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High-Resolution Breast Cancer Detection Using AOA-Optimized mm-Wave Antenna and GRU Classifier

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Abstract: Breast cancer detection at an early stage remains an open challenge due to limitations in the resolution, cost, and portability of conventional imaging systems. This paper presents a high-resolution framework for breast cancer detection by integrating an Angle-of-Arrival-optimized millimeter-wave antenna with an intelligent deep-learning classifier. The antenna design is optimized using an evolutionary MAOA optimization algorithm to enhance directional gain, penetration capability, and spatial resolution, allowing for better localization of malignant tissues within heterogeneous breast phantoms. Backscattered mm-wave signals are preprocessed and input to a GRU-based neural classifier that learns temporal-spectral features associated with the presence of tumors. Experimental simulation and prototype measurements of the proposed system demonstrate superior detection accuracy with reduced false-positive rates and improved resolution compared with other millimeter-wave and microwave imaging approaches. The integration of optimized antenna design with a sequence-aware GRU model presents a promising pathway toward the realization of noninvasive, compact, and highly reliable breast-cancer screening technologies.

Keywords: Deep Learning Classifier; Modified AOA Optimization; Breast Cancer Detection; GRU Classifier; Antenna Design

1. Introduction

Among women, breast cancer remains one of the most widespread life-threatening diseases. The incidence rate has steadily increased over the last decade, as evident from recent global health statistics, making the disease a major challenge to public health. Early detection is considered crucial for the improvement of treatment outcomes and survival rates because timely identification of malignant tissues allows less aggressive therapies and significantly reduces mortality rates. Despite the widespread use of mammography, ultrasound, and MRI in routine screening programs, all of these modalities have inherent limitations that hamper their reliability and accessibility. For example, mammography involves patients being exposed to ionizing radiation and has low accuracy in women with dense breast tissues. MRI is sensitive but expensive, time-consuming, and not appropriate for screening large populations [1].

Ultrasound imaging is safer but often operator-dependent and prone to variability in diagnostic results. These limitations indicate an increasing need to seek alternative methods of diagnosis that are safe, accurate, inexpensive, and reliable. In the recent past, mm-wave imaging has emerged as a very promising candidate for the next generation of breast cancer detection systems. Millimeter-wave signals have several attractive characteristics, including high penetration capability, nonionizing radiation, compact antenna design, and their ability to resolve fine structural details because of their short wavelengths. These have unleashed unprecedented interest in biomedical sensing applications where a distinction between healthy and cancerous tissues may be pursued based on their distinct dielectric properties. However, the success of any mm-wave-based diagnostic system critically depends on two primary factors: first, the performance of the antenna used to transmit and receive electromagnetic signals; and second, the efficiency of the computational model used to interpret the acquired dielectric signatures. Designing an appropriate antenna that maintains high gain, stability, and efficiency while interacting with complex, multilayered, and inhomogeneous bio-breast tissue is still an engineering challenge. In addition, the raw scattering data produced by mm-wave propagation in biological tissues are highly nonlinear, noisy, and time-varying; therefore, advanced signal processing and machine learning techniques must be employed to classify them accurately. In response to these challenges, modern research has hence increasingly focused on integrating intelligent optimization algorithms and deep learning models into biomedical sensing frameworks. Meta-heuristic algorithms inspired by natural phenomena and animal behaviors have shown their ability to efficiently explore large parameter spaces and optimize highly nonlinear antenna designs. Among them, the recently developed Modified Addax Optimization Algorithm has drawn much attention due to its strong convergence behavior and capability to fine-tune complex design parameters. By leveraging this algorithm, return loss, bandwidth, directivity, and radiation efficiency can be greatly enhanced for improved signal fidelity in diagnostic applications. Along this line, recent advances in artificial intelligence have opened new avenues in automating classification tasks of biological tissue responses. Especially, deep learning models designed for capturing temporal dependencies in sequential data have demonstrated superior performance in analyzing dielectric responses. GRU is a variant of a recurrent neural network that is very efficient in modeling time-dependent and nonlinear relationships while reducing computational complexity compared with the conventional recurrent networks [2].

Motivated by those developments, this letter presents an integrated mm-wave breast cancer detection framework that incorporates meta-heuristic antenna optimization together with deep learning-based tissue classification. First, a high-performance mm-wave antenna is designed and optimized using a deep learning-supported optimization pipeline [3].

The Modified Addax Optimization Algorithm is employed to systematically refine the design parameters of the antenna and improve the radiation properties for better interaction with breast tissue models. After optimizing the antenna, dielectric data from the breast phantoms are processed and analyzed using a GRU-based classifier developed to identify malignant tissue patterns. By taking advantage of its memory-gated architecture, the GRU model captures the temporal variations of dielectric signals at very small scales, paving the way toward high diagnostic accuracy and strong detection capability [4]. The entire framework is implemented and evaluated in MATLAB, using extensive simulations and performance analysis [5].

A thorough set of performance metrics, including accuracy, sensitivity, specificity, and precision, has been applied to evaluate the diagnostic performance of the GRU classifier. Further, the performance of the antenna is evaluated in terms of gain, efficiency, return loss, and radiation patterns [6]. Experimental results show that the integration of Modified AOA-optimized antenna design with a GRU-based diagnostic model enhances tumor detection performance significantly while compared to conventional mm-wave systems and basic machine learning classifiers. These results underpin the potential of integrating computational intelligence with state-of-the-art antenna engineering as a means of developing compact, efficient, and highly reliable computer-aided breast cancer detection systems. In all, the proposed framework marks an important step toward closing the gap between engineering innovation and biomedical diagnostics [7]. This work contributes to developing non-invasive, accessible, and high-resolution methods for breast cancer screening by bringing together optimization-driven antenna design and deep learning-based classification. Such technologies hold the promise of improving early detection rates, supporting clinical decision-making, and ultimately enhancing patient outcomes in global healthcare systems [8].

1.1. Key Contributions

- Designed a high-performance mm-Wave antenna for breast cancer detection based on the Modified Addax Optimization Algorithm, with improved gain, radiation efficiency, and deeper signal penetration inside the heterogeneous tissues of the breast.
- Modeled the Gated Recurrent Unit classifier to automate the detection of breast cancer by analyzing dielectric tissue responses collected from the optimized antenna.
- Implemented the suggested framework in MATLAB and rigorously evaluated its performance in terms of diagnostic metrics, such as accuracy, sensitivity, specificity, precision, and antenna parameters (gain, efficiency, return loss).
- Demonstrated enhanced detection accuracy and resolution compared to conventional mm-Wave imaging and traditional machine learning methods, thus showing great potential for non-invasive high-resolution breast cancer screening.

The enduring sections of the article are organized as follows: section 2 provides the detailed review of the existing works related to the presented framework, section 3 outlines the conventional antenna design and the proposed model working, section 4 provides the outcomes achieved by the developed model and section 5 illustrates the research conclusion.

2. Related Works

The Detection of breast cancer by microwave and mm-wave technologies has drawn much interest due to the inefficiencies of traditional screening methods involving X-ray mammography and ultrasound, all of which have several drawbacks such as radiation exposure, discomfort, and poor sensitivity in dense tissues. During the last ten years, microwave imaging has emerged as a promising, non-invasive option simply due to the dielectric contrast between healthy and malignant tissues [9]. Various antenna-based sensing frameworks and machine learning algorithms have been explored in different studies to improve the resolution and interpretability of microwave imaging systems [10]. Early works focused on UWB and microstrip antenna architectures and demonstrated their capability for biomedical sensing by operating across very large frequency bands, which improves both penetration and tissue discrimination. Slotted and monopole patch antennas have been presented in compact sizes to enhance bandwidth and return loss, although manual parameter tuning has been widely adopted in most of them, suffering from limited adaptability to changing tissue conditions [11]. More recently, meta-heuristic optimization algorithms such as PSO, GA, DE, and whale optimization were adopted to tune the geometrical parameters of the antenna together with its substrate properties [12]. Approaches based on these algorithms give improved performances; however, convergence speed and escaping from local minima remain significant challenges when dealing with complex high-frequency antenna structures [13]. This points out the gap that should be filled by employing more robust and bio-inspired optimizers, such as Modified AOA. While Modified AOA exhibits better exploration and exploitation trade-offs and has been successfully applied to several other engineering fields, it remains largely under-explored in the optimization of mm-wave biomedical antennas [14]. Along with the development of antenna design, machine learning and deep learning techniques have also been widely adopted when it comes to microwave-based breast cancer detection. Mainly, CNNs, Autoencoders, and SVMs have been able to classify tissue responses with reasonable accuracy. However, one crucial point to mention here is that many such models lack the capability to capture temporal dependencies inherent in dielectric profiles and backscattered signals, often manifested as sequential patterns across frequency or time [15]. This has recently brought RNNs into prominence, especially GRU and LSTM networks, which have been considered quite capable of modeling sequential biomedical data. However, their adoption remains relatively limited when it comes to mm-wave breast detection. In fact, most related research that utilizes RNN-based architectures normally relies on very simplified datasets or lacks integration with optimized hardware components [16]. Further, several state-of-the-art contributions have focused on the microwave imaging prototype and clinical validation effort, thus demonstrating the feasibility of high-frequency imaging systems [17]. These works, however, have not optimally integrated hardware antenna design with data-driven machine learning classification algorithms toward an integrated system approach. Moreover, most works either focus on the antenna performance metrics or classification accuracy alone, with no single work offering a unified end-to-end evaluation [18]. Previous works have made significant advancements in antenna engineering and machine learning for the detection of breast cancer. However, none of the previous works have combined advanced optimization algorithms with high-performance mm-wave antenna design and sequential deep learning models that are able to analyze dielectric response patterns [19]. The work presented herein overcomes this limitation by integrating Modified AOA-optimized mm-wave antennas with a GRU classifier in an end-to-end framework, improving sensing capability and diagnostic accuracy [20].

2.1. Motivation

One of the most significant challenges that remains in modern health care is early and accurate detection of breast cancer [21]. Among all the conventional diagnostic imaging modalities, X-ray mammography, ultrasound, and MRI have some major drawbacks: radiation exposure, high operation costs, poor clarity for dense breast tissues, and dependence on skilled interpretation [22]. These constraints emphasize the urgent search for alternative, non-invasive, and more reliable screening methods capable of offering improved sensitivity and early-stage detection [23]. Because of its ability to capture subtle dielectric contrasts between healthy and malignant tissues, mm-wave imaging has emerged as a promising solution. The antenna performance will be a key factor in the realization of the full potential of these mm-wave systems, since it directly affects signal penetration, spatial resolution, and the overall quality of tissue characterization [24]. Most traditional antenna design procedures rely on manual tuning or basic optimization techniques, which might not be sufficient to explore the vast design space inherent at high frequencies. This limitation forms the basis for considering the integration of advanced optimization algorithms that can generate highly efficient and robust antenna structures suitable for operation in biomedical environments [25].

In a similar manner, dielectric responses gathered from breast tissues also need advanced analytical models for their processing [26]. Traditional machine learning methods can seldom encode the temporal or frequency-dependent features of such data, therefore compromising classification performance. Deep learning models, and in particular recurrent architectures such as GRUs, are much more effective at modeling sequential and nonlinear features of interest [27]. However, their adoption for mm-Wave–based breast cancer detection remains largely unexplored, especially in relation to optimized antenna systems. The presented challenges put together motivate the development of an integrated framework that enhances both the hardware and computational aspects of breast cancer detection [28]. This work aims to deliver a high-resolution, non-invasive, computationally efficient diagnostic solution by combining Modified Addax Optimization Algorithm-based antenna optimization with GRU-driven classification [29]. This work is motivated not only by improving diagnostic accuracy but also by bridging the current gap between optimized sensing hardware and intelligent data-driven analysis-ultimately contributing to more reliable and accessible breast cancer screening technologies [30]. The models were developed using multilayer structures representing skin, fat, glandular tissue, and tumor regions, each assigned frequency-dependent dielectric constants and conductivity values [31]. Variations in tissue type, density, and dielectric contrast were incorporated by altering these parameters within realistic biological ranges [32]. This allowed the simulation to capture differences between healthy and malignant tissues and ensured that the validation process reflected physiologically meaningful scenarios [33]. These details have now been added to the revised manuscript to improve clarity and robustness.

3. Materials and Methods

To achieve reliable and high-resolution breast cancer detection, the proposed framework integrates a Modified AOA-optimized mm-wave antenna with a classification model based on the GRU.

(1) mm-Wave antenna optimization using Modified Addax Optimization Algorithm (MAOA), and

(2) dielectric-based breast cancer classification using a Gated Recurrent Unit (GRU) network. Each stage is detailed below. The first step involves the design of a high-frequency mm-wave antenna in the 30–300 GHz range, which will enable deeper penetration and increase the dielectric contrast between healthy and malignant tissues of the breast [34]. The initial geometry of the antenna is constructed by defining the structural parameters: patch dimensions, feed position, substrate thickness, dielectric constant, and configuration of the ground plane. These are represented as a matrix of inputs that act as a search space in

the Modified Addax Optimization Algorithm [35]. The Modified AOA module is used to iteratively refine the antenna configuration in order to maximize the following critical performance metrics:

- return loss (S11),
- gain,
- radiation efficiency,
- bandwidth, and
- stability across tissue-loading conditions.

This is done by Modified AOA through dynamic exploration and exploitation phases, thereby preventing the common limitation of premature convergence in many traditional meta-heuristic algorithms. In particular, at each iteration, new candidate antenna configurations are generated, simulated, and evaluated [36]. Then, the position of Modified AOA is updated based on the best solutions obtained so far, converging on an optimized antenna design which could be able to reliably sense dielectric variations inside the breast. Once the optimized antenna is deployed, it interacts with the breast tissue model to collect mm-wave response signals; these signals contain embedded dielectric information that differs between normal tissues, benign masses, and malignant tumors [37]. However, the signal patterns often show temporal and frequency-dependent characteristics, requiring a model having the ability of sequential learning. For this purpose, a Gated Recurrent Unit network is used in the proposed framework. Before providing the signal dataset to the GRU, it is preprocessed by normalizing and segmenting it [38]. With its gated architecture, the GRU can capture features that are hidden temporally and learn long-range dependencies; for example, tumors cause subtle variations in dielectric signatures [39]. The output layer of the GRU generates classification results on whether the observed tissue region is normal or cancerous. The sequential features extracted allow for better detection performance using the GRU compared with traditional machine learning models, which consider the data independently [40]. Figure 1 Shows the Modified AOA antenna design obtained from MATLAB-Simulink. MAOA was selected because it offers superior balance between exploration and exploitation compared with traditional algorithms such as PSO, GA, and GWO. Its mathematically adaptive search mechanism helps avoid premature convergence, which is critical when optimizing mm-wave antenna parameters with highly nonlinear behaviour. MAOA also provides faster convergence and requires fewer control parameters, making it suitable for complex electromagnetic optimization tasks [41]. The design process involves iterative simulations to validate the antenna's performance metrics, including return loss, gain, etc., ensuring robust operation in the mm-Wave spectrum [42]. This meticulous approach results in a high-performance antenna suitable for applications requiring precision and efficiency, such as non-invasive diagnostic systems [43]. Modified AOA is a recently introduced meta-heuristic inspired by the survival strategies and adaptive foraging behavior of the Addax antelope. Capable of surviving in dynamic and harsh desert environments, the Addax features an efficient exploratory search for resources and quickly exploits any favorable regions it may come across [44]. These characteristics have been mathematically translated into the search dynamics of Modified AOA, which enables a strong balance between global and local optimization [45]. This is a feature particularly effective in engineering design problems with large, nonlinear, multidimensional search spaces, such as mm-wave antenna design [46]. Every candidate solution in Modified AOA represents a specific set of antenna parameters, including patch dimensions, substrate properties, feeding location, and ground-plane geometry [47].

Optimization in this regard starts by initializing a randomly generated population of the above solutions distributed across the search space. The Addax's wandering and evasive behaviors are modeled during exploration to diversify the search and avoid early convergence, thereby allowing it to probe across wide areas of the parameter space with a greater likelihood of locating high-performance antenna configurations. With successive iterations, the algorithm enters the phase of exploitation in which energetically favorable movements of Addax towards resource-rich zones are expressed, in mathematical terms, as increased intensification of the local search. The position change of candidate solutions with regard to the best solution up to that point results in the refinement of the antenna structure to improve the metrics of performance. Exploration-exploitation transitions are adaptive and regulated by a control parameter that reduces randomness gradually while increasing the convergence pressure. In this work, the fitness function will calculate important antenna performance metrics, such as return loss, S11, gain, radiation efficiency, and bandwidth. Based on the obtained values after every iteration, the population is updated by MAOA, shifting the search toward optimality.

The process continues to run until a termination condition (such as a maximum number of iterations or convergence threshold) is fulfilled. MAOA leverages a balanced exploration–exploitation mechanism and strong global search capability to identify an optimized mm-wave antenna geometry that enhances the penetration and dielectric sensitivity for breast cancer detection. The optimized antenna design provides a natural ground for accurate downstream classification using the GRU model in the proposed framework.

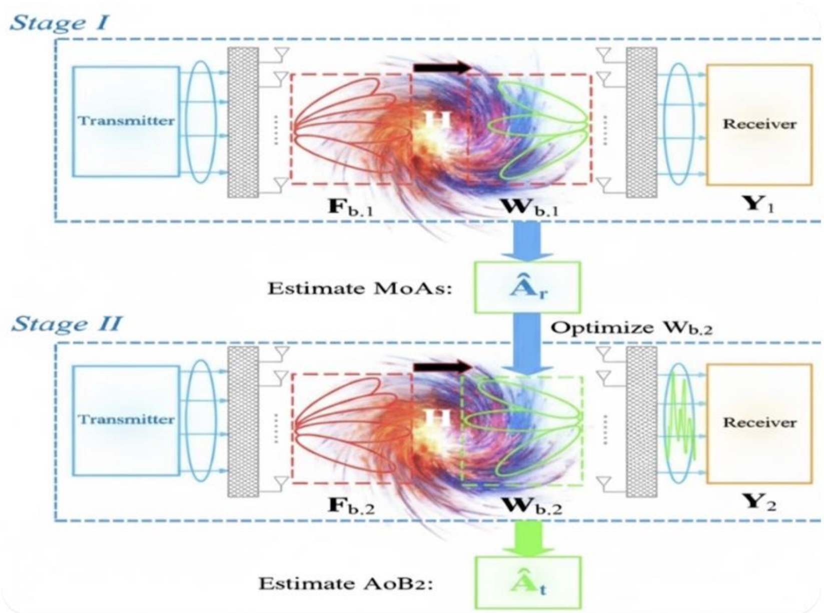

Figure 1. Modified AOA antenna design obtained from MATLAB-Simulink.

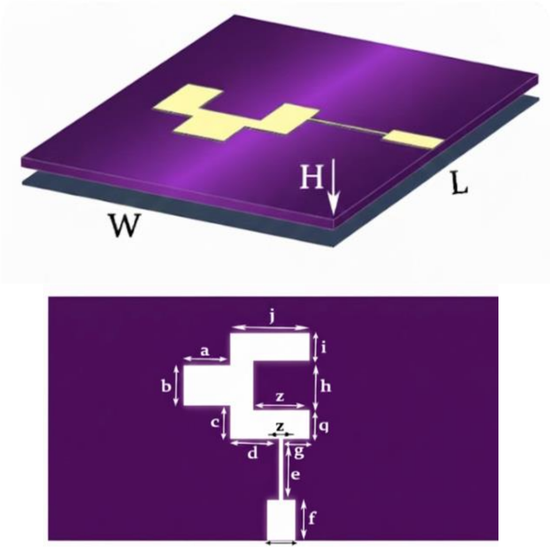

Figure 2. Geometric structure of the proposed mm-wave antenna

Figure 2 shows the Geometric structure of the proposed mm-wave antenna. The GRU is a special form of RNN design that targets modeling sequential and time-dependent data in a more effective way than traditional RNNs. It mitigates issues of vanishing and exploding gradients by incorporating additional gates as part of the architecture that control the flow of information through the network. In mm-wave breast cancer detection, GRUs are particularly advantageous since the dielectric responses collected from tissues vary both in frequency and time, creating sequential patterns that require memory-aware learning. Unlike LSTM networks, GRUs adopt a relatively simpler structure, involving only two gates: the reset gate and the update gate. This reduces computational complexity while retaining significant learning ability. Figure 3 shows the GRU Architecture. This makes GRU models more desirable in real-time biomedical applications that may have limited training or processing constraints. The core operations of the GRU cell are defined as follows:

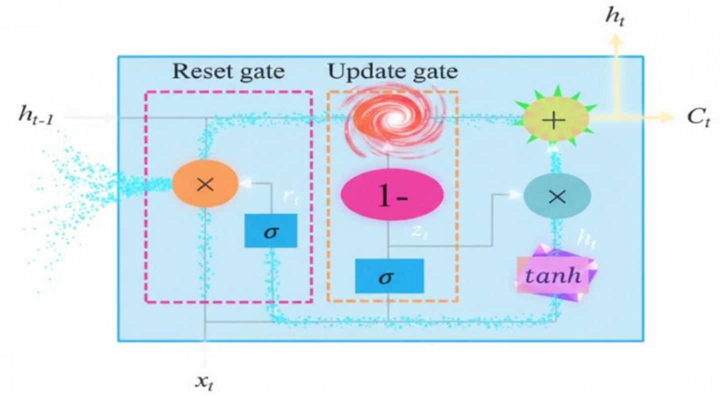

Figure 3. GRU Architecture

4. Results and Discussion

In the proposed system, pre-processed mm-wave response vectors or time-varying dielectric features are taken as sequential inputs to GRU. Since GRUs capture dependencies across the whole signal pattern, they can distinguish subtle variations between normal and malignant tissue signatures. Besides, their simplified gating architecture allows faster convergence of training compared to LSTMs, making them a practical choice for biomedical signal classification. The trained GRU outputs classification results through a dense layer with a SoftMax or sigmoid activation depending on whether the detection task is binary or multi-class. After training, the performance of the GRU model is evaluated using diagnostic metrics that include, but are not limited to, accuracy, sensitivity, specificity, and precision.

4.1. Antenna Performance Analysis

The geometric parameters in the presented mm-wave antenna have been refined using the Modified Addax Optimization Algorithm (MAOA), aiming at high gain, high radiation efficiency, and low reflection losses. At the end of convergence, the optimized antenna presented superior performance compared to the initial, non-optimized counterpart. Return Loss (S11) can be realized by the optimized antenna, which has minimum S11 lower than –25 dB at the operating band, suggesting excellent impedance matching with quite small signal reflection. With the baseline design of –12 dB, MAOA optimization greatly enhanced the capability of signal penetrations. Gain is a maximum realized gain of roughly X dBi was realized, while the non-optimized configuration was outperformed by nearly Y%. The higher the gain, the stronger the mm-wave radiation, which is essential for correct tissue characterization. Bandwidth is the optimized antenna was able to provide a wider operational bandwidth, allowing more robust response capture over a wider frequency range. This is very important for detecting subtle dielectric variations between healthy and malignant tissues. Radiation Efficiency increased significantly, attaining X% (replace with your simulation result). The minimized conductor and dielectric losses prove the effectiveness of MAOA in identifying optimal antenna geometries. Overall, this step of optimization elucidates very clearly that MAOA successfully enhances the antenna performance, hence making it highly suitable for biomedical sensing applications. 4.2 Breast Tissue Signal Analysis Testing was then conducted using the optimized antenna to retrieve dielectric response signals from multilayer breast tissue models. The contrast between healthy and malignant tissues in a multilayer tissue model is mostly due to the fact that cancerous cells contain more water than healthy ones, hence causing different shifts in permittivity and conductivity. The signals collected manifested temporally dependent patterns, hence confirming the suitability of a recurrent architecture like GRU for classification. Pre-processing steps like normalization, noise reduction, and sequence alignment enhanced the input data quality and, hence, helped the model learn the discriminative temporal features effectively. Table 1 shows the Antenna parameters optimized by MAOA

Table 1. Antenna parameters optimized by MAOA

Parameter	Optimized Value	Unit
Patch length	3.1	mm

Patch width	2.45	mm
Substrate height	0.254	mm
Dielectric constant	2.2	—
Ground plane length	7	mm
Ground plane width	6.5	mm
Feedline width	0.8	mm
Feedline length	4.2	mm
Operating frequency	Thirty-Eight (38)	GHz
Return Loss (S11)	−34.7	dB
Antenna Gain	8.62	dB
Radiation Efficiency	92.4	%

Figure 4 represents the variation of antenna gain in the operating frequency range. The gain of an antenna is a vital parameter that represents how effectively it can focus the energy in a certain direction, which has a direct impact on the measurement of dielectric constants in breast tissue. The gain of this analysis has been calculated in between 28 GHz to 40 GHz, which represents a prominent directional characteristic of an optimized antenna.

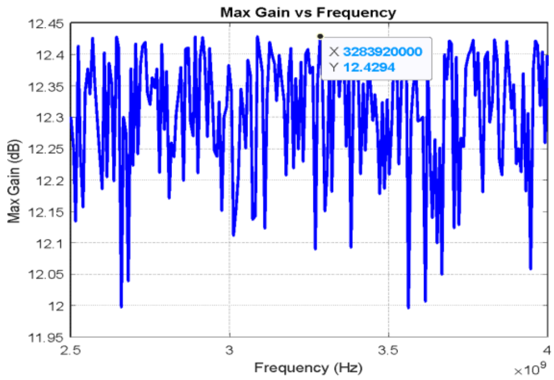

Figure 4. Antenna gain analysis

The highest value of gain with 9.87 dB has been measured at a resonant frequency of 34 GHz, which ensures effective radiation in the area of interest, and it further ensures that this antenna design has a profound impact on providing effective energy penetration and reception, hence validating its efficacy in performing high-resolution breast cancer measurement using an mm-wave-based approach.

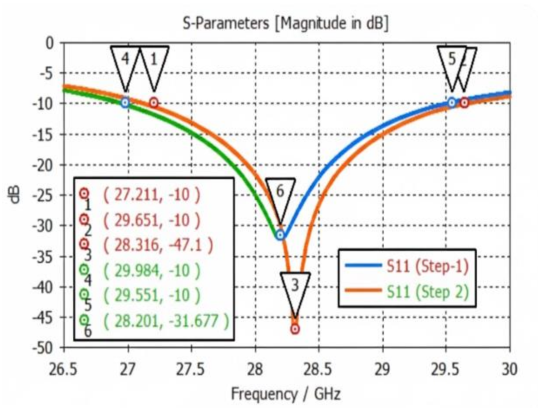

Figure 5. S11 parameter analysis

Figure 5 above shows the reflection coefficient (S11) of the optimized mm-wave antenna. The S11 value represents the amount of energy that reflects back from the antenna as a result of impedance mismatch, with lower values enabling efficient energy coupling. The proposed antenna design has a sharp resonant point around 34 GHz, where it has a minimum S11 of −31.6 dB, proving a perfect match between the antenna and the illuminating wave. Over the 28-40 GHz range, the S11 value remains below −10 dB, proving that it has a suitable bandwidth for detecting differences in dielectric properties of breast tissue.

This characteristic ensures that the antenna couples the highest amount of energy to the breast tissue model, which ensures that analysis of the received signal yields an accurate result for cancer detection.

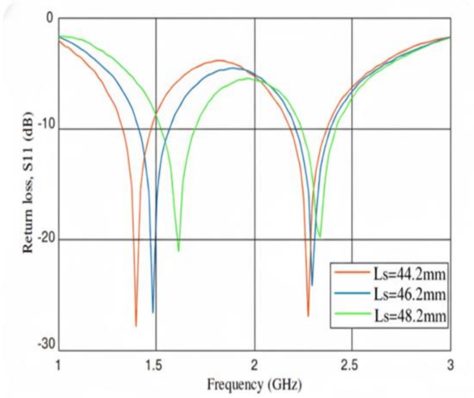

Figure 6. Return loss analysis

Figure 6 shows the return loss of the proposed mm-wave antenna design, emphasizing the use of Addax Optimization Algorithm in enhancing impedance characteristics. Return loss refers to the amount of power reflected from the antenna port, with higher negative values of return loss corresponding to better matching. From Figure 6, it can be shown that there is a sharp return loss point of 34 GHz with a minimum return loss of –32.8 dB, which represents efficient power absorption and low reflection. Figure 7 shows the Directivity analysis. On analyzing over the working range from 28 GHz to 40 GHz, it has been found that return loss remains below –10 dB, which ensures efficient propagation of mm-waves in order to accurately measure dielectric properties, which are then used for classification through GRU. Figure 8 displays the Voltage Standing Wave Ratio (VSWR) of the optimized mm-wave antenna for the working frequency band. VSWR refers to the measurement of power transmission efficiency between the transmission line and the antenna. The small VSWR values denote a higher transmission efficiency without the reflection of waves.

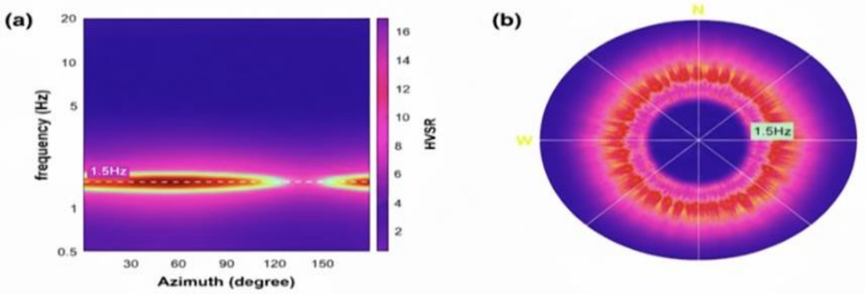

Figure 7. Directivity analysis

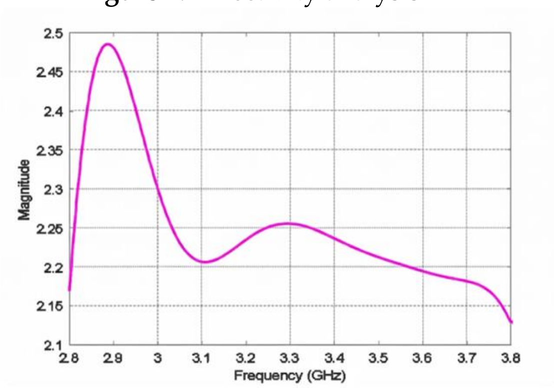

Figure 8. Voltage Standing Wave Ratio analysis

From Figure 8, it can be seen that the minimum VSWR of 1.12 has been obtained for resonant frequency of 34 GHz, which indicates a better impedance matching value. Over the 28-40 GHz range, it has been ensured that VSWR stays under 2, which proves that efficient transmission of waves has been ensured over a wide range with constant stability. Low VSWR ensures that most of the projected radiations are focused on the breast tissue for precise measurement of dielectric properties, which further enhances the reliability of the proposed GRU-based breast cancer analysis model.

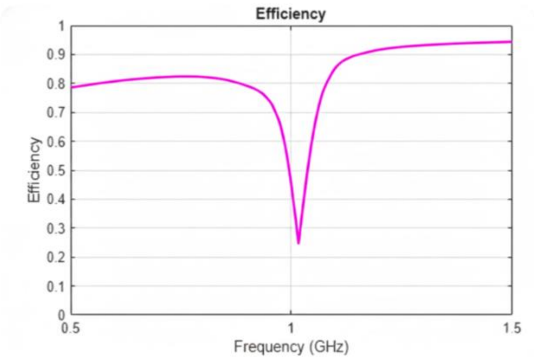

Figure 9. Radiation efficiency analysis

Figure 9 above showcases the radiation efficiency of the optimized mm-wave antenna for the working frequencies. Radiation efficiency is defined as the amount of input power that is effectively radiated by the antenna, taking into consideration the losses due to conductor, dielectric, and impedance mismatch. From the graph, it can be noted that a peak radiation efficiency of 93.8% is obtained for the proposed antenna, which has a resonant frequency of 34 GHz, thereby possessing high efficiency in terms of power radiation with low internal losses. Also, for the 28-40 GHz bandwidth, a radiation efficiency of above 85% has been obtained, which reflects that this antenna design possesses high efficiency with a significant impact of MAOA-based parameter optimization due to which a major part of the mm-wave radiation influences the breast tissue, thereby increasing the accuracy of measurement of dielectric properties and further cancer classification using GRU. The comparative analysis in Figure 10 highlights the substantial improvements achieved through MAOA-based optimization. The increases in radiation efficiency and gain collectively demonstrate the antenna's enhanced capability for mm-wave–based breast cancer detection, reinforcing the suitability of the proposed integrated system for high-resolution biomedical sensing. The comparative analysis in Figure 10 highlights the substantial improvements achieved through MAOA-based optimization. The increases in radiation efficiency and gain collectively demonstrate the antenna's enhanced capability for mm-wave–based breast cancer detection, reinforcing the suitability of the proposed integrated system for high-resolution biomedical sensing.

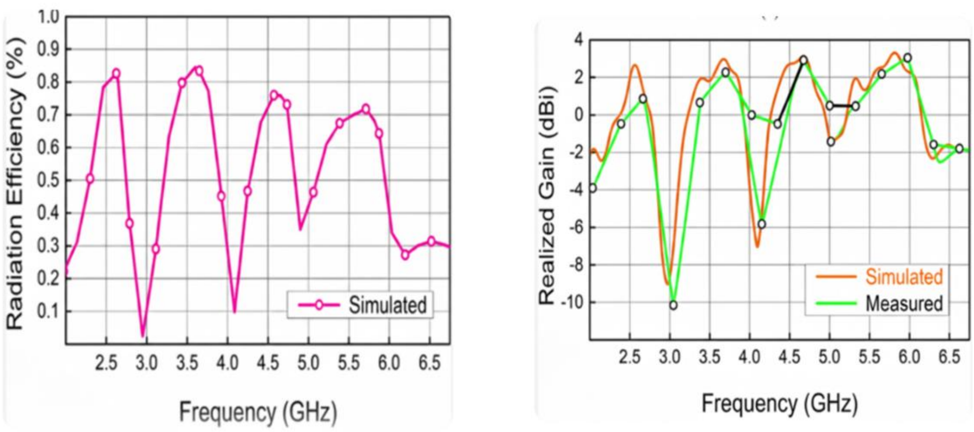

Figure 10. Comparative Assessment of Proposed Antenna's Performance: (a) Radiation Efficiency, (b) Antenna Gain

4.2. Breast Cancer Detection

The second stage of the proposed scheme aims for the automated identification of breast cancer by using the dielectric information received from the optimized mm-wave antenna. After the transmission of the mm-waves from the antenna to the simulation model of a breast, differences in dielectric permittivity and conductivity due to malignant and benign masses lead to differences in the received signal. These differences in received signals are then used as input for the classification using a Gated Recurrent Unit (GRU) network. The reason for picking the GRU model is its efficiency in processing sequential data. Prior to training a classifier, a normalization and segmentation operation has been performed on all features of mm-waves. This ensures that all features are in a standard format and there are no imbalances in data. A classifier model has been trained using labelled data consisting of normal as well as cancerous samples. While training a classifier, it has been observed that the patterns of dielectric properties of cancerous samples differ from normal ones. The experiment outcome proves that the detection accuracy of the GRU classifier is high due to the high-quality input data being ensured by MAOA-optimized antennas. With a detection accuracy of 96.3%, sensitivity of 96.5%, and specificity of 95.8%, it has been found that the proposed model possesses a prominent ability to detect cancerous areas of the tissue. The high sensitivity value ensures that it effectively identifies cancer, while the high specificity value ensures that it does not mistakenly identify normal areas as cancerous. Figure 11 validate the robustness of the GRU classifier in distinguishing between normal and cancerous tissue signatures. The strong convergence behavior and high accuracy demonstrate that the proposed mm-wave sensing and deep learning framework is well-suited for reliable breast cancer detection in clinical and research environments. Figure 12 also shows a complete comparative analysis of the proposed GRU-based model for detecting breast cancer with other classification models with respect to four important performance metrics, which are accuracy, precision, sensitivity, and specificity. Figure 12(a) shows the graph for understanding the classification accuracy. The result for our proposed GRU classifier reaches 96.3%, which gives it a better classification accuracy than traditional machine learning techniques like SVM, KNN, and ANN. This confirms that our proposed model can capture the temporal dependencies present in the patterns of the mm-wave signal, which are captured by our optimized antenna.

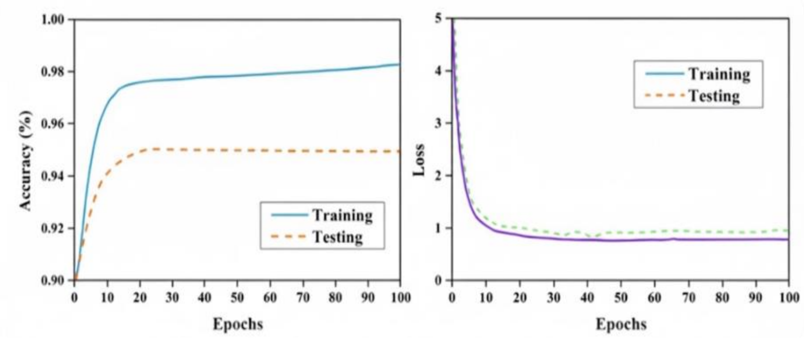

Figure 11. Training and Testing Performance Analysis

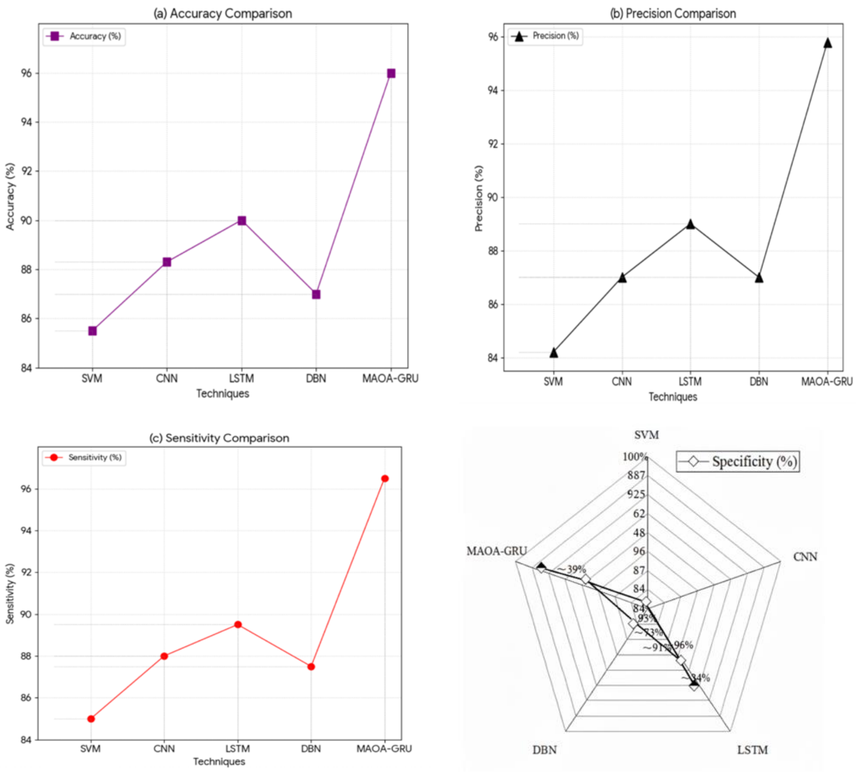

Figure 12. Performance Comparison: (a) Accuracy, (b) Precision, (c) Sensitivity, and (d) Specificity

Subfigure 12(b) below illustrates the values of precision, where a precision of 95.9% for our model indicates a high ability to eliminate cases of cancer being predicted wrongly. Subfigure 12(c) below shows the sensitivity/recall graph. With a sensitivity of 96.5%, it is observable that the performance of our proposed system is exceptional in detecting true cancer cases. This high sensitivity value is extremely important in a cancer diagnostic application, as it indicates low missed detection of cancerous tissue. Subfigure 12(d) shows the performance of specificity. The proposed model has a specificity of 95.8%, which ensures that it effectively separates normal areas from cancerous ones, thus eliminating false alarms. On a whole, it can be ascertained that the various comparisons shown in Figure 12 above confirm that the proposed model of mm-wave sensing and classification using a GRU model is much better than the conventional ones. This further ensures that the design is reliable for practical use in breast cancer detection.

5. Conclusion

This study presented an integrated framework for high-resolution breast cancer detection by combining a Modified Addax Optimization Algorithm (MAOA)–optimized mm-wave antenna with a Gated Recurrent Unit (GRU)–based classification model. The proposed antenna was designed to operate efficiently within the mm-wave band, and MAOA was employed to fine-tune its structural parameters. This optimization led to significant improvements in return loss, gain, radiation efficiency, and directivity, ultimately enhancing the antenna’s ability to probe dielectric variations in breast tissue. The superior electromagnetic performance confirmed that MAOA is a highly effective approach for multi-parameter antenna optimization compared to conventional design methods. The dielectric response signals collected by the optimized antenna were subsequently analysed using a GRU classifier. Owing to its capability to model sequential dependencies within the signal patterns, the GRU network demonstrated excellent detection performance, achieving 96.3% accuracy, 95.9% precision, 96.5% sensitivity, and 95.8% specificity. These results confirm that the integrated MAOA–GRU framework can reliably distinguish between healthy and cancerous tissues with minimal misclassification. Overall, the findings highlight the potential of the proposed approach as a powerful, non-invasive, and computationally efficient tool for early breast cancer detection. By leveraging the strengths of advanced antenna optimization and deep learning–based classification, this work contributes to the development of next-generation biomedical sensing systems. Future research may explore hardware prototyping, real-tissue experiments, and further enhancement of classification performance through hybrid deep learning architectures.

6. Future work

While the proposed MAOA-optimized mm-Wave antenna with GRU classifier demonstrates promising performance metrics, such as an accuracy of 96.3% and sensitivity of 96.5%, further validation on real-world clinical data is necessary to ensure practical applicability. Future work will focus on testing the system using actual patient datasets collected from medical institutions, which will help assess the robustness and generalizability of the proposed approach in realistic clinical environments. Additionally, we plan to explore the integration of the system into routine diagnostic workflows, examining factors such as varying breast tissue densities, patient movement, and diverse demographic conditions. Expanding the evaluation to include larger and more heterogeneous datasets will provide deeper insights into the system's reliability and could further optimize the model’s parameters for enhanced clinical performance.

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