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Advanced microwave imaging and artificial neural networks for early detection and localization of breast tumors

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ABSTRACT

This study investigates the detection and localization of breast tumors based on dielectric property differences between cancerous and normal tissues. A microwave imaging technique integrated with artificial neural networks (ANNs) is proposed as a noninvasive alternative to conventional screening methods such as mammography and magnetic resonance imaging (MRI). A breast model with a 2.5 mm spherical tumor was designed using CST Microwave Studio. Simulation results show that the ANN achieves a detection rate close to 100%, providing negative outputs for tumor-free cases and positive outputs for cases with tumors. Additionally, ANN outputs strongly correlate with the actual tumor positions in the simulated environment. These findings suggest that microwave imaging combined with ANNs offers a cost-effective, radiation-free, and patient-friendly solution for the early detection and localization of breast cancer, with promising potential for clinical translation.

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1. INTRODUCTION

Breast cancer remains a significant worldwide public health issue, especially affecting adult women. The global rise in breast cancer incidence underscores the urgent need for early detection to improve survival rates. In 2015 alone, nearly 40000 lives were lost to this disease, and by 2020, over 2.3 million cases had been diagnosed globally. In many regions, late-stage detection continues to account for nearly half of breast cancer–related deaths. In our country, approximately 3500 deaths are recorded annually, largely due to delayed diagnosis [1], [2]. These figures emphasize the pressing need for innovative, noninvasive diagnostic tools capable of identifying tumors at an early stage with greater accuracy [3]–[5].

Mammography is still the primary technique used for breast cancer screening. Although it is effective, it involves exposure to ionizing radiation and necessitates uncomfortable breast compression, which may reduce patient compliance with routine screening. Magnetic resonance imaging (MRI) provides excellent diagnostic performance but is costly and often associated with long waiting times. Ultrasound offers a safe and noninvasive option but relies on bulky and expensive equipment, making it less practical for mass screening programs [6]–[8].

Over the past decades, microwave imaging techniques have attracted increasing attention due to their potential applications in the medical field, particularly for breast cancer screening and early diagnosis. Their main advantage lies in the use of non-ionizing electromagnetic waves, which are low-cost and potentially suitable for repeated screenings. At the same time, the development of increasingly advanced image reconstruction algorithms has helped to address challenges related to breast modeling, interference correction, and tumor detection [9], [10].

Numerous works have explored the integration of microwave imaging with artificial intelligence techniques especially artificial neural networks (ANNs) and convolutional neural networks (CNNs) as a means to bypass the explicit resolution of the inverse scattering problem typically associated with microwave imaging. These methods have demonstrated promising performance in simulated environments and on experimental breast tissue samples [11], [12].

In this work, we investigate a microwave imaging system using a well-defined database and CST Microwave Studio simulations. ANNs are then applied to process the microwave data for tumor detection and three-dimensional localization. The novelty of this study lies in combining microwave imaging with ANN-based analysis, demonstrating both accurate tumor detection and reliable spatial localization within a simulated breast model.

2. METHOD

The breast phantom was modeled with dimensions and dielectric parameters consistent with ranges commonly reported in experimental studies of breast tissues. Large-scale ex vivo characterization studies have established dielectric properties for normal tissues (adipose, glandular, and fibroconnective), malignant tissues (invasive and non-invasive), and benign samples (fibroadenomas and cysts). Based on these findings, the dielectric properties adopted in our model ensure realistic contrast between healthy and tumor regions. The tumor was modeled as a spherical inclusion with a radius of 2.5 mm, which corresponds to sizes reported as detectable in early-stage breast cancer imaging [13]–[15].

Over the past decade, various breast phantoms have been developed, with differences in shape, size, and dielectric distributions. In this study, CST Microwave Studio was used to simulate a 3D breast model containing a tumor [16], [17]. The simulated setup included both the breast phantom and a pair of transmitting and receiving antennas. The collected simulation data served as the input database for training the ANN. While multiple geometrical configurations exist in the literature, a hemispherical breast model was selected for this work due to its wide adoption in microwave breast imaging studies and its balance between anatomical realism and computational efficiency. The dimensions of this model are summarized in Table 1, and its geometry is shown in Figure 1 [18], [19].

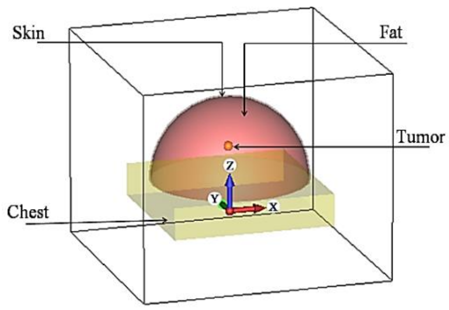

Figure 1. View of the model in electromagnetic software

The dielectric properties used are presented in Table 2, where σ represents tissue conductivity in Siemens per meter (S/m) and εr denotes relative permittivity [18]. In this work, two bowtie antennas were used: one for transmitting Gaussian pulses and the other for data retrieval Figure 2. The two antennas are separated by the breast model [20].

Table 1. Dimensions of each part of the model

Breast dimension	Dimension (cm)
Breast size	10
Breast height	6
Skin thickness	0.2
Chest thickness	2

Table 2. Dielectric properties

Breast tissue	Conductivity σ (S/M)	Permittivity εr
Skin	1.49	37.9
Fat	0.14	5.14
Chest	1.85	53.5
Tumor	1.20	50

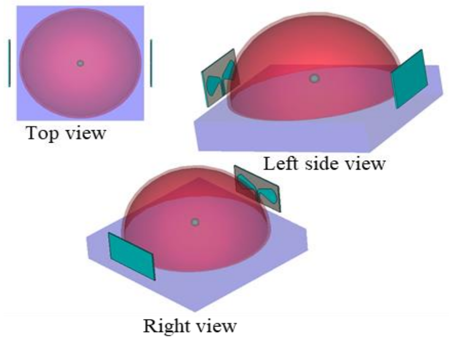

Figure 2. Transmitter-receiver system for database collection

We employed a 4 GHz Gaussian pulse, predefined in the simulation software, to transmit signals and collect scattered data from the breast model. This standardized pulse enabled precise signal transmission and analysis across the experimental setup Figures 3(a) and (b) [21].

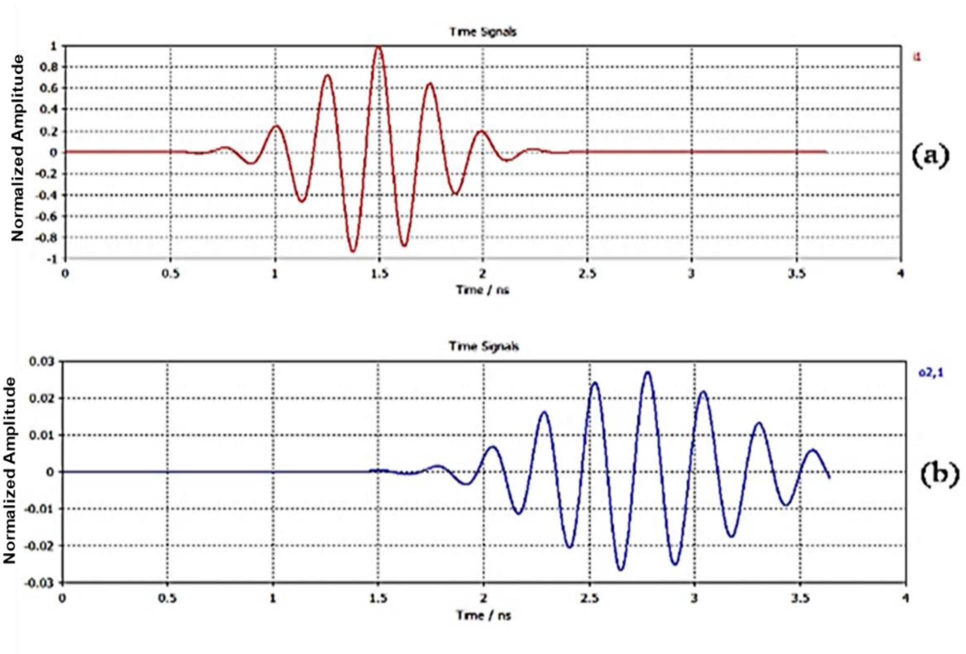

Figure 3. Used gaussian pulse: (a) transmitted wave and (b) received wave

Variations in the object's dielectric properties cause multiple wave diffractions inside it, leading to a nonlinear inverse scattering problem [22]–[24].

$$[E^{DIFF}] = \left[K_{R,o}\right][C][E^{TOT}] \tag{1}$$

To overcome this constraint, we implemented ANN in microwave imaging.

The neural network is built iteratively using samples extracted from a database specifically created for this study. This database gathers pairs of input–output data generated through electromagnetic simulations. The overall procedure followed can be summarized as follows:

a. Position the transmitting and receiving antennas on the two opposite faces of the breast model;
b. Insert the tumor in any selected position inside the breast model;
c. Generate and transmit a Gaussian-shaped excitation pulse;
d. Receive the signal at the opposite side;

e. Modify the tumor location and perform steps (3–4) again.

This data-generation process was performed for 19070 different tumor positions by shifting the lesion throughout the breast model. In addition, the healthy (tumor-free) model was simulated three times to capture the signals propagating solely through normal breast tissues. Consequently, two categories of received signals were obtained: Group 1 includes 18 770 samples for ANN training: 18 769 signals containing tumors and a single signal obtained from a healthy breast model. Group 2 contains 302 test samples: 300 tumor cases and 2 without tumors.

3. RESULTS AND DISCUSSION

To the best of our knowledge, there are no established theoretical rules or universally accepted empirical guidelines to determine the optimal size of an ANN for a specific problem. Consequently, the network topology was determined experimentally through multiple trials, with the performance evaluated at each iteration [25]–[27].

The input layer comprised 271 neurons, corresponding to the number of features in the input vector, whereas the output layer consisted of three neurons, each representing one of the target classes. Several hidden-layer configurations were tested to identify the architecture that achieved the best compromise between detection accuracy and localization performance [25].

The results revealed that all tested topologies achieved a detection rate of 100%, indicating that the classifier was highly effective in distinguishing the classes. However, the topology presented in Figure 4 and summarized in Table 3 provided the highest localization rate, confirming its suitability for the considered application.

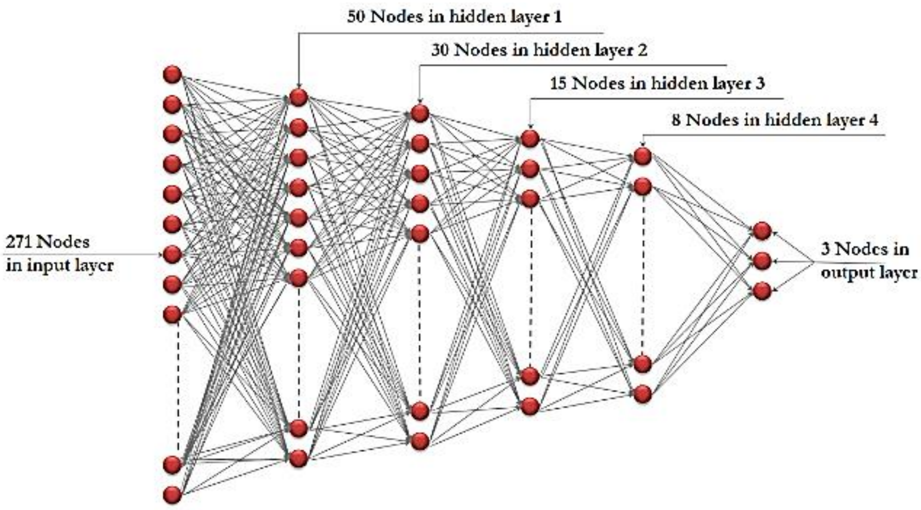

Figure 4. Optimal proposed topology for ANN

Table 3. ANN parameters in (3-D)

ANN parameters	Values
Training function	traingscg
Activation function	sigmoid
Number of iterations	1 000 000

Figure 5 compares the actual tumor positions within the simulated breast model with those predicted by the ANN. The ANN achieved a moderate localization accuracy of approximately 40%, with minor discrepancies primarily attributed to variations in tissue density within the breast phantom. Edge cases, such as the last samples presented in Figure 5, highlight the need for further refinement of the prediction model to improve spatial precision. Despite these limitations, the overall results confirm the feasibility of combining microwave imaging and ANNs for early breast cancer detection.

Following the training phase, the ANN performance was evaluated using the Group 2 test set, specifically designed for validation purposes. The relative error between the actual tumor location and the ANN-predicted position is depicted in Figure 5, confirming the previously mentioned localization rate. This outcome suggests that while the proposed network demonstrates strong detection capabilities, its spatial resolution still depends on the physical properties of the simulated tissue and the network configuration.

To assess the clinical significance of these results, a comparison was made with conventional mammography. Previous studies indicate that mammography has very limited sensitivity for tumors smaller than 2 mm, with detection rates close to 0%, and sensitivity increases significantly only for tumors larger than 5–10 mm [28], [29]. In contrast, the proposed microwave imaging system combined with an ANN achieved a 100% detection rate for tumors with a radius of 2.5 mm a size typically undetectable by mammography.

Although the localization accuracy obtained in this study remains moderate (40%), this performance still represents a meaningful advancement compared to the inability of mammography to both detect and localize tumors of such small dimensions. These findings highlight the promise of the proposed approach as a complementary and non-invasive technique for early-stage breast cancer screening, supporting the growing body of research that integrates artificial intelligence with microwave imaging for medical diagnostics.

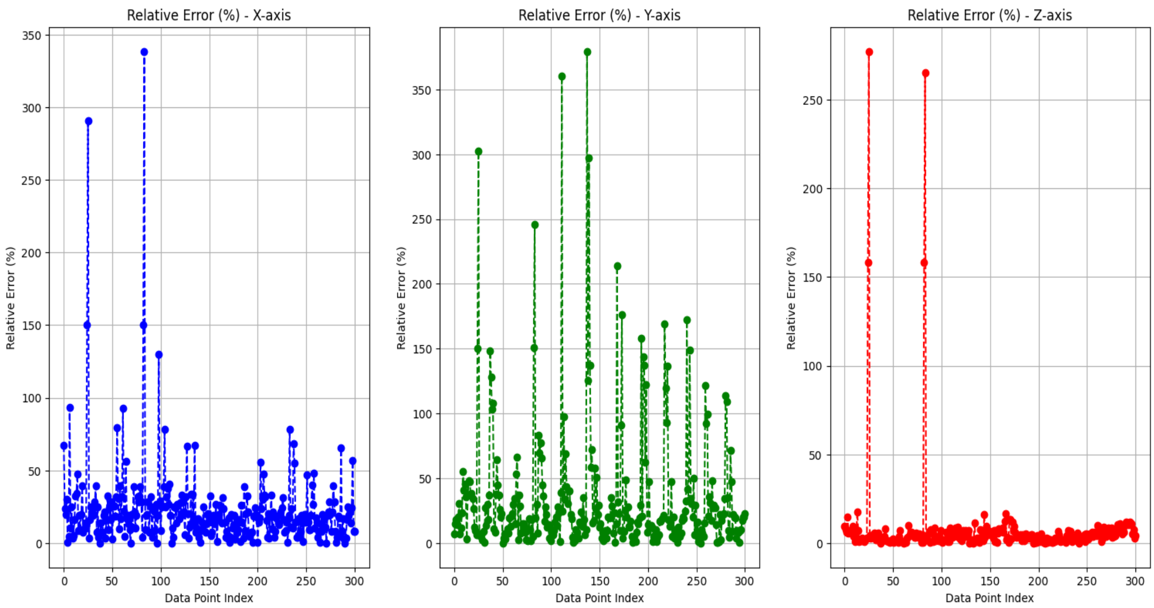

Figure 5. Relative error between the actual position in the breast model and the position given by ANN

To visualize the tumor in the breast and compare the tumor positions predicted by the ANN with their actual positions in the breast model, only the signal images from group two were plotted. The interpretation of magnetic resonance (MR) images presented in Figures 6 and 7 must be approached carefully. In examples where tumor overlap was observed in MR data, as shown in Figures 6 (a)-(f), this indicated effective localization. Conversely, the increased spatial separation between the tumors, as illustrated in Figure 7, is likely due to variations in tissue density, which may be correlated with low localization accuracy. It is important to note that, although MR data provides a useful comparative baseline, the main focus of this research remains microwave imaging.

The main contribution of this work lies in the development and evaluation of a method that combines microwave imaging with ANNs for the detection and localization of breast tumors. The results, detailed in the "results" section and illustrated in Figures 5 and 6, demonstrate the effectiveness of this technique, achieving high detection and moderate localization rates. In particular, the system has shown the ability to detect and localize tumors by exploiting the dielectric contrast between malignant and healthy tissues.

In the current landscape of breast cancer screening technologies, the proposed microwave imaging technique presents a compelling alternative. Compared to mammography, a widely used method for detecting abnormalities in breast tissue, this approach demonstrates comparable performance in detection and localization, while avoiding the high rates of false positives and false negatives often associated with mammographic screening, which can compromise diagnostic reliability. Despite its contributions, this study has certain limitations. Specifically, the database relies on a homogeneous model, which does not completely capture the heterogeneity found in actual breast tissues.

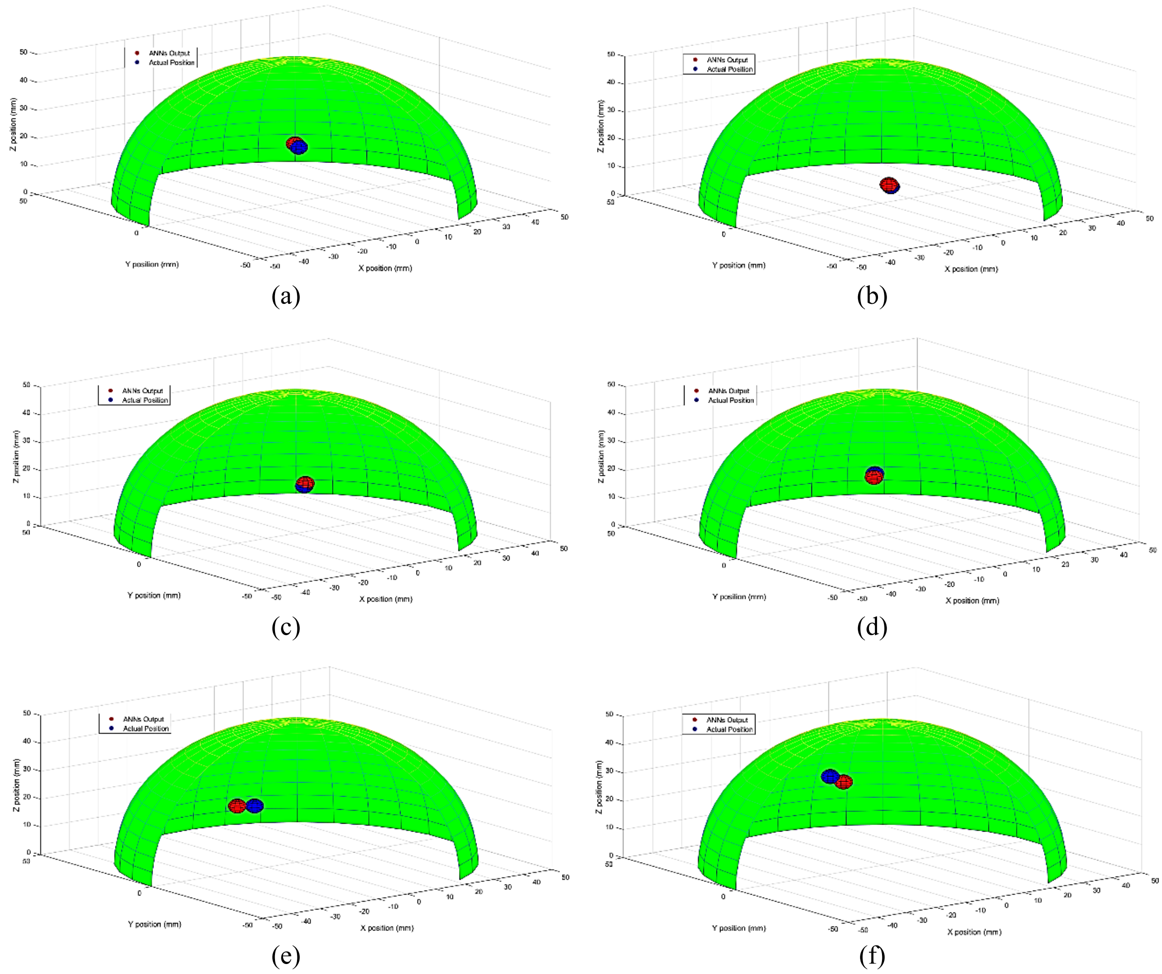

Figure 6. Detection and localization of the tumor at multi positions (X, Y, and Z) in mm; (a) X=0 mm, Y=2 mm, and Z=22 mm, (b) X=2 mm, Y=-2 mm, and Z=6 mm, (c) X=0 mm, Y=-4 mm, and Z=18 mm, (d) X=2 mm, Y=6 mm, and Z=20 mm, (e) X=4 mm, Y=24 mm, and Z=14 mm, and (f) X=-4 mm, Y=18 mm, and Z=28 mm

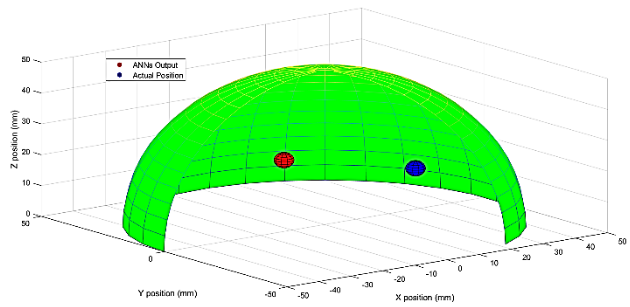

Figure 7. Detection and localization of the tumor at X=10 mm, Y=-24 mm, and Z=22 mm

4. CONCLUSION

The results of this work show that microwave imaging can serve as a strong alternative to conventional breast-cancer screening techniques such as mammography and MRI. Unlike these methods, it does not expose patients to ionizing radiation and does not require breast compression, which improves comfort and makes it more suitable for repeated screening especially for younger women with dense breast tissue. The performance metrics reported in the "results" section demonstrate both a high accuracy in tumor detection and a reliable ability to localize lesions.

Nonetheless, the study is limited by its reliance on simulated data, which requires further validation through experimental measurements and clinical trials. Future work should therefore focus on testing the proposed approach in clinical environments, using larger datasets and comparisons against established imaging modalities. In addition, integrating advanced machine learning techniques such as CNNs may further enhance detection accuracy and robustness. Another important direction is the development of anatomically realistic breast models that capture tissue heterogeneity, thereby improving the reliability of simulation-based studies.

Overall, this research establishes a foundation for the advancement of microwave imaging techniques for early breast cancer detection and localization. Ongoing refinement, combined with clinical validation and hardware implementation, could contribute to improved diagnostic performance and ultimately better patient outcomes.

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AUTHOR CONTRIBUTIONS STATEMENT

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Lotfi Merad	✓	✓	✓				✓	✓	✓	✓				
Djalal Ziani-Kerarti		✓	✓				✓	✓	✓	✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors confirm that there are no conflicts of interest.

DATA AVAILABILITY

Data supporting the conclusions of this research are available from the corresponding author, A.M., upon reasonable and justified request.

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