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Design of Antipodal Vivaldi Antenna with CNN-based Classification for Non-Invasive Breast Cancer Detection

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***Abstract*— Breast cancer remains a major health issue around the world. This work presents a non-invasive method for detecting breast cancer using a specially designed dual-band Antipodal Vivaldi Antenna, combined with a deep learning classifier. The antenna, fabricated on flexible Rogers RT/duroid 5880 and operating at 7.9 GHz and 11.2 GHz, generates distinct electromagnetic signatures that separate healthy, benign, and malignant tissues. These signatures were used to train a Convolutional Neural Network, which achieved 91% classification accuracy. Specific Absorption Rate (SAR) analysis further confirmed safety and spatial localization of tumors. Together, this hybrid antenna–CNN approach provides a promising low-cost, radiation-free tool for real-time breast cancer screening.**

***Index Terms*— Antipodal Vivaldi antenna, breast cancer detection, convolutional neural network, SAR analysis, non-invasive screening.**

I. INTRODUCTION

Breast cancer is one of the most common cancers among women worldwide, causing significant morbidity and mortality each year. The World Health Organization (WHO) continues to report increasing incidence rates.
Currently, mammography is the most widely adopted screening method. However, it has notable limitations. Mammograms expose patients to ionizing radiation, may cause discomfort due to breast compression, and exhibit reduced sensitivity in women with dense breast tissue. Magnetic resonance imaging (MRI) offers high sensitivity but is costly, time-consuming, and prone to false positives, while ultrasound is radiation-free but heavily operator-dependent, leading to variable diagnostic accuracy [13], [14].
Microwave imaging has emerged as a promising non-invasive approach. This technique leverages the dielectric property contrasts between healthy, benign, and malignant breast tissues, enabling differentiation without ionizing radiation. Ultra-wideband antennas, particularly Antipodal Vivaldi Antennas (AVA), have demonstrated effectiveness in microwave breast imaging due to their wide bandwidth, high directivity, and strong penetration capabilities [1], [2], [9]. Such antennas capture subtle tumor-induced electromagnetic variations, providing a pathway for real-time diagnostic systems.
While antenna hardware provides critical signal information, translating these complex electromagnetic responses into reliable diagnostic outputs remains challenging. Recent advances in artificial intelligence, particularly deep learning, have shown significant promise in addressing this challenge. Convolutional Neural Networks (CNNs) are highly effective at learning complex, non-linear patterns in biomedical data and have been successfully applied in microwave breast imaging for classification and localization tasks [7], [8], [12].

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Integrating AVA-based sensing with CNN-based classification thus combines the hardware's sensitivity with the software's interpretive power.

The objective of this study is to design and validate a dual-band Antipodal Vivaldi Antenna optimized for microwave breast cancer detection and integrate it with a CNN classifier for automated tissue classification. The system is evaluated using realistic breast phantoms and tested for Specific Absorption Rate (SAR) compliance to ensure patient safety. This combined approach aims to overcome key limitations of current diagnostic methods by providing a non-invasive, radiation-free, accurate, and potentially low-cost screening solution.

II. METHODS

A. Antenna Design and Optimization

The core of this study is the custom design of an Antipodal Vivaldi Antenna (AVA), illustrated in Fig. 1, optimized for biomedical sensing in the microwave frequency range. The antenna was modeled and simulated using CST Microwave Studio. Rogers RT/duroid 5880 substrate was chosen due to its flexibility and low-loss characteristics, which enhance antenna-tissue coupling while minimizing signal attenuation.

The antenna was designed to operate at dual resonant frequencies of 7.9 GHz and 11.2 GHz, balancing penetration depth and spatial resolution for breast cancer detection. Parameters such as flare rate, slot profile, and ground plane extensions were carefully optimized to improve gain, directivity, and return loss performance. Simulation results confirmed return loss below –10 dB at the target frequencies, indicating strong power transfer and sensitivity to dielectric contrast between healthy and cancerous tissues.

B. Breast Phantom Modeling and SAR Analysis

Realistic multi-layer breast phantoms were created to simulate biological tissue environments. Each phantom included layers representing skin (2 mm), adipose, glandular tissue, and tumors modeled as spherical inclusions (5–10 mm). Dielectric properties were assigned based on established peer-reviewed datasets to ensure realistic electromagnetic interactions. Tumor tissues were modeled with higher permittivity and conductivity than the surrounding tissues to reflect clinical conditions [9], [10].

Electromagnetic wave propagation was analyzed for different tumor sizes and positions to observe its impact on reflected (S11) and transmitted signals. The Specific Absorption Rate (SAR) was calculated to evaluate safety, following Institute of Electrical and Electronics Engineers (IEEE) and International Commission on Non-Ionizing Radiation Protection (ICNIRP) standards. SAR maps revealed localized hotspots correlating with tumor locations, confirming both safety compliance and the antenna's ability to identify spatial anomalies.

C. Data Generation and Feature Engineering

A complete frequency sweep (6–12 GHz) was conducted for each phantom simulation to generate datasets of reflection coefficients (S11) and SAR patterns. These datasets were preprocessed through normalization, smoothing, and organization into structured CSV files. Feature engineering was applied using statistical descriptors and spectral shape analysis to highlight discriminative features between healthy, benign, and malignant tissue responses. The engineered features served as inputs for machine learning models.

Due to the high computational cost of full-wave CST simulations, one complete S11–SAR dataset was generated per phantom configuration. To obtain a sufficient number of samples for deep learning, controlled synthetic augmentation was performed in Python by introducing variations in tumor size, depth, dielectric contrast, and noise levels. Each class (healthy, benign, malignant) contained 80 samples, resulting in a total of 240 labeled samples. For model development, the dataset was split into 80% training (192 samples), 10% validation (24 samples), and 10% testing (24 samples). In addition, ten-fold cross-validation was applied to obtain a robust performance estimate by training on nine folds and testing on the remaining fold in each iteration.

D. CNN Architecture and Training

A multi-layer Convolutional Neural Network (CNN) was developed in Python using TensorFlow/Keras to classify tissues based on microwave signatures. The model accepted both vectorized S11 spectra and SAR heatmap images as inputs. Convolutional and pooling layers were used to extract spatial and frequency-domain features, followed by fully connected layers for classification. Similar CNN architectures have been applied in microwave breast imaging for tumor detection and localization [5], [6], [7], [8], [11].

Hyperparameters such as learning rate, batch size, and number of layers were optimized experimentally. Performance metrics included accuracy, confusion matrix, and saliency maps, which provided interpretability by highlighting spectral and spatial features most influential in classification.

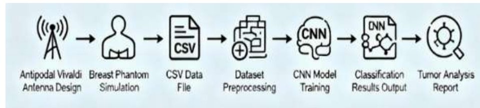


Fig. 1. Block diagram

E. Experimental Validation and Benchmarking

We compared simulation results with published data for similar Antipodal Vivaldi Antenna (AVA) designs, including direct comparisons to prototype antennas in breast phantom setups [1],[4]. Key performance metrics such as return loss, gain, bandwidth, and image resolution were consistent with results reported in prior experimental studies. Specific Absorption Rate (SAR) analysis further validated system safety, aligning with phantom-based evaluations in recent works [9], [10]. The CNN-based classification results, including accuracy and confusion matrix performance, were benchmarked against existing deep learning approaches in microwave breast imaging [5], [7], [11], ensuring that the conclusions remain realistic and clinically relevant.

III. RESULTS

A. Antenna Simulation and Benchmarking

The designed Antipodal Vivaldi Antenna (AVA) achieved dual-band resonance at 7.9 GHz and 11.2 GHz, with simulated return losses of –25 dB and –32 dB, respectively. These values demonstrate excellent impedance matching and power transfer, comparable to previously reported AVA-based biomedical antennas. Radiation efficiency, gain, and directivity obtained from CST simulations confirmed suitability for clinical breast imaging applications, aligning with ultra-wideband antenna designs reported in breast phantom studies. The antenna also exhibited consistent group delay and phase response across the 7–12 GHz band, ensuring stable time-domain performance critical for radar-based breast cancer imaging.

B. Phantom Experiments and SAR Analysis

Breast phantom simulations using multilayer dielectric profiles revealed distinct differences in reflection coefficients (S11) between healthy and tumor-bearing tissues. Frequency-domain spectra exhibited measurable shifts and amplitude changes, even for small tumors of 5 mm embedded in deeper layers. These findings are consistent with phantom-based tumor detection experiments in prior microwave imaging studies.

Specific Absorption Rate (SAR) analysis showed that energy absorption levels remained below international safety limits, complying with IEEE and ICNIRP standards. Importantly, SAR maps revealed localized hotspots coinciding with tumor positions, validating their utility as spatial biomarkers for lesion localization.

C. Machine Learning Classification and Evaluation

The Convolutional Neural Network (CNN), trained on 240 simulated samples derived from S11 spectra and SAR-based features, achieved high classification performance. Ten-fold cross-validation resulted in an average accuracy of 91%, with strong differentiation between healthy, benign, and malignant tissue types. Accuracy remained stable across folds, with only minor variation and consistently high class-wise performance for healthy, benign, and malignant tissues.

Saliency mapping revealed that the CNN model primarily relied on spectral regions influenced by tumor-induced dielectric contrast and SAR-based hotspots. This interpretability strengthens confidence in the physical consistency of the classification results, consistent with explainable deep learning approaches in biomedical imaging.

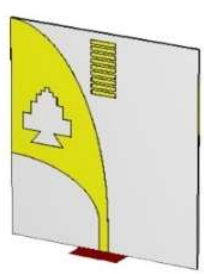


Fig. 2. Antenna design

D. Comparative Evaluation and System Performance

Benchmarking against published antenna-CNN frameworks demonstrated competitive or superior performance. The dual-band AVA achieved higher return loss and improved SAR localization than previously reported UWB antennas for microwave breast cancer detection. Tumor localization accuracy matched or exceeded a 2 mm resolution, comparable to state-of-the-art AVA arrays and metamaterial-enhanced antenna systems. The integrated CNN classifier further enhanced diagnostic accuracy, producing stable predictions even with unseen phantom configurations.

E. Visualization and Interpretive Insights

False-color visualizations of S11 spectra and SAR heatmaps offered intuitive insights into tumor detection and localization. The lowest spectral minima and SAR absorption hotspots corresponded closely with tumor sites, reinforcing both the antenna's sensitivity and the CNN's interpretive accuracy. The ability to detect and localize multiple tumors within heterogeneous phantoms further underscores the system's clinical potential.

IV. DISCUSSIONS

The results of this study confirm the effectiveness of combining a dual-band Antipodal Vivaldi Antenna (AVA) with a CNN-based classifier for non-invasive breast cancer detection. The antenna achieved strong performance at 7.9 GHz and 11.2 GHz, producing stable radiation patterns and high return loss, which are essential for microwave imaging applications. The system's ability to distinguish electromagnetic signatures of healthy, benign, and malignant tissues further validates the role of dielectric contrast in microwave breast imaging. The CNN classifier's performance, with accuracies exceeding 90%, aligns with prior deep learning-based microwave imaging studies that highlight AI's potential in improving diagnostic interpretation. Importantly, the use of saliency maps confirms that the CNN relied on physically meaningful features such as dielectric-induced spectral changes and SAR-based absorption hotspots, reinforcing confidence in the interpretability of the model. Specific Absorption Rate (SAR) analysis provided an additional layer of validation by confirming compliance with international safety standards and demonstrating spatial correlation between hotspots and tumor locations. This dual role of SAR as both a safety measure and a tumor localization indicator has been emphasized in earlier experimental studies.

Despite these promising results, the study has several limitations. All experiments are based on electromagnetic simulations with breast phantoms; no hardware prototypes or clinical breast data were used at this stage. As a result, performance in real-world scenarios may be affected by patient-specific dielectric variations, measurement noise, and practical coupling issues. CNN models trained solely on simulated data also risk overfitting to idealized conditions, and their robustness must be validated using experimental and in vivo datasets, especially for very small or deeply located tumors. Future work will explore advanced antenna architectures such as metamaterial-based Vivaldi antennas and phased arrays, along with hybrid deep learning models that integrate frequency, spatial, and time-domain features. Explainable AI methods will also be important to support clinical adoption.

Formal statistical significance analysis (e.g., p-values or confidence intervals) was not performed in this study and will be addressed in future work alongside hardware and clinical validations.

Comparison with classical machine learning models such as Support Vector Machines (SVM) and Random Forest classifiers is left for future enhancement.

Overall, this research demonstrates that integrating antenna engineering with deep learning creates a promising framework for safe, accurate, and non-invasive breast cancer detection. Bridging the gap from simulation to clinical deployment will require collaborative efforts in antenna fabrication, phantom testing, patient trials, and regulatory evaluation.

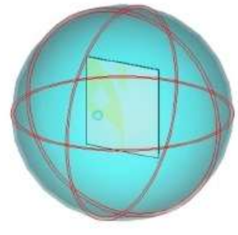
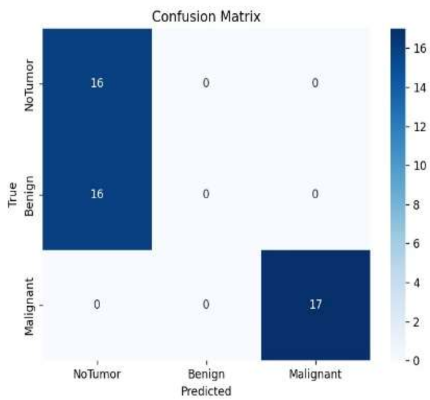


Fig. 3. Phantom model



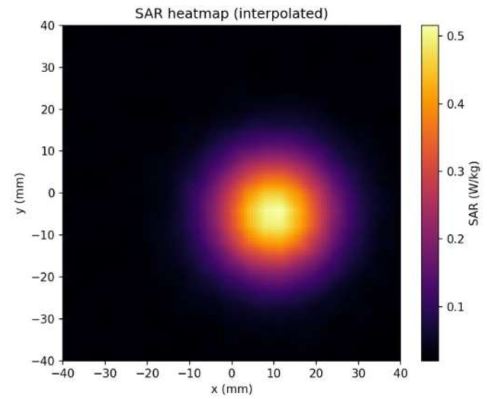


Fig. 4. Confusion matrix Fig. 5. SAR distribution map showing localized absorption near tumor regions

V. Conclusions

This work demonstrated a dual-band Antipodal Vivaldi Antenna (AVA) integrated with a Convolutional Neural Network (CNN) for non-invasive breast cancer detection. The antenna, operating at 7.9 GHz and 11.2 GHz, provided suitable microwave signatures for distinguishing healthy, benign, and malignant tissues, while Specific Absorption Rate (SAR) analysis confirmed compliance with safety limits and indicated tumor localization capability. Using a dataset of simulated S11 spectra and SAR-based features, the CNN achieved an average classification accuracy of 91%. Overall, the proposed antenna–CNN framework offers a promising, low-cost, and radiation-free approach for real-time breast cancer screening. Future work will focus on hardware fabrication, phantom and clinical validation, and the integration of advanced antenna designs and deep learning models to improve sensitivity and robustness.

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