracy; metrics not specified
MDLI-Net (Pang et al. 2021)	Model-driven learning network for high-resolution imaging	Handles sparse sampling; Efficient HR generation	Requires training data; Needs application-specific tuning	High-resolution imaging with sparse data	Outperforms traditional methods in challenging scenarios
DL-MITAT (Zhang et al. 2022)	Deep-learning enabled thermoacoustic tomography	Superior sparse-data quality; Reduced artifacts	Dataset-specific training; Tissue-dependent performance	Breast cancer detection	Reliable reconstruction with only 15 measurements

DEEP LEARNING APPROACHES

Deep learning has revolutionized microwave imaging in medical diagnostics, enhancing accuracy, efficiency, and the potential for real-time applications. Various neural network architectures have been employed to improve image reconstruction and analysis across different medical imaging domains.

In brain imaging, a study (Hossain, Islam, and Almutairi 2022) presented an automatic classification and detection system for human brain abnormalities using the YOLOv5 object detection model in a portable microwave head imaging system (MWHI). The YOLOv5l model achieved impressive results, with accuracy, precision, and sensitivity all above 94%, demonstrating its potential for real-time tumor detection and classification in microwave brain imaging.

For breast imaging, a deep learning approach (Mojabi, Khoshdel, and Lovetri 2020) was proposed for tissue-type classification of tomographic microwave and ultrasound property images. This method, based on a CNN with U-net architecture, not only classifies tissue types but also quantifies uncertainty in the classification of each pixel. This uncertainty quantification is crucial for distinguishing between cancerous and healthy tissues, outperforming previous Bayesian-based classification methods.

Addressing challenges in microwave imaging with large rotating angles and sparse sampling, a new learning imaging framework called MDLI-Net (Pang et al. 2021) was developed. This model-driven learning imaging network efficiently generates high-resolution and focused target images from 2-D sparse complex-valued target echoes, overcoming limitations of traditional imaging methods like Range-Doppler, back projection, and sparse recovery.

In the realm of microwave-induced thermoacoustic tomography (MITAT), a novel deep-learning-enabled MITAT (DL-MITAT) modality (Zhang et al. 2022) was proposed to address sparse data reconstruction problems in breast cancer detection. Using a domain transform network (FPNet + ResU-Net), this approach demonstrated superior image quality and artifact reduction compared to traditional imaging algorithms, reliably recovering breast tumor images with as few as 15 measurements.

Finally, a novel deep learning approach (Yao, Jiang, and Wei 2020) was introduced to resolve electromagnetic inverse scattering (EMIS) problems. This method, based on a complex-valued deep fully convolutional neural network, effectively addresses challenges such as high contrast, high computational cost, and strong ill-posedness in EMIS problems. The approach opens new possibilities for real-time quantitative microwave imaging of high-contrast scatterers.

TABLE 3. Methodological Comparison of Imaging Techniques in Microwave Imaging for Medical Diagnostics

Reference	Method	Technique	App-lication	Key Features	Advan-tages	Limit-ations
(Ruiz, Cavagnaro, and Crocco 2022)	Physics-Assisted Deep Learning Framework	Combines qualitative imaging with deep neural networks	Real-time shape reconstruction of unknown targets	Automates thresholding process, reducing user bias	Reliable, user-independent shape reconstruction	May require high computational resources
(Bicer 2023)	Neuro-computational Models	Deep Neural Networks and CNNs for radar-based microwave imaging	Breast tumor imaging	High accuracy in image generation	Improves diagnostic accuracy	Dependent on quality of training data
(Alsaedi et al. 2021)	Hybrid Technique	Combination of microwave radiation and infrared thermography, supported by CNN	Enhanced breast cancer detection	Exploits differences in electromagnetic power transmission	Promising for tumor detection and localization	Integration complexity of different modalities
(Zhang et al. 2019)	CNN-Based Ultrasound Imaging Technique	CNN for detecting and monitoring thermal lesions induced by microwave ablation	Porcine liver thermal lesion monitoring	Out-performs traditional B-mode images	Enhanced lesion detection and monitoring	Specific to ultrasound and microwave ablation scenarios

TABLE 4. Methodological Comparison of Deep Learning Approaches in Microwave Imaging for Medical Diagnostics

Ref	Application	Deep Learning Model	Key Features	Advantages	Limitations
(Hossain, Islam, and Almutairi 2022)	Brain Tumor Detection	YOLOv5 Object Detection Model	Automatic classification and detection system	High accuracy, precision, and sensitivity (above 94%)	Requires extensive labeled data for training
(Mojabi, Khoshdel, and Lovetri 2020)	Breast Tissue Classification	CNN with U-net Architecture	Tissue-type classification with uncertainty quantification	Outperforms Bayesian-based methods in distinguishing cancerous tissues	Computationally intensive, especially for uncertainty quantification
(Pang et al. 2021)	High-Resolution Imaging	MDLI-Net (Model-Driven Learning Imaging Network)	Efficient high-resolution image generation from sparse data	Overcomes limitations of traditional methods (e.g., Range-Doppler)	May require fine-tuning for specific applications
(Zhang et al. 2022)	Breast Cancer Detection	DL-MITAT (Deep-Learning-Enabled Microwave-Induced Thermoacoustic Tomography)	Superior image quality and artifact reduction with sparse data	Reliable tumor image recovery with minimal measurements	Specific to thermoacoustic applications; may need adaptation for other uses
(Yao, Jiang, and Wei 2020)	Electromagnetic Inverse Scattering Problems	Complex-Valued Deep Fully Convolutional Neural Network	Real-time quantitative imaging of high-contrast scatterers	Addresses challenges like high contrast and ill-posedness	High computational cost, requires significant processing power

ANTENNA DESIGN AND TECHNOLOGIES

Antenna design plays a crucial role in the advancement of microwave imaging, particularly in medical applications such as breast cancer detection. The development of suitable antennas is driven by the need for improved radiating systems and identification algorithms in microwave imaging.

Recent advances in antenna design for energy harvesting applications have shown promising developments in MEMS technology. (Sampe et al. 2023) demonstrated the design and performance evaluation of radio frequency micro energy harvesting MEMS antennas specifically optimized for low power electronic devices, achieving efficient energy conversion for wireless sensor applications. This work aligns with the miniaturization trends observed in medical imaging antenna system.

Ultra-wideband (UWB) antennas have gained significant attention in biomedical imaging applications due to their unique characteristics. As discussed in (Rafique et al. 2022), these antennas must meet demanding requirements, including operation in close proximity to the examined objects, adequate bandwidth, reduced dimensions, and low production costs. The study presents a comprehensive review of UWB antenna designs for near-field microwave imaging, classifying them based on manufacturing technology and radiative performance. It also explores radiation mechanisms and techniques for size reduction and bandwidth improvement.

In the context of breast cancer detection, microwave breast imaging has emerged as a promising alternative to conventional techniques. A survey (El Misilmani et al. 2020) highlights the need for specifically designed antennas to meet the requirements of microwave breast imaging systems. These antennas must comply with critical criteria such as bandwidth, size, design complexity, and manufacturing cost. The study provides a comprehensive analysis of different array configurations and antenna elements proposed for microwave breast imaging, evaluating their suitability based on operational bandwidth, size, radiation characteristics, and improvement techniques.

Advancing the field further, recent research (Das, Chowdhury, and Jang 2022) introduces a novel miniaturized millimeter-wave (mmWave) antenna sensor for breast tumor detection and 5G communication. This low-cost, miniaturized antenna sensor operates in the frequency range of 32.626 GHz to 33.96 GHz, with a peak gain of 6.65 dB and radiation efficiency of 91.46%. The compact size (5 mm × 5 mm × 0.578 mm) and ability to detect malignancies as small as 1 mm inside breast phantoms make it a promising development in breast cancer screening technology.

MWI WORKING PRINCIPLE

Microwave imaging encompasses three fundamental techniques: Passive, Active, and Hybrid methods. In passive microwave radiometry (MWR), the system measures natural emissions between 1 to 10 GHz from cells, proteins, organs, and the body, with the emission strength determined by biochemical and biophysical processes. Active MWI techniques, on the other hand, operate by directing electromagnetic signals at microwave frequencies toward the area of interest and collecting the reflected or scattered energy to form images, primarily through either tomography or radar-based imaging. In microwave tomography (MWT), antennas surround the object of interest in an imaging chamber filled with a matching medium, and the system measures changes in the electromagnetic field to create two-dimensional visualizations based on dielectric properties. Radar-based MWI specifically utilizes reflected signals from sudden variations in electrical properties to construct images. Hybrid MWI techniques combine multiple approaches to leverage their respective benefits for improved outcomes. What makes MWI particularly valuable for healthcare applications is its ability to provide deep tissue imaging without using ionizing radiation or requiring fluorescent or radioactive tagging, making it a safe and cost-effective imaging solution. A practical implementation of MWI technology is demonstrated in Figure 1, which shows a complete experimental setup for head imaging using an Ultra-Wideband (UWB) antenna system. The setup consists of a 3D-printed head phantom positioned on an experimental platform, with a UWB antenna for signal transmission and reception. The system is controlled through a user interface on a laptop, connected to a microwave transceiver for signal processing. The resulting image on the right displays a color-coded visualization of the head's internal structure, where different colors represent varying dielectric properties of the tissues, demonstrating the system's capability to detect and image internal structures non-invasively.

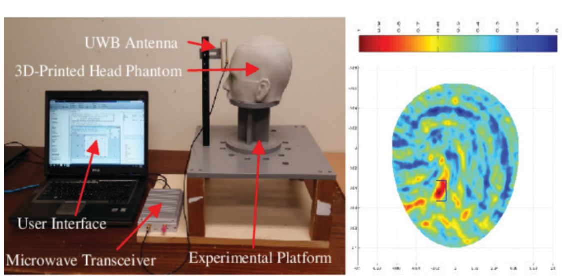

FIGURE 3. Working Principle of MWI

SENSING AND DATA ACQUISITION

Sensing and data acquisition are critical components of microwave imaging, enabling the accurate collection of electromagnetic signals for further processing. Advances in antenna design, signal acquisition, and hardware systems significantly influence the overall performance of imaging systems.

Figure 3 demonstrates a complete microwave imaging experimental setup for head imaging, showcasing the practical implementation of the theoretical principles discussed throughout our survey. The system integrates a UWB antenna operating at 3.1-10.6 GHz with a 3D-printed head phantom that incorporates realistic dielectric properties matching brain tissue, skull, and cerebrospinal fluid for controlled validation testing. The laptop-based control system executes the advanced reconstruction algorithms and deep learning approaches analyzed in our methodological sections, transforming raw electromagnetic measurements into the color-coded brain image displayed on the right, where different colors represent varying tissue dielectric properties enabling identification of brain structures and potential abnormalities. This experimental validation approach represents a critical bridge between the simulation-based research predominantly found in current literature and the clinical implementation requirements discussed in our future directions, demonstrating how theoretical advances in antenna design, signal processing, and reconstruction algorithms translate into functional diagnostic imaging systems capable of generating clinically interpretable results through non-invasive, non-ionizing electromagnetic sensing.

The conceptual framework for sensing and data acquisition, as illustrated in Figure 4, outlines the sequential stages involved in the process, from signal generation to reconstruction and analysis.

(Wan et al. 2023) proposed a dipole antenna array optimized for microwave-induced thermoacoustic imaging. Operating within a frequency range of 1--4 GHz, the antenna was designed using 3D electromagnetic simulation software. The results indicated superior radiation characteristics suitable for early cancer detection. However, the study was limited to simulations, and experimental validation was not performed.

(Sluÿters, Lambot, and Vanderdonckt 2022) developed an innovative pipeline for radar-based sensing using electromagnetic modeling and inversion. The approach significantly reduced dataset complexity, enabling high accuracy in gesture recognition with minimal training data. Despite its success in gesture applications, the study did not explore medical imaging contexts, leaving room for future expansion.

(Fang, Bakian-Dogaheh, and Moghaddam 2022) presented a GPU-accelerated variational Born iterative method (VBIM) for real-time 3D microwave medical imaging. The system achieved frame reconstructions within five seconds, demonstrating its potential for real-time clinical use. However, the validation was confined to synthetic phantoms, and clinical trials are needed to establish broader applicability.

(Gupta et al. 2024) designed a dielectric resonator antenna for breast tumor imaging, achieving wideband performance (6.5--12.5 GHz). The antenna's backscattered signal analysis, combined with a ground-penetrating radar algorithm, improved tumor localization. The lack of comparisons with alternative antenna designs was a notable limitation.

(Liu et al. 2023) reviewed microwave-induced thermoacoustic tomography (MITAT), integrating the benefits of microwave and ultrasound imaging. The study identified challenges, such as miniaturization and sensitivity, necessary for clinical adoption. While comprehensive in scope, the review highlighted unresolved technical obstacles.

(Hossain et al. 2024) proposed a deep transfer learning model (FT-FEDTL) for brain tumor classification using microwave imaging data. The model utilized InceptionV3 for feature extraction and fine-tuned additional layers for improved performance. Despite achieving 99.65% accuracy, its reliance on augmented datasets raises concerns about real-world generalizability.

(Suzuki and Kidera 2021) introduced a region-of-interest (ROI) limiting scheme to improve the resolution of the distorted Born iterative method (DBIM). This approach enhanced dielectric profile reconstruction for breast imaging, particularly in dense breast tissues. The method's computational complexity remains a challenge for real-time applications.

(Karthikeyan et al. 2024) reviewed the design, fabrication, and simulation of flexible wearable antennas for tumor detection. The study emphasized the role of substrate materials and performance optimization for biomedical applications. However, practical implementation in clinical settings remains unexplored.

(Al-Naser et al. 2024) explored the integration of augmented reality (AR) systems in image-guided microwave tumor ablation. The review highlighted AR's ability to reduce radiation exposure and improve procedural accuracy. Challenges include small sample sizes and the need for large-scale clinical trials.

(Shu et al. 2024) proposed a nanoplatform for synergistic therapies combining glutathione depletion and microwave dynamic therapy. This approach demonstrated significant efficacy in treating bone metastases, but concerns remain regarding scalability and safety in clinical environments.

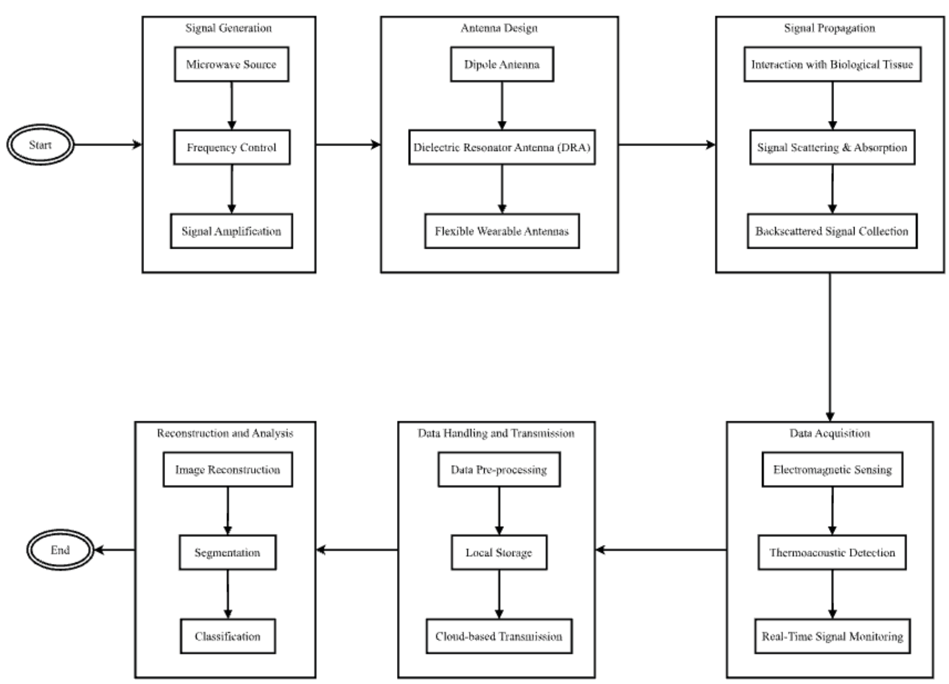

FIGURE 4. Enhanced conceptual framework for sensing and data acquisition in microwave imaging. The diagram outlines the sequential stages involved, starting from signal generation and antenna design to data acquisition, handling, and reconstruction for diagnostic applications. Each stage plays a critical role in ensuring accurate imaging and analysis.

TABLE 5. Comprehensive Summary of Articles on Sensing and Data Acquisition

Article Title	Key Contributions	Limitations
Design and Simulation of Dipole Antenna Array for Microwave-induced Thermoacoustic Imaging (Wan et al. 2023)	Optimized dipole antenna array for thermoacoustic imaging	Limited to simulations without experimental validation
Hand Gesture Recognition for an Off-the-Shelf Radar by Electromagnetic Modeling and Inversion (Sluÿters, Lambot, and Vanderdonckt 2022)	Pipeline combining electromagnetic modeling with ML for gesture recognition	Unexplored applications in medical imaging
Real-Time 3D Microwave Medical Imaging With Enhanced Variational Born Iterative Method (Fang, Bakian-Dogaheh, and Moghaddam 2022)	GPU-accelerated VBIM for real-time frame reconstruction	Validation limited to synthetic phantoms.
Enhanced Breast Tumor Localization with DRA Antenna Backscattering and GPR Algorithm in Microwave Imaging	Designed wideband antenna for enhanced tumor localization.	No comparative analysis with other designs.
Microwave-induced Thermoacoustic Tomography: System, Application, and Reconstruction (Liu et al. 2023)	Integration of microwave and ultrasound imaging for tissue reconstruction.	Challenges in miniaturization and sensitivity
FT-FEDTL: A Fine-Tuned Feature-Extracted Deep Transfer Learning Model for Brain Tumor Classification (Hossain et al. 2024)	Fine-tuned DTL model achieving 99.65% accuracy in classification	Dependency on augmented datasets
Resolution Enhanced Distorted Born Iterative Method Using ROI Limiting Scheme for Microwave Imaging (Suzuki and Kidera 2021)	ROI-based scheme for high-resolution dielectric imaging	High computational complexity
A Review on Fabrication and Simulation Methods of Flexible Wearable Antennas for Tumor Detection (Karthikeyan et al. 2024)	Comprehensive review on wearable antenna design and simulation	Lacks practical clinical validation.
The Applications of Augmented Reality in Image-Guided Tumor Ablations (Al-Naser et al. 2024)	Highlighted AR's potential in improving tumor ablation accuracy	Small sample sizes and limited clinical trials.
Targeting Nanoplatform Synergistic Therapies for Bone Metastasis (Shu et al. 2024)	Combined nanoplatform for microwave and dynamic therapies	Scalability and safety concerns.

RADAR-BASED RECONSTRUCTION ALGORITHMS

Radar-based techniques are widely used in microwave imaging due to their computational efficiency and relatively straightforward signal model. These methods typically produce qualitative images where regions of high reflectivity are displayed, indicating potential tumor locations. The most common radar-based reconstruction method is the Delay-and-Sum (DAS) beamformer, which has been extensively used in clinical studies. The DAS algorithm works by summing time-delayed radar signals acquired during the scan protocol. The mathematical formulation for DAS in a monostatic system is given by:

$$I(r) = \sum_a \sum_f S(a,f) e^{-2\pi j f 2t(r,a)} \tag{1}$$

where:
$S(a,f)$ is the measured radar signal at antenna position a and frequency f
$I(r)$ is the image intensity at position r
$t(r;a)$ is the time delay for signal propagation from the antenna to the target position

The DAS algorithm assumes a homogeneous propagation speed and isotropic antenna characteristics, which simplifies the reconstruction process but may not accurately reflect real-world conditions.

To improve upon the DAS method, the Delay-Multiply-and-Sum (DMAS) beamformer was introduced. DMAS enhances the DAS approach by incorporating signal-pair multiplication before summation, which helps reduce clutter and improve tumor localization accuracy. The DMAS algorithm is expressed as:

$$I(r) = \sum_a \sum_{a'} \sum_f S(a,f) e^{-2\pi j f 2t(r,a)}\, S(a',f) e^{-2\pi j f 2t(r,a')} \tag{2}$$

DMAS has been shown to outperform DAS in both phantom and patient studies, particularly in terms of clutter reduction and tumor localization accuracy.

TOMOGRAPHIC RECONSTRUCTION

ALGORITHMS

In contrast to radar-based methods, microwave tomography aims to reconstruct quantitative images of the dielectric properties of the breast. This approach uses a full electromagnetic scattering model to solve the inverse problem, which is computationally expensive and challenging to apply to experimental data. Microwave tomography typically involves solving a nonlinear optimization problem to estimate the dielectric properties of the breast tissue. While this method can provide more detailed information about the tissue properties, it is less commonly used in clinical settings due to its computational complexity and sensitivity to noise.

OPTIMIZATION-BASED RADAR RECONSTRUCTION (ORR)

To address the limitations of traditional radar-based methods, a novel approach called Optimization-Based Radar Reconstruction (ORR) has been developed. ORR reframes the radar image reconstruction process as an optimization problem, allowing for the incorporation of nonlinear components into the signal model. The ORR method uses a gradient descent optimizer to minimize the difference between the forward model predictions and the experimentally measured signals. The forward signal model in ORR is defined as:

$$S_{fwd}(a,f,\sigma) = \int d\tau\, \sigma(r) e^{-2\pi j f 2t(r,a)} \tag{3}$$

where $S_{fwd}(a,f,\sigma)$ is the forward model S-parameter at measurement position a, frequency f, due to the reflectivity profile σ. The optimization problem is formulated as:

$$\sigma_{img} = argmin_{\sigma} \left(\sum_a \sum_f \left|S_{fwd}(a,f,\sigma) - S_{expt}(a,f)\right|^2\right) \tag{4}$$

ORR has been shown to improve both sensitivity and specificity compared to DAS and DMAS, particularly in reducing image artifacts and improving tumor detection accuracy.

PSEUDOCODE FOR THE THREE ALGORITHMS

DELAY-AND-SUM (DAS) ALGORITHM

The delay-and-sum (DAS) beamformer serves as the standard method for radar-based image reconstruction in breast microwave sensing (Reimer and Pistorius 2021b). While computationally efficient, DAS employs a simplified radar signal model that assumes homogeneous propagation speed and neglects critical physical aspects like signal attenuation, partial transmission at interfaces, and propagation media losses.

The DAS beamformer algorithm as presented in Algorithm 1 operates by iterating through each position in the imaging domain, where for each position r, it initializes the image intensity $I(r)$ to zero. The algorithm then processes measured signals $S(a,f)$ from each antenna position a across all frequencies f. For each combination of position and frequency, it calculates the time delay $t(r,a)$ and accumulates the phase-adjusted signal contributions using complex exponential terms $e^{-2\pi jf2t(r,a)}$, ultimately producing a reconstructed image intensity value for each spatial position.

ALGORITHM 1 Delay-and-Sum (DAS) Beamformer

```
Require Measured signals S(a, f), antenna positions,
target positions
Ensure Image intensity I(r)
for each position r in imaging domain
   Initialize I(r) = 0
   for each antenna position a
      for each frequency f
         Calculate time delay t(r, a)
         I(r) += S(a, f)e^{-2πjf2t(r,a)}
      end for
   end for
end for
return I(r)
```

DELAY-MULTIPLY-AND-SUM (DMAS) ALGORITHM

The delay-multiply-and-sum (DMAS) beamformer enhances DAS by implementing signal-pair multiplication before summation (Reimer and Pistorius 2021b). Through computing autocorrelation at each antenna measurement position while excluding autoproduct terms, DMAS demonstrates superior performance in both phantom and patient studies, particularly in clutter reduction and tumor localization accuracy compared to DAS and its derivatives.

The DMAS beamformer algorithm as presented in algorithm (Desai et al.) extends DAS by implementing a pair-wise signal multiplication approach. For each position *r*, it processes pairs of antenna positions (*a* and *a*', excluding self-pairs) across all frequencies. The algorithm calculates time delays for both antenna positions, generates the corresponding phase-adjusted signals (*signal*1 and *signal*2), and multiplies them together before accumulation. This pair-wise multiplication approach enhances clutter reduction and improves tumor localization compared to the simpler DAS summation.

ALGORITHM 2 Delay-Multiply-and-Sum (DMAS) Beamformer

Require Measured signals $S(a, f)$, antenna positions, target positions
Ensure Image intensity $I(r)$
for each position r in imaging domain
  Initialize $I(r) = 0$
  for each antenna position a
    for each antenna position $a' \neq a$
      for each frequency f
        Calculate time delays $t(r, a)$ and $t(r, a')$
        $signal1 = S(a, f)e^{-2\pi jf2t(fr,a)}$
        $signal2 = S(a', f)e^{-2\pi jf2t(r,a')}$
        $I(r) += signal1 \times signal2$
      end for
    end for
  end for
end for
return $I(r)$

OPTIMIZATION-BASED RADAR RECONSTRUCTION (ORR) ALGORITHM

(Reimer and Pistorius 2021b) The Optimization-Based Radar Reconstruction (ORR) algorithm (Reimer and Pistorius 2021b) as presented in Algorithm 3 reframes the reconstruction problem as an optimization task using gradient descent. Starting with an initialized zero reflectivity profile, the algorithm iteratively calculates a forward model of S-parameters, computes a loss function comparing predicted and experimental measurements, and updates the reflectivity profile using gradient descent. This process continues until the relative change in the loss function falls below a convergence threshold ϵϵ, with each iteration refining the reconstruction by minimizing the difference between forward model predictions and experimental measurements.

ALGORITHM 3 Optimization-Based Radar Reconstruction (ORR)

Require Experimental S-parameters $S^{expt}(a, f)$, convergence threshold ϵ
Ensure Reconstructed reflectivity profile σ_{img}
Initialize $\sigma^0(r) = 0$ for all r
$n = 0$
while not converged
  Calculate forward model $S^{fwd}(a, f, \sigma^{(n)})$
  Compute loss function $l(\sigma^{(n)}) =$
$\sum_a \sum_f \left|S^{fwd}(a, f, \sigma^{(n)}) - S^{expt}(a, f)\right|^2$
  Calculate gradient $\nabla_\sigma\, l(\sigma$^((n)))
  Update $\sigma^{(n+1)} = \sigma^{(n)} - \alpha\, \nabla_\sigma\, l(\sigma^{(n)})$
  $n = n + 1$
  if $\frac{l(\sigma^{(n+1)} - l(\sigma^{(n)})}{l(\sigma^{(n)})} \times 100\% \leq \epsilon$
    converged = true
  end if
end while
return $\sigma_{img} = \sigma^n$

APPLICATION ASPECT OF MICROWAVE IMAGING

BREAST IMAGING

Microwave imaging has emerged as a promising alternative to traditional medical imaging techniques such as X-ray mammography, ultrasound, and magnetic resonance imaging, which are central to the early detection and management of breast cancer. However, these conventional modalities have their limitations, including the use of ionizing radiation in mammography and the lower sensitivity in dense breast tissues, emphasizing the need for more accurate and sensitive alternatives.

Recent advancements have significantly enhanced the capabilities of microwave imaging in the early detection of breast cancer. A notable study by (Wang 2023) highlights how the integration of microwave sensing with machine learning techniques offers a non-ionizing, non-invasive, and cost-effective solution. This approach not only helps in identifying and classifying breast tumors but also overcomes some of the primary limitations of traditional methods. By leveraging the specific permittivity contrasts between malignant and healthy tissues, microwave imaging can achieve high-resolution images that are crucial for early diagnosis.

Microwave imaging is appreciated for its rapidity and affordability, which are vital in clinical settings where time and cost constraints are significant. As discussed in the review (Moloney et al. 2020), the application of microwave technologies in medical diagnostics, particularly breast cancer detection, has shown considerable progress. The review critically examines the shortcomings of current imaging modalities and posits microwave imaging as a potential non-ionizing and painless alternative that could be integrated into routine diagnostic care, provided its efficacy is substantiated through further research.

The practical application of microwave imaging in clinical environments has also been explored. According to (Adachi et al. 2021), the feasibility and safety of a portable microwave breast imaging device were assessed through a retrospective study involving breast cancer cases

The study found that microwave imaging could detect all examined breast cancer cases, including those missed by mammography due to dense breast tissues. The ability of this technology to accurately delineate the location and size of tumors correlates well with pathological findings, supporting its potential use as a complementary or alternative tool in breast cancer screening.

EXPERIMENTAL AND REVIEW STUDIES

Microwave imaging (MI) has advanced significantly as a promising non-invasive, non-ionizing alternative for breast cancer detection, particularly in addressing the limitations posed by traditional imaging techniques such as X-ray mammography, MRI, and ultrasound. These traditional methods often suffer from excessive costs, harmful radiation, and discomfort to patients, particularly those with dense breast tissue. The exploration of microwave imaging technologies aims to overcome these barriers through innovative techniques and experimental studies.

(Aldhaeebi et al. 2020)provides a comprehensive overview of the evolution and current state of microwave imaging techniques, specifically focusing on microwave tomography and radar-based techniques. This review discusses the fundamental principles behind these methods and the ongoing challenges that have stymied their commercial application despite decades of research. Key obstacles identified include the need for high-sensitivity sensors, the complexity of imaging systems that utilize multiple antennas, and the inherent difficulties in imaging the highly dispersive tissues of the human breast. Despite these challenges, the non-invasive and harmless nature of microwave imaging continues to hold significant promise for breast tumor detection, motivating further exploration and development in this field.

The article (Modiri et al. 2017) addresses a critical niche between the understanding of microwave imaging technology by engineers and its practical implications for clinicians. It highlights the significant potential of microwave imaging in detecting breast cancer, particularly in patients with dense breasts, where traditional mammography shows reduced sensitivity. This review underscores the importance of aligning microwave imaging results with current breast imaging standards and calls for larger clinical trials to validate the efficacy of MI as both a standalone and supplementary screening tool.

In a more focused study on a specific device, (Janjic et al. 2021) introduces SAFE (Scan and Find Early), a novel microwave imaging system designed for breast cancer screening and early detection. This device utilizes harmless electromagnetic waves to produce diagnostic images without the need for physical compression of the breast, making the scanning process pain-free and non-invasive. Preliminary clinical evaluations indicate a sensitivity of 63%, with the device showing higher sensitivity in larger breasts. While these results are promising, further studies are required to fully ascertain the clinical viability and effectiveness of the SAFE device, particularly in diverse patient populations.

The ongoing experimental studies and reviews of microwave imaging for breast cancer detection illustrate both the challenges and the potential of this technology. While significant progress has been made, the transition from experimental to practical clinical application requires overcoming substantial technical and regulatory hurdles. Future research should continue to focus on enhancing image resolution, simplifying system complexity, and validating these technologies through extensive clinical trials. These efforts are crucial in moving microwave imaging from a promising experimental approach to a reliable, routine diagnostic tool in the battle against breast cancer.

BRAIN IMAGING AND STROKE DIAGNOSTICS

The application of microwave imaging in brain imaging and stroke diagnostics represents a promising frontier in medical diagnostics. While still in its early stages, initial results have shown considerable potential for this technology to provide valuable insights into neurological conditions.

A significant study by (Hossain et al. 2021) employed the YOLOv3 model in a portable electromagnetic imaging system to detect brain tumors. The model was trained and validated on a dataset of 1000 images, achieving high detection accuracy and F1 scores. This research underscores the potential of combining microwave imaging with advanced deep learning techniques for real-time, non-invasive brain tumor detection.

Building on this work, (Hossain et al. 2023) introduced an eight-layered lightweight classifier model, MBINet, for classifying brain tumors from microwave brain images. The model, trained on a dataset of 1320 images, achieved high classification accuracy, indicating the feasibility of using lightweight models in resource-constrained environments. This advancement is particularly significant for portable diagnostic tools and point-of-care applications.

In the realm of stroke diagnostics, (Lai et al. 2023) introduced an explainable deep learning scheme for stroke localization using microwave imaging. The method incorporates the gradient-weighted class activation map (Grad-CAM) to enhance the explainability of the model's predictions, making it more suitable for clinical applications. This approach not only improves the accuracy of stroke detection but also provides insights into the decision-making process of the AI model, which is crucial for building trust in clinical settings.

The experimental validation of a microwave system for brain stroke 3-D imaging, as described by (Rodriguez-Duarte et al. 2021), further demonstrates the potential of this technology. Their study showcased the ability of microwave imaging to provide real-time, continuous monitoring of brain status, which could be invaluable in stroke management and rehabilitation.

These advancements in brain imaging and stroke diagnostics using microwave technology highlight its potential as a valuable tool in neurology. The non-invasive nature of microwave imaging, combined with its ability to provide real-time data, makes it an attractive option for monitoring and diagnosing neurological conditions. However, as with breast imaging applications, further research and clinical trials are necessary to fully establish the efficacy and reliability of these techniques in diverse patient populations and clinical scenarios.

FLEXIBLE ANTENNA CONSIDERATIONS FOR PATIENT COMFORT

Patient comfort and safety represent critical considerations in the design of microwave imaging systems for medical applications. Traditional rigid antenna arrays, while effective for signal transmission and reception, can cause discomfort during extended imaging sessions and may not conform adequately to varied patient anatomies. Recent developments in flexible antenna technology have addressed these concerns by introducing conformable designs that enhance patient experience while maintaining imaging performance.

TABLE 6. Comparative Analysis of Deep Learning Methods in Microwave Imaging for Medical Diagnostics

Method (Citation)	Application	Deep Learning Model	Key Features	Dataset	Performance Metrics
Neurocomputational Models (Mojabi, Khoshdel, and Lovetri 2020)	Breast Tumor Imaging	DNNs and CNNs with CSAR technique	High accuracy in image generation	1000 numerical simulations	PSNR, UQI, SSIM
Hybrid Technique (Alsaedi et al. 2021)	Breast Cancer Detection	CNN with microwave radiation and infrared thermography	Capitalizes on electromagnetic power transmission differences	Not specified	Promising results in tumor detection and localization
YOLOv3 Model (Hossain et al. 2021)	Brain Tumor Detection	YOLOv3 in portable electromagnetic imaging system	High detection accuracy	1000 images	Detection accuracy, F1 score
MBINet (Hossain et al. 2023)	Brain Tumor Classification	8-layered lightweight classifier	Suitable for resource-constrained environments	1320 images	High classification accuracy
Explainable DL Scheme (Lai et al. 2023)	Stroke Localization	Incorporates Grad-CAM	Enhanced explainability of model predictions	Not specified	Suitability for clinical applications
Self-Organized Neural Networks (Devecioglu et al. 2021)	Glaucoma Detection	Self-organized neural networks	Promising for addressing challenges in complex biological issues	Not specified	Not specified

Flexible antennas offer several advantages in medical microwave imaging applications. These devices can conform to the natural contours of the human body, reducing pressure points and improving patient comfort during scanning procedures (Karthikeyan et al. 2024). The conformability also enables better coupling between the antenna and tissue surface, potentially improving signal quality and reducing artifacts caused by air gaps (Singh et al. 2021). Additionally, flexible antenna designs allow for more versatile positioning arrangements, accommodating patients with different body types and medical conditions (Alibakhshikenari et al. 2020).

Recent research has focused on developing flexible substrate materials and conductive elements that maintain electromagnetic performance while providing mechanical flexibility. Polymer-based substrates, textile-integrated conductive elements, and stretchable materials have shown promise in creating antennas that can bend and flex without significant degradation in radiation characteristics (Rafique et al. 2022). These developments are particularly important for breast imaging applications, where patient comfort during compression-free scanning is a significant advantage over traditional mammography (Janjic et al. 2021). The integration of flexible materials with ultra-wideband characteristics has enabled the development of wearable antenna systems that maintain operational bandwidth while conforming to body contours (El Misilmani et al. 2020).

Wearable antenna technology has evolved to incorporate advanced materials such as conductive textiles and flexible polymers that enable seamless integration with clothing or medical garments (Das, Chowdhury, and Jang 2022). These innovations are particularly relevant for continuous monitoring applications where long-term patient comfort is essential. The miniaturization of antenna elements, combined with flexible substrates, has enabled the development of unobtrusive sensing systems that can be worn for extended periods without causing discomfort or restricting patient movement.

However, flexible antenna implementation presents unique challenges including maintaining consistent impedance matching during deformation, ensuring durability under repeated flexing, and managing the trade-offs between flexibility and electromagnetic performance (Sampe et al. 2023). The mechanical stress introduced during bending can affect the electrical properties of conductive elements, requiring careful design optimization to maintain stable performance across different deformation states. Additionally, the integration of flexible antennas with rigid electronic components presents packaging challenges that must be addressed for practical clinical implementation.

Future research directions should focus on optimizing flexible antenna designs for specific medical imaging applications while addressing manufacturing scalability and cost considerations for clinical deployment. The development of self-healing materials and adaptive impedance matching circuits could further enhance the reliability and performance of flexible antenna systems in medical environments. Integration with emerging technologies such as metamaterial structures and active tuning mechanisms may enable next-generation flexible antennas with enhanced performance and adaptability for diverse medical imaging scenarios.

SPECIFIC ABSORPTION RATE (SAR) CONSIDERATIONS IN MEDICAL MICROWAVE IMAGING

Specific Absorption Rate (SAR) represents a critical safety parameter in medical microwave imaging systems, quantifying the rate at which electromagnetic energy is absorbed by biological tissues. SAR is defined as the power absorbed per unit mass of tissue, typically expressed in watts per kilogram (W/kg), and serves as the primary metric for assessing potential thermal effects and ensuring patient safety during imaging procedures.

International safety standards have established strict SAR limits for medical and consumer devices to prevent adverse thermal effects. The International Commission on Non-Ionizing Radiation Protection (ICNIRP) and Federal Communications Commission (FCC) have set whole-body SAR limits of 0.08 W/kg for occupational exposure and 0.08 W/kg for general public exposure over 6-minute averaging periods (Alibakhshikenari et al. 2020). For localized exposure, the limits are typically 2.0 W/kg averaged over 10 grams of tissue in the head and trunk regions. These limits are designed to prevent tissue heating exceeding 1°C, which could potentially cause physiological stress or tissue damage.

Medical microwave imaging systems must undergo rigorous SAR evaluation during the design and testing phases. The assessment involves computational dosimetry using numerical phantoms that represent human tissue properties at microwave frequencies (Rafique et al. 2022). Finite-difference time-domain (FDTD) and finite element method (FEM) simulations are commonly employed to calculate SAR distributions in realistic tissue models. These simulations consider factors such as antenna design, operating frequency, power levels, and tissue dielectric properties to ensure compliance with safety standards.

The primary concern with electromagnetic exposure in medical imaging relates to tissue heating caused by dielectric losses in biological materials. At microwave frequencies used in medical imaging (typically 0.5-10 GHz), tissues with high water content exhibit significant dielectric losses, leading to localized heating (Das, Chowdhury, and Jang 2022). The temperature rise depends on several factors including SAR magnitude, exposure duration, tissue perfusion rates, and thermal regulatory mechanisms. Breast tissue, being highly heterogeneous with varying water content, requires careful SAR analysis to ensure uniform and safe exposure levels across different tissue types.

Modern antenna designs for medical microwave imaging incorporate SAR optimization as a fundamental design criterion. Ultra-wideband antennas used in breast imaging systems are specifically designed to minimize SAR while maintaining adequate imaging performance (El Misilmani et al. 2020). Design strategies include optimizing antenna geometry, implementing ground plane modifications, using metamaterial structures, and employing feeding techniques that reduce near-field coupling with tissues. The development of miniaturized millimeter-wave sensors has enabled significant SAR reduction due to lower power requirements and improved focusing capabilities (Das, Chowdhury, and Jang 2022).

Clinical implementation of microwave imaging systems requires continuous SAR monitoring and control mechanisms. Real-time power monitoring, automatic exposure control systems, and patient positioning protocols are essential for maintaining SAR levels within safe limits during imaging procedures (Janjic et al. 2021). Additionally, operator training and clear safety protocols must be established to ensure proper system operation and patient protection. The integration of SAR feedback control systems enables dynamic adjustment of transmission parameters to maintain optimal imaging performance while respecting safety constraints.

Emerging technologies such as beamforming techniques, adaptive power control, and advanced antenna arrays offer promising approaches for further SAR reduction in medical microwave imaging systems (Alibakhshikenari et al. 2020). The development of temperature-controlled imaging environments and real-time thermal monitoring systems could enable more precise SAR management during extended imaging sessions. Additionally, the integration of machine learning algorithms for predictive SAR modeling may enable proactive safety management in future imaging systems.

DATASET FOR MICROWAVE IMAGING

Microwave imaging has emerged as a promising technique for breast cancer screening, offering potential advantages such as non-ionizing radiation, cost-effectiveness, and patient comfort. However, despite decades of research, the field has been predominantly reliant on simulation studies, limiting its clinical validation. To address this critical gap and advance the assessment of Breast Microwave Imaging (BMI) systems' clinical viability, Reimer et al. have introduced the University of Manitoba Breast Microwave Imaging Dataset (UM-BMID) (Reimer, Krenkevich, and Pistorius 2020).

TABLE 7. Key Characteristics of the UM-BMID Dataset

Characteristic	Description
Number of scans	1257 phantom scans
Phantom type	MRI-derived breast phantoms
Data type	Experimental (not simulated)
System used	Pre-clinical BMI system (University of Manitoba)
Measurements	Antenna measurements and scattering parameters
Accessibility	Open-access, publicly available
URL	https://bit.ly/UM-bmid
Supplementary materials	Code and supportive scripts on GitHub

The UM-BMID represents a significant leap forward in BMI research, providing an open-access resource of unprecedented scale and quality. Table 7 summarizes the key characteristics of this dataset, highlighting its comprehensive nature and potential for advancing BMI research.

As shown in Table 7, this comprehensive collection of experimental data derived from MRI-based breast phantoms offers researchers a substantial sample size for large-scale analysis. This extensive dataset, acquired using a pre-clinical BMI system developed at the University of Manitoba, significantly surpasses the scope of previous phantom studies, potentially bridging the gap between theoretical models and clinical applications.

The importance of the UM-BMID lies in its potential to accelerate the development and validation of BMI technologies. By providing researchers with a rich, diverse set of experimental data, as detailed in Table 7, it enables more robust testing and refinement of imaging algorithms, tumor detection methods, and system designs. This resource is particularly valuable for developing and evaluating machine learning approaches in BMI, as demonstrated by Reimer et al.'s application of logistic regression for tumor detection, which achieved a promising diagnostic accuracy of (85 + 4)%.

Accessibility is a key feature of the UM-BMID, with the dataset publicly available at the URL provided in Table 7. This open-access approach fosters collaboration and knowledge sharing within the scientific community, potentially accelerating advancements in the field. Furthermore, the availability of supplementary materials, including code and supportive scripts, through an associated GitHub repository enhances reproducibility and facilitates further research.

The significance of the UM-BMID extends beyond its immediate application in algorithm development. By providing a standardized, large-scale experimental dataset, it establishes a common benchmark for comparing different BMI approaches. This standardization is crucial for objectively evaluating the performance of various techniques and systems, potentially guiding future research directions and investment in the most promising technologies.

Moreover, the UM-BMID has the potential to play a pivotal role in translating BMI technology from laboratory settings to clinical applications. The dataset's foundation in MRI-derived phantoms, as noted in Table 7, provides a realistic representation of breast tissue properties and geometries, offering insights into the challenges and opportunities of real-world BMI implementation. This could be instrumental in addressing regulatory requirements and facilitating clinical trials, ultimately expediting the path to clinical adoption.

In conclusion, the UM-BMID represents a cornerstone resource in the field of breast microwave imaging. Its comprehensive nature, accessibility, and potential for standardization, as outlined in Table 7, make it an invaluable tool for researchers and developers in the field. As the scientific community leverages this dataset, we can anticipate accelerated progress in algorithm development, system optimization, and clinical validation of BMI technologies. Ultimately, the UM-BMID could play a crucial role in realizing the potential of microwave imaging as a safe, effective, and widely accessible method for breast cancer screening, potentially improving outcomes for millions of patients worldwide.

METHODOLOGICAL CHALLENGES AND FUTURE DIRECTIONS

IMAGING TECHNIQUES

The advancement of electromagnetic sensor technologies for healthcare applications represents a growing area of research interest. Recent developments in RF device and antenna design, particularly in broadband microstrip antennas, reconfigurable antennas, and electromagnetic sensors for healthcare applications, have shown promising potential for medical diagnostic systems. These technological advances support the continued evolution of microwave imaging systems toward clinical implementation

While significant progress has been made in developing sophisticated reconstruction techniques, the inherent complexity of the inverse scattering problem (ISP) remains a major challenge (El Misilmani et al. 2020), (Wang 2023), (Ruiz, Cavagnaro, and Crocco 2022). Advanced techniques like physics-assisted deep learning frameworks offer promising solutions by improving reconstruction fidelity and reducing user bias (Ruiz, Cavagnaro, and Crocco 2022), (Bicer 2023). However, these methods are computationally intensive and require extensive training data, which may limit their applicability in real-time clinical environments. Future research should focus on optimizing these algorithms for faster and more efficient processing, as well as exploring the potential of hybrid techniques that combine traditional imaging methods with deep learning (Alsaedi et al. 2021).

DEEP LEARNING APPROACHES

Deep learning has demonstrated its potential to revolutionize microwave imaging by enhancing diagnostic accuracy and efficiency (Hossain et al. 2021), (Lai et al. 2023), (Bicer 2023), (Pang et al. 2021). However, the variability in biological tissues and the complexity of the underlying physics pose significant challenges in developing generalizable models (Devecioglu et al. 2021),(Mojabi, Khoshdel, and Lovetri 2020), (Pang et al. 2021). The integration of uncertainty quantification, as seen in some breast imaging techniques, is a step towards addressing these challenges (Mojabi, Khoshdel, and Lovetri 2020). However, the high computational demands and the need for large, labeled datasets remain significant barriers (Hossain, Islam, and Almutairi 2022), (Yao, Jiang, and Wei 2020). Future work should aim to develop more robust, explainable, and computationally efficient models that can handle the non-linearities inherent in microwave imaging data (Hossain, Islam, and Almutairi 2022), (Pang et al. 2021), (Zhang et al. 2019), (Yao, Jiang, and Wei 2020).

ANTENNA DESIGN AND TECHNOLOGIES

Antenna design is critical for the success of microwave imaging applications, particularly in sensitive areas like breast cancer detection. The development of ultra-wideband (UWB) antennas and miniaturized millimeter-wave (mmWave) sensors reflects the ongoing efforts to create more efficient and precise imaging systems (El Misilmani et al. 2020),(Das, Chowdhury, and Jang 2022),(Rafique et al. 2022) . However, maintaining performance while reducing antenna size and addressing integration challenges in broader systems are ongoing concerns (Das, Chowdhury, and Jang 2022),(Rafique et al. 2022). Innovations in materials science and antenna technology will be crucial for overcoming these limitations and enabling the widespread clinical adoption of MWI.

TABLE 8: Methodological Comparison of Antenna Designs in Microwave Imaging for Medical Diagnostics

Ref	Antenna Type	Application	Key Features	Advantages	Limitations
(Rafique et al. 2022)	Ultra-Wideband (UWB)	Biomedical Imaging (Near-field)	Close proximity operation Adequate bandwidth Reduced dimensions	Meets demanding operational requirement Low cost	Performance challenges with size reduction
(El Misilmani et al. 2020)	Microwave Breast Imaging	Breast Cancer Detection	Designed for microwave breast imaging systems	Comprehensive analysis of array configurations and antenna elements	Complex design and manufacturing Cost considerations
(Das, Chowdhury, and Jang 2022)	Miniaturized mmWave Sensor	Breast Tumor Detection & 5G Communication	Compact ($5 \times 5 \times 0.578$ mm) 32.626--33.96 GHz range	High radiation efficiency (91.46%) Detects 1 mm malignancies	Limited frequency range Challenging system integration

SIMULATION-BASED RESEARCH LIMITATIONS

A critical limitation in the current microwave imaging literature is the overwhelming reliance on simulation-based studies and synthetic datasets, which creates a significant gap between theoretical capabilities and practical clinical implementation. This section addresses the urgent need for experimental validation and clinical trials to bridge this gap and advance MWI technology toward widespread clinical adoption.

The majority of studies reviewed in this survey are predominantly based on computational simulations and phantom experiments rather than real-world clinical data. While simulation studies provide valuable insights into theoretical performance and proof-of-concept validation, they inherently incorporate several limitations that may not accurately reflect clinical realities (Reimer and Pistorius 2021b). Simulated environments typically assume idealized conditions including homogeneous tissue models, perfect coupling between antennas and tissues, and noise-free signal acquisition—conditions that rarely exist in clinical practice.

Furthermore, computational phantoms, while useful for initial algorithm development, often fail to capture the full complexity of human tissue heterogeneity, breathing artifacts, patient movement, and inter-patient anatomical variability (Aldhaeebi et al. 2020). The dielectric properties assigned to simulated tissues are frequently based on limited experimental measurements that may not represent the full spectrum of tissue variations encountered in diverse patient populations. This limitation is particularly pronounced in breast imaging applications, where tissue density, age-related changes, and pathological variations significantly impact electromagnetic wave propagation patterns (El Misilmani et al. 2020).

REAL-WORLD DATASET SCARCITY

The scarcity of real-world medical datasets presents a fundamental barrier to the development and validation of robust MWI systems. Unlike other medical imaging modalities such as MRI or CT, which benefit from extensive publicly available datasets, the microwave imaging field lacks standardized clinical datasets that enable comparative algorithm evaluation and performance benchmarking. The UM-BMID dataset (Reimer et al. 2020), while representing a significant contribution, remains limited in scope and is based on phantom measurements rather than clinical patient data.

This dataset scarcity is further compounded by the challenges associated with collecting clinical MWI data, including regulatory approval requirements, patient consent processes, and the need for specialized equipment that is not yet widely available in clinical settings. The absence of large-scale clinical datasets hinders the development of robust machine learning models, particularly deep learning approaches that require extensive training data to achieve reliable performance across diverse patient populations (Hossain et al. 2022).

The reliance on synthetic and phantom data also limits the ability to validate the clinical efficacy of proposed methods. Many deep learning approaches demonstrate impressive performance on controlled datasets but may fail to generalize to real clinical scenarios where tissue properties, imaging conditions, and patient characteristics vary significantly from the training environment (Mojabi, Khoshdel, and Lovetri 2020).

CLINICAL TRIAL REQUIREMENTS

The transition from experimental studies to clinical implementation requires rigorous clinical trial validation following established medical device approval pathways.

Current MWI research has largely bypassed this critical validation phase, focusing primarily on technical development rather than clinical effectiveness assessment. Future research must prioritize the design and execution of properly controlled clinical trials that evaluate not only technical performance but also clinical utility, diagnostic accuracy, and patient outcomes.

Clinical trials for MWI systems must address several key validation criteria including sensitivity and specificity compared to gold-standard imaging methods, inter-operator reproducibility, patient safety and comfort assessment, and cost-effectiveness analysis in realistic clinical workflows (Adachi et al. 2021). These trials require collaboration between engineering researchers, clinical investigators, and regulatory bodies to ensure that technical innovations translate into clinically meaningful improvements in patient care.

REGULATORY AND STANDARDIZATION CHALLENGES

The lack of standardized protocols for MWI system evaluation and comparison represents another significant barrier to clinical translation. Unlike established imaging modalities that benefit from well-defined performance metrics and standardization protocols, the MWI field lacks consensus on evaluation methodologies, performance benchmarks, and safety assessment procedures (Moloney et al. 2020),.

Regulatory approval pathways for MWI devices remain unclear, with different regulatory bodies potentially requiring different validation approaches. The development of standardized testing protocols, safety assessment methodologies, and performance evaluation criteria is essential for facilitating regulatory approval and clinical adoption of MWI technologies.

CASE STUDY: A LOW-COST UWB MICROWAVE IMAGING SYSTEM FOR EARLY-STAGE BREAST CANCER DETECTION

To illustrate the practical application and potential of microwave imaging in breast cancer detection, we examine a recent study by Hammouch et al. (Hammouch et al. 2024). This research demonstrates the development and testing of a low-cost, ultra-wideband (UWB) microwave imaging system designed for early-stage breast cancer detection, showcasing the real-world implementation of concepts discussed earlier in this article.

The system developed by Hammouch et al. consists of a circular array of 12 UWB antennas operating from 3.1 GHz to 11.6 GHz, complying with Federal Communications Commission (FCC) frequencies. This frequency range allows the imaging system to balance deep penetration and high resolution, addressing limitations of conventional imaging methods. The compact size of the system (21 × 21 × 12 cm^3) allows for the integration of multiple elements while maintaining acceptable coupling between them, a crucial factor in achieving accurate and high-resolution imaging.

In their methodology, the researchers first designed and fabricated a UWB antenna on an FR-4 substrate, covering the entire FCC band from 3.1 to 11.6 GHz. They then arranged 12 of these antennas in a circular configuration around the breast phantom to ensure comprehensive coverage of all breast positions. To test the system's efficacy, they created two artificial breasts – one with a tumor and one without – designed to mimic the dielectric properties and physiological arrangement of natural breasts.

The data collection phase involved taking measurements in different scenarios using both artificial breasts. This approach allowed the researchers to compare the system's performance in detecting tumors against a tumor-free baseline. The collected data was then processed using a microwave confocal imaging method to reconstruct 2D images of the breast and detect tumors.

The study's findings were significant and promising. The system successfully detected and identified all targets, demonstrating its effectiveness in detecting breast tumors. Notably, the transmission coefficient between antennas showed clear differences between scenarios with and without tumors, indicating the system's sensitivity to tumor presence. The 2D reconstructed images clearly showed the tumor as a high-intensity area, enabling its detection and localization within the breast. Perhaps most importantly, the system achieved this performance while maintaining a low-cost and compact design, making it potentially suitable for widespread clinical use.

These results have several important implications for the field of microwave imaging in breast cancer detection. Firstly, they demonstrate the feasibility of developing low-cost, compact UWB systems for early-stage breast cancer detection, potentially making this technology more accessible for widespread screening programs. The use of UWB technology in this system allows for a balance between deep penetration and high resolution, addressing key limitations of conventional imaging methods. Furthermore, the non-ionizing nature of the system and its ability to operate without breast compression offer potential advantages in terms of patient comfort and safety, which could lead to increased patient compliance with regular screening protocols.

Looking to the future, this case study points to several promising directions for further research and development. While the current system demonstrates impressive capabilities, there is potential for further improvement in image reconstruction algorithms. The integration of artificial intelligence techniques could potentially enable 3D image generation and automated tumor classification, further enhancing the system's diagnostic capabilities. Additionally, more extensive clinical trials would be beneficial to validate the system's performance across a wider range of breast types and tumor characteristics.

In conclusion, this case study provides concrete evidence of the potential for microwave imaging systems to become a viable tool for early-stage breast cancer detection. By addressing key limitations of conventional methods while offering advantages in terms of cost, safety, and patient comfort, such systems could complement or potentially replace current imaging methods in certain scenarios. As research in this field continues to advance, we may see microwave imaging playing an increasingly important role in the fight against breast cancer, potentially saving lives through earlier and more accessible detection.

APPLICATION-SPECIFIC INSIGHTS

BREAST IMAGING

MWI has shown considerable promise as a non-invasive and cost-effective alternative to traditional imaging techniques like mammography, especially for patients with dense breast tissues (Wang 2023), (Moloney et al. 2020) , (Adachi et al. 2021). However, the transition from experimental studies to routine clinical practice requires addressing several challenges, including the need for high-sensitivity sensors and the validation of these technologies through extensive clinical trials (Modiri et al. 2017), (Adachi et al. 2021), (Aldhaeebi et al. 2020). The development of portable MWI devices for breast cancer screening is a significant step forward, but further research is needed to fully establish their efficacy and reliability in diverse patient populations (Janjic et al. 2021),(Adachi et al. 2021) }

BRAIN IMAGING AND STROKE DIAGNOSTICS

The application of MWI in brain imaging and stroke diagnostics is still in its early stages, but initial results are promising (Hossain et al. 2021), (Lai et al. 2023), (Hossain et al. 2023),. The adaptability of MWI to complex diagnostic scenarios, such as brain tumor detection, highlights its potential as a valuable tool in neurology. However, the sensitivity and specificity of these techniques need to be further improved to ensure accurate and reliable diagnostics in clinical settings. Additionally, the development of explainable deep learning models is essential for enhancing the clinical acceptability of these technologies (Lai et al. 2023).

BROADER IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS

The survey highlights the need for interdisciplinary collaboration in advancing MWI technologies. Integrating insights from fields such as machine learning, materials science, and clinical medicine will be crucial for overcoming the current limitations of MWI. Moreover, addressing the gaps identified in the literature, particularly the lack of comprehensive studies that integrate both methodological and application aspects, will be essential for fully realizing the potential of MWI in medical diagnostics.

In conclusion, while microwave imaging holds great promise for revolutionizing medical diagnostics, several challenges must be addressed before it can be widely adopted in clinical practice. Future research should focus on optimizing existing technologies, developing more robust and explainable models, and conducting large-scale clinical trials to validate the efficacy of these approaches. By addressing these challenges, microwave imaging has the potential to become a standard tool in the early detection and management of various medical conditions, ultimately improving patient outcomes and advancing the field of medical diagnostics.

CONCLUSION

This comprehensive survey of microwave imaging (MWI) in medical applications demonstrates its transformative potential across multiple diagnostic domains. Through systematic analysis using our bifurcated taxonomy approach, we have identified significant developments in both methodological and application aspects of MWI technology.

In terms of reconstruction techniques, the field has evolved from traditional qualitative imaging methods to sophisticated deep learning-enabled approaches. Our analysis reveals that while traditional methods (Ruiz, Cavagnaro, and Crocco 2022) offer computational efficiency and practical applicability, advanced reconstruction techniques incorporating deep learning (Bicer 2023) provide enhanced accuracy and reduced user bias. Novel approaches like MDLI-Net (Pang et al. 2021) and DL-MITAT (Zhang et al. 2022) have particularly demonstrated promising results in handling sparse data and reducing artifacts, though challenges remain in computational requirements and dataset dependencies.

The advancement of imaging techniques has been particularly noteworthy in three key medical applications. In breast imaging, MWI has emerged as a viable alternative to conventional methods, offering non-invasive and cost-effective screening solutions (Wang 2023), (Moloney et al. 2020). For brain imaging and stroke diagnostics, the integration of deep learning approaches has enhanced detection accuracy and real-time monitoring capabilities (Hossain et al. 2021), (Lai et al. 2023). The development of portable devices (Adachi et al. 2021) represents a significant step toward clinical implementation, though further validation through extensive clinical trials remains necessary.

Antenna design and technology developments have significantly contributed to system performance improvements. Ultra-wideband antennas (Rafique et al. 2022) and miniaturized mmWave sensors (Das, Chowdhury, and Jang 2022) have enhanced imaging precision while addressing practical constraints of medical applications. These innovations, combined with advanced reconstruction algorithms, have improved both the quality and reliability of diagnostic imaging. Key challenges identified through our survey include:

1. The need for more efficient computational methods to handle complex reconstruction algorithms
2. Requirements for extensive validation through clinical trials
3. The balance between imaging accuracy and real-time processing capabilities
4. Integration challenges of various technological components

Future research directions should focus on:

1. Development of more robust and computationally efficient deep learning models
2. Enhancement of real-time processing capabilities while maintaining accuracy.
3. Standardization of evaluation metrics and validation protocols.
4. Integration of multimodal imaging approaches for improved diagnostic accuracy.

In conclusion, while MWI technology has shown remarkable progress, particularly in the integration of deep learning approaches and advanced antenna designs, several challenges must be addressed before widespread clinical adoption. The field shows promise in revolutionizing medical diagnostics, but success will require continued innovation in both methodological approaches and practical implementations. This survey provides a foundation for future research by highlighting current achievements, identifying challenges, and suggesting promising dire directions.

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DECLARATION OF COMPETING INTEREST

None.

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