Frequency Selection to Improve the Performance of Microwave Breast Cancer Detecting Support Vector Model by Using Genetic Algorithm

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Abstract— **This paper presents an innovative paradigm for breast cancer detection by leveraging a Support Vector Machine (SVM) based model fueled with numerical data obtained from the cutting-edge MammoWave device. Operating in the microwave spectrum between 1 to 9 GHz and boasting a 5 MHz sampling rate, MammoWave emerges as a groundbreaking solution, specifically addressing the limitations posed by conventional methods, particularly for women under 50. This technological advancement opens a promising avenue for more frequent and precise breast health monitoring.**

To enhance the efficacy of the SVM model, our research introduces a metaheuristic-based methodology, strategically navigating the selection of frequencies crucial for breast cancer detection within the MammoWave dataset. Overcoming the challenge of judicious frequency selection, our approach employs wrapper methods in metaheuristic algorithms. These algorithms iterate through subsets of frequencies, guided by the SVM model's performance, culminating in the identification of the optimal frequency subset that significantly refines precision in breast cancer detection. Moreover, a novel cost function is proposed to strike a balanced trade-off between sensitivity and specificity, ensuring an acceptable accuracy rate. The results exhibit a noteworthy 10% increase in specificity, a milestone achievement for the MammoWave device, yielding an overall detection rate of approximately 62%. This research underscores the potential of seamlessly integrating metaheuristic algorithms into frequency selection, thereby contributing significantly to the ongoing refinement of MammoWave's capabilities in breast cancer detection.

Keywords— Breast cancer, Frequency selection, MammoWave device, Optimization.

I. INTRODUCTION

Breast cancer is the second leading cause of death in women globally [1]. Monitoring breast health involves using various technologies like mammography, ultrasound, and MRI. Mammography, used within screening programs, has limitations: generally, it is not recommended for women under 50. Also, it can't be performed frequently, restricted to once every 2 years in the EU. MammoWave, an innovative technology using microwave radiation (1-9 GHz), overcomes age-related and frequency limitations, providing numerical data and images for comprehensive information. This paper focuses on the numerical data obtained through microwave antennas [2].

Integration of Artificial Intelligence (AI) and Machine Learning (ML) in breast cancer care enhances diagnostic precision, treatment efficacy, and patient outcomes [3]. These technologies enable early detection, minimizing false positives and negatives in medical image interpretation. In the realm of AI and ML-based models for medical purposes, the choice of a suitable feature extraction method is paramount to ensure the efficacy and accuracy of the model.

Support Vector Machine (SVM) stands out as a prominent classifier in machine learning-based breast cancer detection due to its exceptional attributes [4-6]. Renowned for its high accuracy, SVM excels in distinguishing between malignant and benign cases. Its versatility in handling both linear and non-linear relationships within complex data structures is crucial for capturing the intricate patterns often present in breast cancer datasets. SVM's robustness in the face of noisy data and outliers enhances its reliability in medical contexts where variations are common. The flexibility provided by kernel functions allows SVM to effectively map data into higher-dimensional spaces, accommodating the complexity of medical imaging and diagnostics. Additionally, SVM's efficient use of memory, effectiveness in high-dimensional spaces, and established performance in real-world applications contribute to its widespread recognition and adoption in the field of breast cancer detection using machine learning.

Feature extraction involves identifying and highlighting relevant information from raw data, particularly crucial in medical applications where intricate patterns and subtle nuances can significantly impact diagnostic outcomes. So far different types of features have been introduced in breast cancer detection models; some of the most frequently used ones are statistical features (SF), Principal Component Analysis (PCA) [7], t-Distributed Stochastic Neighbor Embedding (tSNE) [7], Uniform Manifold Approximation and Projection (UMAP) [7], Hough transform [8], and Gray Level Co-occurrence Matrix (GLCM) [9]. On the other hand, a judicious selection of features not only enhances the model's ability to discern meaningful information but also aids in reducing computational complexity. Additionally, feature selection plays a vital role in streamlining the model by identifying the most pertinent variables, eliminating redundant or irrelevant ones. This process not only improves the model's interpretability but also contributes to mitigating overfitting issues. Ultimately, the careful integration of appropriate feature extraction methods and strategic feature selection not only refines the performance of AI and ML models but also holds the potential to revolutionize medical diagnostics, offering more accurate, efficient, and clinically relevant results.

Feature selection methods can be broadly classified into three main groups: filter methods, embedded methods, and wrapper methods. In filter methods, the relevance of features is assessed based on their statistical properties, and these methods operate independently of the machine learning algorithm. Notable techniques in this category include Variance Thresholding, which eliminates features with low variance to enhance informativeness; Correlation-based Methods, focusing on identifying and removing highly correlated features to reduce redundancy; and Univariate Feature Selection, which evaluates the relationship between each feature and the target variable independently. Embedded methods seamlessly integrate feature selection into the model training process. Prominent techniques within this group include LASSO (Least Absolute Shrinkage and Selection Operator) [10], which penalizes the absolute size of coefficients, forcing some to be precisely zero and effectively selecting features. Additionally, Tree-based Methods, such as Random Search [11] and Gradient Boosting [12], inherently perform feature selection by assigning importance scores to features. Regularized Regression Models also fall into this category, incorporating penalties for the number of features selected during model training. Wrapper methods assess the performance of different feature subsets by iteratively training and testing the model with each subset. Commonly used techniques in this group include Forward Selection, which incrementally adds features one at a time, selecting the one that most improves model performance; Backward Elimination, which starts with all features and removes them one at a time based on their impact on model performance; and Recursive Feature Elimination (RFE) [13], which systematically eliminates the least important features until the desired number is achieved.

The MammoWave device offers the capability to provide the complex S21 parameters within a frequency range of 1 to 9 GHz, employing a 5 MHz sampling, resulting in 1601 individual frequencies. The judicious selection of optimal frequencies is crucial for the development of a precise and dependable breast cancer detection model. This paper focuses on leveraging metaheuristic algorithms to strategically identify these optimum frequencies. Within the realm of feature selection (here frequency selection), metaheuristic algorithms operate through an iterative process of selecting, evaluating, and modifying subsets of features to identify the most effective subset based on a predefined objective or fitness function. These algorithms are categorized as wrapper methods, as they employ the performance of a specific machine learning model (the black box) to guide the search for an optimal subset of features. Prominent metaheuristic algorithms such as Genetic Algorithms (GA) [14], Simulated Annealing (SA) [14], and Particle Swarm Optimization (PSO) [15] are employed as iterative optimization techniques. These algorithms facilitate the exploration of a vast solution space, aiding in the identification of an optimal solution.

To ensure the robustness of the proposed model, the method is executed through five separate runs. In each run, 20% of the entire dataset is randomly selected as test data, while the remaining data undergoes evaluation using a 4-fold cross-validation technique embedded within an optimization procedure to identify the optimum features (frequencies). A novel cost function is introduced, emphasizing a balanced rate between sensitivity and specificity while maximizing accuracy. This novel approach demonstrates a substantial increase in sensitivity and specificity rates, reaching up to 60%, marking a significant milestone for the MammoWave device. Moreover, SVM with linear kernel has been used as classifier to develop a robust model.

In the subsequent sections of the paper, the proposed method, data collection process, and the newly introduced cost function are elaborated upon in the following section. Subsequently, the outcomes obtained from the experimentation will be thoroughly discussed in Section III. Finally, Section IV will encapsulate the conclusion derived from the findings, providing a comprehensive summary and insights into the implications of the study.

II. Proposed Method

A. Data Collection and Preparation

MammoWave (UBT Srl, Italy) is comprised of a transmitter (Tx) and a receiver (Rx) antenna as shown in Fig. 1. These antennas are positioned around a cup, ensuring the breast's secure enclosure during the scanning process. The system, divided into five sections, defines transmitter positions with 72-degree steps, executing meticulous movements for optimal data acquisition. With 10 unique positions for the transmitter and 80 for the receiver, comprehensive spatial coverage around the breast is achieved. Throughout the scanning process, the transmitter emits microwave radiation ranging from 1 to 9 GHz, utilizing a 5 MHz sampling rate and covering 1601 different frequencies. The receiver captures complex S21, forming a matrix (80 × (1601 × 2)), denoted as MTx. This extensive dataset, encompassing both real and imaginary values, supports an AI-driven method for assessing breast health. Ten MTxs are employed in this method to make informed decisions, distinguishing between different breast conditions. The amalgamation of microwave technology and artificial intelligence heralds a revolutionary and nuanced approach to breast screening.

Let $S_{21} = a + jb$, where a and b are real and imaginary parts of S_{21} respectively. Since S_{21} parameters are complex numbers, magnitude, phase, real part and imaginary part can be used as raw data. Since, the magnitude of a complex number combines information about both amplitude and phase in a single scalar value. It represents the overall strength of the signal, irrespective of its phase. In many cases, the magnitude is more robust to phase variations and can simplify the representation. Equations (1) to (3) represent how raw data is generated by using the complex S21 parameters.

$$S_{21}^{\text{Magnitude}} = \sqrt{a^2 + b^2} \tag{1}$$

Moreover, for each MTx we have:

$$MTx = \begin{cases} MTx(i\,,j) = \mathrm{real}\big(S_{21}^{i,j}\big) \text{ for odd columns of } MTx \\ MTx(i\,,j+1) = \mathrm{imag}\big(S_{21}^{i,j}\big) \text{ for even columns of } MTx \end{cases},\ \mathrm{i} = 1,2, \ldots, 80 \text{ and } \mathrm{j} = 1, 3, \ldots, 3201 \tag{2}$$

where, i is the index of the receiver's position and j is the frequency sampling corresponding to each transmitter. By considering (1) and (2), the magnitude matrix MGx is a (80 × 1601) matrix that for each individual position of Tx, we have:

$$MGx(i,k) = \sqrt{MTx(i,j)^2 + MTx(i,j+1)^2}, k = 1,2,\dots,1601 \quad (3)$$

As a result, for each individual breast scanning we have 10 magnitude matrixes $MGx = \{MGx^1, MGx^2, \cdots, MGx^{10}\}$ as raw data for using to develop AI-based diagnosis model.

A dataset of 1024 breasts from 526 women was considered; such women participated in two MammoWave clinical trials (Clinicaltrials.gov identifiers NCT04253366 and NCT05300464) carried out at different EU Hospitals. For each breast, we used as reference standard the radiologic study output integrated with histological one (if deemed necessary by the responsible investigator); thus, the reference standard allows to classify breasts in non-healthy (NH, i.e. breasts with malignant findings) or healthy (H, i.e. breasts without any findings or with benign findings). Specifically, reference standard led to 161 NH and 863 H (of which, 436 breasts were without any findings and 427 breasts with benign findings).

B. Proposed Cost Function

In medical applications, the evaluation of ML-based models often involves using the F1-score, which is the harmonic mean of precision and sensitivity (recall). While the F1-score considers both false positives and false negatives, it lacks an explicit mechanism to ensure a balance between sensitivity and specificity. Our research focuses on developing a breast cancer detection model tailored for the MammoWave device, with a key emphasis on achieving balanced rates. To address this, we propose a dynamic cost function (7) that ranges between 2 and zero. The first term of the cost function is designed to minimize overall error, while the second term is dedicated to enforcing a balance between sensitivity and specificity rates. This dual-term structure acts as a corrective measure, penalizing the cost function when it tends towards unbalanced rates. This approach enhances the model's capacity to maintain equilibrium between sensitivity and specificity, aligning with the specific requirements of our breast cancer detection goals.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP} \quad (4)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (5)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (6)$$

$$\text{Cost function} = \big(2 - (\text{Sensitivity} + \text{Specificity})\big) + |\text{Sensitivity} - \text{Specificity}| \quad (7)$$

where, TP and TN are True Positive (breast with cancer correctly classified as NH) and True Negative (healthy breast correctly classified as H), respectively.

C. Frequency Selection

As mentioned before, MammoWave device provides raw data across the 1 to 9 GHz frequency range, presented in the form of an 80 by 1600 magnitude matrix for each Tx position. This format allows for the segmentation of the entire frequency range into eight distinct sub-bands (SBs), as depicted in Fig. 2. Each sub-band comprises 200 frequency values. For instance, sub-band five (SB 5) spans frequencies from 5 to 6 GHz (5000 to 6000 MHz). Observations indicate that frequency values within each sub-band exhibit closely related behavior, particularly concerning machine learning performance. Consequently, the process of selecting frequencies can be considered synonymous with selecting sub-bands. It means that for an Optimization Algorithm (OA) search space dimension is eight and the optimum solution could be one of the sub-bands or a combination of them. Moreover, we used binary representation for selecting procedure. For example [0 0 0 1 0 0 1 1] means sub-bands 4, 7, and 8 are selected.

Experimental results were conducted through 5 distinct runs. In each run, 20% of the available data was randomly set aside as test data, comprising 173 H and 32 NH samples. In each iteration of the optimization algorithm, as shown in Fig. 3. 4-fold cross-validation is employed to assess the combination of SBs (selected SBs) suggested by the optimization algorithm. Within each fold, unselected frequencies are removed from MGx matrices, and a feature extraction method is applied to remained raw data. Subsequently, standard (Z-score) normalization is utilized to normalize the data, followed by the evaluation of a trained SVM classifier using validation data. The average cost function across the 4 folds serves as the performance metric for the selected frequencies.

Finally, during the testing phase, blind test data were assessed by the trained classifiers using the training data. Frequency selection, feature extraction, and normalization were applied prior to the evaluation.

III. Results and discussion

Five independent runs were conducted, incorporating a 20% test data subset randomly selected from both H and NH cases. This approach was employed to ensure the robust evaluation of the proposed method's performance. Initially, the entire frequency information was considered, signifying no specific selection, and various feature extraction methods and classifiers were employed to identify the optimal combination of classifier and features for microwave data. Subsequently, in the ensuing stage, the obtained results were scrutinized using the proposed method, considering the suggested cost function and F1-score for a comprehensive performance assessment.

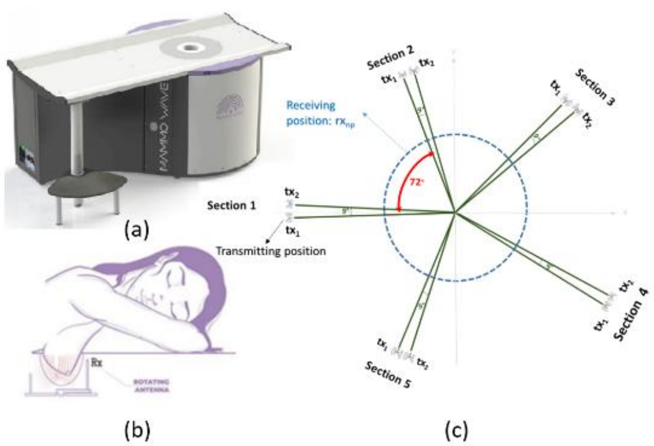

Fig.1. (a) MammoWave prototype, (b) sketch of MammoWave's scanning configuration showing the hole and antenna positions, (c) transmitting and receiving antenna configurations.

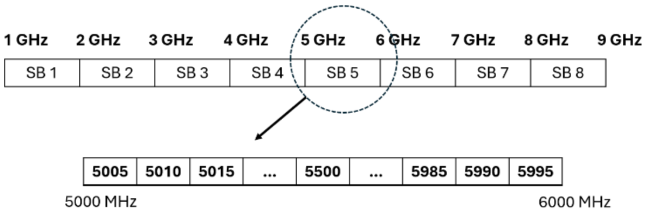

Fig.2. Sub-bands in the available range of frequencies.

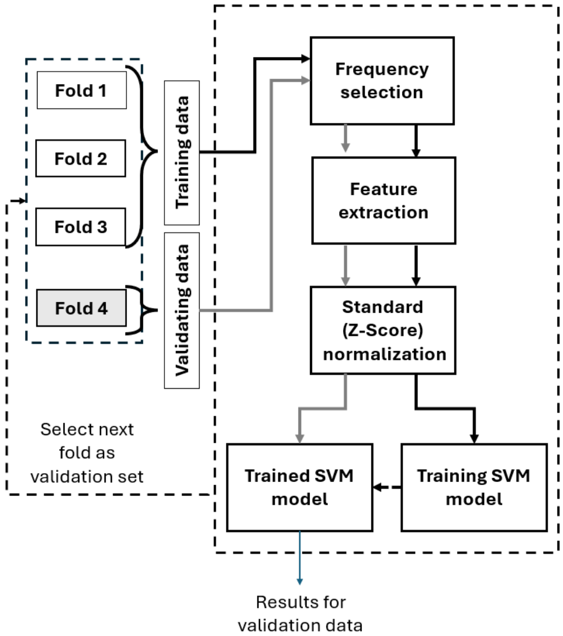

Fig. 3. Overall framework for k-fold validation in training step of the proposed method.

A. No Frequency Selection

As previously mentioned, the primary classifier for the proposed model is the SVM classifier with a linear kernel. However, the identification of the best and most suitable features for this classifier necessitates further investigation. In this section, a comprehensive exploration was undertaken by considering the entire frequency information, and four well-known feature extraction methods (SF, PCA, tSNE, and UMAP) were selected for breast cancer detection. It is important to note that for SF features, statistical information such as mean, median, standard deviation, minimum, maximum, variance, summation, and entropy values were employed. Furthermore, experimental results reveal that the optimal number of components for PCA, tSNE, and UMAP in this study are 70, 2, and 4, respectively. Fig. 4 illustrates a box-chart depicting the sensitivity, specificity, and accuracy of these features.

Overall, SF exhibits higher rates compared to others, while PCA demonstrates more balanced results. SF, with its superior performance in detecting cancer cases, showcases commendable accuracy and sensitivity rates. Conversely, tSNE excels in identifying H breasts. Given that SF boasts higher accuracy and sensitivity rates with an acceptable specificity rate, it was selected as the feature for the remainder of this paper.

B. Proposed Method

Five distinct runs were executed during the proposed optimization approach to determine the optimal Optimization Algorithm (OA) for breast cancer detection. Table I provides a comprehensive comparison of the performance achieved by Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). The evaluation metrics utilized for assessing the models included the proposed cost function and (1 - F1-score), reflecting the error of the models. The results indicate that when employing (1 - F1-score), optimization algorithms tend to prioritize frequencies that enhance the model's ability to accurately detect Malignant cases, resulting in a lower specificity rate. Conversely, the proposed cost function, in most cases, compels the OAs to seek a more balanced performance. A closer examination of the selected SBs reveals that SB1 consistently appears in all optimum solutions, SB2 significantly contributes to increasing sensitivity, and SB8 demonstrates its effectiveness in elevating specificity. Consequently, utilizing GA as the optimization technique alongside the proposed cost function yields a more balanced, robust, and reliable model.

Furthermore, Fig. 5 illustrates the enhanced performance of the proposed breast cancer detection model through the proposed frequency selection method. The confusion matrices' results represent the average rates across five separate runs on testing data. In an ideal scenario, True Positives (TP) should be 32, and True Negatives (TN) should be 173. A comparison of these two confusion matrices reveals that TN and False Negatives (FN), associated with sensitivity, remain constant, while there is a noteworthy increase in the TP rate. This translates to a 10% improvement in specificity and, consequently, accuracy.

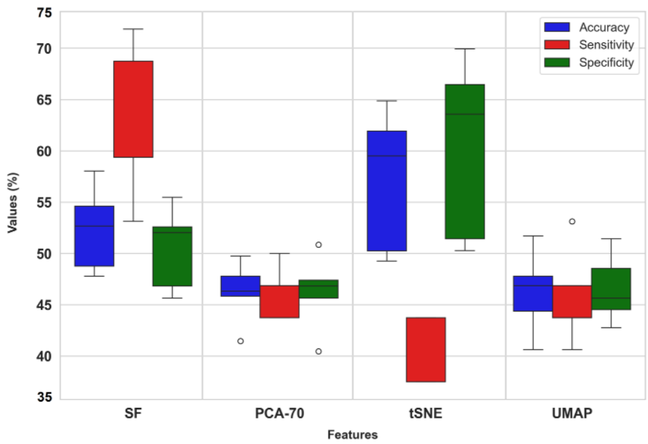

Fig. 4. Performance of different feature extraction methods and classifiers by considering whole frequency information.

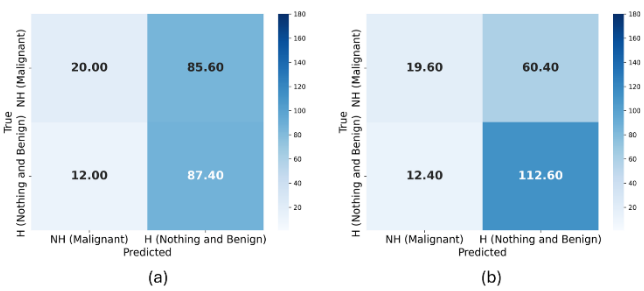

Fig. 5. Comparison between confusion matrices. (a) without frequency selection, (b) with frequency selection.

TABLE I. Performance of different optimization techniques by using the proposed cost function and (1 - F1-score) as an error function.

Error function	OA	Error	Selected SBs	Acc	Sen	Spe
Proposed Cost function (between 0-2)	GA	0.783	11000001	64.49	61.25	65.08
	PSO	0.936	11000100	53.85	62.50	52.25
	SA	0.937	10000101	52.88	53.12	52.84
1 - F1-score (between 0-1)	GA	0.641	11000011	54.05	81.87	48.90
	PSO	0.689	11110100	51.80	69.37	48.55
	SA	0.692	11111110	53.36	66.25	50.98

C. Comarision With Other Methods

As illustrated in Fig. 6, the presented method stands out for its superior performance when juxtaposed with alternative techniques. Despite the acceptable levels of accuracy and specificity demonstrated by LASSO and random search, their sensitivity rates exhibit notable shortcomings. Moreover, while Grid Search manages to produce balanced rates, it still falls behind the exceptional performance achieved by the proposed method. However, it is essential to acknowledge certain drawbacks associated with both LASSO and grid search. LASSO, although proficient in feature selection and regularization, is susceptible to model instability when dealing with multicollinearity, potentially leading to unreliable coefficient estimates. Additionally, LASSO tends to arbitrarily select one variable among highly correlated ones, potentially overlooking valuable information.

On the other hand, grid search, while systematically exploring hyperparameter combinations, can be computationally expensive and inefficient, particularly in high-dimensional spaces. The exhaustive search across a predefined parameter grid may result in extended processing times, making it less practical for large datasets or resource-intensive scenarios. In contrast, the proposed method excels in addressing these challenges. It not only outperforms LASSO and grid search in terms of sensitivity, specificity, and accuracy but also demonstrates an optimal balance among these metrics. This underscores the method's efficacy and robustness in achieving a comprehensive and well-rounded performance in breast cancer detection. The ability to overcome the limitations of LASSO and grid search positions the proposed approach as a promising advancement in enhancing the precision and reliability of breast cancer diagnostic models.

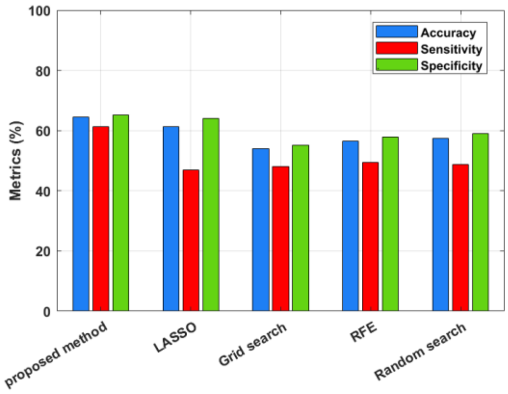

Fig. 6. Comparison between proposed model and well-known selection strategies.

IV. Conclusion

In conclusion, the MammoWave device emerges as a novel tool in breast cancer detection, particularly in younger age groups. This paper has advanced the MammoWave technology by developing an optimized model that incorporates heuristic algorithms and leverages the SVM classifier with a linear kernel. The overarching focus has been on addressing key issues related to features, error function, and frequency selection.

By exploring the information provided by MammoWave in the 1 to 9 GHz range, our findings underscore the efficacy of statistical features in achieving higher sensitivity rates while maintaining competitive accuracy compared to other feature types. The subsequent step involved the introduction of a novel error function, assessing the model's performance based on a fair trade-off between sensitivity and specificity. A comprehensive study of various metaheuristic algorithms revealed that Genetic Algorithm outperformed other optimization approaches, pinpointing sub-bands 1, 2, and 8 as the optimal frequency contents for developing the SVM-based breast cancer detection model. This strategic frequency selection resulted in a notable enhancement, elevating the specificity rate to 65%, while maintaining a robust sensitivity level at approximately 61%. The optimization achieved through GAs in identifying these optimal frequency contents underscores their efficacy in fine-tuning the MammoWave device for heightened precision in breast cancer detection. It is worth noting that these results are very promising for MammoWave, because these results have been obtained with low amount of data and we believe that they could be improved in the future.

Furthermore, the integration of a proposed cost function contributed to the model's reliability, robustness, and accuracy. While prioritizing sensitivity through F1-score and allowing optimization algorithms to emphasize frequencies sensitive to malignant cases, the cost function introduced a crucial balance, enhancing the overall dependability of the model. In essence, this research not only advances MammoWave's performance, but also provides a comprehensive framework for developing precise and trustworthy breast cancer detection models.

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