



(RESEARCH ARTICLE)



Breast cancer detection in ultrasound imaging

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World Journal of Advanced Research and Reviews, 2021, 12(01), 308-314

Publication history: Received on 09 September 2021; revised on 15 October 2021; accepted on 17 October 2021

Article DOI: <https://doi.org/10.30574/wjarr.2021.12.1.0522>

Abstract

Breast cancer has become one of the most cancers among women in worldwide countries, as well as a leading cause of death. The use of ultrasound images in medical diagnosis and treatment of patients is critical. The success of cancer treatment and outcome is largely dependent on early detection. Imaging modalities such as ultrasonography are used to identify cancer. Ultrasound imaging is noninvasive, widely available, simple to use, and less expensive than other imaging technologies. As a result, ultrasonography is becoming more used as a cancer detection tool. Ultrasound imaging, on the other hand, is prone to noise and speckle artifacts. First, the ultrasound machine's raw picture data extraction is disabled. As a result, the process of recognizing malignant spots is prioritized. Artificial neural networks and other tissue characterization approaches are used. This technique was chosen because categorization and detection systems have greatly increased in their ability to assist medical experts in diagnosis. Manually classifying ultrasound images not only takes a long time and effort. As a result, a neural network classification-based automatic tissue characterization technique is proposed. Finally, the newly developed algorithms can aid specialists in recognizing suspicious aberrant tissue locations.

Keywords: Breast Cancer; Ultrasound Imaging; Neural Networks; K-means

1. Introduction

Breast cancer is the most often diagnosed cancer in women in the world, with over half of all occurrences occurring in poor nations. There is currently no effective strategy to prevent the occurrence of breast cancer. As a result, early detection is the first and most important step in treating breast cancer. It is crucial in the detection and treatment of breast cancer. This procedure necessitates picture segmentation and analysis. Breast density segmentation and classification is done using a variety of methods, including the k-Means algorithm [1-3], the Fuzzy C-Means (FCM) algorithm [4], and the Dogs, Rabbit (DaR) algorithm [5], Fourier Analysis [6-9], Hough Transform [10-12], and Template matching [13-15].

In general, tumor has different characteristics such as geometrical and statistical [16-17]. In addition, due to its capacity to visualize human tissue without causing harm, ultrasound imaging is a commonly utilized technology in the diagnosis of soft tissues. Meanwhile, it allows the operator to quickly identify the necessary image plane in order to accurately display normal or pathological tissue. As a result, the vision that guides medical imaging analysis and processing is crucial to enhancing patient health. The visual interpretation of radiologists is crucial when studying medical images. However, this takes time, and it is usually subjective because it differs depending on the radiologists' expertise. The introduction should be typed in Cambria with font size 10. Author can select Normal style setting from Styles of this template. The simplest way is to replace (copy-paste) the content with your own material. In this section highlight the importance of topic, making general statements about the topic and presenting an overview on current research on the subject. Your introduction should clearly identify the subject area of interest. The major goal of this work is to develop

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diagnostic tools for early cancer diagnosis that can meet the classification process's standards without requiring operator intervention. Furthermore, the suggested technique should work well on ultrasound images without the requirement for any preparation steps to remove speckle noise and other known image artifacts. Because it is automated, accurate, and quick, the proposed technique can be employed in everyday clinical practice.

2. Ultrasound Imaging

The term "ultrasound" refers to cyclic sound pressure with a frequency higher than the human hearing limit. Ultrasound, like infrared and sound waves, is an acoustic wave. Their distinctions are in their frequency ranges, not in their qualities. The frequency range of infrasound is 0 to 20 Hz. The sound that the human ear can detect is called (20 Hz to 20 KHz). The ultrasonic frequency range is typically 20 KHz to 30 MHz. Ultrasound is similar to an acoustic wave in that it must propagate through a medium because it cannot exist in a vacuum. Ultrasound is employed in a wide range of imaging applications. It is a type of medical imaging that uses sound waves that are far higher in frequency than what the human ear can hear. Sound waves are emitted by a transducer and reflected back by organs and tissues, allowing a picture of what's within the body to be drawn on a screen. Ultrasound can be used to detect cancers, assess bone structure, and check the health of an unborn child[18]. The advantages of using Ultrasound in medical imaging can be listed as:

- Ultrasound scanning is usually pleasant and noninvasive (no needles or injections).
- Ultrasound imaging is more widely available, simple to use, and less expensive than other imaging techniques.
- There is no ionizing radiation used in ultrasound imaging.
- Ultrasound scanning provides a clear view of soft tissues that are difficult to see on x-rays.
- Ultrasound has no side effects and can be done as often as needed.
- For the diagnosis and monitoring of pregnant women and their unborn offspring, ultrasound is the preferred imaging modality.
- For nearly four decades, ultrasound has been used to assess pregnancy, with no evidence of harm to the patient, embryo, or fetus. [19].

In the other hand, the disadvantages of using Ultrasound in medical imaging can be listed as:

- Ultrasound results may reveal a potentially cancerous area of concern.
- These false-positive results could lead to more unnecessary treatments, such as biopsies. According to preliminary data from a trial now underway, ultrasounds have a higher probability of false-positive outcomes than mammography.
- Although ultrasonography is frequently used to avoid intrusive diagnostic procedures, it is sometimes unable to tell whether or not a tumor is malignant, in which case a biopsy will be needed.
- Many malignancies are not detectable by ultrasound.
- Calcifications evident on mammograms are not apparent on ultrasonic scans, impeding early detection of the subset of breast tumors that start with calcifications.
- Ultrasounds aren't available everywhere, and they're not covered by all insurance plans.
- To detect a cancerous mass, an ultrasound demands a highly experienced and professional operator as well as good equipment.

The malignant tissue will not be recognized as early as feasible if it is not detected during the scan. [19].

Ultrasonography is widely regarded as a risk-free imaging technique. However, minor negative effects have been found on occasion. During pregnancy, diagnostic ultrasonography scans of the fetus are usually thought to be safe. Only when there is a genuine medical indication should this diagnostic technique be conducted, and the lowest possible ultrasonic exposure setting should be used to get the necessary diagnostic information under the "as low as reasonably achievable" standard. Series 875 of the World Health Organization's technical reports (1998). Supports the idea that ultrasonography is safe: "Diagnostic ultrasound is widely acknowledged as a safe, effective, and highly adaptable imaging modality capable of rapidly and cost-effectively giving clinically useful information about most areas of the body." The user, who has a substantial impact on the examination's total benefit, is critical to the proper, safe, and effective use of diagnostic ultrasonography. In truth, the user's competence and training are frequently more crucial. As a result, criteria for Ultrasonography training are a requirement for providing high-quality diagnostic ultrasound services [20].

3. Neural Networks

The basic and simple nonlinear elements known as neurons or nodes are interconnected in the ANN, and the strength of the interconnections is expressed by weights. These weights are modified based on the work at hand in order to increase the system's performance. The computational elements or nodes (artificial neuron) used in the ANN are depicted in Figure (1). The basic node of the network sums the n weighted inputs and delivers the results to the final output via one of the nonlinear functions available [20].

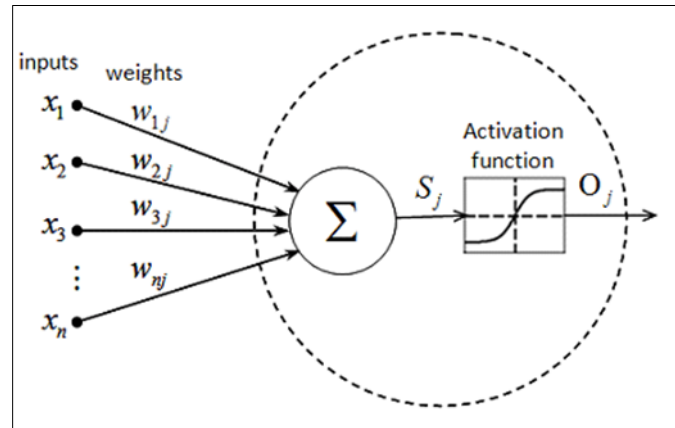


Figure 1 Neural Network Structure

BPNNs are one of the most commonly used neural network designs in machine learning. They begin with a network of nodes that are organized into three layers: input, hidden, and output. The weights for the nodes are random before any data is processed through the network.

When given an input pattern, each input node takes the value of the corresponding attribute. These values are fired, and each node in the hidden layer multiplies each attribute value by a weight before adding them together. It fires a value of '1' if this is greater than the node's threshold value; otherwise, it fires a value of '0'. In the output layer, the same process is performed with the values from the hidden layer, and if the threshold value is exceeded, the input pattern is classified. Once a classification has been supplied, it is compared to the actual categorization when training the network. This is then "back-propagated" across the network, causing the hidden and output layer nodes to modify their weights in response to any classification errors, if any are detected. The weights are changed in accordance with the error curve's gradient, which leads in the direction of the local minimum near the instance [9].

In the problem fields of pattern recognition, supervised ANNs such as the Hopfield and perceptrons networks are employed as classifiers. These types of ANNs are provided with additional side information or labels that identify the right class of the input vector during the training process. Unsupervised ANNs, such as kohonen networks, on the other hand, are employed as vector quantizers to generate clusters during the recognition process when no information about the right class of the investigated pattern (tumor in our scenario) is provided during the training period. [20].

4. Methodology

A multistage technique is described in this section to automatically classify and extract the exclusion from ultrasound pictures. It consists of the stages depicted in the Figure (2).

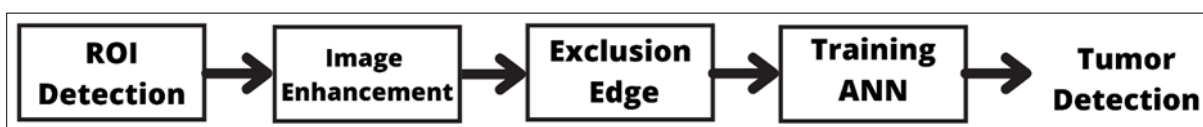


Figure 2 Proposed Methodology

The actual authors can be referred to, but the reference number(s) must always be given. e.g.: 'Barnaby and Jones [19] obtained a different...'

4.1. Region of Interest Cropping

Crop the Region of Interest (ROI) is the first step in this methodology as seen in Figure (3). The noise from both sides due to the transducers' backscattering. The rest of the image is ignored because the purpose is to diagnose exclusion. As a result, cropping the image during the classification of the malignant spots in the image saves computational time and storage space.

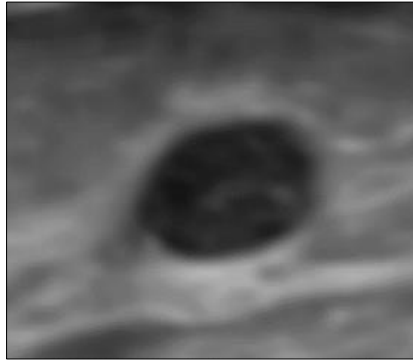


Figure 3 Tumor image cropping

4.2. Image Enhancement

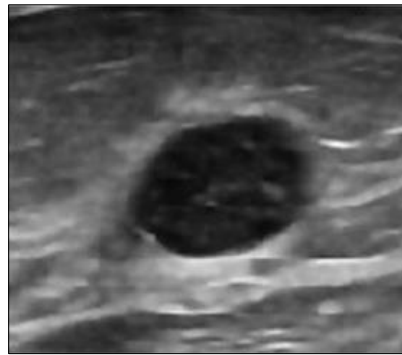


Figure 4 Image Enhancement

Ultrasound picture classification is difficult due to speckle noise. The preprocessing stage's purpose is to remove speckle noise and improve the edges. A Gaussian filter is used to diminish the image that has been enhanced by employing noise. Image enhancement is used to increase the interpretability or perception of information in images for human viewers, as well as to offer better input for other automated image processing techniques. Spatial domain approaches, which work directly on pixels, and frequency domain methods, which operate on an image's Fourier transform, are the two broad groups of image enhancing techniques, the output of this phase is shown in Figure 4.

4.3. Detecting the Exclusion Edge

In the field of image analysis, edge detection is a critical issue. Edges in normal photographs represent object boundaries, making them valuable for segmentation. Edge detection algorithms are often used in image segmentation to locate edges in an image. Edge detection operators based primarily on gradation, such as Sobel, Robert, and Prewitt edge detectors, are commonly used in traditional edge detection techniques. At the junction of two zones of varying intensities, edges arise. These approaches are most effective on photos with good contrast between regions. They identify all the edges, which is a disadvantage. As a result, determining the relationship between the edges and the region of interest is quite challenging. Furthermore, the algorithms are susceptible to noise. The edge map is created by finding the weak edges with the Prewitt edge detector. The Prewitt approach uses the Prewitt approximation to the derivative to find edges. It returns edges at the points on the image where the gradient is the greatest. Figure 5 below illustrated this process.

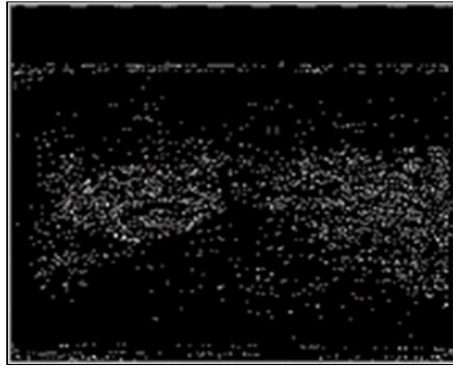


Figure 5 Detecting the Exclusion Edge

4.4. Feed forward, Back-Propagation

A feedforward neural network is a type of artificial neural network in which nodes' connections do not form a loop. As a result, it differs from its offspring, recurrent neural networks. The feedforward neural network was the first and most basic artificial neural network to be created. The information in this network flows exclusively in one direction: forward, from the input nodes to the output nodes, passing through any hidden nodes (if any). In the network, there are no cycles or loops. The core of neural network training is backpropagation. It's a technique for fine-tuning the weights of a neural network based on the previous epoch's error rate (i.e., iteration). By fine-tuning the weights, you may lower error rates and improve the model's generalization, making it more dependable. Backpropagation is a short form for "backward propagation of mistakes" in a neural network. It's a common way to train artificial neural networks. This method is useful for calculating the gradient of a loss function with respect to all of the network's weights.

4.5. Training Neural Network

The right class for each record is known during the training phase (this is referred to as supervised training), thus the output nodes can be given "correct" values — "1" for the node corresponding to the correct class and "0" for the others. Values of 0.9 and 0.1 have been proven to be more practical in practice. Thus, the network's calculated output node values may be compared to these "right" values, and an error term for each node can be produced (the "Delta" rule). Training process show in Figure 6. These error terms are then utilized to change the hidden layer weights in the hopes of getting the output values closer to the "right" values the next time around.

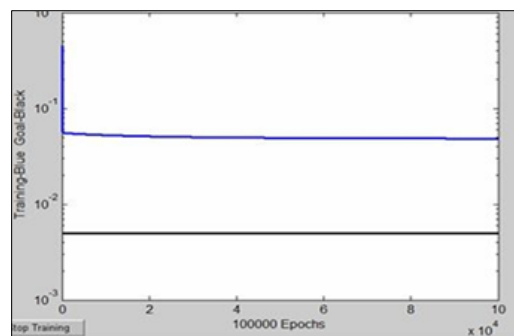


Figure 6 Training Data

5. Results and discussion

In ultrasonic imaging, a multistage computational technique is presented to automatically find the exclusion boundary. The results demonstrate the efficacy of classifying the exclusion region in an ultrasound image. Ultrasound images are used to test the suggested tissue characterization algorithm. In ultrasound raw images, the system successfully determines the exclusion boundary. The proposed approach is implemented in Matlab R2021b. Algorithms complement each other by producing classification accuracy, sensitivity, and specificity that are all the same. The output of the resultant detection was showed below.



Figure 7 Output of the detection Algorithm

6. Conclusion

Ultrasound pictures are commonly employed in a variety of medical settings. As a result, proper exclusion classification is critical for early diagnosis of malignant regions. Low contrast, speckle noise, and fuzzy boundaries are the most common issues in ultrasound images. As a result, an automated, precise, and quick technique is required. We have presented a new technique for tissue characterization in this paper. The suggested method is primarily based on the Feedforward neural network, which is frequently utilized in the classification of medical images. Finally, new algorithms can assist specialists in recognizing suspicious aberrant locations that should be investigated, as well as detecting previously unreported regions.

Compliance with ethical standards

Acknowledgments

I would like to thank my supervisor Dr Khaled Al Gamry for his support and encouragement during this work.

Disclosure of conflict of interest

The Authors declares that there is no conflict of interest.

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