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Segmentation of Mammograms Using Invasive Weed Optimization Algorithm

Kotte Sowjanya*, L Gayatri**

*(Assistant Professor, Department ECE, Kakatiya Institute of Technology and Science (A), Warangal
Email: ks.ece@kitsw.ac.in)

** (UG Student, Department ECE, Kakatiya Institute of Technology and Science (A), Warangal
Email: gayatrilagishetty1999@gmail.com)

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Abstract:

Cancer of the breast is the largest cause of death among women, particularly in developed and less developed nations. This cancer's cause and prevention are still unclear, thus early discovery is the only hope for a better prognosis. Early diagnosis of cancerous tumours can boost the chance of survival. The most common method of identifying breast cancer is mammography. To make matters more difficult, breast cancer and healthy dense tissue look very much alike on mammograms. To isolate cancers from digital mammograms, a variety of image processing techniques, such as histogram-based methods, region-based algorithms, and edge detection approaches, have been developed. As they use fixed threshold levels to exclude suspicious areas from the non-uniform image backgrounds, these methods are ineffective. Using the Invasive Weed Optimization (IWO) algorithm, a new automatic segmentation approach for suspicious breast masses has been developed. The new method was compared to current algorithms like PSO in terms of efficiency. In terms of improved segmentation findings, the proposed strategy was superior.

Keywords **—** Image segmentation, Invasive Weed Optimization (IWO), Mammograms.

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I. INTRODUCTION

In the breast cells, a form of cancer called breast cancer develops. It is the most frequent invasive cancer in women and the second largest cause of cancer-related death in females. To understand breast cancer, we first need to know how cancers begin to form in the first place. It's when cells in a specific area of the body begin to grow uncontrollably that cancer begins to take root. Most cancers are caused by aberrant cell proliferation in any part of the body, regardless of the kind. There is a definite pattern to how cells in the human body divide, develop, and die. In order to replace damaged or dead cells and heal wounds, the body's cells rarely divide for any other reason than that. Cancerous cells, on the other hand, continue to grow and divide in the human body, but they outlive normal cells and give rise to new abnormal ones.

Deoxyribonucleic Acid (DNA) damage causes cancer cells to proliferate (DNA). Every cell contains this chemical, which is responsible for regulating all of the cell's functions. Usually, the body has the ability to repair DNA that has been damaged. Cancer cells are unable to repair or mend damaged DNA. Cancers that are passed down from generation to generation are caused by defective DNA that is passed down from one generation to the next. The DNA of a person is damaged permanently when exposed to toxins in the environment, such as smoking.

Among women, breast cancer is the greatest cause of death, both in industrialised and developing nations. An early diagnosis is the only approach to increase survival odds for this malignancy, which has no known cause or prevention method. Early discovery of malignant tumours can increase a patient's prognosis for recovery. In the majority of cases, mammograms are the best way to detect breast cancer. This type of x-ray scan of a woman's breast is called a mammogram. The diagnosis of abnormalities in thick mammograms is difficult because malignant tissue and normal dense tissue share many of the same characteristics.

It has been established that screening mammography is the most effective imaging approach for detecting breast cancer in its early stages, making it the gold standard for early detection. Cancer can be detected by mammography up to four years before the onset of clinical signs. The ongoing development of new breast imaging modalities and the improvement of mammography are all aimed at providing earlier detection of breast disease, more accurate assessment of the disease's extent and response to treatment, and better detection of recurrence.

Mammogram abnormalities can be identified using a variety of image processing techniques. Histogram-based methods include edge-based methods, region-based approaches, and evolutionary algorithms. An Invasive Weed Optimization strategy is proposed in this study (IWO). These researchers want to find the appropriate threshold for extracting problematic areas from mammograms by using an algorithm called Invasive Weed Optimization (IWO). When it comes to extracting problematic areas from mammograms, the IWO algorithm is helpful in selecting the optimal threshold.

Initialization, replication, spatial dispersion, and competitive elimination are all phases of the method. For thick breasts in particular, this technology outperforms current methods in recognising suspicious areas.

An image can be plainly viewed when it has been segmented into a number of distinct regions or sectors. It is one of the most commonly used methods for segmentation, and it is straightforward to implement. Foreground and backdrop can be distinguished more clearly because to this feature. Thresholding can be divided into two broad categories: bi-level and multi-level.

The goal of this project is to automate clustering-based image thresholding, or the conversion of a grayscale image to a binary image, using Otsu's method. Based on a bimodal histogram, the algorithm determines the ideal threshold for dividing the two classes of pixels so that their aggregate spread (intra-class variance) is as small as possible. In the original Otsu approach, multi-level thresholding has been included. This is a template.

II. EXISTING METHODS

Many image processing techniques have been proposed to extract abnormalities from mammogram backgrounds. Histogram-based methods, edge-based techniques, region-based approaches, and evolutionary algorithms are among the techniques classified.

A. *Histogram-Based Method:*

Histogram-based segmentation is one of the early approaches of detecting breast cancer. A method described by T. Ojala et al. employs histogram intensity values to recover the breast region while removing the different artefacts from the backdrop and is known as "global thresholding." The rough edges of the segmented region were smoothed out using morphological techniques. In conjunction with snake contour approaches, the Fourier transform helped to determine the breast boundary. Using the results, it can be concluded that the histogram intensity values of fatty breast work effectively.

For each division of an image, Haar Wavelets pyramidal were used to provide a nonlinear enhancement before the reconstruction of the final image. Using histogram adaptive thresholding (continuous-valued adaptive resonance theory), undesirable black pixels and false positives are then removed. Mammograms don't have a homogeneous background, thus these techniques benefit global thresholding, which is unsuccessful at separating anomalies from the rest of the breast tissue. A single thresholding level is only appropriate for fatty breast category mammography, as a result.

B. Edge-Based Technique:

Detecting abnormalities in mammograms using edge detection is a common practise. An extraction strategy for mass lesions, for example, was proposed by Song and colleagues. From a set of potential boundary pixels, they were able to pick out the ideal mass contour. Geometric active contour mass segmentation was employed by Yuan et al. The original contour was determined by use of a radial gradient index. Gradually, it grew closer and closer to the edge of the anomaly. Because it is dependent on the initialization of a contour, edge-based segmentation can only detect questionable areas. It also doesn't perform well on malignant tumours, which are known for their hazy edges.

C. Region-Based Technique:

Detecting abnormalities in the breast using a region-based approach is also frequent practise. A new technique based on seeded region growth was developed by Berber et al. to extract aberrant lesions. An Otsu segmentation was utilised to obtain the edge value of the brightest pixel in the mass, which was afterwards used as an initial seed point for the seeding algorithm. The method worked well, but the seed point was always selected from the brightest area, which resulted in over and under segmentation. Furthermore, bright pixels in dense mammograms aren't always indicative of malignant tumours, as they can come from healthy tissue as well.

D. Evolutionary Algorithms:

As a means of improving the sensitivity of breast mass detection, many scientists turned to evolutionary algorithms. These nature-inspired techniques were put to good use in a wide range of fields. Based on our research, we came up with a way to help assist the PSO algorithm (Particle Swarm Optimization). Masses and microcalcifications can be spotted with the help of this method. However, there are some issues with image segmentation, such as thick breasts, that it cannot overcome. In dense mammograms where the traditional and abnormal tissues are comparable, existing approaches are not yet capable of defining the ideal global threshold for identifying suspicious regions.

III. INVASIVE WEED OPTIMIZATION ALGORITHM (IWO)

A numerical stochastic search algorithm called Invasive Weed Optimization (IWO) simulates the natural process of weed colonisation in opportunity spaces. As a population-based optimization method, it was designed in response to specifics of weed colonies.

Unnatural tillage and subsequent long-term use of a field allow invasive weeds to establish strong root systems and take advantage of previously unoccupied regions. As a result, their population grows at an exponential rate. As the colony becomes more dense, there are less chances for those with lower fitness to survive. As far as functionality is concerned, the invasive weed optimization method and the colonisation weed optimization algorithm are nearly identical.

There are four steps to the invasive weed optimization algorithm in general. The following is a list of each of them:

i. Initialization
ii. Reproduction
iii. Spatial reproduction
iv. Competitive elimination

A. Initialization:

The Invasive Weed Optimization Algorithm(IWO) begins with this step . A finite number of points are spread across the search space in this step (input image). The threshold value will be determined by the dimensions of the number of points generated.

B. Reproduction:

In the second stage of the algorithm, the points that are formed in the search space and the fitness values of each of those points are calculated. The number of points created increases linearly when fitness values are plotted on a graph. The number of points created and their fitness scores are shown in the graphical depiction. Pictured below is how it's done: Fig1.

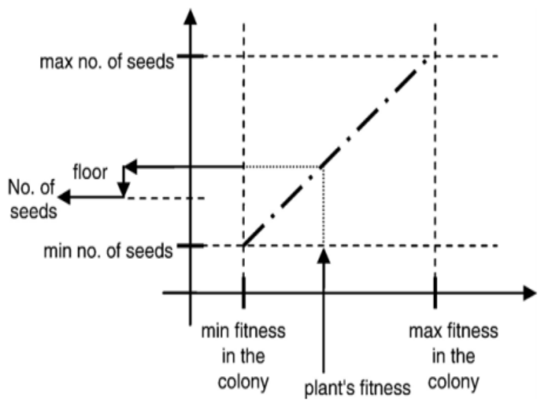

Fig 1: Seed production procedure In a colony of weeds

An important part of the algorithm, this is used in most evolutionary algorithms. Since only the points with low fitness values can be generated in the search space, those with high and other fitness values are barred from generating new points in the search space.

But the evolutionary algorithm is a probabilistic and recurrent process, therefore this overlooks a crucial point. There are times when infeasible individuals may have more useful information than feasible people during the evolution process. A system that can "cross" an infeasible zone frequently gets to its optimal point more quickly. It is proposed that infeasible persons can live and reproduce in a manner that is similar to that which occurs naturally through the use of the aforesaid reproduction method.

C. Spatial Reproduction:

In this step, the algorithm incorporates randomness and adaptability. In the third step of the IWO, random integers with a mean of zero but varying variances are used to spread the generated points over the d-dimensional search space. The random function's standard deviation (SD) will be lowered from an initial value, initial, to a final value, final, at each step. A nonlinear alteration, provided in Eq., has demonstrated good performance in simulations.

$$\sigma_{\text{iter}} = \frac{(\text{iter}_{\max} - \text{iter})^n}{(\text{iter}_{\max})^n} (\sigma_{\text{initial}} - \sigma_{\text{final}}) + \sigma_{\text{final}}$$

D. Competitive Elimination:

If a plant doesn't produce any offspring, it may become extinct, whereas if it does, it could take over the world. In order to limit the maximum number of plants in a colony, there is a need for some rivalry amongst the plants. However, it is envisaged that the fitter plants will be replaced by less attractive ones after a few rounds, resulting in an overpopulation of unwanted plants. Pmax, a mechanism for eliminating plants with low fitness, is activated when the colony reaches the maximum number of plants. When the maximum number of weeds in a colony is achieved, each weed is allowed to supply seeds in accordance with the aforementioned procedure for eliminating them. The resulting seeds are then allowed to spread over the search area.

When all of the seeds have been located in the search region, they are placed in order of proximity to their biological parents (as a colony of weeds). Next, low-fitting weeds are culled to ensure that a colony can thrive at its maximum capacity. As a result, plants and their offspring are ranked in order of fitness, and only those with the greatest fitness are allowed to reproduce. Plants with lower fitness can use this technique to reproduce, and if the offspring they produce have a high fitness within the colony, they will live.

IV. THRESHOLDING

To segment data, the most straightforward method is thresholding, and it is also the most used. In image segmentation, known as thresholding, the pixels of a picture are altered to facilitate analysis.

Tweaking a colour or grayscale image to make it black and white is known as "thresholding." Most of the time, we utilise thresholding to isolate the bits of an image that matter while leaving out the rest.

As a grayscale image's intensity levels are separated into sets or classes, so are its pixels (L). Thresholds come in two varieties. In fact:

1. Bi-Level Thresholding
2. Multi-Level Thresholding

V. OTSU'S METHOD

Using Otsu's method, image thresholding or the conversion of a grayscale image to a binary image can be performed automatically. If an image has two classes of pixels (foreground and background), then bi-model histogram is used. The method selects the appropriate threshold for dividing these classes in order to keep their total spread small (intra-class variance). The Multi Otsu method, a multi-level expansion of the original one, is used for thresholding.

With the grayscale image's 'L' intensity levels, a probability distribution of the intensity values may be determined:

$$ph_i^c = \frac{h_i^c}{NP}$$

$$\sum_{i=1}^{NP} ph_i^c = 1; where, c = 1$$

where, 'i' depicts the specificlevel of intensity, 'C' is the image component, 'NP' is for total number ofimage pixels, 'h' is the number of pixels that corresponds to the 'ith'intensity level in 'C'.

The histogram is normalised within the context of a probability distribution ph_i^c . Two classes are defined for the most basic segmentation (bi-level) as

$$C_1 = \frac{ph_1}{\omega_1(th)}, \ldots\ldots\ldots\ldots, \frac{ph_{th}}{\omega_1(th)}$$

$$C_2 = \frac{ph_{th+1}}{\omega_2(th)}, \ldots\ldots\ldots\ldots, \frac{ph_L}{\omega_2(th)}$$

Where,

$\omega_1(th)$ and $\omega_2(th)$ are probability distributions for C1 and C2 as it is shown by

$$\omega_1(th) = \Sigma_{i=1}^{th} ph_i$$

$$\omega_2(th) = \Sigma_{i=th+1}^{L} ph_i$$

The mean levels u1 and u2 of classes C1 aand C2 are:

$$\mu_1 = \Sigma_{i=1}^{th} \frac{iph_i}{\omega_1(th)}$$

$$\mu_2 = \Sigma_{i=th+1}^{L} \frac{iph_i}{\omega_2(th)}$$

$$\sigma^2 = \sigma_1 + \sigma_2$$

Where,

$$\sigma_1 = \omega_1(\mu_1 - \mu_T)^2$$

$$\sigma_2 = \omega_2(\mu_2 - \mu_T)^2$$

We also have

$$\mu_T = \omega_1\mu_1 + \omega_2\mu_2$$

$$\omega_1 + \omega_2 = 1$$

The objective function is given by

$$J(th) = \max(\sigma^2(th)), 0 \le th \le L-1$$

As a result, the optimization problem is condensed to determining the intensity level(th) that maximizes the objective function.

VI. EXPERIMENTAL RESULTS

k	Th	OF value	PSNR	MEAN	SSIM
2	61 147	1.9067	16.565	1906.7	0.2578
3	58 111 176	2.0029	17.822	2002.9	0.3152
4	45 77 138 205	2.0607	19.870	2060.7	0.4147

5	32 68 108 129 212	2.0718	19.936	2071.8	0.4444
6	42 63 88 129 157 215	2.1076	21.155	2107.6	0.4920

VII. CONCLUSION

Using the metaheuristic algorithm IWO based-region methodology, we have suggested a method for detecting anomalies in the breast. According to their density and image quality, DDSM database photographs were categorised into four groups. We next used the IWO algorithm-based technique's optimal thresholding to extract the questionable zones. Mammograms with dense or exceptionally dense tissue responded well to the proposed method.

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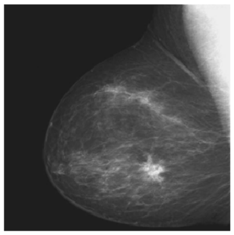
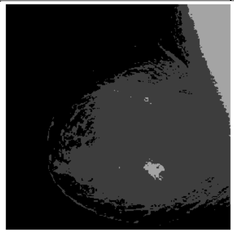
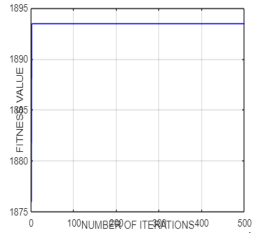
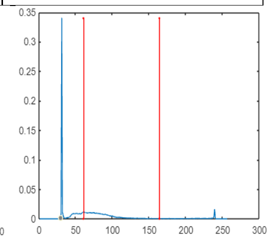
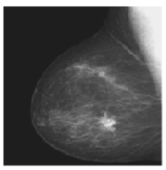
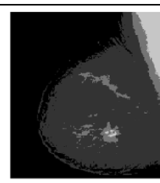
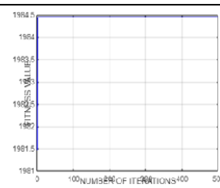
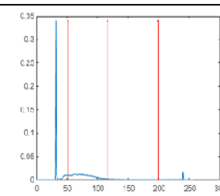
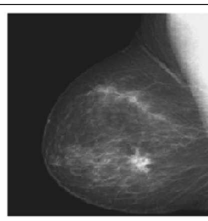
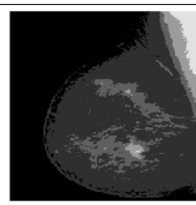
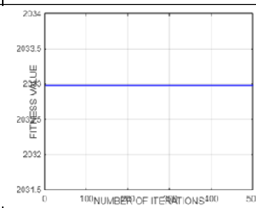
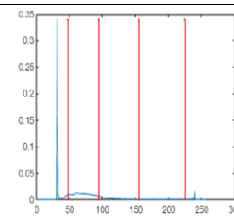
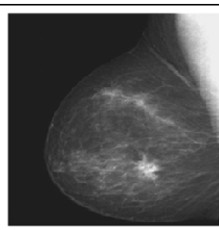
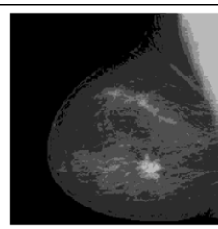
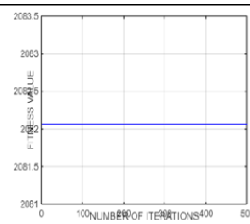
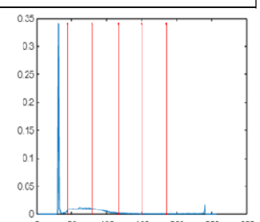
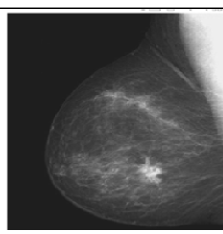
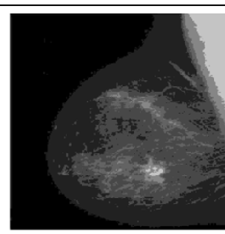
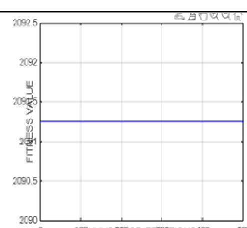
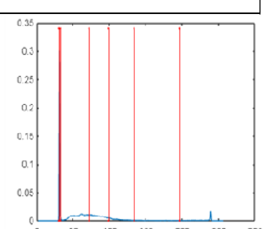
K	INPUT IMAGE	OUTPUT IMAGE	CONVERGENCE	HISTOGRAM
K=2				
K=3				
K=4				
K=5				
K=6				

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