

A Study on the Improvement of Security Image Analysis Capability Using Artificial Intelligence

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Abstract: The mining of patient data in the health care industry is becoming an increasingly important field because of the direct effect it has on the lives of patients. In the field of medicine, one use of data mining is the early diagnosis of medical diagnostic conditions. However, extracting information from medical records is a laborious process that involves a lot of time and effort. Communities that are dominated by females have an elevated risk of developing breast cancer. Even though mammography is one of the most common ways to use computer-assisted diagnostics, there is still a chance that breast cancer will not be found even if it is one of the most common ways to find and screen for the disease. This indicates that just thirty percent of breast cancers are diagnosed at the appropriate time. Digital image pre-processing includes grayscale-to-binary conversion, noise reduction, and character separation. Most picture recognition algorithms employ statistical, syntactic, and template matching. Neural networks and support vector machines have enabled recent photo identification advances. This article discusses the second stage of the pre-processing procedure, which is adding a filter to the image after it has been segmented in order to make it seem more appealing. It works to identify the area of interest and improve the image by removing the breast border in order to apply filtering algorithms. The breast image's edge is reconstructed using morphological processes in the segmentation method that has been proposed, and breast masses are found by subtracting the two images. In addition, a modified bi-level histogram and homomorphic filters were used in order to improve the image's quality by reducing noise and enhancing contrast.

Keywords: bilateral subtraction; cancer; deep learning; enhancement filter; image segmentation; image security; mammography

1 INTRODUCTION

The sophisticated image processing techniques, such as segmentation and enhancement, are the primary emphasis of this study's investigation [1]. The strategy entails finding the area of interest, masking off the breast border, and then applying various filtering algorithms to the image in order to improve it. The suggested method for image segmentation includes many components [2-3], including breast image edge restoration via the use of morphological processes, as well as breast mass identification through the use of bilateral image subtraction. A modified bi-level histogram and homomorphic filters were applied to the image that had previously been processed in order to find noise and boost the contrast level.

In Sections 2 and 3, we discuss the principles of algorithms for image segmentation [4], border detection, and contrast enhancement. These topics are covered in more detail below. In the article's fourth and final part, a discussion of how the problem may be fixed is presented. A summary of the proposed approach is provided in the third section of this article. In Section 6, we demonstrate how to segment images with mathematical morphological operations, improved morphological border recognition, and bilateral subtraction. In Section 7, we provide a comprehensive explanation of the suggested approach to improving contrast, which makes use of a modified bi-level histogram and a homomorphic filter (MBH-HF). The experimental analysis is the subject of the eighth part of the research, and it covers a wide range of issues, including the assessment measures, the datasets that were employed, and the interpretation of the results. The findings of the investigation are detailed in Section 13 of the report in this package.

The Major Contributions of the research article are as follows:

- In order to classify the current state of artificial intelligence application and the difficulties that are linked with it, this essay takes a case study method.
- The authors of the study investigate several ideas and methods for applying AI to the creation of unique goods in a variety of industries.

2 MEDICAL IMAGE SEGMENTATION WITH BOUNDARY DETECTION

Mammography is by far the most successful way of screening for breast cancer due to the fact that it produces an image of the breasts inside. The fact that these images are hard to understand because of the high degree of distortion and disruption they include [5] contributes to the difficulty of finding malignant tumors early in their development, which already presents a challenge in and of itself. Image pre-processing is an important approach that should be used whenever there is a need to improve the accuracy of the classification of malignant tissues. This is due to the fact that it improves the image by getting rid of unimportant factors that might otherwise have an effect on the genuine positive rate. Before the underlying photo can be digitally processed, all of the labels, markers, the pectoral muscle [6] and the background need to be removed. The digital image is used to generate a histogram, which is then applied to the image in order to modify it and normalize it.

2.1 Contrast Enhancement

The histogram of an image is often a graphical representation of the different gray-level intensities as well as a description of how the image looks. It is possible to utilize histogram methods in order to increase the overall quality of an image as well as its look. Utilizing the histogram

in conjunction [7] with the histogram equalization technique is a common method for increasing contrast and improving the overall image quality. When equalization is accomplished, the needed intensity is converted into a constant intensity that is spread over the whole image in a manner that is consistent [8]. Retaining the brightness of the light Bi-Histogram Histogram equalization was used so that the situation might be improved upon (BBHE). The histogram of the input image is divided into two sub-histograms based on the average intensity value, and then each sub-histogram is equalized on its own to keep the image bright.

2.2 Histogram Equalization

The technique for histogram equalization places a greater emphasis on the total amount of data than it does on any other consideration. This served as the impetus for the development of a method known as adaptive histogram equalization (AHE), which makes adjustments for alterations in the local context of an image rather than the context of the image as a whole. However, the approach results in an unhealthy increase in contrast and modifies the image's component parts in undesirable ways. CLAHE [9], which stands for contrast level adaptive equalization, is a revolutionary method that decreases the contrast level by raising it (CLAHE).

Histograms of colours display the distribution of colours across pixels in an image. The red, green, and blue components of a picture cannot each have their own histogram equalisation performed on them separately without having a significant impact on the image's colour balance. If the image is converted to the HSL/HSV colour space, the technique may be used to adjust either the brightness or value channel of the picture without affecting the hue or saturation.

2.3 Contrast Limited Adaptive Histogram Equalization (CLAHE)

Unsharp During the masking-based image enhancement process, a low pass filter is used. If you remove the filter from the original photo, you will be able to get an image that is more pleasing to the eye. It emphasizes the most distinguishable aspects of an otherwise straightforward image. However, the mistake that occurs the most often is the excessive amplification of contrast regions, which just helps to enhance the background noise.

The contrast-limited adaptive histogram equalisation (CLAHE) algorithm was used to chest CT scans for the purpose of this investigation. In a matter of seconds, a machine may solve CLAHE. A parallel engine that is built from off-the-shelf components can calculate CLAHE in under four seconds, after an initial loading period of five seconds. Because of differences in how different observers calibrate their equipment, agreement tests are unable to prove that the processing is successful for a variety of medical pictures.

2.4 Unsharp Masking (US)

In order to get the best possible results, equalization based on the histogram is used. The mapping component from the prior technique is included into this new approach, and a modified histogram is also included. After the facts have been gathered, the technique organizes them in a manner that enhances the value of the local area [10].

2.5 Histogram Modified – Local Contrast Enhancement (HMLCE)

The contrast of the image will be enhanced. Another method called the Bi-level Histogram Modification-Adaptive Nonlinear Filter (BHM-ANF) [11] is capable of producing results that are similar to those of the first method. In this method, the filter technique is responsible for improving the local contrast, while the bi-level histogram is responsible for improving the overall contrast.

3 LITERATURE REVIEW

Even before you segment an image, you get rid of the distracting background and bring the most important parts to the front. This makes it easier for the viewer to understand the image. In a nutshell, the process involves cutting the image into many small images, called "pixels," so that patterns can be searched for based on a set of rules. Several methods, such as thresholding [12, 13], filtering [14, 15], area expansion [15], statistical models [16, 17], convolutional networks [18, 19], and clustering [18, 19], are used to break the image into pieces that are easier to understand.

[16] Protocols for finding breast cancer were written down in great detail. Mammograms and MRIs are both good ways to find out if someone has breast cancer. Mammograms may help find breast cancer, but MRIs are better. Several different methods, such as edge detection and threshold-based approaches, were used to separate the tumors that could be seen in the image. Several operators worked on the final image, and the entropy of the images they made afterward was looked at to see how well they did their jobs [17] showed a way to find and get rid of the border that was based on how the intensity of the data changed. This was done by using a spatial averaging filter to smooth the image and then a gradient-based histogram thresholding algorithm to separate the image into its parts.

4 PROPOSED METHODOLOGIES

New prospects for study have opened up thanks to developments in machine learning and image processing methods. Extracting and analysing visual data is now a capability of machine learning. It's possible that machine learning and image processing may make security even better. Image processing contributes to both online and offline security. Examples of these types of applications include homeland security, surveillance software, ID verification, and physical security programmes. Protecting data is essential to ensuring digital safety. There are a few

ways to protect digital data, including steganography, network security, and digital watermarking.

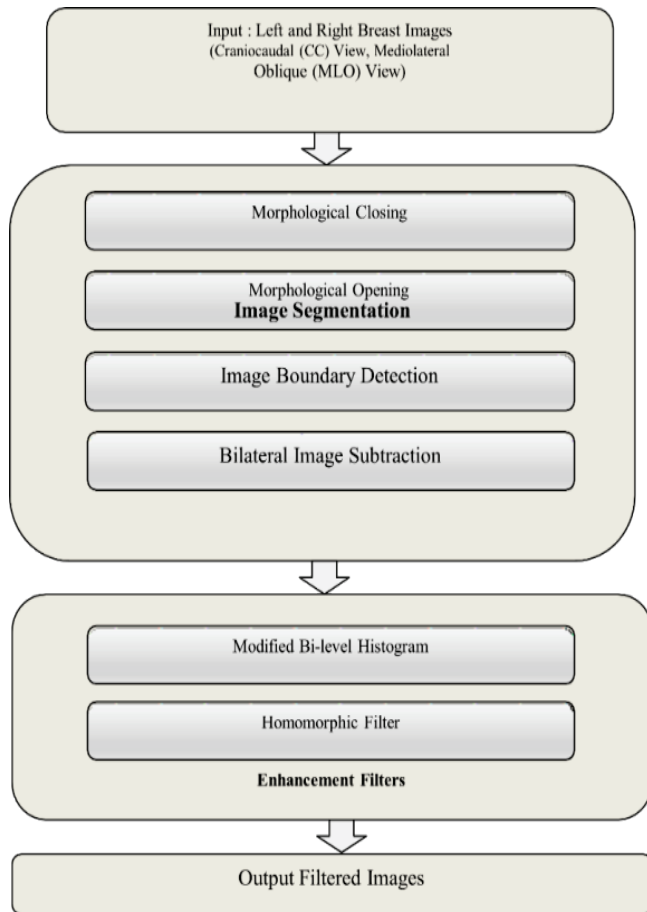


Figure 1 Showing the work flow of the proposed methodology

5 MEDICAL IMAGE SEGMENTATION FOR SECURITY

When preparing a photo for segmentation, the unneeded background is first eliminated, and then the main elements are brought to the front. This helps to improve the overall understanding of the image. In a nutshell, what it includes is dividing the image into numerous separate images ("pixels") so that patterns may be looked for using a certain set of criteria that has been specified beforehand. There are a variety of methods that may be used to simplify the image, including: thresholding [12, 13], filtering [14, 15], enlarging the area [15] using statistical models [16, 17] convolutional networks [18, 19] and clustering [18, 19].

There is a comprehensive record of the processes involved in breast cancer detection [16, 20, 21]. It's possible that breast cancer may be diagnosed with the use of mammograms as well as magnetic resonance imaging (MRI). Despite the fact that mammograms may be helpful in the identification of breast cancer, magnetic resonance imaging scans are far more accurate. Several different methods, such as threshold-based algorithms and edge detection, were used in order to isolate the tumors present in the image. The final image was created by a number of different operators, and the performance of those operators was judged based on the

entropy of succeeding images they generated. Changes in the data intensity were used in order to detect the border and then remove it [17]. To achieve this, a spatial averaging filter was employed to generate a uniform backdrop, and a gradient-based histogram thresholding approach was used to remove individual items from the resulting image. Both of these techniques are described in the following paragraphs.

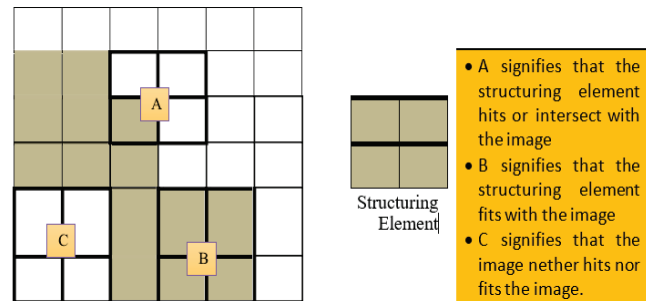


Figure 2 Probing of the binary image for the security in medical image analysis

In the event that the test is successful, the result of the morphological operations carried out on the binary image should be another binary image with the same size and a value of 1. This method makes it possible to conduct an examination of the shape of the image as well as to modify its features while still preserving the data and defining traits that it has. Erosion and expansion are two of the most basic morphological processes, and they may be seen almost everywhere. The dilation method often results in an increase in the number of pixels located at the image's borders. In order to produce an image denoted by the letter g , an image denoted by the letter f must first be subjected to a dilation operation, which is represented by the equation $g = f \times s$. By comparing the values of the pixels to the structuring element one may get a technique for obtaining the final image.

When, these are the coordinates that are input (x, y) . This process is repeated several times for each individual pixel. In addition, the number of additional pixels that are added to the image that is being used as the basis for the output image is determined by the size and shape of the structuring element. Since the margins of objects do not often need a great deal of attention, it is possible for them to "erode" away over time. Assuming that we started with an image denoted f and then added a structural element denoted s by a process known as erosion, the resulting image, denoted g , may be mathematically expressed as $g = f + s$. The answer, which is denoted by the equation, is the letter g in the image.

Once the pixel coordinates have been entered (x, y) . This process is repeated several times for each individual pixel. To generate the output image from the source image, a certain number of pixels will need to be extracted, and this number is determined not only by the size of the structuring element but also by its shape. The binary image may be seen as a result of using a method that involves both erosion and dilation [17]. In the end, morphological openness brings to a rounding off of the image's corners, a weakening of linkages, and the removal of any minute projections or relationships between things. On the basis of the whole structure, the

boring zone has been removed. This strategy, denoted by the equal sign (=), is the fairest of the other options.

In order to improve the visibility of the image under the surface, it has been suggested that a bi-level histogram, in combination with a homomorphic filter, be used. There are two separate levels in this building. Increasing the image's contrast is the primary objective of the first step of the process, during which the bi-level histogram is modified. To achieve more clarity, step two's processing makes use of the homomorphic filter.

6 PROPOSED CONTRAST ENHANCEMENT USING MODIFIED BI-LEVEL HISTOGRAM WITH HOMOMORPHIC FILTER (MBH-HF)

Increasing contrast may be accomplished in a number of ways, the one that is the most common and easy being the adjustment and levelling of the image's intensities. Equalization of the histogram's intensity levels is accomplished according to the notion that intensity levels should be dispersed evenly over the graph. The fact that there is no opportunity for the user to modify the amount of contrast in the image is the most significant drawback of this strategy. This is because the level of contrast is automatically applied owing to the uniform distribution. The process of developing the framework for the new and improved histogram. The histogram of the original image is altered by these two methods in such a way that it resembles the uniform histogram in a greater degree. Now is the moment to make any necessary adjustments to the histogram so that the image's brightness may be maintained while the contrast is increased. The histogram is cut in half using this method, with each section corresponding to one half of the image's mean intensity value (Imean) [11]. Histogram, abbreviated as H, and uniform histogram, abbreviated as Hu, are both terms that refer to the same thing. The primary histogram may be subdivided into two sub histograms, which are denoted by the names Hlower and Hupper respectively. It is advised that the chosen histogram have an intensity value that is lower than the mean intensity value of the other histograms. Histogram Hupper is the one in which the intensity values are greater than the value that is considered to be the norm for the intensity values (Histogram Imean).

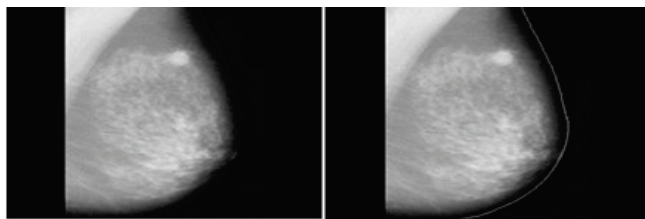


Figure 3 Breast border extraction for the image

$$H_{\text{higher}} = (1 - \alpha) \cdot H_{\text{lower}} + \alpha H_u, \quad (1)$$

Where $0 \leq \alpha \leq 1$. When we use the equations that were just discussed, we are able to understand that calculating the value of α is the most difficult part of the process. When this

function is told to create H_u , a uniform histogram with increased contrast, setting it to $\alpha = 1$ has this effect. A decrease in H may be thought of as the opposite of what occurs when $\alpha = 0$. In Eq. (1), the function returns the input H_{upper} when the parameter $\alpha = 1$; however, when the parameter $\alpha = 0$, the function returns the uniform histogram H_u . The significance of the number 0.55 was highest among all of those that we tested. As a consequence of this, 0.55 has been decided to be the best possible value for the new histogram. (Agarwal et al.). The final modified histogram, denoted by the symbol H' , is obtained by adding the values of the altered sub-histograms, denoted by the symbols H'_{lower} and H'_{higher} .

Table 1 Comparison of breast boundary extraction methods

Breast border extraction methods	Number of images used in the study	Detection Rate
Intensity Gradient Based	322	89%
Region Growing	40	100%
Adaptive Histogram	320	98%
Active Contour	84	96%
Morphology	322	98.75%
Enhanced Morphological based boundary detection	100	99%

As a consequence of this, the strategy that was described ends up producing a histogram that is quite similar to the standard histogram. A modified bi-level histogram is used in Phase I for the purpose of improving contrast.

7 RESULTS AND DISCUSSIONS

The technique that is described in this chapter has been tested experimentally before being included here. In order to evaluate how successful, the suggested technique is, we make use of the database maintained by the Mammographic Image Analysis Society (MIAS). It has been shown that the one-of-a-kind way for locating the breast's margins and improving the overall image is more effective than the methods that have been used in the past. A database of digital mammograms has been established by the Mammographic Image Analysis Society (MIAS) in response to the requirements of research groups in the UK. The films from the UK National Breast Screening Programme are digitized to a pixel edge of 50 microns, and the database is used to evaluate the approach. A Joyce-Loebl scanning micro densitometer is one tool that may be used for the purpose of digitizing the 8-bitword of a pixel. The archive contains 161 pairs of images of the right and left breasts of the same patient, as well as 322 digitalized films and comments from the radiologist describing where and what was wrong.

In order to test the boundary extraction by image segmentation approach, we picked 100 breast images at random from the MIAS database for the purpose of this experiment. The strategy that is advocated makes use of openness and closure approaches that are derived from the study of morphology. The suggested method was applied to a total of one hundred images drawn from the MIAS image database in order to test its efficacy. Using the technique that was proposed, the borders of ninety-nine images were completely restored, while the border of the one remaining

photo was only partially restored. A knowledgeable radiologist performs a manual check at the method-generated border to ensure its accuracy. The reference that was utilized to generate the sample boundary for the breast image does not appear in Fig. 4.

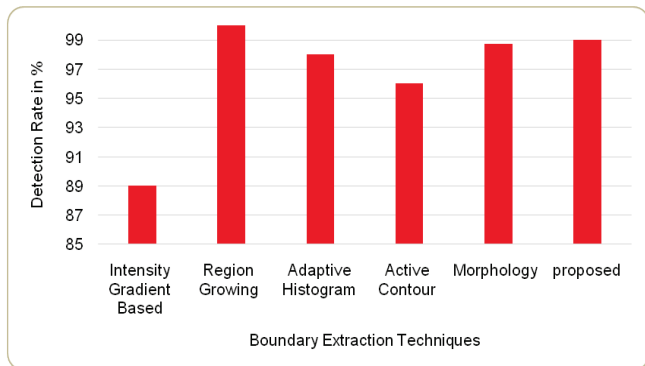


Figure 4 Comparison of boundary extraction techniques

Comparison to other approaches that are currently being used demonstrates that the suggested technique is more successful. Tab. 2 provides an illustration of the difference. The novel technique, which is based on morphology, is evaluated in comparison to the existing methods of Intensity Gradient Based Threshold with Region Growing, Active Contour, and Morphology.

The technique that has been suggested has a success record of 99 percent. The region-expanding strategy, which yields a result of 100% and requires an input size of forty, produces the greatest possible outcome. However, when

applied to a set of one hundred images, the augmented morphological technique is shown to be quite successful. This study examines the effectiveness of the suggested method by applying it to 14 mammograms taken from the MIAS dataset, which include both normal and cancerous tissue. The calculated EME value for the original image is 16,563, and the same calculation is performed on both the original image and the suggested method. You may see the results in their entirety in Tab. 2. On the other hand, the values of the average EME for the HE, BBHE, US, and HM-LCE methods are, respectively, 5.896, 13.581, 8.125, and 14.25. These values are less than the average EME value of the original photos, and they are undesirable since they are unable to improve the information that is being hidden from view. The average EME for CLAHE is 26.501, which is fairly high and obscures some of the more subtle aspects of the image. The average EME values are extremely high when considering the MBH-HF and BHM-ANF methods that have been recommended. Therefore, MBH-HF is superior to the methods that we are now aware of. AMBE is a different approach of determining whether or not an image has been successfully modified. The purpose of this exercise is to see how various techniques compare and contrast with one another.

In the Tab. 3, the value of entropy that is the lowest indicates that the image enhancement was effective. As can be seen in table 4.6, the original image has an entropy value that is around 4,818 on average. Entropy values on average ranged from 5.050 for CLAHE to 4.939 for HM-LCE to 4.828 for the US to 4.715 for BHM-ANF to 4.611 for BBHE.

Table 2 Comparison of EME values various enhancement techniques

File Name	Original	HE	BBHE	CLAHE	US	HM-LCE	BHM-ANF	MBH-HF
mdb005	5.141	6.885	13.657	25.542	08.456	15.069	18.912	18.514
mdb023	14.652	7.979	14.152	28.389	12.268	15.744	17.652	17.054
mdb025	19.433	6.897	14.647	28.376	8.856	16.245	22.433	21.145
mdb028	17.610	6.136	12.489	25.840	10.808	13.140	20.610	19.450
mdb058	18.813	4.970	14.109	27.187	03.554	14.118	21.813	21.254
mdb063	15.469	3.685	12.457	26.197	04.811	12.156	18.469	17.654
mdb069	15.463	7.388	15.577	30.435	08.919	18.084	21.663	20.456
mdb178	16.561	1.533	09.034	17.266	04.179	05.672	19.561	18.245
mdb184	18.968	5.892	12.072	25.073	06.312	15.024	22.908	21.458
mdb186	19.826	2.802	10.954	20.240	11.633	07.544	22.826	21.698
mdb190	15.282	7.990	18.933	29.666	09.796	17.312	18.282	18.112
mdb193	19.830	6.606	12.999	30.325	06.720	16.653	22.830	22.150
mdb204	17.417	6.761	12.995	24.711	10.097	17.686	20.417	19.123
mdb206	17.412	7.014	16.058	31.767	07.348	15.046	20.412	19.452
Average	16.563	5.896	13.581	26.501	8.125	14.250	20.628	19.698

Table 3 Comparison of AMBE values various enhancement techniques

File Name	HE	BBHE	CLAHE	US	HM-LCE	BHM-ANF	MBH-HF
mdb005	85.071	34.296	20.126	0.091	48.047	16.054	09.874
mdb023	80.075	23.24	17.984	0.069	82.975	17.153	10.214
mdb025	90.501	33.813	18.624	0.058	50.551	16.56	09.745
mdb028	91.299	32.842	19.065	0.034	88.816	18.441	10.879
mdb058	111.726	30.982	22.185	0.049	62.74	20.554	11.475
mdb063	122.218	28.553	18.064	0.071	91.596	16.705	09.874
mdb069	92.974	31.167	14.094	0.052	91.396	15.771	09.945
mdb178	155.884	24.961	13.724	0.041	71.357	7.913	05.241
mdb184	86.604	31.618	19.738	0.047	79.865	18.405	10.425
mdb186	137.29	22.384	14.285	0.039	46.299	10.382	06.785

Table 4 Showing the various performance measure, the proposed method consistently provides better performance and thus the proposed method is proved to be efficient

File Name	Original	HE	BBHE	CLAHE	US	HM-LCE	BHM-ANF	MBH-HF
mdb005	5.176	3.966	4.124	5.417	5.188	5.433	5.189	4.287
mdb023	5.104	4.044	4.564	5.548	5.154	5.607	4.964	3.887
mdb025	5.410	3.987	5.009	5.542	5.415	5.562	5.009	4.125
mdb028	5.580	4.220	4.907	5.691	5.59	5.651	4.907	4.245
mdb058	4.232	3.052	4.122	4.406	4.235	4.396	4.122	3.945
mdb063	4.119	2.896	6.998	4.409	4.118	4.163	4.033	3.245
mdb069	5.519	4.280	4.868	5.662	5.514	5.629	5.868	4.124
mdb178	3.085	2.028	2.985	3.203	3.086	2.924	3.685	3.526
mdb184	4.900	3.673	4.618	5.163	4.909	5.101	4.668	3.887
mdb186	3.536	2.659	3.481	3.778	3.583	3.441	3.481	3.114
mdb190	5.135	4.049	4.574	5.454	5.133	5.374	4.874	3.458
mdb193	5.195	3.953	4.995	5.447	5.195	5.314	4.995	3.214
mdb204	5.422	4.263	4.587	5.683	5.433	5.599	5.487	3.914
mdb206	5.035	3.822	4.722	5.296	5.035	4.947	4.722	3.452
Average	4.818	3.635	4.611	5.05	4.828	4.939	4.715	3.745

The value of the suggested technique is 9.907, which places it in second place among the many ways to make improvements, behind only the US method, which has a value of 0.053. The CEM method is the third strategy that may be used to evaluate how well improvement projects are operating. The CEM values for each of the fourteen images that were produced utilizing a variety of tried-and-true and innovative processes are listed in the table that follows. In the last step, the entropy of an image is evaluated to determine the degree to which it has been enhanced. Tab. 4 displays the entropy values for the initial image, the improved image that was made using the traditional procedures, and the enhanced image that was created using the new methodology.

The strategy that was suggested has the average entropy value of 3,744, which places it in second place. With an average entropy value of 3.635%, HE has the lowest value among the various enhancement techniques when compared to the others was shown in the Tab. 4.

As a consequence of this, the technique that was recommended often results in improved performance across a range of performance metrics, which demonstrates that it is effective.

8 CONCLUSION AND FUTURE WORK

Investigation is being done on various image enhancement and segmentation algorithms. After the noise from the pre-processed image has been eliminated, the images are segmented using the method that has been supplied in order to get the Region of Interest and image border. By removing the breast border, the method that has been suggested draws more attention to the primary subject of the image. In the suggested method of breast image segmentation, the image borders of the breast are reconstructed through the use of morphological processes, and breast masses are eliminated via the use of bilateral image subtraction. We used a modified bi-level histogram in combination with homomorphic filters in order to find noise and increase the contrast of the pre-processed image. A method that is based on morphological opening and closing procedures was created and analysed in order to extract boundaries from the MIAS image database of mammograms. This was done by using the methodology. The recommended

technique searches for the target in a manner that is both more exhaustive and accurate (99.9% of the time). In addition to this, we explore and evaluate the suggested method for improving images (MBH-HF). Several distinct parameters, such as expected mean benefit (EME), average mean benefit (AMBE), maximum mean benefit (CME), and entropy, are used to conduct an analysis of the method's efficacy. The results show that it is superior to a number of other approaches that are already in use, with values of 19.7, 9.1, 1.28, and 3.75 respectively. The primary focus of future research will be on identifying and using fresh mammography imaging datasets and real-time images, in addition to deploying a variety of models for accurate diagnosis at the population level.

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