



Microwave Imaging System of Breast Cancer Detection by Using Support Vector Machine Method

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ABSTRACT

Breast cancer is the most common disease among women in the world. Therefore, many doctors diagnose cancer in its early stages. Because early detection and treatment of the tumor help in faster recovery. The main objective of this paper is to build an application that is capable of “detecting and determining” a breast tumor using image processing in MATLAB. An open-source experimental database of the University of Manitoba Breast Microwave Imaging Dataset (UM-BMID) was used. The most vital part is template design and the formation of the algorithm for breast tumor detection. Some of the key features used in this paper are - image acquisition, noise reduction, image resizing, tumor region identification, marking of tumors, etc. A Graphical User Interface (GUI) is also used to build a better interface for the user, it allows us to understand the algorithm's true potential and how it can be further developed due time. After an image is provided to the algorithm it processes the image and informs the user how harmful the tumor is to the patient, and what necessary steps should she take to find a cure for it. In this work, Support Vector Machines (SVM) were used to detect breast cancer using microwave imaging. We extract features from the data collected by microwave imaging and use SVM to classify them. This work can help to support microwave breast imaging as well as help to move away from false positives to obtain greater accuracy and detect tumors depicted as false negatives.

Keywords: *Breast Cancer, Classification, Microwave imaging, Support Vector Machine*

INTRODUCTION

The cell is the most fundamental and minute component of all living organisms. There are millions of cells in the human organism. Each cell has unique characteristics and functions; these cells divide in an orderly manner to generate new cells. When cells divide and proliferate uncontrollably to form new cells, a mass of excess tissue known as a tumor result. Abnormal cells multiply irregularly to form a breast tumor. It affects the growth and function of normal breast cells and takes up space within

the breast. It disrupts the function of breast cells and causes injury to living organisms. Approximately 25% of breast cancer deaths occur in women between the ages of 40 and 49 [1]. Most breast cancers have an unknown cause. We know that the onset of menstruation at a younger age, menopause at an older age, and delay in family formation increase the probability of breast cancer. The use of birth control pills and hormonal drugs, the type of nutrition, and lifestyle may be effective in this matter; But a lifestyle change will not have much effect [2, 3]. Between 5 and 10% of breast cancers are

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hereditary. In these cases, certain genes in your cells are unhealthy. The probability of breast cancer occurrence in family members with defective genes is higher than in other members of society, but gene mutations related to breast cancer are rarely observed in them. In some cases, the members of these families need to be screened with mammography at a younger age [4, 5].

According to research conducted in 2018, 627,000 women died due to breast cancer, which is 15% of all deaths [6]. This cancer is almost one of the most common types of cancer among women. Therefore, if this disease can be diagnosed by a method, we can see a decrease in human mortality. Generally, the majority is divided into two categories. They are categorized as benign or malignant, and each has distinct visual characteristics. Benign masses are oval in shape, and have clear edges and no angles; While malignant masses have non-uniform and irregular shapes, and indistinct edges [7]. Breast cancer is curable if the surrounding fatty tissue has not spread to other organs. Therefore, many countries have started screening programs to detect cancer in its early stages. Following the digital revolution, hospitals were digitized quickly. At the time, digital mammography used mammography film plates for comparison because they were digital [8]. Computer systems are not meant to replace radiologists, but they are used to help radiologists during image reviews of suspicious areas. In most computer systems, there are also diagnosis errors. However, the evidence also shows that the computer system can increase the performance of the radiologist in the interpretation of diagnostic lesions [9, 10].

Breast cancer screening methods are designed primarily to detect the disease before symptoms emerge [11]. Current breast cancer detection technologies, such as mammography and MRI, have several limitations, prompting the development of a new screening method known as microwave imaging. Microwave imaging is a feasible tool for identifying breast cancer due to differences in electrical characteristics between benign, malignant, and healthy tissues, as well as the use of non-ionizing frequencies [12, 13]. Microwave imaging is one of the most recent approaches for early diagnosis of breast cancer. Microwave imaging is a feasible screening method since it avoids both ionizing radiation and breast compression. It is also less costly and

can detect just minor tumors [12]. The approach is based on the fact that cancerous and benign tissues have different dielectric characteristics. Studies of human tissue dielectric properties in the microwave frequency range [14] demonstrate that the contrast between malignant and benign tissue reaches ten times in dielectric permittivity and conductivity.

A segmentation algorithm is an algorithm used to define certain objects, usually the breast environment or specific types of abnormalities such as microcalcifications and masses. There are two distinct methods for image segmentation. One relies on the uniformity of the intensity values within the image components, while the other relies on the non-uniformity of the image to determine the component boundaries [15]. Another task used in image segmentation is the region's growth, which uses uniformity in the region. This method starts by selecting one or more pixel points, and depending on the number of pixel points, the same number of regions is identified.

Research Contribution

By proposing a novel automated approach, we attempted to achieve high accuracy in identifying and removing breast cancer masses in this research. After pre-processing and recognizing the borders of malignant masses in Microwave pictures, several features are retrieved from the discovered masses, and the feature matrix is then applied to the input of the SVM classifier. In this article, by using this method, the diagnosis and classification of breast cancer masses have been done with high speed and accuracy.

It should be noted that the MATLAB code was used after it was processed and developed. This code is owned by a project entitled (Brain Tumor Detection by Magnetic Resonance Imaging) by researchers Sourav Paul, Saraf Roy, Anushka Day, Surya Das and under the supervision of Professor Roshni Chakraborty.

Research Organization

The remaining portions of this work are organized as follows: The related works section is located in Section 2. Materials and methods are covered in Section 3. Section 4 describes the simulation and results, and Section 5 concludes the paper. Figure 1 depicts the article's outline.

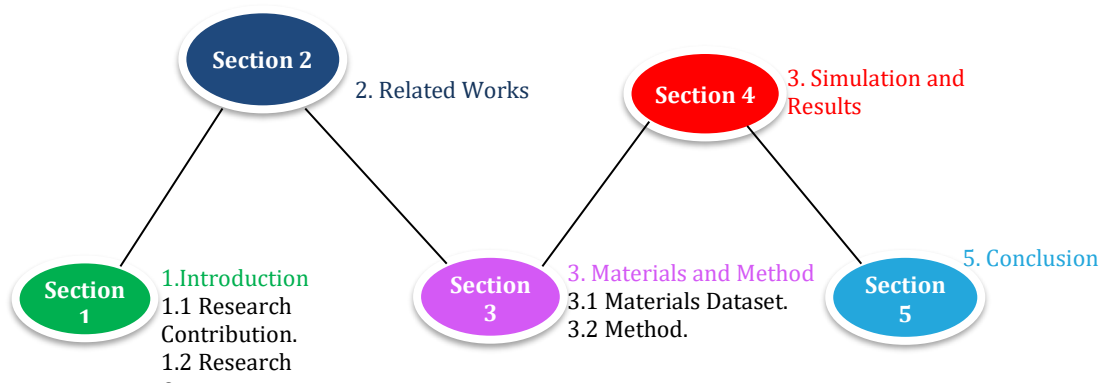


FIG 1: The organization of this paper.

List of Acronyms

Table 1 lists the list of acronyms used throughout this paper.

TABLE 1: Nomenclature.

Acronym	Meaning
DDSM	Digital Database Of Screening Mammography
DFT	Discrete Fourier Transform
DAS	Delay-And-Sum
DMAS	Delay-Multiply-And-Sum
DWT	Discrete Wavelet Transform
GLCM	Gray-Level Co-Occurrence Matrix
GUI	Graphical User Interface
GUIDE	Graphical User Interface Development Environment
itDAS	Iterative Delay-And-Sum
itDMAS	Iterative Delay-Multiply-And-Sum
MIAS	Mini Mammographic
MRI	Magnetic Resonance Imaging
PCA	Principal Component Analysis
RBF	Radial Basis Function
ROI	Region Of Interest
SCR	Signal-To-Clutter Ratio
SMR	Signal-To-Mean Ratio
SVM	Support Vector Machines
UM-BMID	University Of Manitoba Breast Microwave Imaging Dataset
UWB	Ultra-Wideband
VNA	Vector Network Analyzer

RELATED WORK

Previous studies have dealt with the subjects of classifiers and their use to define areas of scattering obtained by breast imaging. Many methods have been worked on for this purpose including Support Vector Machines (SVM) [16]. In recent years, extensive research has been

conducted to assist radiologists in reducing errors in the identification and diagnosis of breast cancer masses and improving their speed and accuracy. In general, the research in this field entails selecting a database containing digital mammography images, image pre-processing, identifying and extracting portions of breast

tissue with cancerous masses, and expanding the suspicious area of the mass to the borders of a revealed mass; That is, first disclosing the borders of the mass, and then detection the pixels of the image that contain the cancerous mass in the target tissue. Intelligent algorithms are used to determine the type of cancerous mass (benign or malignant) by extracting various features (such as morphology, geometric, tissue-based, violet, etc.) From the mass and then classifying the extracted features. This section provides an overview of some of the most significant studies conducted in this field.

In 2015, Nik Roan and his colleagues presented a new method to detect breast cancer masses [17]. This research included three stages pre-processing, feature extraction, and classification. A pre-processing stage includes removing noise and background from the image. The extracted features include texture features obtained from the co-occurrence matrix and mass histogram and geometric features. The number of 24 features extracted from each cluster with the use of a perceptron neural network was classified into benign and malignant categories. The accuracy obtained from the designed system is reported to be 3.93% [17].

In 2007, Pegah Tokulkhah et al. presented a method for classifying and segmenting breast cancer images [18]. In this research, image segmentation is done using a regional growth algorithm. In that study, the statistical features and spatial dependence were extracted from the images, and then the entropy-based adaptive fuzzy thresholding method was used to extract the cancerous masses. The final accuracy obtained in this research using 38 features to classify the data into two healthy and sick groups is 66.86% and 5.83%, respectively [18].

In 2019, Pezeshki H. et al. presented a new method to classify breast cancer [19]. In this research, at first, the sum of the differences between the central pixel and neighboring pixels in different directions has been calculated. The smallest difference between two orthogonal perpendicular directions determines the similarity of pixels in one direction as the needle-shaped part of the cluster. These segments are added to the segmented image to enlarge the tumor shape. Finally, the characteristics of the tumor are extracted from the final segmented image, and the tumors are classified into benign

and malignant categories. The final accuracy obtained from this research is reported as 91.37% [19].

In 2018, Bushra Mughal et al. presented a tumor detection system for the correct classification of breast masses into normal, abnormal, benign, or malignant [20]. The proposed method has investigated two data sets, MIAS and DDSM. A new classification algorithm based on the combination of hat-top transform and gray-level co-occurrence matrix with back propagation neural network is used. The final accuracy obtained is reported as 62.97% on average [20].

A recent work by the authors [21] revealed the possibility of a cancer detection algorithm based on Support Vector Machines (SVM) that examines UWB microwave backscatter data to assess whether a malignant area exists in the breast. While the approach has been demonstrated to be resistant to fluctuations in dielectric heterogeneity and tumor size, identification becomes considerably more challenging for tiny, non-palpable tumors. The solution described in this research attempts to overcome this issue.

MATERIALS AND METHODS

Materials Dataset

This section illustrates how an exploratory database with open access for breast microwave sensing was created. During the scans, saline-filled 15 mm and 10 mm spherical glass bulbs were used as tumors' analogs. Scanning was performed twice for each phantom, one with a lesion with a radius of 10 mm, and the other one with a lesion with a radius of 15 mm, for a total of 18 scans. The analogs of tumors were placed at the same height as the antenna. The beamformers Delay-Multiply-and-Sum (DMAS), Delay-and-Sum (DAS), Iterative Delay-Multiply-and-Sum (itDMAS), and Iterative Delay-and-Sum (itDAS) were used to reconstruct pictures from each phantom scan. Every beamformer creates a total of 12 reconstructions that show discernible tumor responses, and only these reconstructions are used for comparison. Figure 2 (a–d) shows typical reconstructions for a Class I phantom created by each algorithm. The reconstructions were 2-dimensional coronal slices at almost the same level as the tumor, with roughly the tumor and breast boundaries outlined.

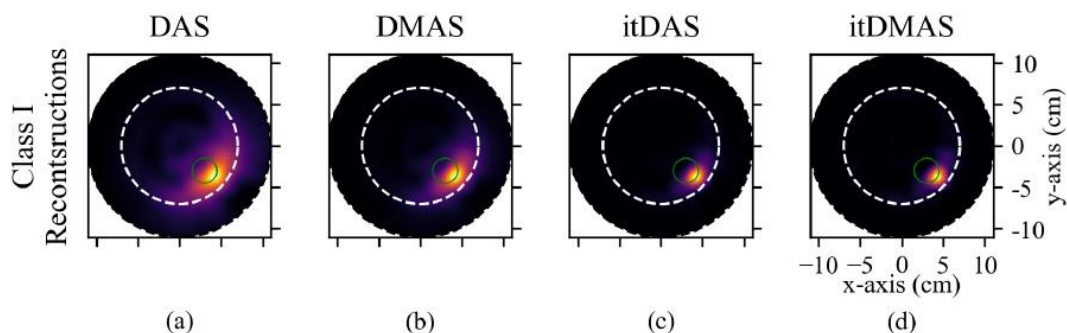


FIG 2: Reconstruction of breast phantoms using the beamformers DMAS, DAS, itDMAS, and itDAS are shown in (a–d) [22].

In all reconstructions, itDMAS and itDAS methods generate photos with high SCR and SMR; nevertheless, photos are generated with less SCR and SMR by using DMAS, and DAS approaches, across all density classes, as seen in Figure 2, showing that iterative techniques result in decreased low-intensity and decreased high-intensity clutter in reconstructions. This study was accomplished based on the data obtained from Reimer et al., at the University of Manitoba where testing datasets for microwave breast sensing were experimented with [23]. UM-BMID can be accessed at <https://bit.ly/UM-bmid>.

Utilizing a microwave breast imaging system based on radar, UM-BMID phantom scans were conducted.

Method

In this paper, the most vital part is template design and the formation of the algorithm for breast tumor detection. Before designing, the process of understanding the location of breast tumors and characteristics of microwave images the summary of the methodology is in the block diagram shown in Figure 3.

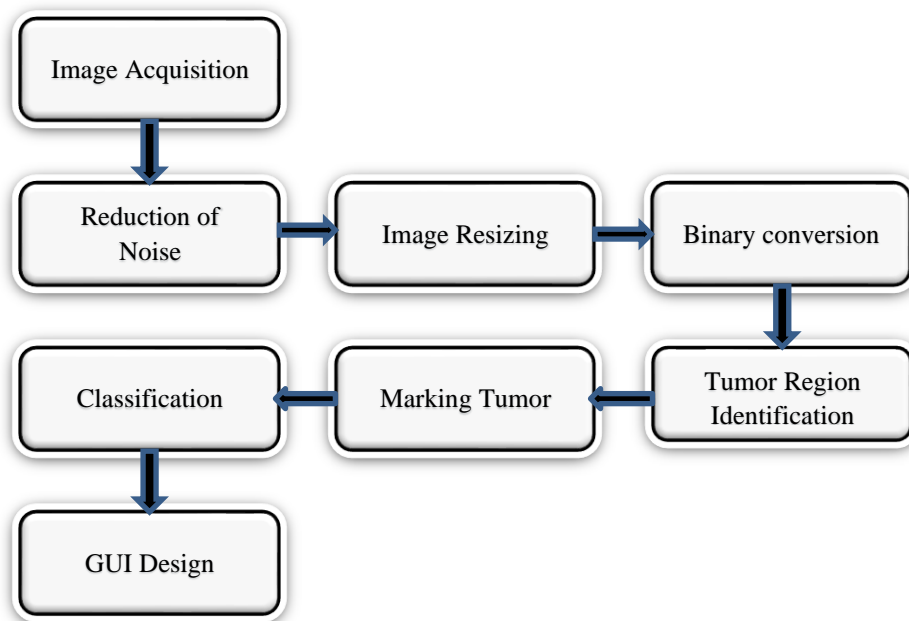


FIG 3: Block diagram of the proposed method.

Regarding the identification, diagnosis, and classification of breast cancer masses, there is a need to conduct research that can provide an

automatic method with high accuracy and speed to perform the mentioned operations. Therefore, in this article, a method is presented in which

after detecting and revealing breast cancer masses from Microwaves images and separating them from healthy breast tissue by using digital image processing methods and extracting different structural features from the masses, to optimize the classification parameters.

Support Vector Machine (SVM) was developed to detect breast cancer masses in two states, the presence and absence of a tumor. In the following, after introducing the database and image preprocessing, the image segmentation algorithm has been investigated. In the next step, the geometric and structural features used in this research and data classification using support vector machine and its optimization are described. Finally, the obtained results have been analyzed.

Image acquisition: The first step is to insert an image obtained through microwaves. Images can be entered into MATLAB using the `imread` (path) function, but this function is not a user input function. This function converts the image into a data format. To get the image as a file input pagefile (path) is used. This function can be used as a user input function.

Reduction of Noise: For the reduction of noise, masking and anisotropic diffusion technique were used. This technique reduces the noise without removing significant parts of the image content, lines, typical edges, or any other details. For masking some extra pixels were added to the image of the same color as the object.

Image Resizing: When an image is acquired in MATLAB, its initial size is 256×256 with the unit 8 class. Variables in MATLAB of data type (class) unit8 are stored as 1-byte (8-bit) unsigned integers. In this project, unit 8 is used to convert an image file into matrix format.

Binary Conversion: The segmentation of an image into a binary image used to differentiate the background from the desired object. For binary conversion, the MATLAB in-built instruction, `im2bw` is used.

The syntax of `im2bw` is as follows: `BW=im2bw(I, level)` It transforms the image(I) to a binary image BW by assigning the value 1 (white) to all pixels in the input picture with a brightness higher level and the value 0 (black) to all other pixels.

Tumor Region Identification: After binary conversion of the Microwave image the binary

matrix is divided into two different matrices depending on 'solidity' and 'area'. After that the high-density parts or the high-solidity parts of the image is being labeled which are greater than 0.6 and with respect to the high solidity maximum area is found and labeled as a tumor.

Marking of Tumor: To mark the tumor first step will be differentiating the tumor pixels from the rest of the image pixels. To do so a boundary is drawn with the same color as the tumor pixel, and then using the `bwboundaries` function the rows and columns are determined, and the color of the boundary changes to red.

Classification: To classify the tumor, the SVM method is used. Classification is divided into three steps:

1. **Feature Extraction:** Feature extraction helps to decide on the classification. The features that are extracted are symmetrical, texture, and grayscale. The classifier classifies based on these features. After that the image further undergoes multiple extraction methods like discrete wavelet transform DWT techniques. Then the important features are extracted and combined. DWT is used because DFT lacks information related to time. One other technique Gray level co-occurrence matrix GLCM is used to extract the features related to texture and grayscale. Among 13 features 9 are extracted from GLCM. The 13 features are: (i) Mean, (ii) Standard Deviation, (iii) RMS, (iv) Variance, (v) Contrast, (vi) Correlation, (vii) Energy, (viii) Homogeneity, (ix) Entropy, (x) Smoothness, (xi) Skewness, (xii) IDM, (xiii) Kurtosis;

2. **Feature Reduction Using PCA:** The principal component analysis is a tool for transforming the extant input features into a new feature space with fewer dimensions. Given a set of data, PCA extracts the significant feature data to create a new, lower-dimensional dataset while preserving the variance of the reconstructed data. The primary purpose of PCA is to reduce the dimensionality of texture features, resulting in a more accurate and efficient classification.

3. **Support Vector Machine:** SVM is applied to both classification and regression problems. One particularity is that it can solve nonlinear and high-dimensional problems effectively. It acts as a discriminant classifier defined by a separation hyperplane of the labeled training data; The main objective of SVM is the selection of the optimal hyperplane, for which the concept of maximum

margin is applied, which is defined by the vectors of each class closest to it. These are called support vectors.

on the features that were extracted from the input. SVM classifies based on two groups: a) linear, and b) non-linear.

SVM classifies an object into two classes based on the data set that is provided to SVM and based

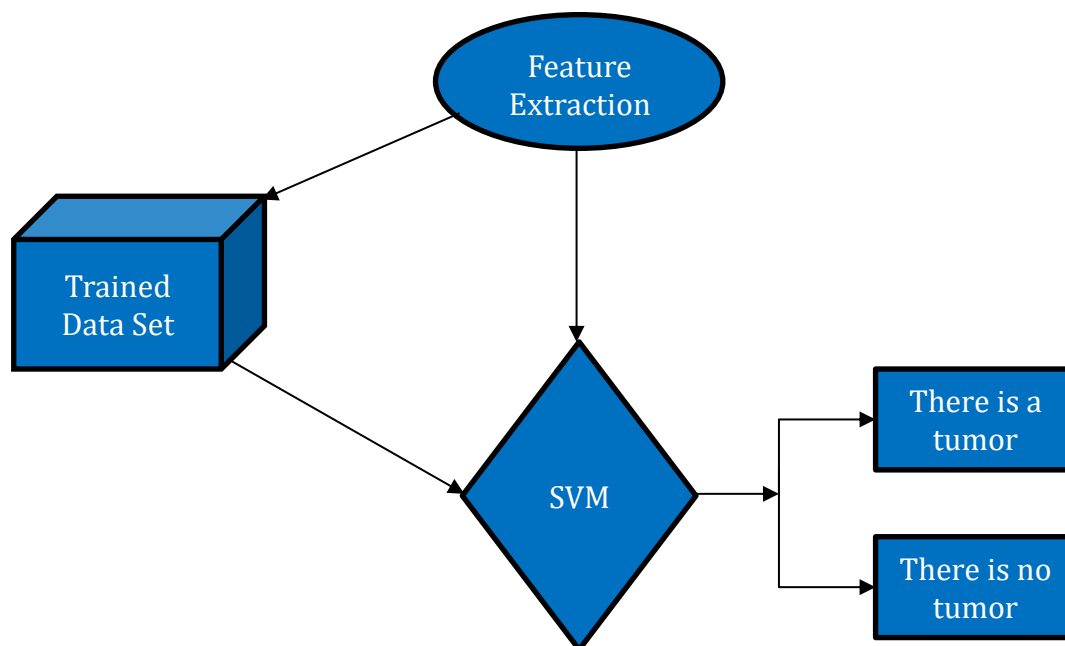


FIG 4: Breast cancer detection system architecture.

Linear class SVM

Linear SVM is used for data that can be separated into two groups using a single straight line. This is called "linearly separable data," and the algorithm that is used is called "Linear SVM."

The linear group where the training samples are the function keeps, $f(k) \geq 0$ for $a_i = +1$, and $f(k) < 0$ for $a_i = -1$, in a simple way, the test set of two different groups are separated by a hyperplane.

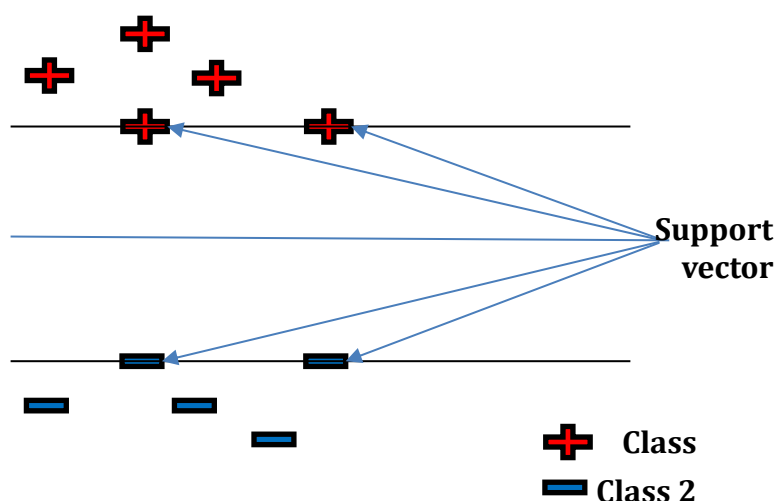


FIG 5: Classification using support vector machines.

Non-linear SVM

Non-linear SVM is used for data that is not split in a straight line. This means that if a set of data cannot be sorted using a straight line, it is called "nonlinear data," and the algorithm used is called "nonlinear SVM.". When the training data are at a different location, then linear classification cannot be used. To overcome this non-linear classification is used such that different kernels are analysed. It will take the input and map into higher space it will distinguish between two hyperplanes resulting in the prevention of data converging to the margin.

In the present work, SVM was used due to the structure of the data, and the performance of the algorithm before a binary classification, that is, there is only the possibility of the presence or absence of cancer cells. Similar to a biological neuron, the artificial neuron has input connections through which they receive external stimuli: the input values, and with these values, the neuron performs an internal calculation and generates the outputs.

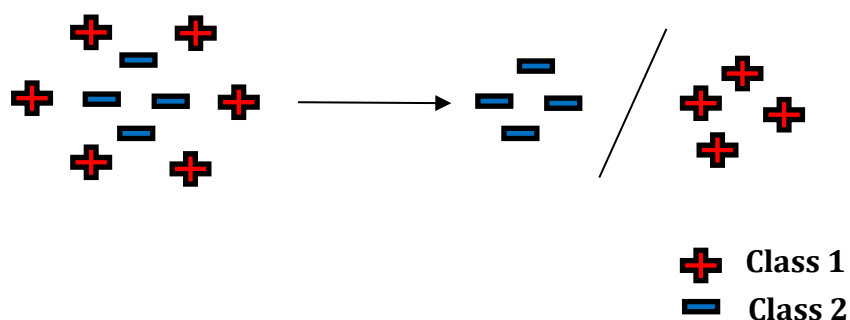


FIG 6: SVM Non-Linear Classifier.

GUI Design: The GUI was built using GUIDE, an inbuilt tool of MATLAB. In the guide, there are two buttons, one for selecting the image and another for detecting the tumor, and three image fields, one for displaying the original image, one of the tumor alone, and the last for the marked tumor.

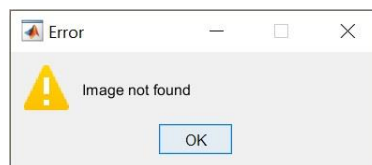
MATLAB R2018b software. The GUI was built and designed using the MATLAB tool GUIDE. For testing the GUI, a device of i3 7th gen processor with 6GB RAM was used. The total size of the GUI is 627 MB. As a tumor in a breast microwave image has a higher intensity than its background, it is easy to locate and extract the tumor. Details of the GUI are shown in Figure 7: Figure 7. a. Interface of the GUI, Figure 7. b. Error screens in case the user does not select any image, and Figure 7. c. Successful detection and classification output.

Simulation and Results

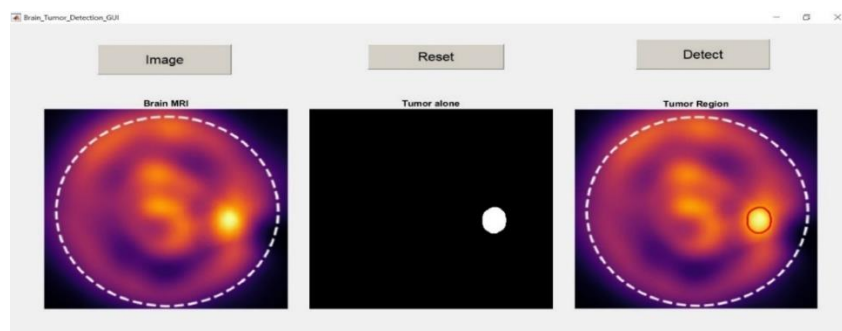
In this study, the Breast Tumor detection and segmentation method is simulated using



(a)



(b)



(c)

FIG 7: (a) Interface of the GUI; (b) Error screen in case user does not select any image; (c) Successful detection and classification output.

Preprocessing an image as an input can enhance its quality. Adjusting the contrast of the input image can help to better display the tumor and

eradicate any white areas that could be misdiagnosed as tumors.

Original Image	Reduced Noise	Binary Image	Tumor Region	Marked Tumor

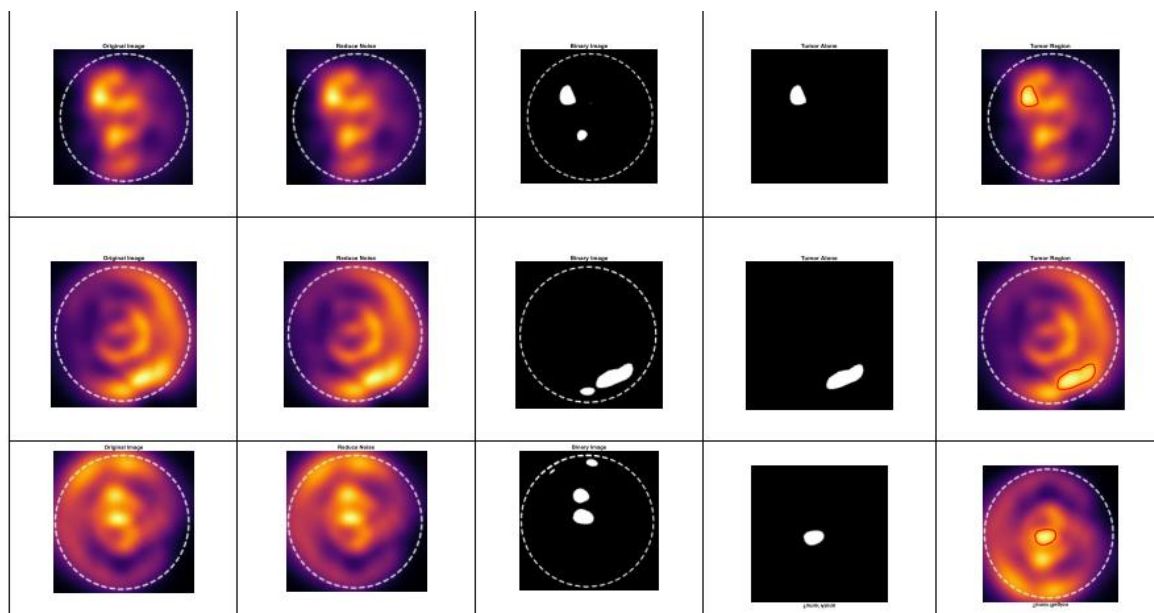


FIG 8: The results of breast microwaves image.

The details of the outputs of the internal process are shown in Figure 8, where the outputs of the process are in several stages, as follows: In the first stage, the original image is inserted, and then the noise is removed from it. In the next stage, the image is converted into a binary image, after that the tumor area is extracted, and finally, the tumor area is marked with a red circle.

CONCLUSION

This study presents a method for extracting a region of interest (ROI) when segmenting microwave images because it plays an important role in the effectiveness of tumor detection. Then, the microwave images were pre-processed to reduce noise and increase contrast. The extent and location of the breast tumor were determined by microwave imaging. Using microwave imaging, radiologists can easily diagnose a tumor and prepare for surgical removal by obtaining information such as the location and size of the tumor. A method for the automatic detection of breast tumors using microwave images is presented to overcome the difficulties associated with the evaluation of breast tumors. This software can be developed to make it even more powerful and by incorporating additional aspects of this data into the software, it will be able to process a variety of breast tumor investigations. Perhaps this neuroimaging processing tool could be used in the medical sector to assist surgeons in laser ablation procedures. In later stages, the

outer margins of the tumor in the microwave images are shiny and dense, with a statement to detect if the edges affect the detection algorithm and to apply a filter to eliminate them.

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