EARLY DETECTION OF BREAST CANCER USING MAMMOGRAMS

Digital Signal Processing System Design Practice Project

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Introduction

Cancer is a disease characterized by irregular cell germination with the ability to spread to many sections of the body, posing a major health risk and ranking first among the leading causes of mortality worldwide. BC is the most common invasive cancer in women and a secondary major cause of mortality in women. In developing nations, it is rapidly becoming the primary cause of disability and death. Breast cancer cell growth is unregulated, and as the cancer spreads, the cell loses its structure.

In 2019, there are expected to be 268,600 new cases of invasive BC diagnosed in women and 2,670 new cases in men. The number of cases of DCIS detected in women is expected to rise to 48,200 in the near future. In 2019, approximately 41,760 women and 500 men are suspected of dying from BC.

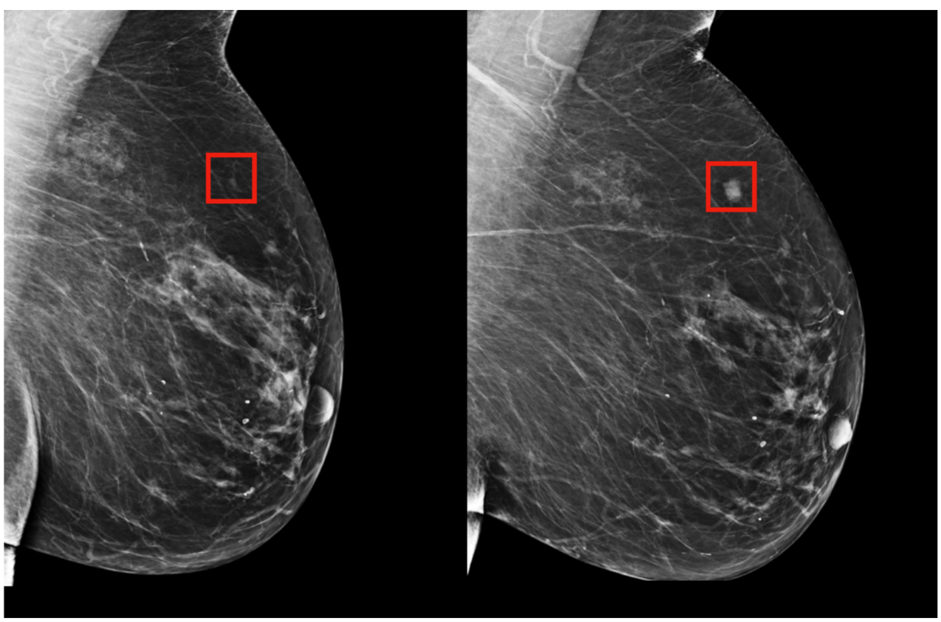

Fig 1: Tumor detection in breast

The stage of the tumor at the time of diagnosis has a significant impact on BC survival rates. Early diagnosis is required for proper treatment of patients, lowering mortality and morbidity rates. A high-performance diagnosis will aid a medical professional in diagnosing and selecting appropriate treatment for various types of cancer.Typically, BC is treated with surgery, followed by chemotherapy, hormone therapy, and radiation therapy. If cancer patients are treated initially, the disease may reoccur at any time. However, the majority of recurrence instances arise in the first five days after treatment. The detection of breast cancer by the use of several imaging techniques. Imaging modalities such as MRI, digital imaging, and ultrasound imaging are commonly employed.

Mammography is a valuable and effective tool for detecting anomalies in the breast. Breast cancer mortality can be reduced by 3075 percent with mammography screening. Experts can identify BC using two components of mammography screening. However, the accuracy of a diagnosis is determined by the specific approaches and views of a medical practitioner.

Background

As impactful image processing and machine learning techniques have advanced, computer assisted diagnosis has become even more common in all areas of medicine. These techniques continue to provide clinicians with stable and accurate large-scale testing of various image types to aid in illness detection. To identify the part which is affected in the breast we will use image processing concepts such as Histogram equalization, Morphological opening and closing, connected components, Filters, and other properties to locate them in this report.To identify the tumor part in breast, we must first do segmentation locate the part affected by the cancer. Histogram equalization is a preprocessing step for all images. After doing some preprocessing steps the part which is affected by the tumor will be detected.

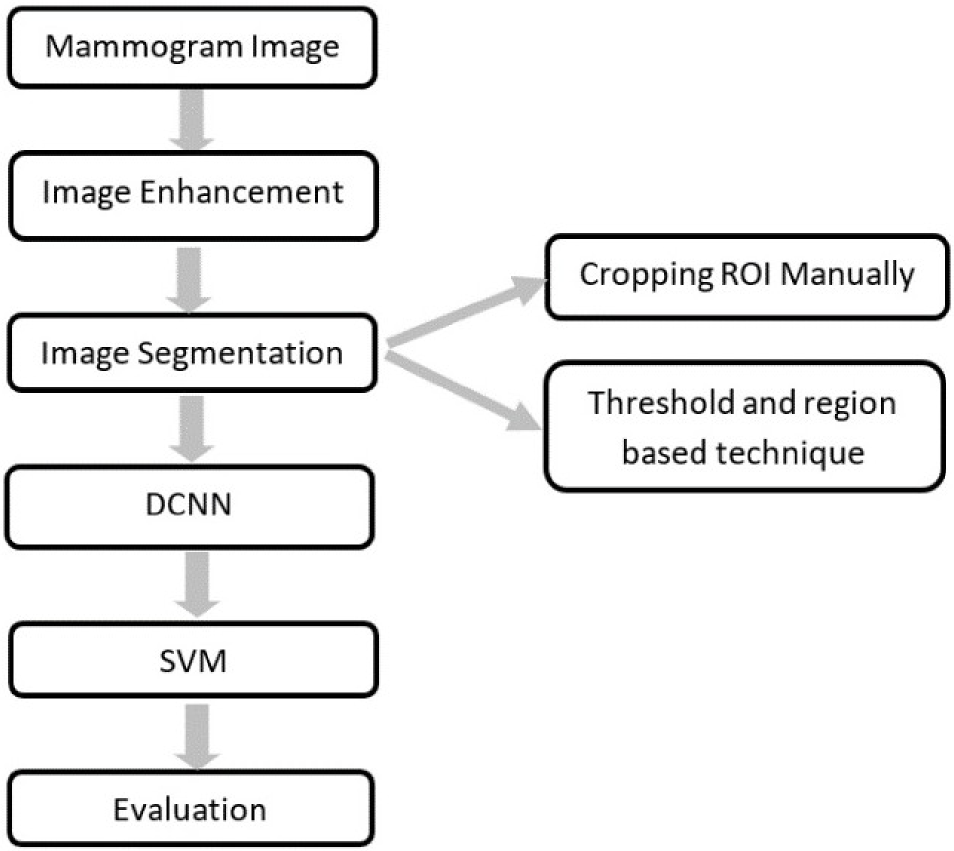

Fig 2: Step in achieving the objective

Proposed Methodology

In the proposed methodology we propose a method with the aim to create the ground truth masks and find the efficiency of the images across various mammograms. The images we took are from the IN-MIAS dataset. We separated the images which are benign and malignant(the cancerous one).

Contrast Limited Adaptive Histogram Equalization (CLAHE)

Histogram equalization is a key tool that is used in image processing and it makes image thresholding and segmentation tasks much easier If the image appears washed out or is of low contrast then the histogram can be stretched to span the entire histogram In this case, we use clahe, a kind of of adaptive histogram equalization in which the contrast amplification is restricted in order to minimize noise amplification. Rather than the complete image,it works on little parts of the image called tiles. To remove the false boundaries, the surrounding tiles are blended using bilinear interpolation. Here we apply this on the luminance channel which we have identified as green There are two parameters that can be assigned while using clahe:

1. Clip Limit –This parameter determines the contrast limiting threshold. The default setting is 40.
2. Title Grid Size –This parameter specifies the number of tiles in each row and column; the default value is 8*8.

Thresholding using otsu's Algorithm

The conversion of an image into a binary image is called thresholding. In general,it is used to transform a grayscale image into a binary image with pixel values as either 0 or 255. In this method we are required to select a value as Threshold T and set all the pixel values less than T to zero and all the other values to 255 Because we manually specified the value of T in the first place, this value is insignificant in the case of simple thresholding. Because we manually specified a thresholding value, there is no certainty that this threshold value T will operate in the event of lighting variations from one image to the next. In real-world situations when we don't know the lighting conditions before-hand then we need to automatically calculate an optimal Threshold value T.

This is where we use Otsu's Algorithm which provides an optimal Threshold value.The approach of Otsu presupposes that our image has two types of pixels: background and foreground. The algorithm looks for a threshold that reduces the intra-class variance,This is calculated using the weighted sum obtained from the 2 class variances

Circular blob Detection

A blob is a collection of connected pixels present in an image that has a common characteristic. Here we use the simpleBlobDetector to detect blobs and filter them on various characteristics . Thresholding, grouping, merging, are among the steps.

Thresholding: Here we convert the images into various binary images starting from a minThreshold and then incrementing this threshold in various iterations with the value of threshold step.

Grouping: In every binary image connected white pixels are connected together.

Merging: The centers of these blobs are identified and if their distances are less than minDistancebetweenblobs then they are combined.

Erosion

Two types of data are used as inputs to the erosion operator. The first input image is the one that is to be degraded . The second is the structural element, which is a (usually a small) grouping of coordinate points (also called a kernel). The structuring feature is responsible for the exact erosion effect on the input image. The mathematical definition of erosion is:

Assume Z contains the set for Euclidean coordinates of the binary image that is inputted, and Y is the set containing the coordinates for the structuring element. Let Yz stand for Y's translation with its origin at z. The erosion of Z by Y is the set containing all points z such that Yz is one subset of Z. As a result, when a binary image is eroded with a structuring element, the result is pixel value=1 in all coordinates(x,y) of the structuring element's origin in the locations where the structuring element fits the input image, otherwise value=0. The erosion with a small structuring element provides a shrinking effect

A larger structuring element generates a more intense erosion effect, yet repeated erosions with a smaller, similarly shaped structuring element can normally yield quite similar effects.

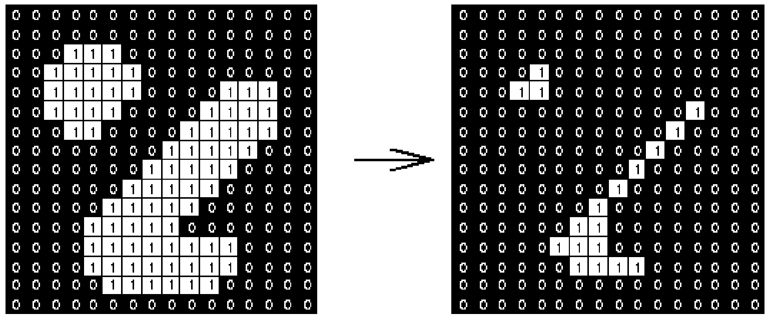

Fig 3: Erosion effect

Dilation

Two pieces of data are used as inputs to the dilation operator. The first input image is the one that is to be dilated. The second is the structural element, which is a (usually a small) grouping of coordinate points (also called a kernel). The structuring feature is responsible for the exact erosion effect on the input image. The mathematical definition of dilation is: Assume Z contains the set for Euclidean coordinates of the binary image that is inputted, and Y is the set containing the coordinates for the structuring element. Let Yz stand for Y's translation with its origin at z. The set of all the points z such that the intersection of Yz with Z is not empty is the dilation of Z by Y.

As a result, dilation of a binary image with a structuring element produces pixel values of 1 in all coordinates(x,y) of the structuring element origin at which the structuring element hits the input image, otherwise value=0. Dilation is the polar opposite of erosion in that it increases the number of pixels on both the inside and outside edges of regions

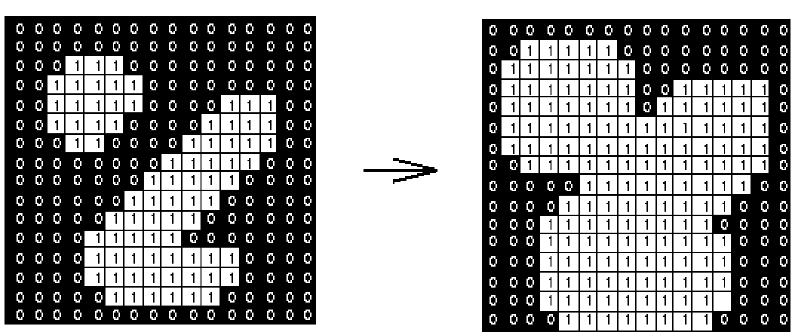

Fig 4: Dilation effect

Dilation causes many small gaps between regions to close and the sharpness of boundary edges is reduced.

Morphological Opening

There are a variety of defects in a binary image, particularly after thresholding, such as noise and texture distortions. By taking into account the image's form and structure, morphological image processing aims to eliminate these flaws. Morphological image processing entails a variety of non-linear operations based on an image's shape or features. The ordering of image pixel values, rather than numerical values, determines morphological image processing. To explore an image, morphological approaches make use of a small grouping of pixels or template known as the structuring element. This structuring element is placed in all of the image's available locations and compared/contrasted to the pixels in its immediate vicinity. Some operations determine whether an element ”fits” into its surroundings, while others determine whether it ”hits” or intersects them.

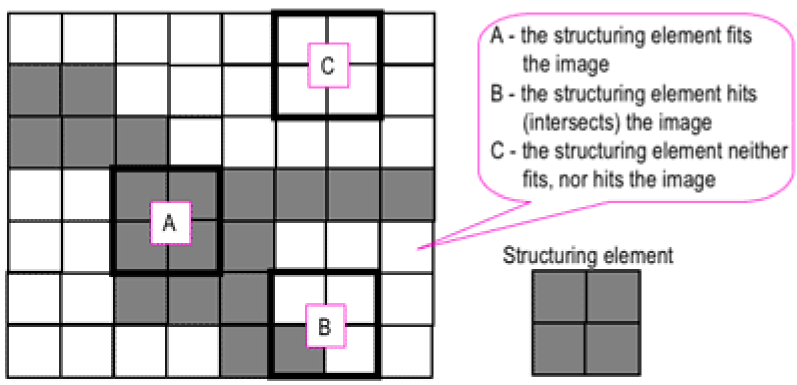

Fig 5: Morphological operations

If the testing at that position of the input image is successful, the output is an image with non-zero pixel values. The structuring element is a small image (a small matrix of pixels with pixel values of 1 or 0). The dimension of the matrix determines the size of the structuring element. The origin of the structuring element is mostly one of its pixels, but it can occasionally be present outside of the structuring element.

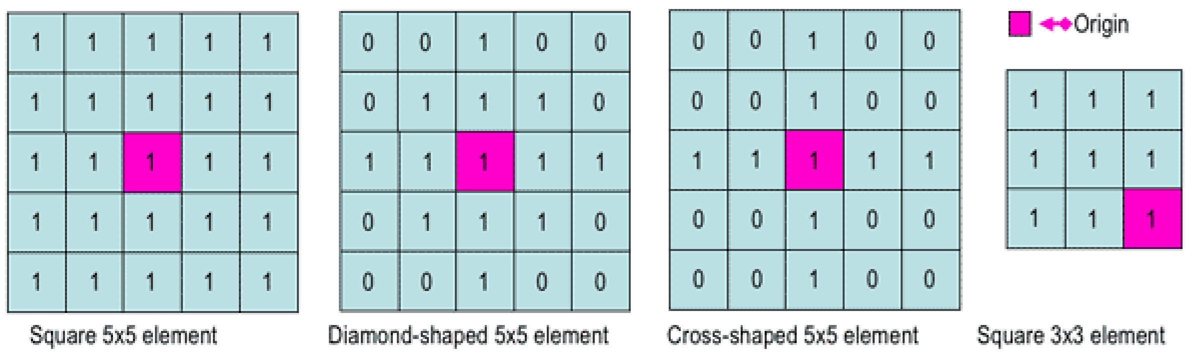

Fig 6: Morphological operations

Whenever the structuring element is inserted in a binary image, each pixel of the structuring element is correlated with an equivalent pixel of the neighborhood present under the structuring element. The structuring element is said to fit the image if each of its pixels is set to one and the corresponding picture pixel is also one. If at least one of a structuring element's pixels set to 1 corresponds to a matching picture pixel, it is said to hit, or intersect, an image.

An erosion followed by a dilation occurs when an image f is opened by a structuring element s denoted by f: $f \odot s = (f \ominus s) + s$

Morphological Closing, on the other hand, is a process in which a dilation operation is performed first, followed by an erosion operation i.e. $(f + s) \ominus s$

Image Preprocessing

We have the original gray scale image for which we need to do preprocessing.

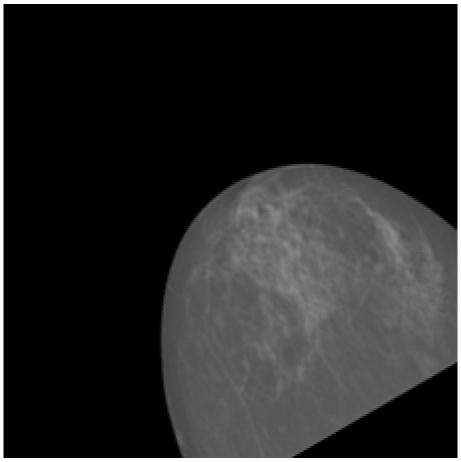

Fig 7: Benign case

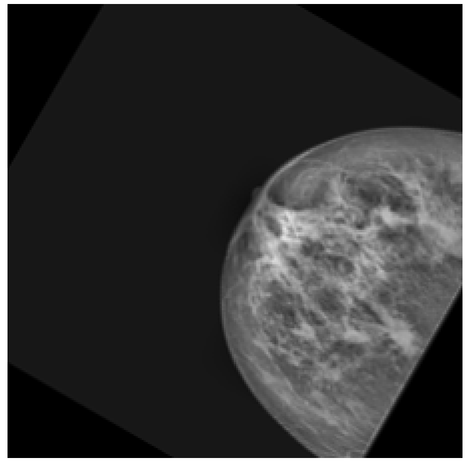

Fig 8: Malignant case

The Green channel of the color image is used as the gray level intensity in many medical images segmentation methods because it provides the most contrast.As a result, we isolated the green channel from the source photos in order to apply image processing procedures on the green channel rather than the gray scale image. We can do image processing operations on a gray-scale image if we like, but the results will be better if we

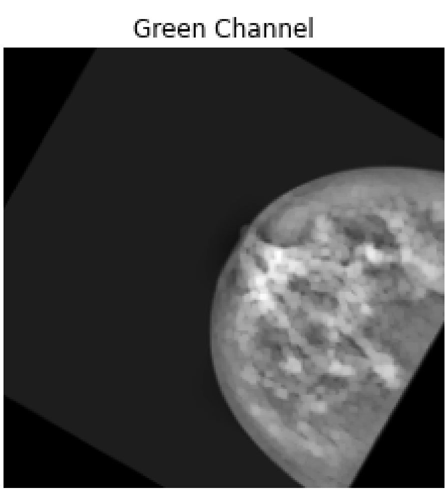

Fig 9 : Green channel of image(M)

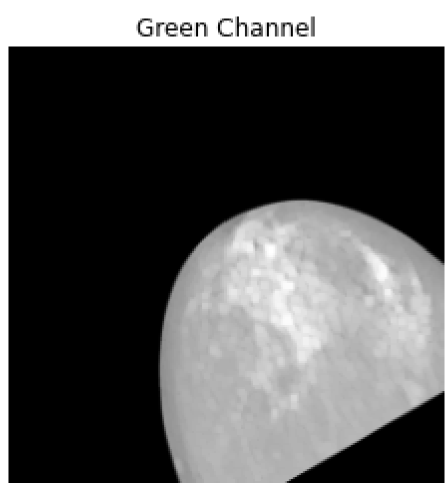

Fig 10: Green channel of image(B)

Now we’ll employ CLAHE, which prevents the contrast from being over-amped. CLAHE only works on small areas of an image, not the complete image. To remove the false boundaries, the surrounding tiny sections are blended using bilinear interpolation. Finally, we improve the image contrast and also the visibility of cloudy images.The Figure 11 shows Enhanced images after CLAHE has been applied on Fig 9 and Fig 10.

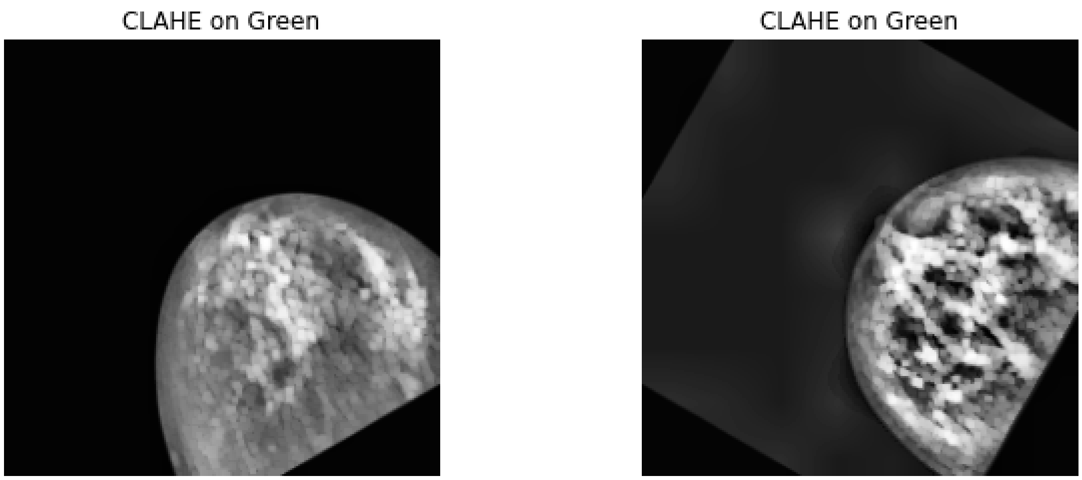

Fig 11: CLAHE of image Benign(left),Malignant(R)

Breast Segmentation

We’ll now use the bitwise not technique to invert the augmented image. Figure 12 shows the output after inverting the Enhanced image (11).

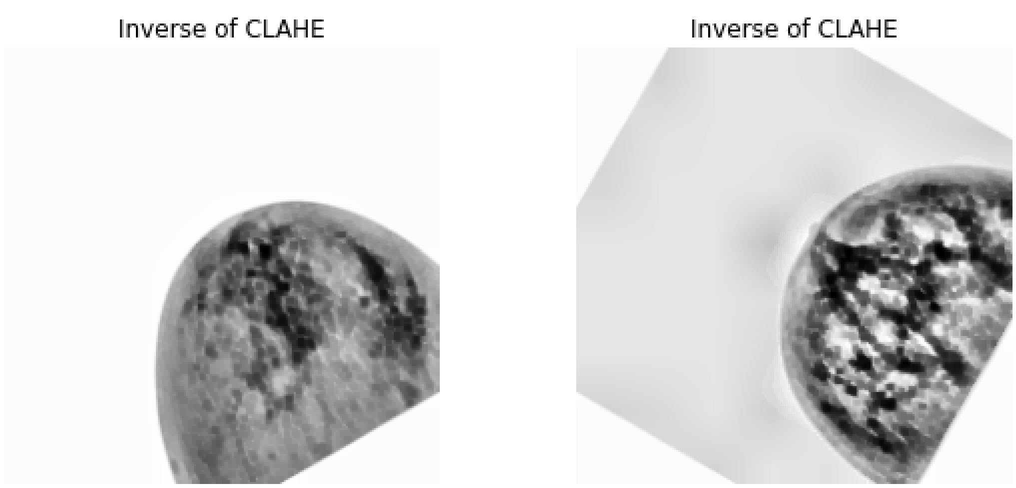

Fig 12: Inverted image of (Fig 11) Benign(left), Malignant(Right)

Now we'll use Morphological opening with a window size of 11 on the inverted image(12) to eliminate the brightly coloured blood vessels from the image, leaving only the backdrop without the blood vessel. The resulting image is depicted in the Figure 13

We now have an inverted image(12) that has the background including the regions with blood vessels with brighter pixels, as well as an image(13) that simply contains the inverted image's backdrop. If we subtract this backdrop from the inverted image, we will receive an output image that roughly has blood vessel structure with a slight white color and a black background, as we subtract each other. Figure 14 show the output after subtracting

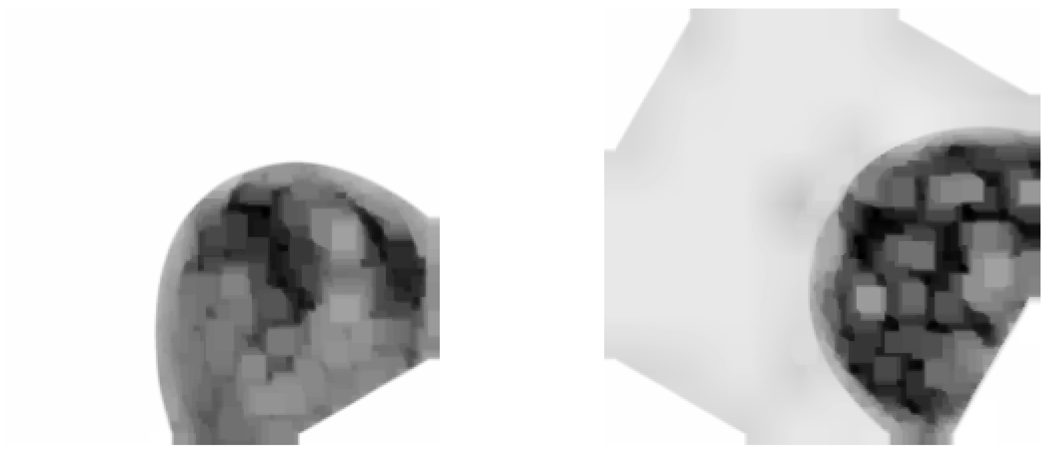

Fig 13: Morphological opening on fig 12

Inverted image from its background. The blood vessel region has a slightly higher intensity in Figure 14, and the image also contains some low and moderate range intensities.

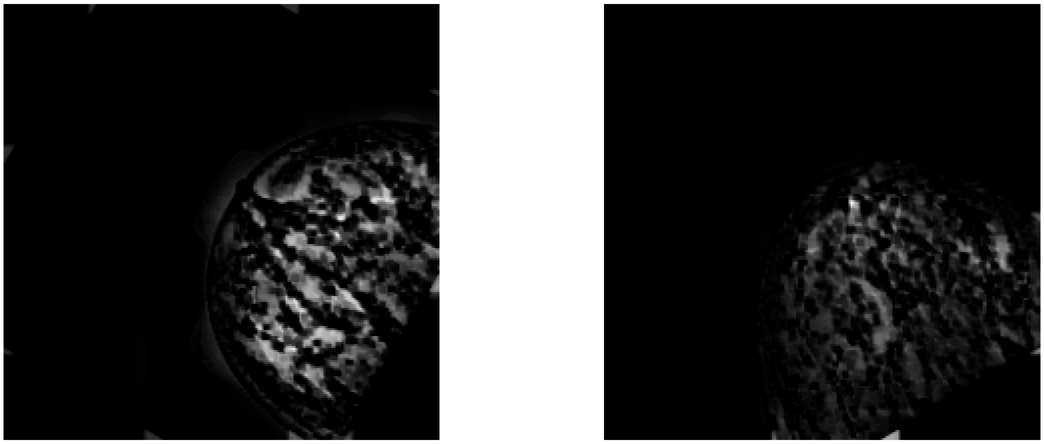

Fig 14: Subtraction of 12-13

Now we must divide all of these diverse parts into dark and light regions, separating the blood vessel from its surroundings. As a result, we'll employ thresholding, which involves changing the pixels in an image to make it easier to analyze. Thresholding is the process of converting a color or grayscale image into a binary image by comparing each pixel value to a predetermined threshold. Because variance is the dispersion of the distribution around the mean, the Optimal threshold will usually be the one with the least within class variance. We'll apply Otsu's thresholding in this scenario, which will aim to find a threshold value that minimizes the weighted within-class variance. Figure 15 show the output after applying Thresholding to Figure 14

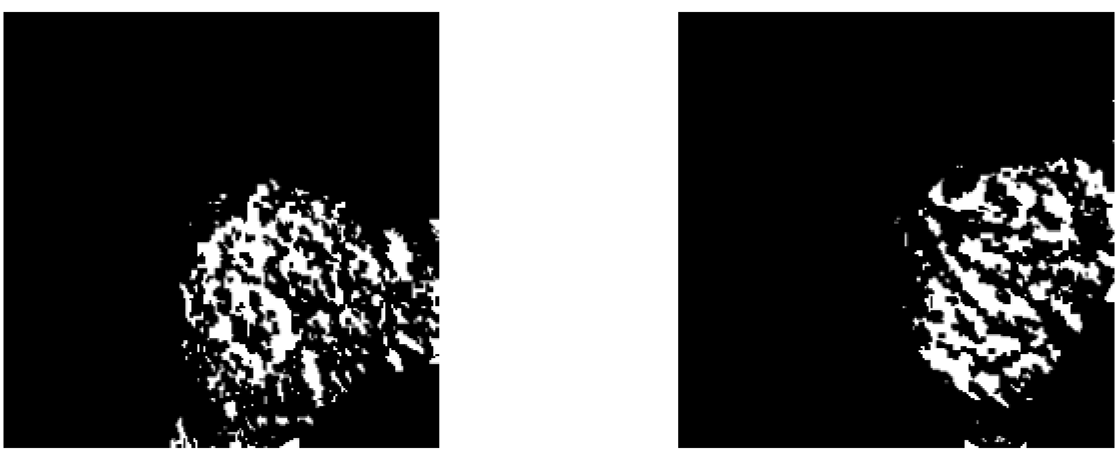

Fig 15: Thresholding of Fig 14

After performing the Closing and Thresholding and Arithmetic operations on the image the final output we will get as the generated ground truths for the images.

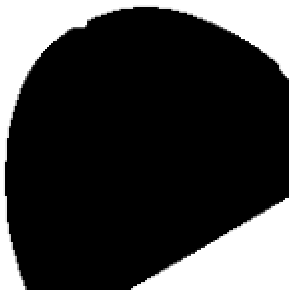

Fig 16: Generated ground truths Benign(left), Malignant(Right)

SEGMENTATION USING THE U NET:

U-Net is a convolutional neural network developed at the University of Freiburg's Computer Science Department for biomedical picture segmentation. The network is built on a fully convolutional network, but its architecture has been tweaked and expanded to allow it to function with fewer training photos and provide more exact segmentations. On a contemporary GPU, segmentation of a 512 512 image takes less than a second. The network has a u-shaped architecture because it has a contracting path and an expanded path. The contracting path is a conventional convolutional network, consisting of convolutions applied repeatedly, each followed by a rectified linear unit (ReLU) and a max pooling operation. The spatial information is reduced while the feature information is increased during the contraction. Through a series of up-convolutions and concatenations using high-resolution features from the contracting path, the expansive pathway combines feature and spatial information.

U-net Architecture

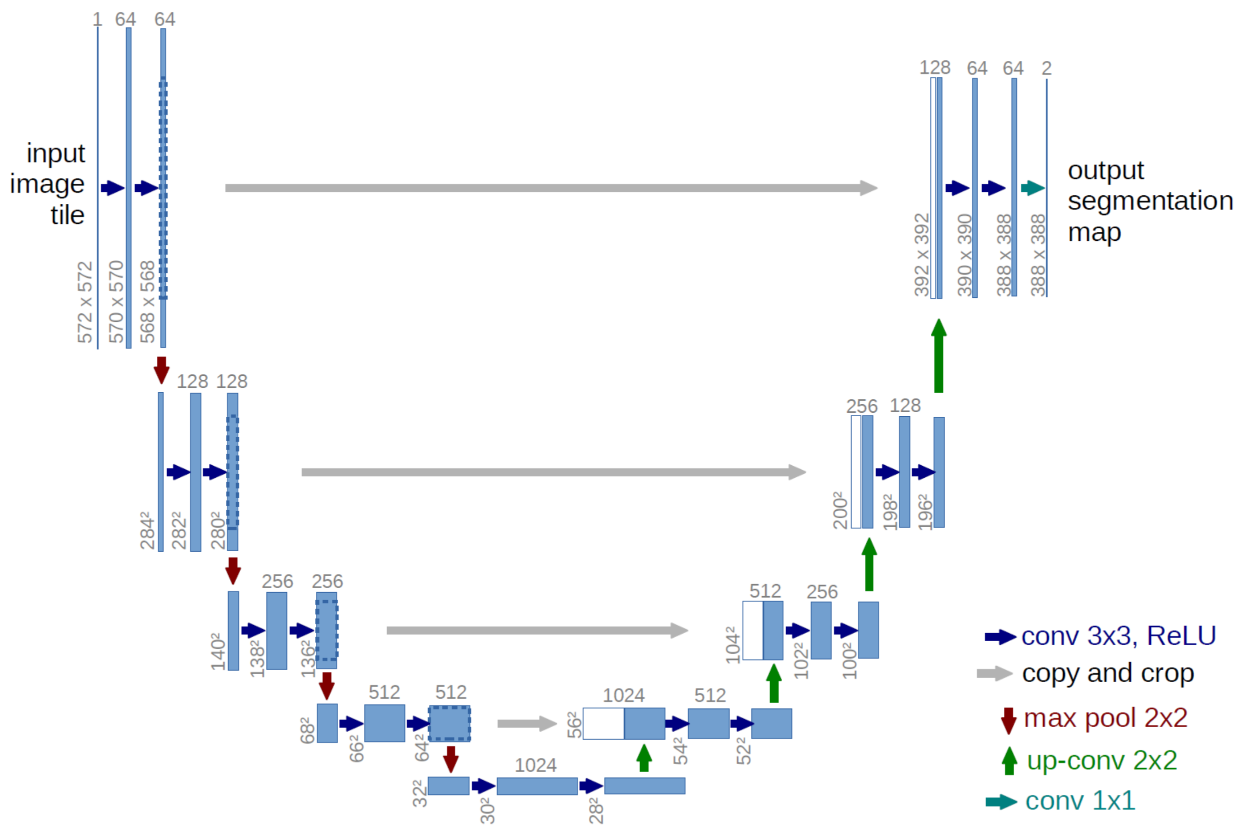

Fig 17: Unet architecture

Results from Unet

Fig 18: Segmented output image

Form fig(18) if we increase the epochs and the training images we increase precision of the output.