Efficient Deep Learning Approaches for Automated Tumor Detection, Classification, and Localization in Experimental Microwave Breast Imaging Data

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***Abstract*—Breast Microwave Imaging (BMI) has emerged as a competitive and potentially disruptive alternative to conventional breast cancer screening techniques owing to its desirable features and improved detection rate. In this paper, we apply various artificial intelligence, and deep learning approaches for automatic breast tumor detection, classification and localization in an open-source experimental BreastCare dataset obtained using our pre-clinical, portable and cost-effective BMI system. We compare the effectiveness of various cutting-edge machine-learning detection algorithms to assess the usefulness of the obtained data-set. Also, we present a deep learning framework that outperforms state-of-the-art microwave imaging methods and ML algorithms for tumor detection, localization, and characterization. The proposed framework gives promising results using our BMI system's measured reflection coefficients (S_{11}). This work shows the potential advantages of applying cutting-edge deep learning algorithms in practical BMI systems.**

***Index Terms*—Microwave Imaging (MWI), Deep learning (DL), Machine learning (ML), Convolutional Neural Networks (CNN), Residual Neural Networks (ResNet), Deep Neural Networks (DNN), and localization.**

I. Introduction

Breast cancer is the most prevalent cancer among women in developed as well as in developing countries. Worldwide, breast cancer has been a leading factor in female fatalities with 2.3 million breast cancer cases identified in 2020 [1]. These numbers demand the need for quick and accurate detection. Microwave Imaging (MWI) has become a widely sought-after technique for medical imaging especially for breast cancer detection it is being developed as a complementary tool with the standard ones. In the last decade, various Tomography-based and Radar-based techniques have been proposed and ongoing effort is being done to improve the outcomes.

Breast Microwave Imaging (BMI) works by bombarding the microwaves on the breast, and the reflected signals from the healthy and affected areas help detect cancerous cells. Microwaves scatter differently in a tumor than healthy breast tissue due to the difference in their electrical properties such as conductivity and permittivity. This scattering microwave property provides the contrast of tumor and breast tissue, making it possible for microwave imaging tools to generate the breast image with tumor location. Consequently, there is a need to further research different MWI detection methods that are effective and precise. Artificial intelligence (AI) has already advanced in several domains. Due to its independence, this approach received a lot of attention. Microwave imaging researchers are drawn to AI as it forges a path in several fields. Many machine learning (ML) techniques have already been applied to diagnose diseases using X-rays, mammograms, and CT scans. These techniques are used to classify or diagnose particular diseases. The researchers employ mammogram images and X-rays for the diagnosis. However, only a tiny amount of research has been done using AI approaches to directly identify, localize, or classify breast cancer from scattering parameters without constructing images from them. The work done in this domain provides state-of-the-art Deep Learning (DL) algorithms that can learn from the data and detect the disease. The BreastCare data-set (BreastCare), which can be accessed at https://bit.ly/3eULOcf[1], is an attempt to open-source the data-set for research, the link would be continuously updated as more data is available. In this work, we designed and developed breast cancer imaging hardware using the mono-static radar-based approach to collect the data-set. Moreover, we created novel DL frameworks for the detection, localization, and characterization of different tumor sizes and phantom compositions directly from scattering parameters captured by the BreastCare dataset and also tested our architecture on the University of Manitoba Breast Microwave Imaging Data-set (UM-BMID) [2].

The salient contributions of this paper are as following:

1) To scrutinize the subtlety of the BreastCare dataset, an open-access BMI data-set is provided for the detection, localization and characterization of tumors of different size in various breast densities. In addition, the data-set is pre-processed for ease of training.
2) To explore the working efficiency of famous ML algorithms on the BreastCare data-set, a comparison of detection techniques is done based on relevant metrics.

[1]This link will be continuously updated as more measurements are available.

3) The novel deep learning frameworks are designed to detect, and localize tumors in the *x*, *y*, and *z*-axis, and characterize tumors based on size. To the best of our knowledge, the developed architecture is state-of-the-art in this domain, it outperforms the existing techniques and image reconstruction algorithms in false negative cases.

II. State-of-the-art

Oliveira et al. [3] uses ML techniques to understand the features of benign and malignant tumors in microwave breast diagnostic systems. They use techniques like random forests and antenna grouping, among others, for classification of data from a microwave scan. Rana et al. [4] presented the first clinical demonstration and comparison of a microwave ultra-wideband (UWB) device with participants having concurrent conventional breast exams in this work. The data is then utilized to develop an intelligent classification system to identify breasts with lesions. These algorithms include nearest neighbor (NN), multi-layer perceptron (MLP), neural network, and Support Vector Machine (SVM). The findings are thoroughly investigated, and statistical measurements are employed to validate them. SVM was found to be the best with 98% accuracy. Reimer et al. [2] provided data from 1257 phantom scans in his data-set UM-BMID and used logistic regression to get 85.4%, diagnostic accuracy. Hamza et al. [5] used the same data-set to train his algorithm and verified on his own data to get 99.7% accuracy using SVM. Conceiccao et al. [6] used signals collected from a mono-static ultra-wideband radar MWI prototype system. They used the Principal Component Analysis (PCA) for the feature extraction and classifiers such as Naïve Bayes (NB), Decision Trees (DT), and k-Nearest Neighbours (kNN). The highest classification accuracy of 96.2% was achieved using kNN. AL et al. [7] proposed a system for DL that uses deep neural network (DNN) with convolutional layers to make it easier to detect, locate, and characterize tumours using measurements of scattering parameters and metadata information.

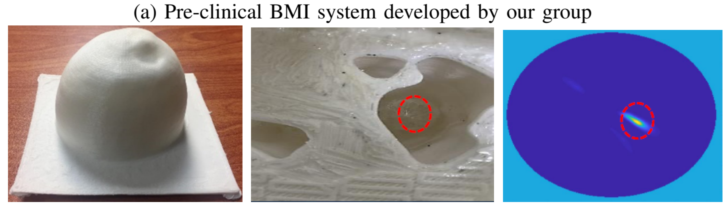
III. Breast Microwave Imaging System

The hardware setup consists of three main parts: antenna, phantom and autonomous rotational setup calibrated with the vector network analyzer (VNA). The image reconstruction algorithm we used with our mono-static design is based on Interferometric Multiple Signal Classification generally referred to as IMUSIC [8]. The data-set was verified on this algorithm before using DL for comparison. Results show that DL algorithms outperform conventional MWI algorithms.

A. Hardware Setup

We used a Tapered slot,10x10 cm Vivaldi antenna [9]. The gain of the antenna is 7.5 dBi with 8.6 dB directivity. As we know that wavelength of the incident wave should be comparable to that of the tumor size for detection, therefore the antenna was designed according to 1-3cm tumor size.

(a) Pre-clinical BMI system developed by our group



(b) 3-D printed realistic breast phantom (left) with inclusion (center) and tumor detection using IMUSIC MWI algorithm(right)

Fig. 1: BMI System and Results using MWI Algorithm

The formation of a realistic phantom is a key factor for accurate analysis. Different compositions of Triton and water have been proposed by Duchene et al. [10] and Massa et al. [11], which have proved to be more robust than other materials in terms of shelf life and ease of handling. Different compositions of Triton X-100 and water have been used for different breast densities. Dimensions of our breast phantom are 9x11 cm, with tumor sizes ranging from 1 to 3 cm. Figure 1b represents our designed phantom.

The measured signals are reflection parameters S_{11}, which are back-scattered from the phantom. Our mono-static approach requires one antenna which transmits and receives signals through our low-cost, portable Pocket VNA. The signals are being recorded at a bandwidth of 2-4 GHz with 40 frequency points. The motor-based antenna arm rotates the antenna at equidistant angles of 8° hence taking 45 measurements for each rotation. The process takes 5 minutes for a complete scan. Figure 1a represents our designed hardware of preclinical BMI.

B. Data-set Collection

The position of the tumor was recorded for training the DL algorithm with our data. Once the algorithm learns the difference between affected and normal phantom it would be able to locate the tumor itself. Different phantoms were prepared for depicting variations in breast densities to accommodate for various fat content and shape. The tumor is made of 10:5.5 of wheat-flour and water mixture with permittivity equivalent to that of a benign tumor. Once the data is collected, the microwave imaging algorithm is applied to get the images to validate the accuracy of the data collected. S-parameters along with the metadata files are provided for features. These metadata files include tumor size, position, BI-RADS class type and location. We have included different tumor sizes and phantom compositions to cater all major BI-RADS densities to diversify data-set. Two-third of the scans are with tumors while one-third are without tumors for training the ML and DL algorithms.

C. Data-set Characterization

We used the BreastCare data set which consists of 900 scans. Each scan is unique and represents different tumor locations to avoid the bias of data set. The data set is split between a training set which consists of 600 scans and a test set of 300 scans. The data set comprised five types of tumor sizes 1, 1.2, 2, 2.5, and 3 cm. The S_{11} parameters are converted from the frequency domain to the time domain using inverse Fourier Transform for feature extraction and lowering of computational time.

IV. Tumor Detection, Localization, and Characterization using Novel DL Frameworks

DL is a subset of ML, which processes data according to a predetermined logical framework to uncover correlations and patterns; therefore, the trends move toward state-of-the-art DL. DL, also known as DNN, employs several hidden layers in the neural network compared to conventional neural networks, which have a limited number of hidden layers. DL algorithms link inputs to previously learnt data to get an accurate result. This technology's underlying idea is remarkably similar to how human brains work (biological neural networks). Therefore we developed DL frameworks that outperform the existing DL techniques to attain better detection, localization, and characterization. Figure 2 represents the whole working of the frameworks.

A. Tumor detection using novel DL framework

Using shortcut connections, we proposed the framework inspired by the residual networks (ResNet). By enabling the gradient to pass through this additional shortcut path, ResNet's skip connections address the issue of vanishing gradients in deep neural networks (DNN). These connections also assist the model by enabling it to learn identity functions, which guarantees that the higher layer will perform at least as well as the lower layer and not worse. The architecture consists of 4 block concatenations, while each block consists of Resnet layers. Each ResNet layer consists of 2 convolutional layers, 2 Batch Normalization layers, Add a layer with rectified linear units, and a shortcut connection. Each block is designed with a different number of ResNet layers. Block1 consist of two ResNet layers, Block2 consist of one ResNet layer, Block3 consists of three ResNet layers and Block4 consist of four ResNet layers. All these block outputs are concatenated and passed through our designed dense layer network inspired by the VGG network. The framework is first trained and tested by using the BreastCare data-set. The framework used only S_{11} parameter and was evaluated using the classification task metrics like F1-Score. The framework obtained F1-score for the detection of 0.973 on the BreastCare data-set. Our framework is further evaluated on UM-BMID second-generation scan data-set and got the F1-score of 0.971, showing the promising efficiency of the model on the exact nature of the data-set. The model can also detect the tumor from the scan, which cannot be detected by the image reconstruction algorithm.

B. Tumor Localization using novel DL framework

The framework is the first approach to localizing tumor directly from the scan in terms of the x, y, and z axis. The architecture is inspired by the convolutional layers working for image localization. The framework consists of two convolutional layers and a dense layer network influenced by the VGG network. The framework is evaluated on the BreastCare data-set. The data-set consists of feature matrices comprised of a matrix of 40x45 for each scan, and data consist of 900

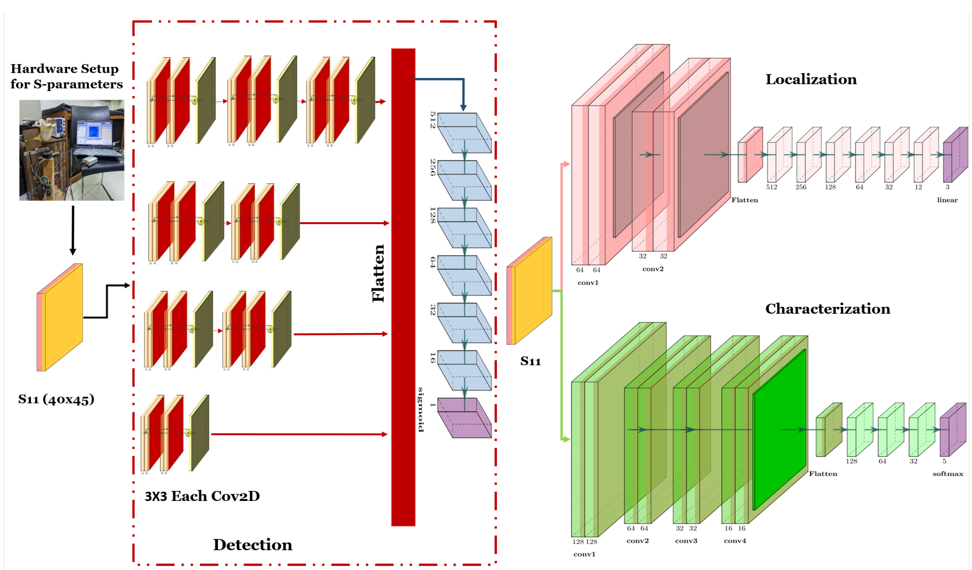


Fig. 2: The illustration of the whole framework working for Detection, Localization in terms of coordinates x,y,z, and Characterization of tumor in terms of size.

TABLE I: The comparison of our DL framework with other detection techniques, the framework localization, and characterization performance .

Techniques	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	MSE (%)	R2-Score (%)
Logistic Regression	69.3	85.45	84.54	79.9	-	-
KNN	80	80	80	82	-	-
Naive Bayes	66	83.5	20	77	-	-
CART	77.3	85	55	83	-	-
SVM poly	92	92.7	92	92.9	-	-
SVM Gaussian	93	96.7	85.7	94	-	-
SVM sigmoid	56	69	20	66	-	-
SVM Linear	93	94.5	90	93.9	-	-
LDA	81	85.4	70	85.9	-	-
DL Framework						
Detection	97	95	94.5	97.3	-	-
Localization	-	-	-	-	30	84
Characterization	97	96	96.5	97	-	-

such scans making it the same as the image numeric data and can apply image localization problem. The data-set is divided randomly between train, validation, and test split. Seventy percent of data is used for training and validating the model, while 30 percent is used for testing. The convolutional layers are used for feature extraction, and a dense network with linear activation is used for the prediction. The regression problem is evaluated using mean square error (mse) and the Coefficient of Determination (R2) score.

The model obtained a Mean Squared Error (MSE) during training of 0.13 and an R2 score of 0.98; during the testing phase, the R2 score was 0.84. The MSE was 0.30, which shows the good working of our architecture to predict, the x, y, and z axis of tumor location on the BreastCare data-set.

C. *Tumor Characterization using novel DL framework*

The framework characterises tumor size directly from the S_{11} parameter. It consists of three convolutional layers using different filters, kernel sizes, and a dense layer network. The BreastCare data-set is split between train, validate and test split. Seventy percent of data is used in training and validation, while 30 percent is used for testing randomly. The model during the validation phase gets a 0.96 F1-score, while during testing, a 0.92 F1-score shows the outstanding performance of the framework.

D. *Performance Comparison of ML algorithms on BreastCare*

The algorithms used for the detection of tumors are KNN, NB, CART, and SVM with kernels Polynomial (Poly), Gaussian, Sigmoid, and Linear Discriminant Analysis (LDA). Table I shows the complete comparison of the algorithm's performance based on evaluation metrics with our designed DL frameworks.

V. Summary

We designed a portable breast microwave imaging system prototype, and the data-set is collected using realistic breast phantoms. Our novel DL frameworks outperform different state-of-the-art ML algorithms in terms of tumour localization, detection, and characterization. It also provides more accurate results as compared to standard radar-based MWI reconstruction algorithms. The F1-score for tumor detection and characterization are found as 0.973 and 0.92, respectively. The mean square error of localization is 0.32, and the R2 score is 0.84. These results show the efficient working of the proposed architectures. In the future, more diverse and large amounts of data can be generated for real-time DL implementation of microwave imaging modality for the diagnosis of various life-threatening diseases.

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