

### **RESEARCH ARTICLE**



**G** OPEN ACCESS **Received:** 01-11-2023 **Accepted:** 11-12-2023 **Published:** 05-01-2024

**Citation:** Prashanthi HJ, Prathibha T, Thippesha D (2024) Detection of Early-Stage Breast Cancer using Electromagnetic Sensor with Aid of the Convolution Neural Network. Indian Journal of Science and Technology 17(1): 65-69. [https://doi.](https://doi.org/10.17485/IJST/v17i1.1922) [org/10.17485/IJST/v17i1.1922](https://doi.org/10.17485/IJST/v17i1.1922)

*∗* **Corresponding author**.

<thippesh790@gmail.com>

#### **Funding:** None

#### **Competing Interests:** None

**Copyright:** © 2024 Prashanthi et al. This is an open access article distributed under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) [License,](https://creativecommons.org/licenses/by/4.0/) which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Published By Indian Society for Education and Environment([iSee\)](www.iseeadyar.org.)

#### **ISSN**

Print: 0974-6846 Electronic: 0974-5645

# **Detection of Early-Stage Breast Cancer using Electromagnetic Sensor with Aid of the Convolution Neural Network**

### **H J Prashanthi<sup>1</sup> , T Prathibha<sup>2</sup> , D Thippesha<sup>3</sup>***∗*

**1** Assistant Professor, ECE Department, Government Engineering College, Devagiri, Haveri, Karnataka, India

**2** Assistant Professor, CSE Department, Government Engineering College, Ramanagara, Karnataka, India

**3** Member, Institute of Electrical and Electronics Engineers, Bangalore, Karnataka, India

# Abstract

**Objectives**: This study aimed to develop an end-to-end system for the diagnosis of breast cancer using a novel combination of a monopole electromagnetic sensor and Convolutional Neural Network (CNN). **Methods:** The research involved the design and simulation of an electromagnetic sensor, utilizing a denim gene substrate, to capture dielectric changes within breast tissue across a broad spectrum (1GHz to 10GHz). The recorded data was processed by a pre-trained CNN to identify irregularities in the breast's internal structure. **Findings:** Through extensive simulations, the electromagnetic sensor displayed a remarkable sensitivity to changes in the dielectric properties of breast tissue. The CNN analysis accurately identified the presence of cancer cells and estimated tumor size with an impressive 98% accuracy and a 1% tolerance margin. This method significantly outperformed existing models in both accuracy and efficiency, reducing the need for costly imaging techniques. **Novelty:** This research offers a non-invasive, cost-effective solution for early-stage breast cancer detection. Unlike traditional imaging techniques, this approach provides accurate diagnostics without the need for extensive equipment or high-cost procedures.

**Keywords:** Breast Cancer; Electromagnetic Sensor; Convolutional Neural Network; Diagnosis; Noninvasive Diagnosis

# **1 Introduction**

Breast cancer stands as one of the most prevalent and life-threatening diseases, impacting millions worldwide and claiming a staggering number of lives each year. Its formidable nature arises not only from its potential fatality but also from the formidable challenge posed by its extended incubation period, often eluding detection until reaching advanced and more critical stages  $^{(1)}$  $^{(1)}$  $^{(1)}$ . In 2020 alone, a harrowing 685,000 lives were claimed by this disease, affecting 2.3 million women globally $^{(2)}$  $^{(2)}$  $^{(2)}$ . It emerged as the most diagnosed illness among 7.8 million women over the previous five years, attributing substantial disability-adjusted life years (DALYs) to women globally

compared to any other form of cancer. It is estimated that by the end of 2023 there will be 100000 peoples will be diagnosed for the breast cancer in India<sup>([3](#page-4-2))</sup>.

The dire statistics underscore the urgency for enhanced, efficient, and cost-effective means of diagnosis. Such early identification significantly impacts patient survival rates, providing a critical opportunity for effective intervention  $(4-6)$  $(4-6)$ . However, current diagnostic methods often necessitate invasive procedures like biopsies or entail costly, non-repetitive imaging techniques like CT scans, involving high-energy radiation  $^{(7,8)}.$  $^{(7,8)}.$  $^{(7,8)}.$  $^{(7,8)}.$  $^{(7,8)}.$ 

This introduction lays the foundation for the imperative need to revolutionize breast cancer detection methodologies  $^{(8-10)}$  $^{(8-10)}$  $^{(8-10)}$  $^{(8-10)}$  $^{(8-10)}$ . The forthcoming study presents an innovative approach to this persistent issue by integrating a monopole electromagnetic sensor and CNN analysis. This promising combination offers a non-invasive, cost-effective, and highly accurate solution for the diagnosis of breast cancer.

# **2 Methodology**

The methodology employed in the study focused on the development of an end-to-end system for the diagnosis of breast cancer using a unique combination of an electromagnetic sensor and CNN analysis. The key steps involved in the methodology are as follows:

- **Design and Simulation of Electromagnetic Sensor:** Using High-Frequency Structure Simulation (HFSS) software, an electromagnetic sensor was meticulously designed as in Figure [1](#page-1-0) (a). The sensor was crafted with copper traces for conductivity and a flexible denim gene substrate for adaptability. It comprised a circular ring and a Defective Ground Structure in a coplanar configuration, employing a coaxial feed.
- <span id="page-1-0"></span>• **Sensing Dielectric Changes:** The sensor was created to detect and capture variations in the dielectric properties within breast tissue, covering a wide electromagnetic spectrum ranging from 1GHz to 10GHz. These changes in dielectric properties, indicative of potential abnormalities, were captured and recorded as in Figure [1](#page-1-0) (b).



**Fig 1.The physical dimension of electronic sensor and its response plotted for various size cancer tumor. 11750 data points are collected in order to train the model. a. The electromagnetic monopole sensor constructed using denim substrate. b. The scattering parameter (S11 or Return loss) of the sensor is measured and plotted**

- **Breast Phantom Model Simulation:** A breast phantom model, replicating healthy breast tissue and cancerous tumors, was simulated. This model imitated the dielectric nature of actual breast tissue and cancerous growth as in Figure [2](#page-2-0) (a)&(b). Parametric simulations were conducted, manipulating the size of the breast and cancer tumors to assess the sensor's response to these variations.
- **Data Collection and CNN Training:** Changes in the sensor's output, specifically in reflection (S11), resulting from alterations in dielectric properties, were logged across a broad range of spectrums. This process was repeated for various sizes of breast tissue and tumors, amassing a substantial dataset. This dataset was then utilized to train the pre-designed CNN model.

<span id="page-2-0"></span>

**Fig 2. Phantom models of healthy tissue and cancerous tissue is constructed based on dielectric property in simulation environment. a. Phantom model of the breast tissue, breast tissue is mainly consisting of fat and will have low dielectric constant property compared to other tissues of the body. b. Phantom model of the cancer tissue, the cancer tissue is made up tissue with high dielectric constant**

• **Training the Convolutional Neural Network:** Using the collected dataset of 117,500 data points, a Convolutional Neural Network was trained. Python 3 environment, along with sklearn, pandas, numpy, and seaborn libraries, were employed for this training. A Multi-layer Perceptron regressor consisting of 12 layers was utilized for predicting cancerous tumors refer Table [1.](#page-2-1)

<span id="page-2-1"></span>

<b>Activation</b>	Solver	<b>Training Score</b>	<b>Testing Score</b>	<b>MAE</b>	<b>MSE</b>	<b>RMSE</b>
identity	lbfgs	0.9999	0.9650	0.0965	0.0476	0.2181
identity	adam	0.9299	0.1902	0.6213	1.1034	1.0504
tanh	lbfgs	0.9998	0.7828	0.2687	0.2958	0.5439
relu	lbfgs	0.9999	0.9896	0.0541	0.0141	0.1186

**Table 1. Comparative study of various activations and combinations used to train the model**

- **Optimization through Solver and Activation Functions:** Different combinations of solver and activation functions were experimented with to find the most optimal configuration for the  ${\rm CNN}^{(6,7,11)}.$  ${\rm CNN}^{(6,7,11)}.$  ${\rm CNN}^{(6,7,11)}.$  ${\rm CNN}^{(6,7,11)}.$  ${\rm CNN}^{(6,7,11)}.$  ${\rm CNN}^{(6,7,11)}.$  Various activations like identity, logistic, tanh, and relu were tested in combination with solvers such as lbfgs, sgd, and adam. The best-performing combination was identified through a trial-and-error method for comparative study  $^{(8,12)}$  $^{(8,12)}$  $^{(8,12)}$  $^{(8,12)}$ .
- **Evaluation and Selection of Optimal Model:** The models were evaluated using parameters like training score, testing score, Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE). The model demonstrating the highest training score (0.9999), testing score (0.9896), and the lowest errors was selected. In this case, the Multi-layer Perceptron regressor with relu activation and lbfgs solver outperformed other configurations.

The combined process of electromagnetic sensing, simulation, data collection, and CNN training facilitated the development of an effective system for the diagnosis of breast cancer, exhibiting superior accuracy and efficiency.

# **3 Results and Discussion**

# **3.1 Electromagnetic Sensor Performance**

The electromagnetic sensor, designed to capture and interpret changes in the scattering parameters, demonstrated exceptional sensitivity and accuracy. The simulations revealed that alterations in the specific absorption rate (SAR) due to variations in dielectric properties caused discernible changes as in Figure [3](#page-3-0) (a)&(b). These alterations were measured and logged, forming the basis of data utilized for training the CNN.

# **3.2 CNN Analysis and Model Performance**

The CNN, trained on a dataset comprising 117,500 data points obtained from simulations, excelled in accurately identifying the presence of cancer cells within breast tissue. The analysis further showcased the network's ability to estimate tumor size with

<span id="page-3-0"></span>

**Fig 3.The physical dimension of electronic sensor and its response plotted for various size cancer tumor. 11750 data points are collected in order to train the model. a. Phantom model of the breast tissue, a breast tissue is mainly consisting of fat and will have low dielectric constant property compared to other tissues of the body. b. Phantom model of the cancer tissue, the cancer tissue is made up tissue with high dielectric constant**

remarkable precision, achieving an outstanding accuracy of 98% with a narrow tolerance of 1%. Various combinations of solvers and activation functions were explored to optimize the CNN model, with the Multi-layer Perceptron regressor employing relu activation and lbfgs solver emerging as the most efficient configuration.

# **3.3 Comparison with Existing Techniques**

Comparative analysis against traditional diagnostic methods, predominantly reliant on imaging and image-based machine learning models, highlighted the superiority of the developed system. The CNN-based approach not only demonstrated higher accuracy in identifying cancer cells but also provided quantitative estimations of tumor size, a feature lacking in many existing models. Furthermore, the non-invasive nature of this method significantly reduces the need for expensive imaging equipment, presenting a cost-effective alternative for early breast cancer detection.

# **3.4 Quantitative Analysis of Model Performance**

<span id="page-3-1"></span>The chosen optimal model, the Multi-layer Perceptron regressor with relu activation and lbfgs solver, exhibited superior performance metrics. With a training score of 0.9999 and a testing score of 0.9896, the model proved its robustness in distinguishing cancerous tissue from normal breast tissue. The lowest errors observed, such as MAE at 0.0541, MSE at 0.0141, and RMSE at 0.1186, solidified the model's accuracy and reliability in predicting cancerous tumors (refer Figure [4](#page-3-1)).



**Fig 4. Analyzing the Impact of Activation Functions and Solvers on Training Efficiency in a CNN-Based Model for Early Breast Cancer Detection**

The combination of an innovative electromagnetic sensor and a CNN analysis framework presents a groundbreaking solution for early-stage breast cancer detection. The exceptional sensitivity of the sensor to minor changes in the dielectric properties of breast tissue, coupled with the high accuracy and quantitative estimation abilities of the CNN, represents a significant advancement in diagnostic technology.

This approach not only addresses the critical need for early cancer detection but also mitigates the limitations of existing methods, particularly the lack of quantitative results and the high cost associated with imaging techniques. The developed system offers a non-invasive, cost-effective, and highly accurate means of identifying cancerous cells and estimating tumor size, enhancing the potential for timely interventions and improved patient outcomes. The superior performance of the optimal CNN model reinforces the reliability and efficiency of the proposed solution for early breast cancer diagnosis.

### **4 Conclusion**

The developed system, integrating an electromagnetic sensor operating within the 1GHz to 10GHz range and a CNN analysis, demonstrated remarkable efficacy in early breast cancer detection. The electromagnetic sensor exhibited a sensitivity of 98% in detecting cancer cells within breast tissue, accurately estimating tumor sizes within a 1% tolerance.

Comparative analysis against conventional imaging techniques revealed the superior accuracy and cost-effectiveness of the proposed system. The optimal CNN model, employing relu activation and lbfgs solver, achieved a training score of 0.9999 and a testing score of 0.9896, with minimal errors (MAE: 0.0541, MSE: 0.0141, RMSE: 0.1186) in predictions.

This innovative approach presents a non-invasive, cost-effective solution for early breast cancer diagnosis, with significant potential for timely interventions. Its impact on healthcare delivery and economic implications in medical diagnostics underscore its pivotal role in improving patient outcomes while reducing the burden associated with conventional diagnostic methodologies. The system's precision, efficiency, and cost-effectiveness herald a promising advancement in the diagnosis of breast cancer, contributing substantially to improved patient care and medical technology.

### **References**

- <span id="page-4-0"></span>1) Husaini MASA, Habaebi MH, Gunawan TS, Islam MR. Self-Detection of Early Breast Cancer Application with Infrared Camera and Deep Learning. *Electronics*. 2021;10(20):1–18. Available from: [https://doi.org/10.3390/electronics10202538.](https://doi.org/10.3390/electronics10202538)
- <span id="page-4-1"></span>2) Rixen J, Blass N, Lyra S, Leonhardt S. Comparison of Machine Learning Classifiers for the Detection of Breast Cancer in an Electrical Impedance Tomography Setup. *Algorithms*. 2023;16(11):1–20. Available from: <https://doi.org/10.3390/a16110517>.
- <span id="page-4-2"></span>3) Bhardwaj PV, Dulala R, Rajappa S, Loke C. Breast Cancer in India: Screening, Detection, and Management. *Hematology/Oncology Clinics of North America*. 2024;38(1):123–135. Available from: [https://doi.org/10.1016/j.hoc.2023.05.014.](https://doi.org/10.1016/j.hoc.2023.05.014)
- <span id="page-4-3"></span>4) Labrada A, Barkana BD. A Comprehensive Review of Computer-Aided Models for Breast Cancer Diagnosis Using Histopathology Images. *Bioengineering*. 2023;10(11):1–27. Available from: <https://doi.org/10.3390/bioengineering10111289>.
- 5) Aljondi R, Alghamdi SS, Tajaldeen A, Alassiri S, Alkinani MH, Bertinotti T. Application of Artificial Intelligence in the Mammographic Detection of Breast Cancer in Saudi Arabian Women. *Applied Sciences*. 2023;13(21):1–12. Available from: [https://doi.org/10.3390/app132112087.](https://doi.org/10.3390/app132112087)
- <span id="page-4-4"></span>6) Rovshenov A, Peker S. Performance Comparison of Different Machine Learning Techniques for Early Prediction of Breast Cancer using Wisconsin Breast Cancer Dataset. In: 2022 3rd International Informatics and Software Engineering Conference (IISEC), 15-16 December 2022, Ankara, Turkey. IEEE. 2022. Available from: [https://doi.org/10.1109/IISEC56263.2022.9998248.](https://doi.org/10.1109/IISEC56263.2022.9998248)
- <span id="page-4-5"></span>7) Momtahen S, Momtahen M, Ramaseshan R, Golnaraghi F. A Machine Learning Approach: NIR Scattering Data Analysis for Breast Cancer Detection and Classification. In: 2022 IEEE 1st Industrial Electronics Society Annual On-Line Conference (ONCON), 09-11 December 2022, Kharagpur, India. IEEE. 2023. Available from: <https://doi.org/10.1109/ONCON56984.2022.10127055>.
- <span id="page-4-6"></span>8) Akhil M, Kumar PVS. Breast Cancer Prognosis using Machine Learning Applications. In: 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), 16-17 December 2022, Greater Noida, India. IEEE. 2023. Available from: [https://doi.org/10.1109/](https://doi.org/10.1109/ICAC3N56670.2022.10074517) [ICAC3N56670.2022.10074517](https://doi.org/10.1109/ICAC3N56670.2022.10074517).
- 9) Ara S, Das A, Dey A. Malignant and Benign Breast Cancer Classification using Machine Learning Algorithms. In: 2021 International Conference on Artificial Intelligence (ICAI), 05-07 April 2021, Islamabad, Pakistan. IEEE. 2021. Available from: [https://doi.org/10.1109/ICAI52203.2021.9445249.](https://doi.org/10.1109/ICAI52203.2021.9445249)
- <span id="page-4-7"></span>10) Rouzi MD, Moshiri B, Khoshnevisan M, Akhaee MA, Jaryani F, Nasab SS, et al. Breast Cancer Detection with an Ensemble of Deep Learning Networks Using a Consensus-Adaptive Weighting Method. *Journal of Imaging*. 2023;9(11):1–13. Available from: <https://doi.org/10.3390/jimaging9110247>.
- <span id="page-4-8"></span>11) Idrees M, Alnahdi AS, Jeelani MB. Mathematical Modeling of Breast Cancer Based on the Caputo–Fabrizio Fractal-Fractional Derivative. *Fractal and Fractional*. 2023;7(11):1–14. Available from: [https://doi.org/10.3390/fractalfract7110805.](https://doi.org/10.3390/fractalfract7110805)
- <span id="page-4-9"></span>12) Gamal S, Atef H, Youssef D, Ismail T, El-Azab J. Early Breast Cancer Screening from Thermography via Deep Pre-Trained Edge Detection with Extreme Gradient Boosting. In: 2023 Intelligent Methods, Systems, and Applications (IMSA), 15-16 July 2023, Giza, Egypt. IEEE. 2023. Available from: <http://dx.doi.org/10.1109/IMSA58542.2023.10217569>.