Mammography: A Review and Experimental Results

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Mammography, which exposes patients to a low dose of radiation, is often regarded as the simplest way for identifying breast cancer in its initial stages. However, there are certain risks associated with the procedure. It helps radio-graphic breast cancer examination detect any growth or lump in the early stages, even before it becomes obvious to the doctor or the woman herself, and that these rays are not dangerous if used at yearly intervals, as recommended by the National Guidelines for early breast cancer diagnosis. Radio-graphic breast cancer examination also helps detect any growth or lump in the early stages. The radiographic examination of breast cancer is another method that helps identify any growth or lump in the latter stages of the disease, even before the growth or lump is noticeable to the woman or the attending physician. Mammography is the only method that has been shown to be helpful in decreasing the mortality rate caused by breast cancer by diagnosing the disease at an earlier stage. This is because mammography detects breast cancer at its earliest stages. Mammography, despite the fact that it cannot prevent cancer 2, 9, has been found to be the approach that is the most successful in diagnosing breast cancer in its early stages.

LITERATURE REVIEW

In the computer-aided diagnosis (CAD) system that **Dheeba et al. (2016)** created to identify breast cancer based on mammography imaging modalities, the incorporation of textural information as an input was one of the researchers' primary focuses. In this investigation, the region of interest (ROI) is used to derive the laws texture energy measures (LTEM). This is accomplished by using five one-dimensional (1-D) convolutional kernels of length five. The processing of the images requires a convolutional kernel that is likewise two-dimensional (2-D), since the images themselves are structures that are only two dimensions in length and width. Convolving a one-dimensional vertical kernel with a one-dimensional horizontal kernel results in the production of this kernel. First, a set of features must be extracted, and then a non-linear filter must be applied to that set of features in order to calculate the LTEM value for each of the 15x15 pixels that make up the ROI. This will allow you to determine the LTEM value for each of the 15x15 pixels individually. Using this method, a feature map of the input image is constructed by first getting 25 TEM for each pixel and then normalising those values using zero-mean. The output of this process is the feature map. At the conclusion of the procedure, the recovered feature map is fed into a wavelet neural network for the classification, which yields an accuracy of 93.671% when applied to the dataset of 1064 mammography photos collected from 54 patients.

A wavelet-based covariance descriptor was used by Keskin et al. (2017) in order to categorise 14 different types of photos depicting human cancer cell lines. Cancer of the breast was the topic for seven of the sessions, while cancer of the liver was the topic for the other seven classes. In order to classify the photographs, the researchers used a number of different morphological criteria and performed calculations on them. The researchers arrived to the conclusion that dual-tree complex wavelet transform (DT-CWT) coefficients were the most effective choice when it came to features. This was due to the fact that edges are the most prominent feature in photographs of cancer cell lines. Because DT-CWT has the ability to characterise edges in a variety of orientations, it may be able to extract more discriminative properties from images. This would make it possible to conduct a more in-depth investigation of the morphology of cancer cells. In the current investigation, the process of segmentation comes first, followed by the selection of characteristics from the photographs. This is done because the photos in the dataset include a large quantity of background pixel, which makes the need for segmentation absolutely necessary. After modelling the image as a combination of two Gaussians and acquiring noisy patterns, the Expectation-Maximization (EM) approach is used to the data in order to get the best possible result. In order to reduce the amount of background noise, the morphological 'closure' operation and median filtering are being used. Following the selection of square windows at random from the image, a covariance matrix is created for each window on its own before moving on. After this, a support vector machine (SVM) classifier equipped with radial basis function (RBF) is trained on the generated matrices, which finally resulted in an accuracy of 98% being obtained on the dataset consisting of 840 photos.

Wentao Zhu (2021) Imaging in medicine is an essential method that may play a key part in both the diagnosis and treatment of a number of medical disorders. Imaging may play an important function in both the diagnosis and treatment of many medical conditions. However, in order to diagnose a patient or recommend a course of treatment, medical experts need to have a high level of education and the ability to interpret medical images. Reading medical photographs in their current format involves a significant amount of physical labour, a significant amount of time, a significant amount of financial investment, and it is fraught with the possibility of making errors. It would be desirable to have access to a computer-aided system that is capable of automatically giving diagnostic and therapeutic recommendations. Because of recent advancements in deep learning, we are now in a position to examine the processes that physicians employ to identify patients based on medical images. In this thesis, we will discuss 1) mammograms for the detection of breast cancers, which is the most common solid cancer diagnosed in women in the United States; 2) lung CT images for the detection of lung cancers, which is the most common malignant cancer diagnosed; and 3) head and neck CT images for the automated delineation of organs at risk in radiotherapy. Mammograms are used to detect breast cancer, which is the most common solid cancer diagnosed in women in the United States. We will explain how to leverage the adversarial approach to generate hard examples that will help enhance mammography mass segmentation in the initial part of this procedure. This will help us improve mammography mass segmentation. In the second section of this talk, we will demonstrate how to successfully develop deep learning for multi-instance learning in order to detect breast cancer using mammograms utilising data that only contains a few labels. This will be done using data that has been collected from patients. Third, the thesis will talk about the DeepLung system, which is an automated approach for finding and categorising lung nodules that makes use of GBM in combination with deep 3D ConvNets. This method was developed by the author of the thesis. Fourth, we will show how to improve an existing lung nodule recognition system by merging deep learning with a probabilistic visual model. This will be done so that the system can better predict the likelihood of a certain outcome. This will be accomplished by making use of data that only contains a scant amount of labelling. In conclusion, we will discuss the Anatomy Net, which is an automated system for segmenting anatomical data that is both thousands of times faster and more accurate than the systems that came before it.

DIAGNOSIS OF BREAST CANCER

During the course of the breast cancer diagnosis process, a number of different medical imaging techniques will be used. In its early stages, breast cancer may be diagnosed using mammography, ultrasound, and other imaging modalities such as magnetic resonance imaging and x-rays. During the diagnosis procedure for breast cancer, these imaging technologies are some examples of medical imaging techniques that may be used. After the breast cancer has been properly diagnosed, the next step is to begin talking about the various treatment options available. A breast mastectomy is a well-known surgical treatment that may remove malignant tissues from the breast and arrest the course of the illness, if the patient agrees to undergo the surgery. Following the administration of this treatment, one will certainly perish away.

X-RAY MAMMOGRAPHY

Through the use of x-rays and mammography, it is possible to detect breast cancer in its earliest stages. In X-ray mammography, the frequency range of 30 petahertz to 30 exahertz (3 times 1016 Hz to 3 times 1019 Hz) is the one that is most often used for the goal of detecting breast cancer. This is because these frequencies are very high. It is possible to create either a three-dimensional or a two-dimensional image of the patient's whole breast as part of the process of diagnosing breast cancer. The image obtained from the mammogram has a resolution of 20 line pairs per millimetre in terms of space. For women who have full breasts, the sensitivity of mammography, which uses X-rays, has increased by 98 percent over the last 50 years, allowing it to detect invasive breast cancer in 78 percent of cases. This is a significant improvement over the previous 50 years.

The technique has a major drawback in that its sensitivity is significantly reduced when applied to breasts that have dense tissue. This is a severe restriction of the method. Mammograms might be challenging to perform on younger women because the breast tissue in their breasts may be more dense than in older women. There is a correlation between having thick breasts and an increased risk of developing breast cancer; the sensitivity of mammography in women with thick breasts varies from 30–48 percent. The potential for the growth of malignant cells as a result of exposure to ionising radiation, as provided by X-rays, is still another limitation. One of the downsides of this method is the pain that is created by the compression of the breasts between the flat surfaces, which is also an additional drawback of the process. Figure illustrates a sample x-ray mammogram for your reference. This kind of digital mammography has the potential to detect breast cancer in women who are under the age of 50, who are premenopausal, and who have dense parenchyma in their breasts. The accuracy of the test is improved when applied to female patients who have thick breast tissue. Digital mammography does not eliminate the danger of acquiring non-calcified breast tumours that are covered by thick parenchyma, despite the fact that these types of malignancies are very rare. Carkaci et al. (2011).

ULTRASOUND IMAGING

Transmission of sound waves is the fundamental premise upon which ultrasonic imaging is founded in terms of its operational methodology. These sound waves will have a frequency that ranges from 2 MHz to 20 MHz, and in order to transmit them, a probe that has a transducer array will be used. This ultrasonic imaging method poses no danger at all due to the fact that it operates at a low frequency and generates images in a single plane. The ultrasound image that was made has a rate of frame generation that is around 25 frames per second when seen in real time. This ultrasonic imaging technique may detect breast tumours even in their early stages, even if they are as little as 3 millimetres in size. This is made possible by the transducers. The detection value of invasive lobular cancer may be predicted with a level of accuracy of 98% when ultrasonic imaging and mammography are coupled in this manner. With the use of ultrasonic imaging, the vast majority of invasive lobular carcinomas may be identified.

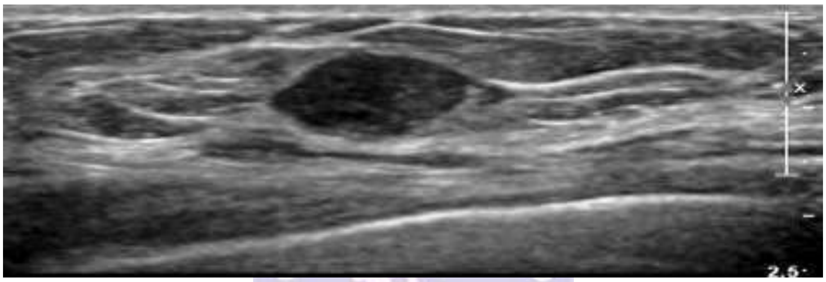

Figure: Ultrasound imaging for breast cancer detection

Even if ultrasonic imaging gives superior outcomes in the diagnosis of breast cancer, it will still have certain limits. These constraints include higher false positive rates, a high degree of operator reliance, gain that is altered in real time, zones that are focused on, a dynamic range, location of the patient, and pressure. The most major drawback is the inability to spot irregularities. Because of this, ultrasound is employed as a supplemental device for the goal of screening; however, in current times, scanning is carried out by transducers that are hand held, therefore the technique needs to be updated. In automated ultrasound imaging, both the image quality and the reliability are reproducible, and any fluctuation that may have been caused by individual users is avoided. In addition, automated ultrasound imaging will have a learning curve, which will require doctors to gain comprehension of datasets in order to properly employ the technology. The image acquired from an automated breast ultrasound has a greater resolution, which makes it more acceptable for use in the screening procedure for breast cancer. Cheng et al. (2010) Ultrasound is utilised to guide biopsies of suspected lesions because of its cheap cost, high comfort level, and great patient relief it brings. Through the use of ultrasound imaging, the need for stereotactic and MRI-guided treatments may be eliminated.

MAGNETIC RESONANCE IMAGING (MRI)

Prior to surgical excision of the breast cancer, magnetic resonance imaging (MRI) is used in order to precisely locate the cancerous growth at its precise location. Recent improvements in the temporal and spatial resolution of breast MRI have made it easier to spot ductal carcinoma in situ and small invasive tumours. These improvements have been made possible by recent technological developments. This is because there is a possibility that both of these forms of cancer might be diagnosed in the same location. Imaging techniques such as magnetic resonance imaging (MRI) and ultrasound are often employed in conjunction with one another in high-risk women. The magnetic resonance imaging (MRI) test is a quite pricey process, and gadolinium has to be given intravenously before it can be performed. As a consequence of receiving this injection, some of the patients wind up getting a condition known as nephrogenic systemic fibrosis. Abnormalities in renal function are one of the distinguishing features of this illness. If the patient has renal issues, they will not be able to reap any benefits from having a breast MRI done. Because it uses strong magnets, the MRI breast cancer test cannot be administered to patients who have previously been implanted with a pacemaker or any other kind of metal device. Figure depicts the mammography that is used as a screening tool for breast cancer.

DIGITAL IMAGE

The process of extracting information from digital photographs through the use of various computer algorithms is referred to as digital image analysis. It is possible to apply it to images in a wide variety of fields, such as the restoration of images in observational astronomy, the guidance of missiles in defense applications, the detection and tracking of small targets in security applications, the monitoring of deforestation through the use of remote sensing, and the diagnosis of breast cancer from microscopic images in medicine, the latter of which is the subject of this thesis. The purpose of the majority of applications for digital image analysis is to extract quantitative information from photographs, and there are many different types of techniques involved in this process. Quantitative information that may be useful to the diagnosis of breast cancer includes the size and irregularity distribution of cells, as well as the ratio of cells that are positive for a certain diagnostic biomarker to the total number of cells (both positive and negative). This chapter will provide an introduction to the fundamentals of digital image analysis, as well as some more advanced ideas that are of particular relevance to this thesis. It starts off with a brief discussion of the digital image and its fundamental constituents, including the relationships between those elements and the various representations of those interactions. After that, the idea of image filtering is presented, and then a more in-depth discussion of the primary topics that are covered by digital image analysis is provided. These topics include segmentation, feature extraction, classification, and registration. The following text describes the few image processing methods that are already in existence to locate the area of the mammography image containing cancer cells.

IMAGE SEGMENTATION

Image segmentation is a technique that may be applied in order to discover and identify objects and boundaries inside photos (such as lines, curves, and other similar features). Its major purpose is to divide a picture into a variety of subparts, each of which corresponds to a certain characteristic of the original image. According to Fan et al. (2005), characteristics might be determined based on certain limitations, contour, color, intensity, or texture pattern, geometric form, or any other pattern. The process of assessing and expressing a picture is simplified as a result of this factor.

Breast cancer is a prevalent illness that mostly affects females and is known to be lethal in most cases. The abnormal division and reproduction of breast duct cells, which is what ultimately leads to the development of a malignant tumor, is the root cause of this condition. Numerous studies have proved that an early identification of breast cancer may lead to successful therapies, which can, in turn, minimize the chance of dying as a result of the illness. Mammography is the approach that has been shown to be the most effective and ubiquitous in its use for the early identification of breast cancer.

Preprocessing Methodology

Mammography is regarded as the method of choice for making an early diagnosis of breast cancer, as stated by both Grady (2006) and Mencattini et al. (2008). Even while computerized analysis of mammograms cannot fully replace the work of human radiologists, an accurate computer-aided analysis technique may help radiologists arrive at results that are both more reliable and less time-consuming.

This section includes a description of the processes that may be used to construct a series of image processing procedures for mammography pictures. These processes can be used to develop a sequence of image processing operations. The algorithm stages I implemented for image preprocessing steps are

- Image segmentation
- Image Binarization
- Image Thinning

Gray Scale Extending

In this section, i discussed about the methodology for each stage of the image preprocessing algorithm, including modifications that have been made.

Segmentation

The basic objective of segmentation is to simplify and/or modify the representation of a picture into a meaningful image that is more suited and easier to analyze. This may be accomplished in a few different ways. Either omitting information that is not essential or reorganizing the information that is there are both viable options for reaching this goal. The word "segmentation" refers to a collection of methods that, when applied, make it possible to spatially divide contiguous parts of an image into individual objects. When discussing the field of digital image processing, the word "image segmentation" refers to a component that is absolutely necessary. According to the definition provided by Pichel et al. (2006), image segmentation is the process of allocating pixels to homogenous and discontinuous parts of an image. These areas distinguish one another within the overall composition and have similar aesthetic qualities. The process of image segmentation may be thought of as an activity.

The most important part of mammography is called the kernel stage, and it consists of accurately extracting breast tumors from a mammogram. This is because this stage has a significant impact on the overall analysis, accuracy, and processing speed of the whole breast tumor analysis. The reason for this is due to the fact that this stage has a significant effect on these aspects. Because of this, the first step in any additional inspection after a mammogram is to find any tumors and carefully separate them from the surrounding breast tissue.

The gray intensity of an area of pectoral muscle in the breast region of a mammogram is comparable to that of the breast tumor cells, and the pectoral muscle's texture may also be akin to that of certain abnormalities in the breast region of the mammogram. Both of these similarities are seen in the breast region of the mammogram. Gonzales and Woods (2002) state that the basis for the majority of segmentation algorithms can be traced back to one of the two primary characteristics of intensity values.

Image gray scale extending

After the previous stage of preprocessing has been finished, the mammography picture will next be stretched making use of the intensity variance. During the post-processing step of the mammography image processing, it will be possible to determine the precise position of cancer cells in the breast. This will be done in order to find their presence.

It is possible to approach it in a number of different ways, some of which include backdrop removal (Su et al., 2010), the water flow model (Hwa et al., 2005), mean and standard derivation of pixel values (Sauvola and Pietikainen, 2000), and local image contrast (Su et al., 2010). All of these methods are viable options. It has been shown that each of these approaches is successful. The global thresholding procedures are used when the background is continuous throughout the picture. However, local thresholding procedures may be especially beneficial in cases in which various parts of a document have different backgrounds or foregrounds that vary in darkness. This kind of scenario might arise when a document has a scanned image that was scanned at a varied resolution.

IMAGE BINARIZATION

After the mammography image has been segmented, it is then converted into binary form and put through a procedure called thinning, which reduces the ridge thickness to a width of only one pixel. When opposed to their binary counterparts, grayscale images are more difficult to interpret and analyze due to their lack of contrast. The process of converting an image into binary begins with selecting a threshold value to use as the basis for the conversion. After this phase has been finished, the pixels in the picture whose values are greater than the threshold are transformed into white pixels, while the pixels whose values are either less than or equal to the threshold are transformed into black pixels. The threshold value for each of the 8x8 blocks was determined by using the mean value of the image pixels as the basis for the calculation. The average of the item is represented by the numeral 1, while the average of the background is represented by the numeral 2. As can be seen in figure 28, the segmented picture was used in the process of creating a binarized version of the grayscale image. Using this procedure, the whole image will be converted into binary form. According to the findings of our own research and experiments, using this strategy produces the best possible outcomes.

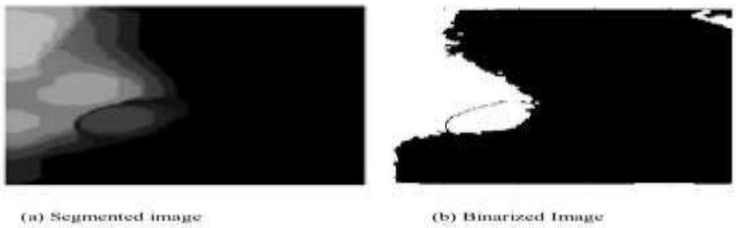

Figure: Result after Binarization process using thresholding method.

Image Size Has Been Reduced The procedure of thinning reduces the thickness of the ridges until they have a width of exactly one pixel. It is not difficult to develop an algorithm for the detection of minute features inside a more generalized image. It will be rather difficult to develop an algorithm for the detection of minute features if the width of the ridge is more than one pixel. When the image is thinned, the amount of space that is taken up by each ridge is just one pixel. A good example of an iterative algorithm is Zhang-Suen's approach for thinning trees, which he invented. The application of it is brisk and does not involve any complications. In this method, it is presumed that the point that represents the region in the image has a pixel value of "1," while the points that represent the background have a value of "0." The Zhang Suen method includes a number of iterations of two primary steps, both of which are carried out on the contour points of the region that is being studied. A pixel is considered to be a contour point if it has the value '1' and at least one of its 8 neighbors has a value of '0'. Figure 29 indicates that the thinning approach is able to correctly extract points without producing any disruptions to the continuity of the ridge flow pattern. This was shown by the fact that there were no interruptions to the flow pattern.

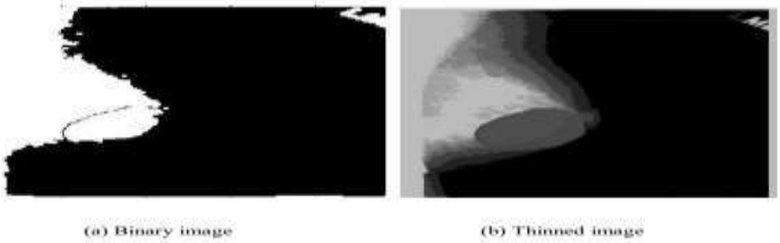

Figure: Results after applying Thinning process to the binarized Mammogram image.

The gradual shift from black to grey Another method, this one requires turning the image into binary format once the thinning process has been completed. This process might also be referred to as thinned binarization in light of this fact. Following the process of thinning, we then used this method to transform the image into a binary format by applying local thresholding in conjunction with global thresholding. The threshold value was established using the local thresholding technique by taking the average of the minimum and maximum intensities of all of the pixels that were included within the window. After then, this figure was used as the threshold value. The image was initially partitioned into 16 by 6 blocks before being binarized using this method approach. This was done so that a local threshold could be separately applied to each block. If the conditions for this threshold are not satisfied inside a block, we proceed to an alternative global thresholding strategy.

Figure 30 shows a depiction of the mammography that was generated by using the thinned binarization approach. This mammography was then shown.

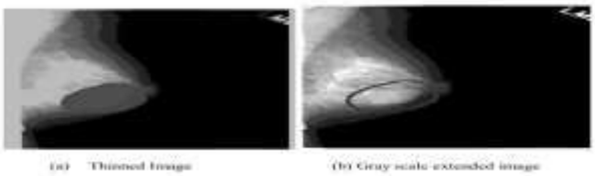

Figure: Result after applying Gray scale extension to thinned image.

Image Triangulation, in addition to Orientation of the Image When doing a mammogram, the pictures are often acquired from a slightly varied angle position on the detector module. This is done so that breast cancer may be better detected. In order for the post-processing stages to effectively evaluate a mammogram, it is necessary to have information about the local orientation of each pixel included within the image. This was determined by employing the pixel's 16 by 16 neighborhood, and it was considerably corrected in this research by dividing the image into 16 by 16 blocks and estimating the local orientation for each block centered at the pixel I(i,j). This resulted in a little more accurate representation of the image. Meshes composed of triangles are often the instrument of choice for the task of segmenting an image into several non-overlapping portions that have similar characteristics. The Delaunay triangulation of a collection of points creates triangles with regular forms and is thus selected above other triangulations for the purpose of image segmentation because it produces triangles from the collection of points. A Delaunay triangulation of a point set is a triangulation whose vertices are the point set, and it has the property that not a single point in the point set is inside the interior of the circum circle of any triangle in the triangulation. This is the defining feature of a Delaunay triangulation. The circle that passes across all three points of a triangle is known as the circumcircle of the triangle.

When deciding which category and pattern an image belongs in, the features of the image are the most significant criteria to take into consideration. In the case of breast mammography, the features that are obtained will be useful in identifying the class of the image (normal or abnormal) through the use of classifiers for training and testing. This will be the case. When comparing the feature values for the same image that were created by employing different segmentation methods, it is possible to see variations of 119 in the feature values. These variations may be noticed in the feature values. The feature that is recovered via the use of segmentation based on the method that we have described has the additional advantage of lowering the number of false positive findings, and it is effective at detecting infiltration sites in mammography pictures. This was offered as a benefit of the methodology that we have presented.

EXPERIMENTAL RESULTS

According to Health et al. (2000), the information that was utilised to create the Mammogram Database that was employed in this study could be found in the Digital Database for Screening Mammography (DDSM), which was made available to the general public. We used ten distinct datasets (Figure 34–43), and each of those datasets had three distinct categories of images (normal, benign, and malignant; a total of thirty photographs). These thirty pictures were chosen to act as input images for the algorithm that our team is currently trying to develop. The algorithm was proposed by another team. The database associated with the approach that was recommended is shown in an uncomplicated fashion in the following figures, which span from Figure.34 to Figure.43. This research has the potential to reduce the number of instances of cancer that are incorrectly diagnosed thanks to the methodologies and algorithms that were used in the study. In order to evaluate how well the proposed plan operates, we will do the following: It is possible to calculate sensitivity, specificity, and accuracy with the use of the following equation:

$$\text{Sensitivity (\%)} = \frac{TP}{TP+FN} \times 100$$

$$\text{Specificity (\%)} = \frac{TN}{TN+FP} \times 100$$

$$\text{Accuracy (\%)} = \frac{TP+TN}{N} \times 100$$

True Positive (TP) → An abnormal classified as abnormal
True Negative (TN) → A normal classified as normal
False Positive (FP) → A normal classified as abnormal
False Negative (FN) → An abnormal classified as normal
N → Total number of images

The whole representation is made up of three columns from left to right. The findings of mammograms that were performed after cancer treatment are shown in the first column of this table. The results of normal mammograms are exhibited in the third column, whereas the findings of benign mammography photographs are displayed in the second column. The statistics indicate the outcomes of each individual step after it has been carried out on each photo in turn. 34 to 43 (a) The preliminary photographs, (b) the results of the segmentation process, (c) the results of the binarization process, (d) the results of the thinning process, (e) the results of the grey scale extending process, (f) the results of the orientation process, (g) the results of the triangulation process, and (h) the results of the Euclidean distance transform. Following the application of all of the algorithms, regions of the mammography photos that include abnormalities are represented by the sign of a circle. This section is going to discuss two significant contributions that were made to the overall body of work that was conducted. When used in this setting, entirely automated algorithms provide a representation of breast cancer in the breast profile region. This method is the first of these four options, and it is also the most often employed. Second, this algorithm has been tested using mammography images taken from a variety of datasets, each of which represents a different stage of cancer, and it has shown a high degree of accuracy in its conclusions.

FUTURE PERSPECTIVES

When it comes to making a diagnosis for a complicated scenario, there are a lot of extra aspects that might be looked at throughout the categorization process. As a result, more research may be carried out to improve the functionality of the system and validate it via the use of more extensive digital mammography datasets in testing. That is not impossible.

- The combination of traits has shown to be a method that can be used to other qualities that were left out of this research, and it has proved that it can do so successfully. Because of the outcomes of the combination of traits, this is something that can be done.
- We have devised and put into practice a reliable set of processes for the extraction of mammography pictures. These techniques might be used to facilitate the continuation of research on small cysts that are benign (meaning they do not cause cancer) and cancer cell discoveries.
- The results of the work that was done for this thesis have been performed to a reasonably decent level. Despite this, there are always going to be a few changes that need to be made in order for us to be successful in achieving our goal.

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