# Proficient Feature Extraction Strategy for Performance Enhancement of NN Based Early Breast Tumor Detection

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***Abstract*— Ultra Wideband is one of the promising microwave imaging techniques for breast tumor prognosis. The basic principle of tumor detection depends on the dielectric properties discrepancies between healthy and tumorous tissue. Usually, the tumor affected tissues scatter more signal than the healthy one and are used for early tumor detection through received pulses. Feedforward back-propagation neural network(NN) was so far used for some research works by showing its detection efficiency up to 1mm (radius) size with 95.8% accuracy. This paper introduces an efficient feature extraction method to further improve the performance by considering four main features of back-propagation NN. This performance is being increased to 99.99%. This strategy is well justified for classifying the normal and tumor affected breast with 100% accuracy in its early stage. It also enhances the training and testing performances by reducing the required duration. The overall performance is 99.99% verified by using thirteen different tumor sizes.**

**Keyword- Breast Cancer Detection, Discrete Cosine Transform, Feature Extraction, Neural Network, Ultra Wide-Band.**

## I. INTRODUCTION

Breast cancer, known as deadly cancer, spreading its brutal steps all over the world. The freaking victim rate found in Europe is about 90 persons per 1,00,000 women and approximately 32 women in South-East Asia [1]. So far, researchers have discovered a good number of techniques but efficient technique is still under investigation and a crying need. Early detection of breast tumor may reduce the death risk. In a recent survey from American cancer society, it is found that 89% of women having chance to survive if the cancer is detected within 5 years. This rate is lower as 82% and 77% if it is detected within 10 and 15 years respectively [2]. Joy et al. [3] and Tabar et al.[4] showed in their researches that, early detection of tumor is important for the long term survival on the way of reducing the risk. So researchers put emphasis on the method which can detect tumor in early stage.

Mammography is currently the most popular method for breast cancer detection, but this diagnostic process is painful to the patient and also having approximately 30% miss detection ratio [5]. As an alternative, researchers are fascinated about microwave imaging that may detect breast cancer[6]. Hence, ultra wide-band(UWB) technology is a candidate for detecting early breast tumor since last two decades. Federal Communications Commission(FCC) has been allocated 3.1GHz to 10.6 GHz for the UWB communication and the power emission rate is -41dbm/ MHz [7]. So that the benefits of using UWB includes low power radiation, early detecting capability, non-invasive and more importantly non-ionization to human body [8],[9],[10],[11]. However, miscellaneous UWB system design techniques are existing and some others are currently under investigation. Microwave tomography is formed of several antennas where one antenna radiates the UWB pulses and rest of the antennas receive the scattered pulse from the object [12],[13]. Confocal microwave imaging is one of them also which consists of an array of UWB antennas, where one specific antenna emits UWB pulses at a time towards breast phantom and captures itself the scattered signal [6]. Unlike using the multiple antennas, the proposed detection technique consists of single transmitting and receiving antennas system and the recorded UWB pulses are forward scattered from the object[14].

There exists a good number of pattern recognition methods from the received UWB pulses. Support vector machine (SVM) can be used, as it has already been utilized to identify tumor in mammographic image[15].

SVM is having auspicious performance in terms of classifying between tumor affected and sound breast [16]. But lack of efficiency, in case of regression problem solving. Particle swam optimization algorithm can also be a better option tool [17]. To the best of our knowledge, fuzzy logic is currently introduced to detect early cancer, but not capable of further screening [18], [19]. But, ANN has been applied for pattern recognition in this paper as it is justified previously[20]. Feedforward back-propagation ANN module utilized for this research that literally shows tremendous successful detection capability and location identifier with 95.8% accuracy[20]. But some crucial factors like training time, feature extraction, etc. which also contributes system performance did not well calculated and considered. Huge feature values increase the ANN training period and reduce the training performance.

This paper depicts a new algorithm for feature reduction technique which includes four diversified features and they are maximum, minimum, mean and standard deviation value of a particular dataset. At the same time, it is shown and compared that better performance can be achieved through this strategy.

This paper is organized as follows. The next section presents the system specification including the method of constructing the breast phantoms, experimental data collection and NN modelling. Followed by simulation results and discussion, and finally the conclusion.

## II. METHODOLOGY

As it is mentioned before that the proposed model describes a single transmitter and single receiver confocal microwave imaging system, propagating UWB signal at resonance frequency of 4.7GHz. Time Domain product called PulsOn evaluation kit [21] is being used in the whole research with its commercial antenna. The system model is visualized in Fig. 1. Transmitter emits a train of UWB Gaussian pulses towards the phantom and receiver captured the scattered UWB pulses from the phantom. Then received signals are preprocessed before feeding to the neural network. Fig. 2 shows experimental system set up configuration.

### *A. Breast Phantom Preparation*

To mimic the human breast, a heterogeneous breast phantom is prepared where the train of UWB pulses passed through it. The used materials and their dielectric properties are given in [20]. A round shaped Phantom having diameter 10cm or 100mm and height 5cm or 50mm is constructed. Several tumor sizes are used for training, testing and validating the neural network. It is declared before that the motto of this paper is to find out the tumor existence and size. Studies show that most of the cases tumor in early stage is benign type and with the passage of time it is turned to deadliest form malignant type. In terms of early detection, it is important to find out benign tumor mostly. In this paper, only benign tumor tissue is considered and no difference exhibits with other types of tumor.

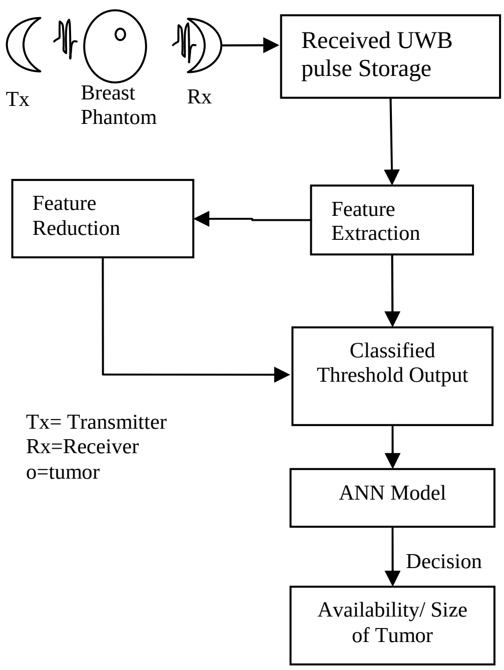



Fig. 1. Proposed System Model

### B. Feature Extraction

Feature extraction is an important factor for any sort of pattern recognition and detection signal processing tool. ANN is also not exclude of that. Usually huge amounts of input data values may disrupt the training process. So, researchers often try to train the ANN using some characteristic values, which are called feature values. Principal Component Analysis (PCA), the mostly used feature reduction method, suffering extensive computing problem and subset choice difficulties for Principle Components (PCs) which having redundant information. Our previous work based on Principal Feature Analysis (PFA) method[22], which solved above two problems, where 50-300 larger DCT values were taken using [20]. Motive of this paper is to reduce the feature values than previous to ease the training and raise the performance simultaneously. Another, feature extraction method described in [23] where, features are selected from EEG features for NEONATAL SEIZURE detection by acquiring the RMS amplitude, line length, and number of maxima and minima values. In this paper, four featured values e.g., MAXIMUM, MINIMUM, AVERAGE or MEAN value and Standard Deviation values are considered. That means the training values are deducted more than 98% from previous featured values. Training efficiency is also increased. After processing the raw data, the data set becomes ready to input into the designed ANN. The equations for Mean, μ and Standard Deviation, σ are illustrated in Eq. 1 and Eq. 2 respectively,

$$\mu = \frac{1}{N}\sum_{n=0}^{N-1}[X_n] \qquad (1)$$

$$\sigma = \frac{1}{N}\sum_{n=0}^{N-1}[X_n - \mu]^2 \qquad (2)$$

where, N is the total no. of feature values.

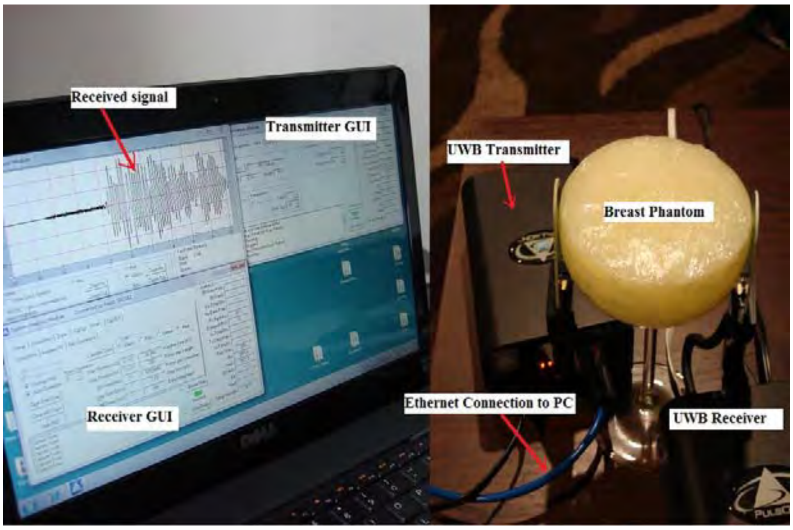



Fig. 2. The Experimental System Configuration [20]

### C. Neural Network

The proposed Feedforward back-propagation model consists of an input, an output and a hidden layer virtually given in Fig. 3. Four neurons in the input layer are stand for four inputs i.e., mean, standard deviation, maximum, minimum of received signal. Three neurons are used in hidden layer and single neuron used in output layer as tumor size. From the general equation of ANN regression problem output, y can be written as,

$y = u + b$;

where u and bias, b can be defined as,

$u = \sum_{i=1}^{n} w_i x_i$ and

$b = w_0 x_0$ respectively.

So that, y can be written as follows,

$$y = \sum_{i=1}^{n} w_i x_i + w_0 x_0 \qquad (3)$$

Here, w and x denote the weight vector and input data set respectively. The value of w will be changed and modified according to error signal at the output neuron. This error can be elaborated at step n as follows,

$$e(n)=d(n)-y(n) \tag{4}$$

According to back-propagation algorithm new weight vector will be modified using Eq. 5.

$$w_{k+1} = w_k + \nabla w \tag{5}$$

where, $\nabla w$ is the modified weight vector from the previous back pass and expressed as,

$$\nabla w = e(n).x_n \tag{6}$$

*D. Signal Pre-processing*

Though system model is already shown in Fig. 1, it is to declare that for each size of tumor, UWB signals are transmitted 25 times. The phantom diameter is 10cm, and tumor sizes like 0.1 cm, 0.16cm, 0.2cm, 0.27cm, 0.3cm, 0.38cm, 0.40cm, 0.42cm, 0.53cm, 0.6cm, 0.65cm, 0.81cm and 0.9cm are considered in this experiment.

Among these 25 times transmission, first 3 times are without tumor and rest of the 22 times with tumor. Discrete Cosine Transform (DCT) is used for analog to digital conversation of signals. Each recorded UWB signal at receiver end having average of 4500 data points. But, it is quite difficult to feed these huge data points into the NN resulting wrong detection output. Besides may either slow down the NN or overwhelmed the NN. Hence, it is recommended to reduce the data points for better output. So, instead of 50-300 DCT featured values as in [20], only four features will be taken for NN input.

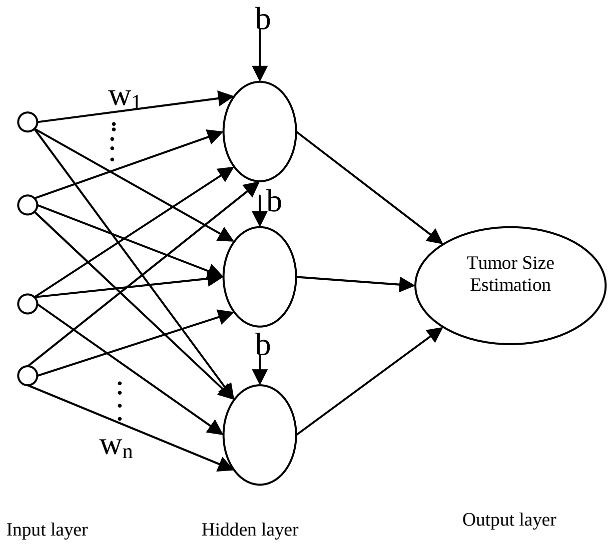



Fig. 3. Neural Network Model

## III. Results and Discussion

ANN model is developed using MATLAB R2012a simulation software. In this paper, back-propagation *'Newfit'* tool is introduced rather than Feedforward tool. Both the tools are utilized in the whole work for the evaluation of system performance. The purpose of using *'Newfit'* tool is that, it is better plotting tool for solving regression problem in Matlab [24].

The smallest tumor size used in this experiment is 0.1cm or 1 mm. To make sure of system performance, tumor sizes are varied 13 times and recorded the training, validation and testing performance for each tumor size. However, we have presented the figures of performances for 1mm tumor only. Rest of the cases, we have accumulated the result and showcase it in Table I and Table II. Performances are compared in terms of mean square error (MSE) which is defined as follows,

$$MSE = \frac{1}{N}\sum_{n=0}^{N-1}[y(n) - y_m(n)]^2 \tag{6}$$

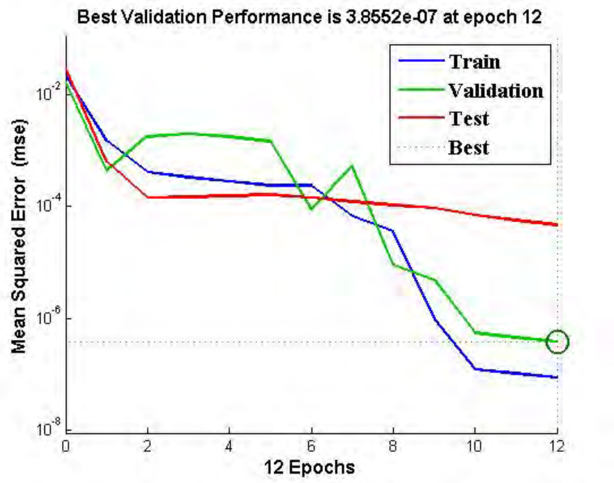
where, $y(n)$ and $y_m(n)$ represent the target and output respectively. Other hand, $N$ is the total number of data points.

To maneuver the simulation smoothly, whole data set are divided in to three categories: (i) 70% data (3150 data points) are reserved for training , (ii) 15% data (675 data points) for validation and (iii) 15% data (675 data points) are used for testing purposes as described in [24]. Levenberg–Marquardt Algorithm [25] is being utilized in the whole simulation process for training.

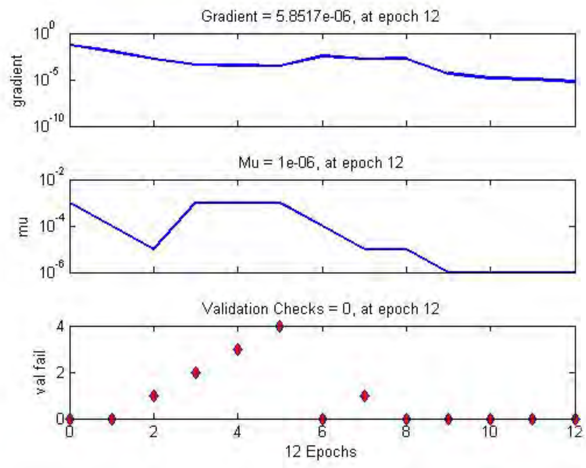
In Fig. 4, training performance, validation performance, training state and regression curves are shown for 1mm tumor. Best validation performance is shown in Fig. 4(a) and MSE value found at 3.855e-07.

The iteration number, called *epoch* is used only 12 for estimating 0.1cm tumor, and learning rate, represented by *mu*, used for training is 1e-06 shown in Fig. 4(b). As it is visible from Fig. 4(b), both gradient and *mu* curve go flat or saturated which indicates the termination of training process. Fig. 4(c) illustrated the cross co-relation between data points and curve fitting plots for training, validation, testing and overall performance. This Fig. 4(d) curve is also known as the regression curve.

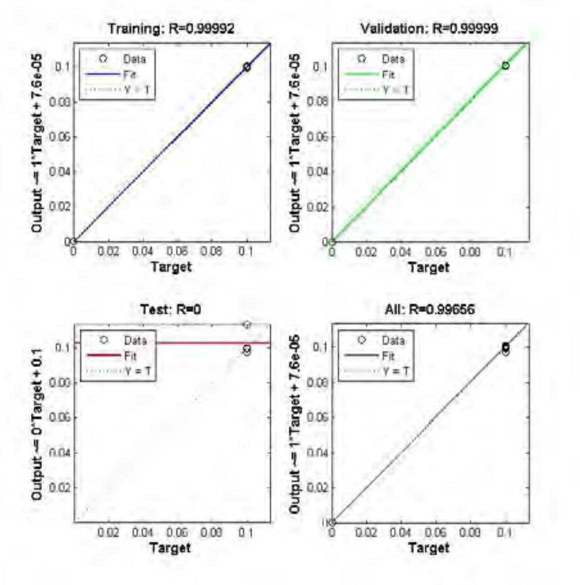
Similarly, validation performance and regression curves of target and training data set are found in the same manner for other tumor sizes but not given here.




(a)




(b)




(c)

Fig. 4. (a) Validation Performance (b) Training state and (c) Cross co-relation between data points and curve fitting plots for 0.1cm Tumor

Training and validation performances used for other sizes of tumor are provided in Table I to exhibit the performances.

TABLE I
TRAINING AND VALIDATION PERFORMANCE EFFICIENCY OF PROPOSED ALGORITHM

| Tumor Size(cm) | Training Performance in MSE | Validation Performance in MSE |
|---|---|---|
| 0.1 | 8.794e-08 | 3.855e-07 |
| 0.16 | 4.218e-14 | 5.701e-05 |
| 0.2 | 3.304e-15 | 3.492e-06 |
| 0.27 | 1.066e-11 | 1.301e-05 |
| 0.30 | 3.722e-07 | 3.953e-06 |
| 0.38 | 1.528e-18 | 3.624e-06 |
| 0.40 | 6.941e-16 | 4.476e-05 |
| 0.42 | 9.899e-20 | 4.340e-05 |
| 0.53 | 6.144e-13 | 7.772e-05 |
| 0.6 | 1.280e-12 | 0.0002658 |
| 0.65 | 4.267e-08 | 8.358e-05 |
| 0.81 | 2.323e-17 | 0.0019978 |
| 0.9 | 7.723e-08 | 0.0027785 |

In Table II, the comparison results are displayed for testing performance analysis. Comparison is done between the previous and proposed feature extraction strategy. From 25 sets of results of a single sized tumor, 3 sets (i.e., worst, average and best output) of results are brought under consideration. It is visible from the Table II, the proposed feature extraction technique provides better result than previous method. Here, MSE calculation using Eq. 6 is also contributes strengthen the much more efficiency of the proposed topology. It shows that 99.99% performance can be achieved by the proposed extraction methodology whereas; it was around 95.8%, previously with 4.1% enhancement.

TABLE II
FEATURE EXTRACTION RESULT COMPARISON BETWEEN PROPOSED AND PREVIOUS WORKS

| Tumor Actual | | Previous Feature Extraction | | Proposed Feature Extraction | |
|---|---|---|---|---|---|
| Size (cm) | Result Type | Size(cm) | MSE | Size(cm) | MSE |
| 0 | | 0 | 0 | 0 | 0 |
| 0.1 | worst | 0.25 | 0.0089 | 0.097542 | 7.65e-06 |
| 0.1 | avg | 0.57 | | 0.099631 | |
| 0.1 | best | 0.1 | | 0.100032 | |
| 0.16 | worst | 0.75 | 0.0008 | 0.174609 | 9.99e-06 |
| 0.16 | avg | 0.3 | | 0.159318 | |
| 0.16 | best | 0.15 | | 0.159506 | |
| 0.2 | worst | 0.4 | 0.0004 | 0.196391 | 8.25e-07 |
| 0.2 | avg | 0.3 | | 0.200055 | |
| 0.2 | best | 0.2 | | 0.200009 | |
| 0.27 | worst | 0.75 | 0.0001 | 0.268352 | 3.63e-06 |
| 0.27 | avg | 0.32 | | 0.269996 | |
| 0.27 | best | 0.25 | | 0.270001 | |
| 0.30 | worst | 0.7 | 0.00012 | 0.298981 | 1.22e-06 |
| 0.30 | avg | 0.25 | | 0.299957 | |
| 0.30 | best | 0.3 | | 0.300004 | |
| 0.38 | worst | 0.75 | 0.00004 | 0.376193 | 1.25e-06 |
| 0.38 | avg | 0.35 | | 0.379998 | |
| 0.38 | best | 0.4 | | 0.380003 | |
| 0.40 | worst | 0.1 | 0.0001 | 0.409441 | 7.63e-05 |
| 0.40 | avg | 0.35 | | 0.399997 | |
| 0.40 | best | 0.35 | | 0.400002 | |
| 0.42 | worst | 0.65 | 0.0002 | 0.42614 | 2.35e-05 |
| 0.42 | avg | 0.35 | | 0.419943 | |
| 0.42 | best | 0.45 | | 0.420004 | |
| 0.53 | worst | 0.01 | 0.0003 | 0.517528 | 1.36e-05 |
| 0.53 | avg | 0.45 | | 0.529998 | |
| 0.53 | best | 0.5 | | 0.530001 | |
| 0.6 | worst | 0.015 | 0.0009 | 0.567797 | 1.52e-04 |
| 0.6 | avg | 0.45 | | 0.599407 | |
| 0.6 | best | 0.6 | | 0.600773 | |
| 0.65 | worst | 0.010 | 0.0002 | 0.707499 | 1.49e-04 |
| 0.65 | avg | 0.42 | | 0.649995 | |
| 0.65 | best | 0.65 | | 0.650001 | |
| 0.81 | worst | 0.01 | 0.0067 | 1.014668 | 0.0063 |
| 0.81 | avg | 0.40 | | 0.813445 | |
| 0.81 | best | 0.75 | | 0.807871 | |
| 0.9 | worst | 0.015 | 0.0064 | 0.920698 | 9.37e-04 |
| 0.9 | avg | 0.5 | | 0.899939 | |
| 0.9 | best | 0.75 | | 0.900006 | |

## IV. CONCLUSION

In this paper, an enhanced feature extraction method is proposed. This method shows better performance and accuracy than the previous ones and added a new dimension to the early detection of breast tumor research. This proposed feature reduction technique is able to act as a universal signal processing tool. In this paper, one dimensional size detection has been investigated with 99.9% accuracy. This extraction method may also be useful to apply to detect tumor in three-dimensional environment in terms of size, location and tumor type.

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