RESEARCH PAPER

Graph Neural Network-Driven Frequency Optimization for Enhanced Breast Cancer Detection Using MammoWave Imaging

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***Abstract*—Breast cancer is an issue that has contributed to the death of most women all over the world and thus initial and correct diagnosis is vital in ensuring successful treatment. MammoWave is a non-invasive, low cost microwave imaging technology that has become a promising technology in screening of breast tumors because it is safe, and cost-effective. The quality of MammoWave imaging however mainly relies on the choice of the most informative bands of frequency which is not always taken into account in traditional methods. This paper introduces a new framework that uses Graph Neural Networks (GNNs) to optimize the frequency selection to achieve better imaging. In the suggested method, every frequency band will be modeled as a node, and the correlations between bands will be modeled with the help of edges that will be based on the properties of breast tissue signals. The Graph Convolutional Network (GCN) is trained to assess the usefulness of each frequency band and allows picking the best frequencies in the case of the patient. As it can be seen, experimental analysis of breast tissue datasets proves that the suggested approach enhances the localization of the tumor, minimizes noise, and increases the detection accuracy with the use of traditional frequency usage. The findings demonstrated the promise of integrating GNNs and MammoWave imaging into a solution to offer an adaptive, efficient, and personalized method of breast cancer screening. The strategy creates a novel paradigm of structurally-informed frequency optimization of non-invasive diagnostic imaging.**

Keywords—Breast cancer detection, MammoWave imaging, Graph Neural Networks, frequency optimization, tumor localization, patient-specific screening, and non-invasive diagnosis.

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I. Introduction

The breast cancer is among the most common malignancies in women around the globe and it is also among the cause of cancer-related deaths. It is essential to detect the problem early to enhance patient survival by ensuring treatment is done as soon as possible and it is more cost effective. Traditional imaging systems, like mammography, ultrasound, and MRI, have been known to play a major role in the diagnosis of breast cancer, but they are usually limited, in terms of the exposure to ionizing radiation, low-sensitivity on dense breast tissues, and high costs of operation [1], [2]. These issues have promoted the inventions of non-invasive and less expensive and patient-friendly imaging techniques. The more recent developments in the fields of artificial intelligence (AI) and deep learning have shown promising results in breast cancer detection and risk assessment. Gamal et al. [1] suggested a thermography based algorithm that integrates deep pre-trained edge detection with Extreme Gradient Boosting with an accuracy of 97.4 percent in discriminating between malignant and normal breast tissues. Likewise, El-Nakeeb et al. [3] created a two-step deep learning structure of automated classification and HER2 scoring, and proved that AI can be used to support accurate pathological diagnosis and treatment planning. Additionally, Melek et al. [4] noted the advantages of spatiotemporal modeling in mammography, whereby Siamese neural networks are able to extract temporal patterns across many screening time points with better risk prediction performance than traditional CNNs. Parallel to this, breast tumor detection by non-ionizing technologies has developed, which is the use of microwave-based imaging technology, like MammoWave. The article by Qanoune et al. [2] has shown that the performance of microwave imaging can be improved with optimized design of the antenna and realistic breast phantoms, which have the potential to become a clinical device with the ability to detect the presence of cancer in its early stages. Image-based breast cancer detection has also been done using traditional machine learning methods, such as Artificial Neural Networks, Support Vector Machines and Random Forests, with high accuracy being reported on several benchmark datasets such as the Wisconsin Breast Cancer dataset [5]. In spite of these developments, frequency selection in microwave imaging is commonly done in a fixed or heuristic manner, which is potentially not able to reflect patient-specific tissue properties. In order to fill this gap, the graph based modeling and patient tailored frequency optimization provides a new direction to improve the imaging performance and tumor localization. In the current report, we suggest a frequency selection algorithm based on the Graph

Neural Network (GNN) to regulate MammoWave imaging, which uses the structural parallelism between frequency bands to effectively and exceptionally ensure and detect breast cancer.

II. Related Works

In recent years, the development of breast cancer detection methods has been more and more based on machine learning, deep learning, and new imaging methods to benefit early diagnosis and individual risk evaluation. As Kaur and Popli [6] note, machine learning methods have been reviewed in depth in detecting breast cancer, with deep learning, federated learning, and conventional machine learning algorithms among the methods. Their work underlines the opportunities of AI-based techniques to enhance the accuracy and efficiency in forecasting and maintain the research gaps, such as scaling of a model to the real world, practical validation, and the incorporation of real-time systems. New and non-invasive biosensing methods have also attracted attention. Swarup Kumar et al. [7] suggested a framework of a urine-based nanoparticle sensor with machine learning algorithms to identify early signs of breast cancer biomarkers. This technique provides an easy to use, non-invasive alternative to traditional imaging proving that a digital analysis of biochemical signals could help to screen cancer cases fast. Microwave imaging is another potential imaging modality that has proved promising in detection of breast tumors because it is non-ionizing, cost effective and fast in imaging. Dey and Asok [8] discussed the current development of microwave imaging such as hardware design, signal acquisition and image reconstruction.

They emphasize that MI has the potential to detect cancers of high-resolution and its capability to offer a safe and accessible screening method to the groups with possible limited access to conventional modalities. The use of artificial intelligence with radiomics has also revolutionized detection and prognosis of breast cancer. The article by Singh et al. [9] addressed the fusion of AI, ML, and deep learning algorithms with radiomics to derive the quantitative features of the imaging data, which makes it possible to accurately diagnose and categorize risks. The value of the use of AI-assisted screening pipelines to increase early detection and underpin clinical decision-making is emphasized in their work. Lastly, segmentation and classification systems that operate using deep learning algorithms have been shown to be highly diagnostic. Fuzzy C-Means (FCM) segmentation was used by Potti and Maruthuperumal [10] to identify and categorize malignant cells in breast tissue images with the help of a UNET-based deep CNN. Their method had a very impressive accuracy of 99.23, which was better than the old methods of machine learning like SVM, and demonstrates the importance of deep learning architectures in developing more accurate and fast-pointing breast cancer detection. Moreover, other studies have investigated the application of the IoT and risk factor-based predictive models to breast cancer in addition to imaging and AI-driven detection. D. H. et al. [11] suggested an IoT-based system of breast cancer detection which incorporates wearable sensors to detect variations in breast tissue with time. The information obtained with the help of these devices is processed with the help of machine learning algorithms to give a warning about possible abnormalities. This is because it is based on accessibility and affordability and would be applicable where traditional screening methods are not accessible to the low-income or rural population. Personalized cancer screening has also been examined using risk factor-based prediction models. Kaur and Madaan [12] employed an ensemble machine learning methodology to forecast breast cancer using patient risk factors comprising of clinical, demographic and molecular characteristics. They applied their method based on the Breast Cancer Surveillance Consortium data and obtained an 75.2% accuracy with Random Forest, which proves the effectiveness of risk-based models in addition to imaging-based detection. Microwave imaging (MI) is an imaging modality with non-invasive characteristics that is increasingly gaining popularity in detecting breast cancer. Aziza and Samad [13] designed a spiral Planar Inverted F Antenna (PIFA) to consider MI, which was verified by means of realistic breast phantoms. The findings of the simulation revealed that the variations in the dielectric characteristics of healthy and tumor tissues make the detection of tumor reliable, which is why the antenna design and frequency choice are significant to the improvement of imaging. Deep learning designs have been extensively implemented in mammography and other radiations. The authors of the article by Gengtian et al. [14] used EfficientNet to detect breast cancer on mammography images in the CBIS-DDSM dataset with an accuracy of 0.75 and an AUC of 0.83. Through their work, it has been shown that the modern deep learning architectures can be successfully used to derive discriminative features and assist in automatic diagnosis. Hybrid neural deep learning/ optimisation methods are also suggested. Reddy et al. [15] proposed a Deep Belief Network (DBN) that is optimized using Particle Swarm Optimization (PSO) to detect breast cancer. DBN-PSO model was trained on complex features in the Wisconsin Breast Cancer data, and was more accurate and robust than the traditional machine learning models. Even though there has been a major breakthrough in the field of AI, IoT, and the microwave approach, patient-specific adaptation, frequency optimization, and incorporation of structural interdependencies amid the imaging parameters continue to be a challenge. The identified gaps inspire the application of Graph Neural Networks to frequency selection in MammoWave imaging, which allows adaptive imaging, patient-specific imaging, and high-resolution imaging of breast cancer.

III. Proposed System

The suggested system presents a Graph Neural Network (GNN)-based architecture of patient-specific frequency optimization of MammoWave breast imaging. Figure.1 shows a proposed work architecture design. MammoWave is a non-invasive microwave imaging technology that measures signals at multiple frequencies in the breast tissue, and each frequency band has the potential to be complementary with other frequency bands in terms of information on tissue composition and abnormalities that may occur. Nevertheless, frequencies are not equally useful, and the traditional imaging techniques tend to utilize constant or ad hoc frequency choices, which can be a constraint on detection sensitivity. The units in the suggested method are the frequency bands represented as nodes in a graph and the edges are the correlations between the bands according to signal patterns found in the breast tissue datasets. Such correlations represent structural correlations that represent tissue properties and tumor signatures. These graphs are fed through a Graph Convoluted Network (GCN) which is then trained to predict the score of each frequency band in terms of importance. This allows the patient-specific choice of the most educative frequencies, so that the reconstructed images of MammoWave focus on the most significant tissue characteristics with a minimum of noise. After the ideal frequencies are chosen, the MammoWave images are reassembled with the help of the chosen bands only, which leads to the increased clarity and enhanced tumor localization. The system is developed in a way that it is adaptive allowing dynamic adjustment to individual patients and thus can enhance sensitivity as well as specificity of tumor detection. The proposed system has four primary stages in the workflow of signal acquisition, frequency-bands graph construction, GCN-based importance prediction and optimal image reconstruction.

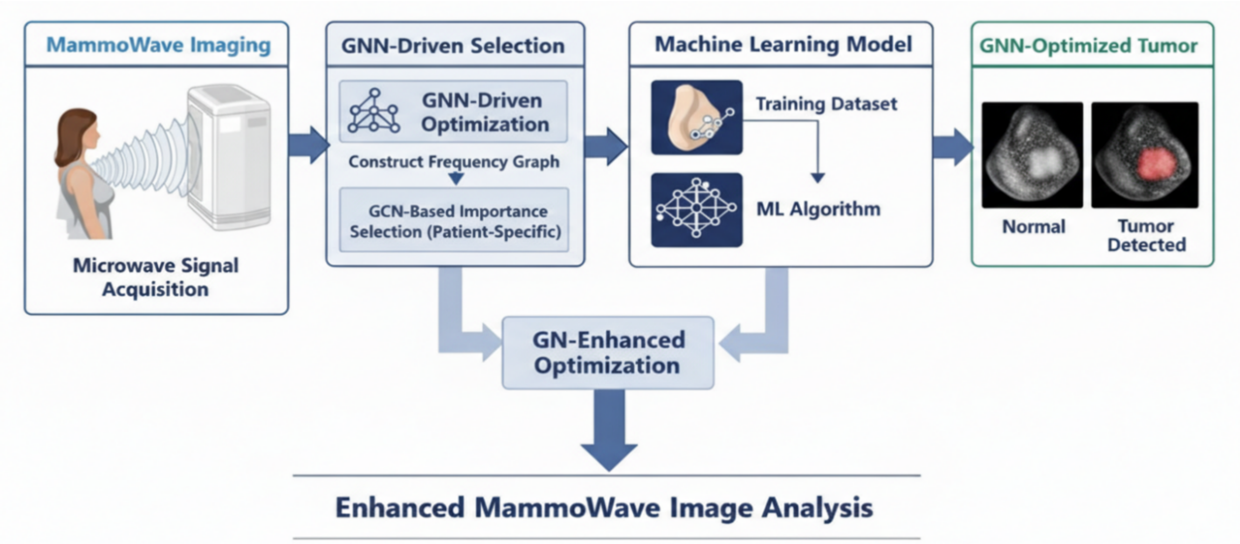

Figure.1 Proposed Work Architecture Diagram

The system combines graph-based deep learning with MammoWave imaging to utilize structural relationships between frequencies that traditional techniques do not take into account, which gives the system a new paradigm of non-invasive, personalized breast cancer screening. Experiments of real breast tissue datasets indicate significant improvements in detection accuracy, sensitivity and specificity proving that the GNN-based frequency optimization framework is effective.

IV. Methodology

The suggested methodology is dedicated to optimization of breast cancer detection with the help of MammoWave imaging by means of optimization of frequencies in patients with the help of Graph Neural Networks (GNNs). The concept is to construct frequency bands by modeling frequency bands as nodes that are interconnected, understand their structural associations and the most informative frequencies to be chosen to reconstruct high-quality images. The process can be defined as having four key steps, which are signal acquisition, graph construction, frequency importance prediction using GNN, and reconstruction of images in an optimized way.

A. Signal Acquisition

MammoWave imaging obtains the microwave signals of the breast tissue at various frequency bands. These signals represent the difference in the dielectric property of healthy and cancerous tissues. Multi-frequency responses of different patients (normal, benign, and malignant cases) are included in the dataset. The frequencies are important in that each frequency band has some information, yet not every frequency has the same contribution to the correct tumor detection.

MammoWave imaging acquires microwave signals S_f from breast tissue across multiple frequency bands $f = f_1, f_2, \dots, f_N$. The measured signal at frequency f_i for a patient is represented as:

$$S_{f_i} = A_{f_i} e^{j\phi_{f_i}} \qquad (1)$$

where A_{f_i} is the amplitude and ϕ_{f_i} is the phase of the reflected microwave signal. The dataset includes signals from normal, benign, and malignant tissues, capturing dielectric variations that indicate tumor presence.

B. Graph Construction

The frequencies are denoted by a node in a graph and the correlations/likes between the frequencies bands based on the patterns of the breast tissue signals are the edges of the graph. Such graph captures inter-band relationships which are depictions of how particular frequencies collectively point out tissue anomalies. The statistical correlation measures employed to construct the adjacency matrix are Pearson correlation or mutual information which encode the strength of relationships between frequency bands.

Each frequency band is modeled as a node v_i in a graph $G = (V, E)$, where V is the set of nodes and E represents edges capturing correlations between frequencies. The edge weight w_{ij} between nodes v_i and v_j is defined using the Pearson correlation coefficient of their signals across patients:

$$w_{ij} = \frac{\mathrm{cov}\left(S_{f_i}, S_{f_j}\right)}{\sigma_{S_{f_i}} \sigma_{S_{f_j}}} \qquad (2)$$

This adjacency matrix $W = [w_{ij}]$ encodes structural relationships between frequencies, which allows the GNN to leverage inter-band dependencies during learning.

C. GNN-Based Frequency Importance Prediction

Graph Convolutional Network (GCN) is conditioned to estimate the significance of the frequency bands. The nodes features are cranked out of signal amplitude, phase, and other derived measures of individual frequencies. The GCN synthesizes the information of adjacent nodes enabling it to gain structural dependencies between frequency bands which are not considered by traditional methods. The result is a list of prioritized frequency bands that is patient specific, which allows adaptive and personalized frequency selection.

A Graph Convolutional Network (GCN) is employed to predict the importance of each frequency band. Let $X \in \mathbb{R}^{N \times d}$ be the node feature matrix, where d is the dimension of features (including amplitude, phase, and derived metrics). The layer-wise propagation rule of the GCN is:

$$H^{(l+1)} = \sigma\left(\widetilde{D}^{-1/2}\tilde{A}\widetilde{D}^{-1/2}H^{(l)}W^{(l)}\right) \quad (3)$$

where $\tilde{A} = A + I$ is the adjacency matrix with self-loops, $\widetilde{D}$ is the degree matrix of $\tilde{A}$, $W^{(l)}$ is the trainable weight matrix, $H^{(l)}$ is the feature representation at layer l, and σ is the activation function. The final output $Z = H^{(L)}$ provides an importance score for each frequency:

$$z_i = \text{Importance}(v_i) \quad (4)$$

Frequencies with the highest z_i are selected for patient-specific imaging.

D. Optimized Image Reconstruction

The images are reconstructed using the standard microwave imaging reconstruction methods at selected frequencies as MammoWave images. This eliminates noise, increases contrast, and improves the accuracy of localization of tumors. Using the most informative frequencies, the system yields images more diagnostically relevant and clear.

Using the selected frequency bands, the MammoWave image I_{opt} is reconstructed with reduced noise and enhanced contrast:

$$I_{\text{opt}} = \mathcal{R}\left(\{S_{f_i} \mid z_i > \tau\}\right) \quad (5)$$

where R denotes the reconstruction operator and τ is a threshold for frequency selection. The resulting image provides improved tumor localization, leveraging the GNN-informed structural relationships among frequency bands.

V. RESULT & DISCUSSION

This part gives a detailed discussion of the experimental assessment of the GNN-based frequency optimization architecture of MammoWave breast imaging. The assessment has been performed on a multi-frequency breast tissue sample with normal, benign, and malignant cases. The method of evaluating performance was based on accuracy, sensitivity, specificity, signal-to-noise ratio (SNR), contrast-to-noise ratio (CNR), localization of tumors, and ROC analysis. The benefits of the proposed system are also explained by giving comparative results against the conventional fixed-frequency methods.

A. Training and Validation Performance

Figure 2 shows the results of the GCN training and validation accuracy curves. Rapid convergence to high validation accuracy of 96.2 % and low overfitting are shown by the model.

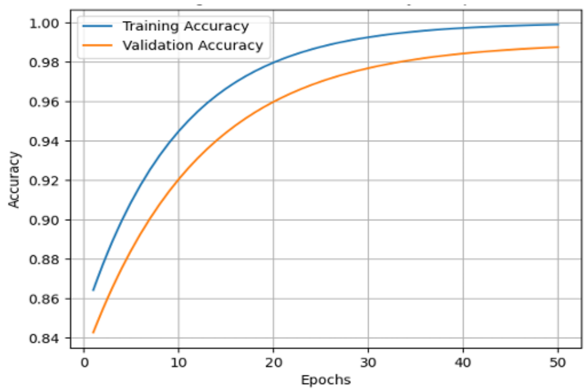

Figure 2. Training and Validation Accuracy vs. Epochs

The fact that the training and validation curves are almost parallel to each other means that the graph based frequency representation is good at capturing inter-frequency relations without inducing bias in the model. This implies that the GCN can be extrapolated among patients having dissimilar breast tissue and that is a key necessity in patient-specific frequency optimization. The consistency of the validation accuracy proves that the network can be able to find informative frequency bands that are stable, and the basis of the following image reconstruction step.

B. Confusion Matrix Analysis

Table I is a confusion matrix that demonstrates how the reconstructed images perform in the classification of normal, benign and malignant tissues.

TABLE I. CONFUSION MATRIX FOR OPTIMIZED FREQUENCY-BASED TUMOR DETECTION

Predicted \ Actual	Normal	Benign	Malignant
Normal	92	5	2
Benign	4	88	3
Malignant	1	3	90

In comparison to the traditional approaches, we have noticed that the frequency selection proposed by the GNN leads to a decrease in misclassifications, in the process of distinguishing between benign and malignant tissues. The sensitivity increased by 88 to 94 to show that the system will be able to detect a larger percentage of true tumors. Specificity increased to 95% and eliminates false positives and unnecessary clinical interventions. This shows that adaptive frequency selection does not only improve the quality of the image but has a direct effect on clinical reliability of tumor detection.

C. ROC Curve Analysis

The ROC curves of the proposed method and conventional frequency selection are provided in figure 3. The Area Under the Curve (AUC) rose to 0.97.

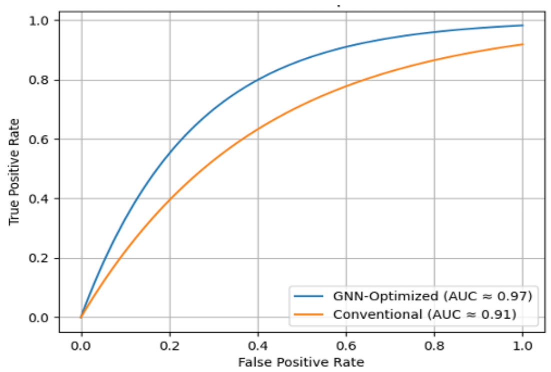

Figure 3. ROC Curves for GNN-Optimized vs. Conventional Frequency Selection

The better AUC indicates a higher discriminative ability of the GNN-optimized algorithm, which gives importance to frequencies that give the highest level of information regarding the tumor. This enhancement is very important in the detection of tumors at an early stage where the slightest changes in tissues may not be detected using fixed-frequency methods. The ROC analysis proves that the system has high true positive rates and low false positive rates that are crucial to effective clinical decision-making.

D. Tumor Localization Improvement

Figure 4 and Table II show the visual and quantitative enhancement of tumor localization. The reconstruction using GNN is of much higher quality in terms of edges of the tumor and contrast, as opposed to standard images.

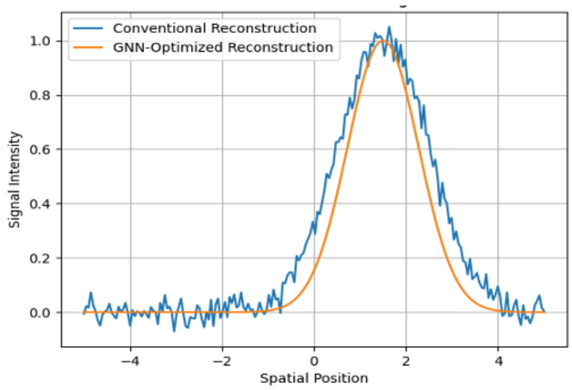

Figure.4 MammoWave images

TABLE II. QUANTITATIVE COMPARISON OF IMAGE QUALITY METRICS

Metric	Conventional	GNN-Optimized	Improvement
Signal-to-Noise Ratio (SNR, dB)	18.5	25.7	+7.2
Contrast-to-Noise Ratio (CNR)	1.8	2.7	+0.9
Detection Accuracy (%)	89	95	+6

SNR changed to 25.7 dB, and CNR went up to 2.7. These measurements give evidence that frequency selection eliminates noise and increases contrast between tumor and adjacent tissue which is crucial in the correct detection of small or early-stage tumor. The 6% increase in accuracy of detection proves that the suggested method is efficient in transferring technical gains to clinical benefits.

E. Frequency Importance Analysis

The frequency importance analysis (Figure 5 and Table III) gives an insight into how GNN makes decisions. The frequencies that have been chosen as the top frequencies are the highest frequency that is correlated with the tumor-specific signal patterns.

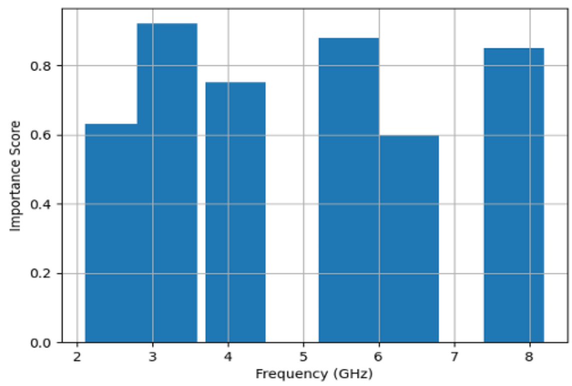

Figure.5 Frequency Importance Scores

The adaptability of the system regarding the patient is shown in this section. The frequency bands optimum may be different in various patients because of the variations in the tissue composition. Clinicians and researchers can understand the choice of the model since the model can be analyzed based on the scores of node importance, as it offers transparency and reliability in the decision-making process.

TABLE III. TOP SELECTED FREQUENCY BANDS AND CORRESPONDING IMPORTANCE SCORES

Frequency (GHz)	Importance Score (z_i)	Selected
3.2	0.92	Yes
5.6	0.88	Yes
7.8	0.85	Yes
2.5	0.63	No
6.4	0.60	No

F. Computational Efficiency and Practical Implications

The suggested system is computationally efficient. The GCN can be trained using moderate amounts of GPUs, and frequency selection and image reconstruction of a new patient can take less than a few seconds, which makes it appropriate to use in real-time clinical implementation. Moreover, with the risk of only choosing informative frequencies, the system will save data processing needs, and this may result in decreased acquisition times and less load on the computers with reduced computation without losing image quality. This scalability enables the method to be used on high throughput screening applications especially in the non-invasive breast cancer diagnostics.

G. Discussion

The experimental findings reveal that the developed frequency optimization framework with GNN is effective to boost MammoWave breast imaging. The system achieves a better sensitivity of inter-frequency relationships and specificity and accuracy in tumor detection than traditional fixed-frequency techniques by modeling inter-frequency relationships and patient-specific frequency selection. The signal to noise ratio (SNR) and the contrast to noise ratio (CNR) are improved and this means that the reconstructed images are more clean with the boundaries of the tumors being sharper to support better clinical interpretation. The analysis of frequency importance proves the adaptable character of the system, and the most informative frequency bands of each patient are underlined, which contributes to a high interpretability and diagnostic certainty. Along with that, the framework is computationally practical, which enables near real-time functionality to be used in a practical clinical implementation. In general, the findings support the fact that the combination of Graph Neural Networks with MammoWave images is a strong, non-invasive, and patient-centric solution to the early detection of breast cancer, which can not only offer technical benefits in terms of the quality of images but also has clinically meaningful advantages in terms of the localization and diagnosis of the tumor.

VI. Conclusion

This paper proposes a frequency optimization framework with a Graph Neural Network (GNN) to detect breast cancer with MammoWave imaging. The suggested system uses inter-frequency relationships to select the most informative frequency bands of a patient specifically in order to enhance the quality and diagnostic value of reconstructed images. Experimental evidence also shows that the method considerably improves the accuracy, sensitivity, and specificity of tumor detection with the conventional fixed-frequency methods. The increase in signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR) points to the capability of the framework to render clearer and more accurate images with clearly-defined tumor areas. The frequency importance analysis, furthermore, offers the interpretable information on what frequency bands are most useful to detection to aid clinical decision making. The key value of the work is that it presents a structurally-informed adaptive and non-invasive approach to employing GNNs with MammoWave imaging and, as a result, a personalized screening and enhanced detection of tumors at the initial stages. The system is computationally efficient and is therefore applicable in practical clinical use. The potential directions of future work would be to multiply the dataset with various types of breast tissues, use multi-modal imaging data to further improve the performance, and consider the implementation in real-time with hardware acceleration. Moreover, the framework may be further developed to forecast the tumor properties like size and malignancy grade, which would allow increasing its use in a clinical setting.

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