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DETECTING BREAST CANCER FROM MAMMOGRAM IMAGES USING A HAAR WAVELET FILTER WITH THRESHOLD-BASED SEGMENTATION

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ABSTRACT

Today, image science rules the domain of computer science. Typically, image processing is a technique to transfer an image into a digital structure and process it to obtain an improved image. It includes scaling the image concerned, removing small objects, smoothing, extracting features and techniques such as these. Engineering and medicine utilize image processing, the latter especially in tracking cancer. Breast cancer is a type of cancer that surfaces and expands in a woman's breast ... cells, and is widely acknowledged as the world's leading cause of death. This deadly malady is curable if detected in the early stages. Earlier, breast cancer detection was carried out through X-ray mammography to arrive at a diagnosis. In recent times, however, numerous computer-aided diagnostic (CAD) proposals have been developed to enhance the radiologist's diagnostic skills. The Haar wavelet filter is applied to facilitate early breast cancer detection and diagnosis effectively. The Haar wavelet transform outlines the simplest compression method of this category. It is perhaps the finest approach to segment images using thresholding-based, connected component pixels applied to group similar types of pixels.The results have been taken from a range of breast cancer computerized tomography (CT) scan mammogram images. In this paper, we used an efficient image filtering system named the OpenCV 2.4.9.0 and cvblobslib for implementation. The improved method was tested over several breast cancer mammogram images and achieved good results. Going forward, advances can include an extension of this work, incorporating its implementation with datasets to augment the detection and treatment of breast cancer.

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KEY WORDS

Breast cancer, connected component pixels, Haar wavelet filter, image processing, mammography image

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INTRODUCTION

Breast cancer occurs mostly in females, and a newly-released update says that 25% of all women suffer from this disease worldwide. Of that number, 20% die. A team that is presently at work to eradicate breast cancer in females concludes that it can be prevented by birthing before the age of 30, breastfeeding, limiting alcohol intake, maintaining a healthy weight, and exercising regularly. Breast cancer first attacks the duct tissues (tubes that carry milk to the nipples and lobule glands that make milk), which form a major portion of the breast. Mammography became a reliable diagnostic tool in the 1950s when industrial-grade X-ray film was introduced. Mammography can detect breast cancer in two ways:

- Screening mammography: used as a preventive search for women who have no symptoms of breast disease.
- Diagnostic mammography: used in X-rays to obtain images showing the affected breast from different regions and angles.

Diagnostic mammography is an X-ray testing technique to detect breast cancer. **Figure-1** shows an illustration of the symptoms of breast cancer. A lump in the breast can be discovered during testing or an abnormality found during screening mammography. Diagnostic mammography takes longer and is a more involved process. It is a perfect test that can detect the size and location of the affected tissues and lymph nodes of the breast region accurately, compared to screening mammography. Images are viewed from different angles and interpreted accordingly.

ENHANCEMENT OF THE IMAGE PRE-PROCESSING TECHNIQUE

Image enhancement considers the process of attenuation and sharpening, as well as image features such as edge, boundaries and outlines to produce a processed image. Image enhancement includes gray-level and contrast manipulation. This process reduces noise, obliterates the background and can be used to take sharp images with crisp edges, filtering, interpolation, magnification, and pseudo-coloring to tweak the image obtained. This process utilizes procedures such as median filtering, normalization and modified tracking algorithms for enhancing mammograms. The performance of the enhancement technique is evaluated by a signal-to-noise ratio (SNR) measure. Enhancement involves four steps in its processing.

Removing the X-ray label in the digital image of the breast previously obtained by testing with diagnostic or screening mammography.

Step [1]. Eliminating high frequencies with the median filter.

Step [2]. Decreasing contrast and brightness with the normalization process.

Step [3]. Destroying the muscle region with the modified tracking algorithm.

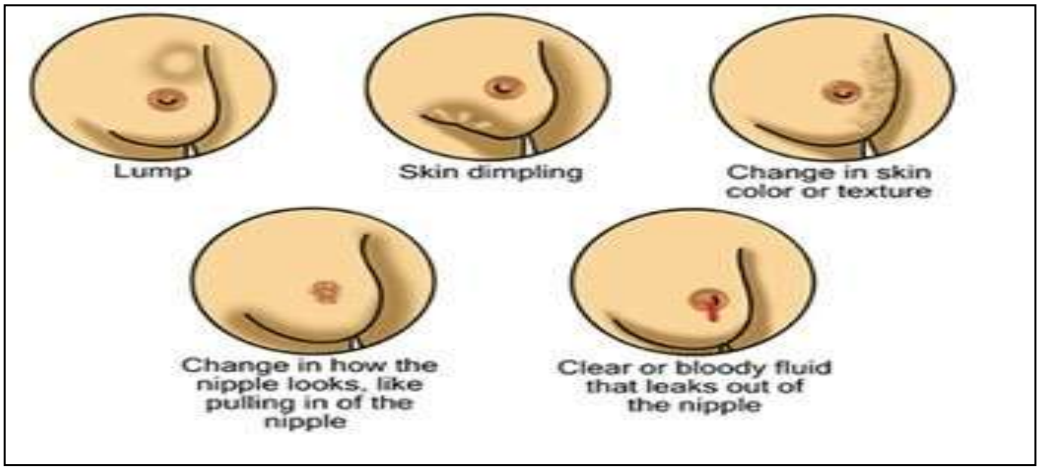

Fig.1: Symptoms of breast cancer

SEGMENTATION TECHNIQUE OF BREAST CANCER

Image segmentation is a key step in pictorial pattern recognition and analysis applications. The segmentation technique defines, in precise terms, the success or failure of analytic procedures.

Segmentation aims to change or alter an image, rendering it more meaningful and simpler to find. The field of pattern recognition involves the usage of image segmentation, in the early phases, to divide an input digital image into different patterns. Each region has characteristics of its own, on the basis of which regions are grouped. These characteristics may be completely mathematical - for example, based on the area of pixels and their neighbours - or visual, such as colour, intensity, or texture repetitiveness.

Segmenting the breast and non-breast region is a major prerequisite for further bilateral filtering differences. This section presents a border detection method with a genetic algorithm. The breast border can be obtained in segmentation from the image of the breast region. Some authors have developed methods to detect the breast area, based on a global histogram analysis. However, a method that depends on global thresholding alone is based, critically, on the selection of threshold values.

FILTERING TECHNIQUE OF BREAST CANCER

From the perspective of digital image processing, a filter is a system used in a mathematical operation on an image represented as a sampled, discrete-time signal. The filter is used to decrease certain enhanced aspects of a signal. The notion of filtering has its origins in the use of the Fourier transform for signal processing in frequencies. Filters may be linear or non-linear, based on the relation of the output with the input.

LITERATURE SURVEY

Mammography is a major image processing technique that diagnoses breast cancer. Mammography establishes the presence of cancer before a physically-evident manifestation. It is also the most sensitive method because it carries both positive and negative results, and can be done using an analog image or a digital one. A digital image uses a full field detector. Today, however, analog images have come into play. Image processing and intelligent systems are the two mainstreams of computer technologies. The K-means clustering algorithm, i.e., clustering all objects into k distinct groups [14], is being used.

A system theoretic method is presented, based on a Markov chain model to analyse the mammography process of breast cancer detection. Formulas are developed to estimate the patient's length of stay and staff efficiency. An empirical formula is suggested and non-Markovian scenarios are also investigated. Results prove that these methods are highly accurate in evaluating performance. In support, a case study is tabled to demonstrate the application of the model. An increase in patient volume is also examined to show that the increase in capacity is mandatory to meet the demand [1].

Markov models and neural networks comprise a step-by-step process. Dialing out medical images using the data mining method with neural networks delivers very good results. It involves grouping, the chief objective being to detect affected areas [15].

The initial step in most imaging situations is to locate the surface of an object. This information may be essential for reconstruction, or required for the cancellation of the surface reflection and also as a preparatory step prior to imaging. Here, two complementary approaches are developed specifically for the purpose of surface localization. Using the data from phantom measurements and volunteer scans, the recommended approaches are evaluated [3].
The clinical prototype of a microwave imaging system with the monthly scans of healthy patient volunteers is tabled. The purpose is to examine how the system's measurements are affected by numerous issues that cannot be side-stepped in the monthly monitoring of human subjects. These factors include biological and measurement variabilities. The study also quantifies the anticipation level of variability when conducting microwave breast imaging. For frequent monitoring of breast health, this is a key step in establishing the validity of the microwave radar imaging system [2].

CS ideas are utilized to regularize the inversion process and decrease the number of unknowns by limiting the solution of the BI method. By minimizing a cost function given by the mean square error amongst the measured and modelled data, the sparse BI method estimates a contrast function. A solution for the sparse BI method is found, using an iterative algorithm. The sparse BI method is tested successfully on a noise-free and noisy synthetic dataset representing a tomographic scan of a cancerous breast. Results prove that the sparse BI method remains convergent as the number of iterations increases, in comparison to the conventional BI method [4].
A clinical prototype with a wearable patient interface for microwave breast cancer detection is examined. By embedding 16 flexible antennas into a bra, the system is operated with a metastatic time-domain pulsed radar, and is also cost-effective. The resulting data is compared with the data obtained from the table-based prototype. The wearable prototype has enhanced the quality of the volunteer data collected. A wearable breast health monitoring array can be further improved in the near future for patients with various breast sizes and tissue densities [5].
Using mammography, a computer-aided detection and diagnosis system for breast cancer is recommended. The breasts are first partitioned adaptively into regions according to the proposal. Two strategies are examined to define the anomaly detector. The first strategy uses manual segmentations of lesions to train an SVM that assigns an anomaly index to each region. The second strategy uses various MIL algorithms to train local and global anomaly detectors. Results prove that the second approach outperforms the first, demonstrating that anomaly detectors have advantages and can be trained on large medical image archives without manual segmentation [6].
A new concept for learning from crowds that handle data aggregation directly as part of the learning process of the convolutional neural network (CNN) through an additional crowdsourcing layer (AggNet) is discussed. Also, an experimental study is tabled to find answers for training on the CNN, as well as training multiple types of annotation datasets by the CNN, and how accuracy is affected by the choice of annotation and aggregation. The experiment involves Annot8 for realizing image annotation tasks for publicly-available biomedical image databases. The results prove the necessity of data aggregation integration [7].

A dual-photon emission computed tomography (DuPECT) mechanism, an alternative to 3-D imaging systems, is proposed, integrating both preoperative and intraoperative information to trace SLNs using cascade isotopes. SLNs can be located using the line-plane intersection. The Monte Carlo software is used to evaluate performance. The random rate increases with increased initial activities, while the scatter rate is lower than 1.2 count/s for a range of activities. Four injection sites and two LNs are placed at various depths in a simulated study. LNs are clearly identifiable in the absence of injection sites. Results prove that the suggested three-dimensional imaging system has the potential to identify injection sites and various SLNs [8].

A new computer-aided detection (CAD) system is considered to reduce human involvement and help radiologists in the automatic diagnosis of malignant/non-malignant breast tissues by using polar complex exponential transform (PCET) moments as texture descriptors. The input ROI of a fixed size of 128×128 is extracted manually to avoid processing the whole mammogram. Also, a new classifier, ADEWNN, is introduced to improve the classification accuracy of the suggested system. The proposed phase-correction method (PCPCET) is compared with a magnitude-based feature extraction (PCET). The best area is found to be 0.984, with a confidence interval ranging from 0.968 to 0.999 and a ±0.0108 standard error under the receiver operating characteristic curve [9].

Magneto-acoustic tomography with magnetic induction (MAT-MI) is a promising technology for the non-invasive detection of breast cancer. This work presents a high-frequency MAT-MI (hfMAT-MI) system, a significant improvement over previous methods. Boundaries between cancerous and healthy tissues, as also the tumours' internal structures, are resolved by hfMAT-MI. For the first time in an in vivo mouse model, a growing tumour was tracked using the hfMAT-MI method. This demonstrates the promise of the magneto-acoustic imaging system for effective detection and diagnosis of early-stage breast cancer [10].

Here, the miRNAs deregulated in breast tumors are identified and the potential of circulating miRNAs in breast cancer detection are examined. miRNA expression profiling of 1919 human miRNAs in paraffin-embedded tissue from 122 breast tumors and 11 healthy breast tissue samples were conducted. From 26 healthy people and 83 patients with breast cancer, the most relevant miRNAs were analyzed in plasma. The results helped in identifying a large number of miRNAs deregulated in breast cancer, and generated a 25miRNA microarray classifier that discriminated breast tumors. Therefore, this supports the use of circulating miRNAs as a method for early breast cancer detection [11].

Actual awareness of breast density, and a knowledge of its impact on breast cancer detection and risk, are unknown. A national cross-sectional study, overseen in English and Spanish, using a probability-based sample of screening-age women was conducted. Around 65% responded out of the 2,311 women surveyed. Overall, 58% of women had heard of BD, 49% were aware that BD affects breast cancer detection, and 53% knew that BD has an effect on cancer. Disparities in BD awareness and knowledge happen by race/ethnicity, education, and income. These findings support continued and targeted efforts to increase BD awareness and knowledge amongst women eligible for mammography screening [12].

The intention behind introducing MRIs is to improve the outcomes of screening programs for women with familial breast cancer. The aim of this study is to assess whether the introduction of MRI surveillance improves 5- and 10-year survival rate of high-risk women and determine the appropriateness of MRI breast cancer detection when compared with mammography. Women with greater breast cancer risk were screened by either mammography alone or with MRIs. Results prove that the rate of survival was higher in the MRI-screened group. Screening with MRIs is more beneficial, particularly in BRCA2 carriers [13]

The author wishes to state that breast cancer is a major issue in this discussion. Two methods for their detection - selection mammography and analytical mammography – are widely used. Selection or screening mammography comprises three approaches. Analytical or diagnostic mammography involves much time because of the number of images and angles to be examined. The drawback of diagnostic mammography is that it is very expensive, though a very effective tool [16].

Image similarity and asymmetry are done after mammography. Image similarity helps categorize breast cancer images, further compared with many others. This technique is specifically used to pinpoint medical imaging on suspicious areas, alongside CAD tools commonly used to improve the detection of breast cancer [17].
An image enhancement algorithm is used to enhance the images in question, after which they are sent for analysis. The Gabor algorithm and several filter algorithms are applied for evaluation and assessment. Image segmentation is done and new features obtained. Developing the quality of the image with the help of MATLAB software is the primary aim of this study, and the Gabor algorithm provides excellent results [18].

Spatial fuzzy clustering is a cluster analysis technique that has to be applied to the segmented image, of use for image processing as well. Pre-processing, a must before segmentation, is used to initialize the seeds in the growing process. A region-growing algorithm can be used to fetch the primary seeds from the obtained outcome or result. Specific regions are detected in this way and the segmentation problem cleared. This is mostly used to reduce the cost factor and the process can be terminated. if needed [19],[20].

Textural feature studies are extensively used in the field of computer vision and image processing, with both identification and microcalcification utilized to detect breast cancer. Image texture provides for a spatial array of colors. There is no single technique of texture imaging that is sufficient for a range of textures. The offered texture analysis contains both arithmetical and structural methods. GLCM and GLRLM techniques, alongside others, can also be applied [21].

PROPOSED METHOD

HAAR WAVELET FOR IMAGE DECOMPOSITION

The Haar wavelet, a sequence of functions, is the simplest wavelet transform. It is a compression process described as

$$H(t) = \begin{cases} 1 & 0 \leq t < 1/2 \\ -1 & 1/2 \leq t < 1 \\ 0 & \text{otherwise} \end{cases}$$

The scaling function f (t) can be described as

$$f(t) = \begin{cases} 1 & 0 \leq t < 1 \\ \text{otherwise} & \end{cases}$$

SINGLE-DIMENSIONAL HAAR WAVELET TRANSFORM

The Haar wavelet transform is a 2-element matrix [x (1), x (2)] and another 2-element matrix [y (1), y (2)] represented by a relation denoted by the equation that follows

$$\begin{matrix} y(1) \\ y(2) \end{matrix} = OM \begin{matrix} x(1) \\ x(2) \end{matrix}$$

Here, OM is denoted as an orthonormal matrix.
The orthonormal matrix is described as

$$OM = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

TWO-DIMENSIONAL HAAR WAVELET TRANSFORM

The 2-dimensional Haar wavelet transform x and y becomes a 2x2 matrix defined by the relation. The transformation can be carried out, at first pre-multiplying the columns of x by the OM (orthonormal matrix) and then post-multiplying the rows of the result by the OMT .

$$y = OM.x.OM^T$$

$$x = OM^T.y.OM$$

To compute the transformation of a complete breast image, first divide the breast image into 2x2 blocks and apply the equation $y = OM.x.OM^T$. Image segmentation is a fundamental step in advanced methods of multi-dimensional signal processing. Haar wavelet functions are generated from a one-dimensional function by means of deletions and translations. The Haar transform forms the simplest compression process of this kind.

CONNECTED COMPONENT PIXELS TO DETECT BREAST CANCER

Based on the specified heuristic assessment-connected components group, all pixels are subsets. Connected component pixels are utilized in computer vision to detect connected regions in binary digital images, though color images and data alongside higher dimensionalities can additionally be processed. Connected component labeling can work on a collection of information after being consolidated into an image recognition system or a human-computer interaction interface. Blob extraction, from a thresholding step, is usually provided in the emerging binary image. Blobs can be counted, filtered and tracked. A graph encompassing vertices and connecting edges is crafted from relevant input data. The vertices encompass data needed by the comparison heuristic, as the edges indicate related 'neighbours.' An algorithm crisscrosses the graph, labelling the vertices established on the connectivity and comparative benefits of their neighbors. The algorithm follows this method and creates new region labels whenever necessary.

The key to a fast algorithm depends on how the merging is done. This algorithm uses the union-find data construction that works admirably at keeping track of equivalence relationships. Union-find stores labels that correspond to the lookalike blob in a disjoint-set data construction, making it simplistic to recall the equivalence of two labels by the use of an interface method. Relatively easy to apply and comprehend, the two-pass algorithm iterates across 2-dimensional binary data. The algorithm passes through the image twice: the first pass to allocate provisional labels and record equivalences, and the second pass to substitute every single provisional label with the small label of its equivalence class.
A faster-scanning algorithm for connected-region extraction is given below.

ONE PASS ALGORITHM

1. Begin the Algorithm
2. {
3. SCAN Each Component Column, THEN through Row
4. IF Component is Not Equal to Background
5. {
6. Acquire the adjacent component of the recent component
7. }
8. IF Neighbor is equal to Zero
9. Mark the present component and continue
10. Else
11. {
12. FIND the neighbor through the least marker
13. Assign it to the present component
14. }
15. Neighboring Marker is Equal to Distance
16. End the Algorithm
17. }

TWO PASS ALGORITHM

1. Begin
2. {
3. SCAN Each Component Column,
a. THEN through Row
4. IF Component is Not Equal to
a. Background
5. Relabel the component with the
a. Lowest counterpart marker
6. }
7. End

RESULTS AND DISCUSSION

CT scan images, with a width of 454 pixels, height of 564, and bit depth of 24 and the image type a PNG file, have been used for simulation purposes

For simulating the breast image, OpenCV 2.4.9.0 and cvblobslib library are utilized. The OpenCV (Open Source Computer Vision Library) is an open source-approved library containing lots of computer vision algorithms. Normally, documents are named OpenCV2. x API, which is fundamentally a C++ API. OpenCV has a modular construction and that way the package includes countless public or static libraries. The pursuing modules available are CORE, IMGPROC, WARPING, VIDEO, CALIB3D, FEATURE2D, OBJDETECT, HIGHGUI, and GPU [17].

CvBlobsLib has a built-in Microsoft Visual C++ (6.0) and, additionally, can be utilized in .NET. CvBlobsLib is distributed in a static library (. lib). A .lib file is to be created prior to its use in a project. To create the .lib file, open the MSVC++ undertaking and set the process in motion.
The blob extraction utilized the CvBlobsLib, a library that presents related component labelling of binary images, obtained at the OpenCVWiki page, and is relatively easy to use. This implementation used the OpenCV libraries to open a colour image, change it to a grayscale and then threshold it to change it to a black and white (binary) image.
[Table- 1] represents the Cvconvert of the Haar filter coding.

Table: 1. Cvconvert of Haar filter

CVCONVERT OF HAAR FILTER

```
cvSmooth(image,image,2,3,0,0);
width=image->width;
height=image->height;
step=image->widthStep;
channels=image->nChannels;
data=(uchar *)image->imageData;
printf("%d",image->nChannels);
```

The proposed method for segmentation of breast cancer images is threshold-based filtering. The threshold point can be set as 245 to 255 pixels. Threshold-based connected component pixel breast cancer images are filtered using the Haar wavelet filter technique. **Table- 2** describes setting a threshold in the Haar wavelet filter.

Table: 2. Setting the threshold in the Haar wavelet filter

Setting Thresholding

```
cvThreshold( grayimage, originalThr, 245, 255, CV_THRESH_BINARY );
```

The next is the filter method in the CBlobResult to remove all blobs in the breast imaging that conform to a precise size, calculate the number of 'proper' blobs discovered and display them in red in a new window.
To build a CBlobResult, use the breast cancer image constructor on an input 1-channel image. This fills the CBlobResult through all the blobs of the breast cancer image. Blobs from the CBlobResult object can be filtered with the Haar wavelet filter method. The criterion to contain or discard blobs is each object from the classes derived from the COperadorBlob (area, perimeter, gray level, etc, or new classes formed by users). **[Table- 3]** shows the segmentation operation on connected component pixels.

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Table: 4. Segmentation operation

Segmentation Operation

```
CBlobResult blobs; int i1, param2=0, param1=0; CBlob *currentBlob;
int height1    = test->height;
int width1     = test->width;
int step1      = test->widthStep;
int channels1  = test->nChannels;
uchar *data1      = (uchar *)test->imageData;
blobs = CBlobResult( originalThr, NULL, 0 );
blobs.Filter( blobs,B_INCLUDE, CBlobGetArea(), B_GREATER_OR_EQUAL, 75 );
printf("%d",blobs.GetNumBlobs());
cvMerge( originalThr, originalThr, originalThr, NULL, displayedimage );
for (i = 0; i < blobs.GetNumBlobs(); i++ )
{
        currentBlob = blobs.GetBlob(i);
        currentBlob->FillBlob(                              displayedimage, CV_RGB(255,0,0));
}
cvNamedWindow("BreastCancer",1);
cvFlip(displayedimage,displayedimage,1);
cvShowImage("BreastCancer",originalThr);
cvFlip(image,image,1);
cvNamedWindow("image",1);
cvShowImage("image",image);
cvNamedWindow("Segmented",1);
cvShowImage("Segmented",displayedimage);
cvWaitKey(0);
```

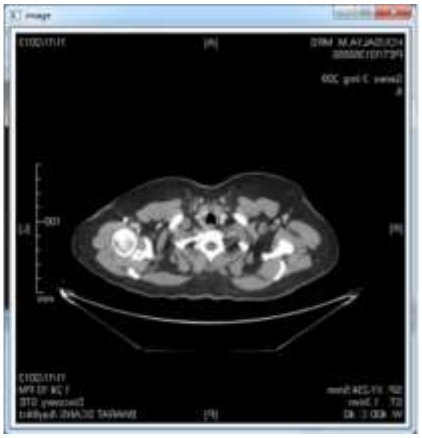

Fig.2.1: Orginal CT Scan Image

Fig.2.2: Segmented Image

Fig.2.3: Breast Cancer / Filtered Image

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Fig.3.1: Orginal CT Scan Image

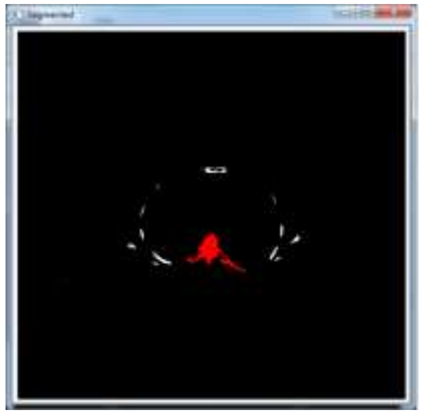

Fig.3.2: Segmented Image

Fig.3.3: Breast Cancer / Filtered

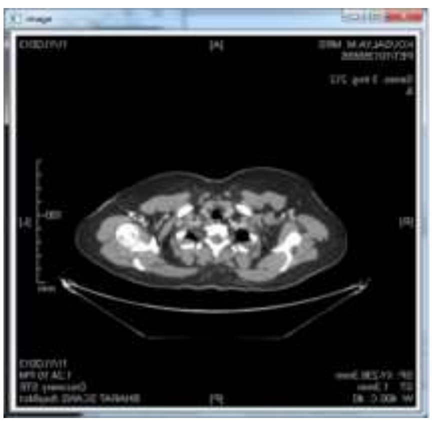

Fig.4.1: Orginal CT Scan Image

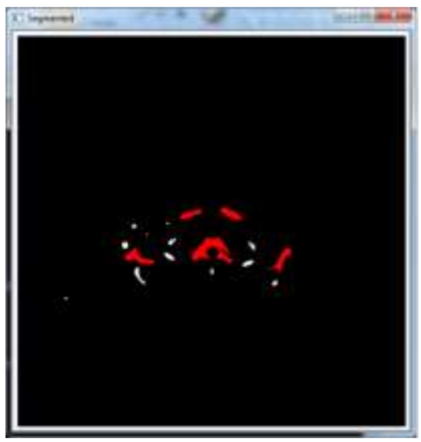

Fig.4.2: Segmented Image

Fig.4.3: Breast Cancer / Filtered Image

Fig 2.1, Fig 3.1 and Fig 4.1 are original CT breast cancer images. While being filtered, they reach an intermediate stage, i.e., that of segmented breast cancer images, as in Fig.2.2, Fig 3.2 and Fig 4.2. The final images are Fig 2.3 and Fig 3.3 and Fig 4.3 comprises filtered images.

CONCLUSION

Breast cancer is the second-foremost reason for deaths from cancer among women worldwide. A general utilization of screening, subsequently through treatment advances in recent years, has led to a major reduction in deaths from breast cancer. Today, finding a radical cure for breast cancer is a major challenge for scientists, to which end researchers invent technologies to detect breast cancer at the earliest. Using the Haar wavelet filter with connected component pixels through an OpenCV implementation gives excellent results, especially in the initial stages of breast cancer. The major advantage of this paper is that connected component pixels are used, and the mechanism of scanning an image from top to bottom, pixel-by-pixel, as well as sequentially, to recognize connected pixel regions are demonstrated as viable propositions. Additionally, working on binary or gray-level images and disparate measures of connectivity is made possible. During the past decades, the Haar wavelet filter became an essential tool with a collection of requests, normally associated with signal processing, data and image compression. Applying Haar wavelet filtering methods produces four components. The estimate point of the image is defined by low frequencies, horizontal and vertical components by mid-range frequencies, and diagonal features by high frequencies. In future, this work will be enhanced with datasets for improved detection of breast cancer.

CONFLICT OF INTEREST

The authors declare no conflict of interests.

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None

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