ASSESSMENT OF VARIOUS SEGMENTATION APPROACHES TO POSTER BREAST CANCER USING THERMAL IMAGES

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Abstract

The awareness of fatal diseases like cancer among human beings is well spread owed to improved technology and sophisticated education. Globally the mortality rate due to cancer is suppressed by 2.5% each year because of advanced treatment and early diagnosis. Among cancer varieties, most dangerous type is the breast cancer next to skin cancer targeting female population of majority risk. Based on age and gender breast cancer may occur without any symptoms for diagnosing the syndrome in early stage. To accelerate the detecting purpose image processing methods along with algorithms and statistical data are implemented for initial analysis of breast cancer. More standard techniques in detecting cancer are available like Digital mammogram, MRI and the recent emerging one is Thermography providing more positive results. The proposed method uses thermal images for detecting breast cancer using innovative segmentation procedures and comparing the performance of the suggested methods.

Keywords**:** breast cancer, syndrome, image processing methods, algorithms, statistical data, Digital mammogram, MRI, Thermography, segmentation.

1. Introduction

In spite of sophisticated screening test and treatment procedure, breast cancer is emerging as threatening weapon in India among young women also. Recent analysis reveals the fact that nearly breast cancer accounts for 13.5 % of other types grabbing around ten percent death due to the attack.[1]. Breast cancer occurs due to abnormal cells that develop without control resulting in lumps or mass. The lumps spread throughout the body if not noticed, slowly invading the tissues resulting in cancer. If primarily diagnosed can be treated for survival otherwise results in death. For this purpose proper screening test followed by standard procedures are necessary. One of the latest techniques based on infra-red images is the Thermography method using the images produced by the emitting light from the source. Thermography proves to be more reliable due to early prediction compared with other methods like mammogram or ultra sound. Thermal images accurately assess the temperature of an entity and precisely tell its heat level relative to its atmosphere.

One of the major applications of thermal images in medical field is the diagnosis procedure of serious syndromes in the early stage. The images are further processed using machine and deep learning techniques to detect the occurrence of the disease and various stages to find the patient phase for further investigation. Machine learning aims at automatic detection of the disease using different images based on the experience without human assistance for accuracy. Machine learning uses the algorithms for the prediction based on the features extracted using standard methods. [2]. The images are segmented to find whether the disease affected by extracting region of interest. If the presence of ailment is confirmed features like shape, color, contour, mass are extricated from the image to be used as input for classification.

The image processing techniques used in medical diagnosis seems to be influential so the extended methods like deep learning modes are implemented for better accuracy. The main advantage of deep learning is the instinctive feature extraction methods embedded in the classification networks so more features are learned useful for better classification of stages in the cancer. Deep learning contains various models like CNN architecture using transfer learning for improved performance to process the breast cancer images. [3]. Both machine learning and deep learning algorithms are used for processing of thermal images to identify whether a person is affected by cancer. The images are preprocessed and segmented using novel segmentation algorithms to find the normal and disease affected person.

2. Stages of Breast Cancer

The foremost symptom of breast cancer is the abnormality found around the breast region especially nearby the nipple part by a lump or form growing inside the skin. The patient should immediately consult the physicians for advance treatment and diagnose the stage the person is experiencing. There are three vital stages in which the patient may be and the treatment depends on the particular stage and dosage of radiation for curing the disease. The basics about the breast cancer can be non-invasive or invasive stage. Breast cancer occurs in either of the two stages and can be classified as advanced, middle and starting or initial stage. The first stage is the initial stage which is curable and does not spread to other parts whereas the other two stages are dreadful. The three important types in stages of breast cancer are given as Table 1 below.

Table1. Different Stages of Breast Cancer

S.NO	STAGE	NATURE	INDICATIONS
1	Initial	Clinical Prognostic	First stage based on family history, self-exam, biopsies. TNM system, Tumour grade, biomarkers are used.
2	Middle	Pathological	Next stage with surgery as treatment. Based on clinical information, lab test and biomarker status
3	Advanced	Anatomic	TNM system based information on size and spread of cancer.

Initial Stage – In medical terms stages 0 and 1 of the patients are represented as initial stage which is non - invasive and curable. The starting stage diagnosed by regular self-exam and by family history. The infection is represented as a rupture and non-spreadable to other regions. Mostly this stage is mild and can be treated easily.

Middle stage – The second stage of a patient is indicated by the middle stage where the mass or lump is shown clearly in the image of size 10mm. The stage needs vital treatment and maximum chances of survival are assured when diagnosed earlier.

Advanced Stage – The third and final stage of the sufferer is the advanced stage where the infection had spread to the extreme level. Vigorous treatment is needed and the survival rate is meagre in this stage.

Different stages of breast cancer syndrome using thermal images are shown in Fig.1 and compared to depict several stages.

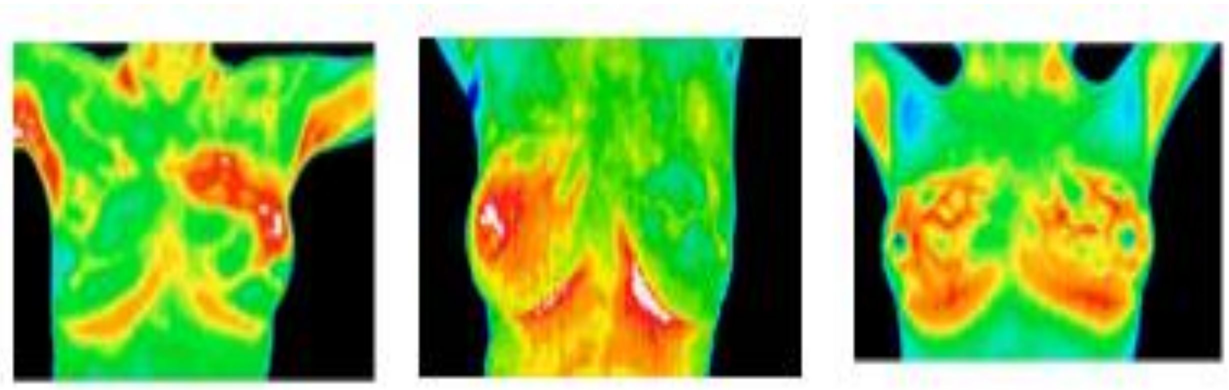

Fig.1. Various stages of Thermal Breast Cancer Images

The above figure contains three images showing three different stages of breast cancer. All are thermal images captured by special infra-red camera in identical dimensions and aspect ratio. The first image is the starting stage with tiny spot of infection indicated by red colour mixed with yellow border. The second image is the middle stage with one side breast region affected with more red surrounded by yellow colour. The last image is the advanced stage with both side breasts affected with full red colour representation. Thermal images can be used for comparison of all three stages.

3. Processing of Thermal Images

Acquired thermal images from different sources both online and from diagnosing clinics are used for processing to detect the presence of breast cancer. Thermal images are basically colour images and tedious pre-processing modes are unnecessary so simple techniques are utilized suitable for the next step. The next important step is segmentation where the images are segmented into uniform blocks to high lighten the affected region. The affected areas in the image are identified by their high pixel value indicated by dark colour probably red when compared with adjacent values. The images with affected regions are grouped as abnormal images used for the next step and the images with ordinary pixel values are normal images. Thus segmentation proves the normal person and differentiates from abnormal cancer affected entities.

4. Data set and Models

Thermal images needed for processing to identify breast cancer are retrieved from various online sources and repositories. Huge databases for breast cancer are available from DMR-IR, Ann Arbor Thermography and DBT-TU-JU thermal images. These images are captured by special cameras like FLIR 400 in JPEG and PNG format with high resolution and aspect ratio. The images are available in websites [4] for open access. Other cameras like FLIRE30 with 160 x 120 IR resolutions produce more clear images for processing of breast cancer. The usual size of the image is regularly 128 x 128 with pixels 16,384 for correct segmentation procedures.

5. Pre-processing of images

The acquired thermal images are colour metaphors with clear dimensions and contour which can be used directly for further investigation. For accurate segmentation some standard steps are used for pre-processing of thermal images. Two steps are implemented for pre- processing the thermal images and they are colour correction and resizing methods. These methods prepare the images for segmentation to receive accurate results.

Colour Correction – Thermal images are raw pictures that can be retrieved from the data bases are not suitable for processing. They are converted into RGB colour model for processing. Python codes are used for the conversion and Mat Lab codes are in built in the algorithm for this step.

Resizing of images – Thermal images received may be of any size cannot be used for segmentation algorithms. So they are converted into standard size using Interpolation method based on pixel relation with the contiguous method. By this method the images can be either zoomed or shrinked to the uniform size for segmentation.

6 Segmentation methods

Thermal images are acquired from the data bases and pre-processing is the initial step used in detection of breast cancer. Next, the vital step is the segmentation method applied on the images to sort normal and abnormal persons. Segmentation is the procedure used to separate the affected regions from the background of the image by isolating the images into uniform blocks based on some criteria to obtain region of interest. Thermal images are segmented to capture affected areas and three novel methods are used for this purpose. They are

- Region based segmentation using codebook generation
- DCNN based segmentation using U-Net architecture
- Segmentation using Enhanced U-Net model with deep learning

Thermal images are segmented using these three original methods and the experimental results are compared for best accuracy. Both machine and deep learning approaches are used for segmentation and three algorithms are developed for processing of thermal images to identify breast cancer.

6.1 Region based segmentation using codebook generation

The proposed method for segmenting thermal images is based on Region Growing approach using super voxel for codebook generation. Thermal image is made up of voxels with similar voxels having the same intensity form the super voxel and code vector is assigned based on the super voxel. For segmentation, hierarchical code book is generated using LBG algorithm. Code book becomes the criteria and based on the code book, the voxels in the image are grouped into three predominant segments like red, green and blue. Boundary connection, region splitting, edge detecting and merging are done in the final step to cluster the image into required groups. The aim is to split the given image into three clusters to identify the cancer affected regions. The following algorithm explains how a thermal image is segmented using super voxel.

Proposed Algorithm

1. Input the acquired thermal image from the data base and pre-process the image using the standard methods.
2. Divide the image into uniform blocks with 16 chunks, each of size 32 rows and 32 columns with 1024 pixels in each block.
3. Initialize super voxel by determining the Position of super voxel using the formula,
   Block size/ Number of blocks.
4. In a single block two pixels are compared for highest intensity value both row and column wise to form a code vector. From all blocks, 16 code vectors are selected to form code book which is Initial code book.
5. Then intermediate and final code book with predominant 3 code vectors namely red, green and blue are selected by Hierarchical codebook generation scheme.
6. The remaining pixel intensities in the image are compared with the code book as criteria using Multi spectral Threshold method. Sigma enables and disables threshold conditions for every pixel to identify seed point in the block.
7. The selected range of RGB components in a pixel is given as
   - Red color - R= 102-255, G=0- 200, B=0-103
   - Green color - R= 0-200, G=193- 225, B= 0-97
   - Blue color - R=0- 207, G= 0- 150, B= 97-220
8. When all 3 components of a pixel lie within the selected range, binary image of the corresponding pixel is created with any three pixels as foreground.
9. Region growing method forms a cluster of corresponding regions selected by the pixel seed point.
10. Edges and boundaries of the image are detected using edge flow vector with intensity level, Boundary in one direction (Θ) and all directions ($\Theta + \Pi$) as triplet functions.
11. Region merging is used for joining adjacent homogeneous regions. Boundary detection and region splitting is performed to differentiate regions. Smooth boundary is generated to connect regions to nearest boundary element.
12. These steps are repeated until all boundaries are connected. Finally region merging is done to get required segmented image.

Using this algorithm thermal images are segmented forming three clusters from the image namely red, green and blue. In the normal image only green and blue clusters are shown clearly whereas in cancer affected image red cluster is depicted deeply indicating abnormality of the image.

The distribution of colours clearly depicts the shade variations for normal and abnormal images. Normal images have uniform distribution whereas abnormal images have wide difference in colour distribution. The variance is clearly shown in both the tables below.

Table 2 Colour Distribution for normal image

Original colours	Red	Green	Blue
Green	0	193	97
Dark Blue	0	0-149	191-221
Red	255	83	0

Table 3 Colour Distribution for abnormal image

Colour Variations	Red	Green	Blue
Green	0	225	113
Dull Blue	0-255	249-83	249-83
Orange to Red	214	75	41

Segmented regions are produced for both normal and abnormal images based on the above table values. The dark colour shows that there is raise in temperature that indicates abnormal regions. Thus using the proposed algorithm thermal image is segmented to sort normal and abnormal persons.

6.2 DCNN based segmentation using U-Net architecture

The next novel approach is based on the Deep Convolutional Neural Network strategy utilized for segmentation of thermal images. The technique depends on the modified U-Net design where a model is made for training and testing the informational collection or dataset. The principle benefit of U-Net model is that the model depends on least data and trains very limited images with great accuracy. The network is quick and requires few moments for segmenting even a large image of size 512X512. Thermal images are segmented using modified U-Net architecture with the mask which is appended with the original image to receive segmented output image of same size.

Basic Architecture of the Model

Thermal images of breast cancer are segmented using modified U –Net architecture and the basic steps are as follows

1. DCNN model using U-Net architecture is constructed taking thermal image as input to produce color mask with size 128x128 x3 as the output.
2. U-Net is a popular semantic segmentation algorithm similar to auto encoder model where pixels are classified either as background or object in the image.

3. Mask is produced using the maximum value for the three channels namely red and green as 255 and blue as 49 to get the required output image.
4. Color mask is appended with the input image to produce final output images where cancer affected areas are segmented.

Description of U-Net model

The modified U-Net model is assembled to segment thermal images with mask used to append with the input image. The required output image is produced by this model.

1. U-Net is a modified CNN architecture used to classify and identify an infection area.
2. The model consists of contracting path (left side) to capture details of input image and a symmetric expanding path (right side) for locating cancer areas.
3. There are 5 convolution layers in left side to produce feature maps to propagate context information to higher resolution layers.
4. There are 7 convolution layers in right side for de convolution on the up sampling side to locate affected regions.
5. There is max pooling layer to overcome feature loss problem.
6. Last layer is the convolutional layer with filter 1x1 to get the output.
7. There is no fully connected layer in U-Net model, so pixels in the border region are symmetrically added around the image and the image can be segmented continuously.

Using the proposed U-net model binary mask is produced in blue color with white background depicting the affected areas in the image based on the difference in the intensity level. When used in algorithm the input image is attached with the mask the infected area is cropped and given as segmented output. So binary image is produced as output with black background and only red cluster is formed. The model performs sound for all stages of the images to detect breast cancer.

Another model using U-Net architecture is proposed with enhanced algorithm to segment thermal images with modifications. The algorithm is explained in detail.

6.3 Segmentation using enhanced U-net model

Another segmentation approach implementing U-net architecture is built by modifying the optimizer. In the former method SGD optimizer was used whereas in the new model the optimizer is modified with RMSprop optimizer for best accuracy in segmenting the thermal images to detect breast cancer. The steps are as follows

1. U-Net model is constructed with encoding path comprising convolutional layers with max pooling operations. For capturing low level features this layer is used. Decoding path is used for up sampling feature maps.
2. Both the paths are connected using skip connections to collect the data like infection areas and location of those areas in the image. Spatial information necessary for segmentation is retained in this layer.
3. Concatenation is used in U-net model to implement connections between the two paths to maintain multi scale data needed for accurate segmentation.
4. Optimizer is generally used in the model to train the network effectively with minimum loss function. In the proposed model RMS optimizer is used to reduce the spatial information loss by modifying the weight in the model and iteratively train the model.

5. So the model is trained more efficiently with accurate output segmented image for cancer detection.

Architecture of the Model

The architecture for the model is constructed using convolutional layers and max pooling layers.

Layer (type)	Output Shape	Para#
Input_1 (input layer)	(None, 128, 128, 3)	0
Conv2d_1 (conv2D)	(None, 128, 128, 64)	1792
Conv2d_2 (conv2D)	(None, 128, 128, 64)	36928
Max_pooling2d_1 (MaxPooling2D)	(None, 64, 64, 64)	0
Conv2d_3 (conv2D)	(None, 64, 64, 12)	73856
Conv2d_4(conv2D)	(None, 64, 64, 12)	147584
Max_pooling2d_2 (MaxPooling2D)	(None, 32, 32, 128)	0
Conv2d_5 (conv2D)	(None, 32, 32, 256)	295163
Conv2d_6 (conv2D)	(None, 32, 32, 256)	590080
Max_pooling2d_3 (MaxPooling2D)	(None, 16, 16, 256)	0
Conv2d_7 (conv2D)	(None, 16, 16, 512)	1180160
Conv2d_8 (conv2D)	(None, 16, 16, 512)	2359808
Dropout_1 (Dropout)	(None, 16, 16, 512)	0
Max_pooling2d_4 (MaxPooling2D)	(None, 8, 8, 512)	0
Conv2d_9 (conv2D)	(None, 8, 8, 1024)	4719616
Conv2d_10 (conv2D)	(None, 8, 8, 1024)	9438208
Dropout_2 (Dropout)	(None, 16, 16, 512)	0
Up_sampling2d_1 (Upsampling2D)	(None, 16, 16, 1024)	0
Conv2d_11 (conv2D)	(None, 16, 16, 512)	2097664
Concatenate_1 (Concatenate)	(None, 16, 16, 1024)	0
Conv2d_12 (conv2D)	(None, 16, 16, 512)	4719104
Conv2d_13 (conv2D)	(None, 16, 16, 512)	2359808
Up_sampling2d_2 (Upsampling2D)	(None, 32, 32, 512)	0
Conv2d_14 (conv2D)	(None, 32, 32, 256)	524544
Concatenate_2 (Concatenate)	(None, 32, 32, 512)	0
Conv2d_15 (conv2D)	(None, 32, 32, 256)	1179904
Conv2d_16 (conv2D)	(None, 32, 32, 256)	590080
Up_sampling2d_3 (Upsampling2D)	(None, 64, 64, 256)	0
Conv2d_17 (conv2D)	(None, 64, 64, 128)	131200
Concatenate_3 (Concatenate)	(None, 64, 64, 256)	0
Conv2d_18 (conv2D)	(None, 64, 64, 128)	295040
Conv2d_19 (conv2D)	(None, 64, 64, 128)	147584
Up_sampling2d_4 (Upsampling2D)	(None, 128, 128, 128)	0
Conv2d_20 (conv2D)	(None, 128, 128, 64)	32832
Total Parameters: 31,033,432		
Trainable Parameters: 31,033,432		
Non trainable parameters: 0		

Thus using the modified U-net model thermal images are segmented and the output of all the three models are displayed in the next section.

6.4 Experimental Analysis

Thermal images are segmented using all the three proposed method and the output are compared for accuracy.

(i) **Region based segmentation using codebook generation**

Both normal and abnormal images are segmented using the proposed method and the output is given as Fig.2a and 2b

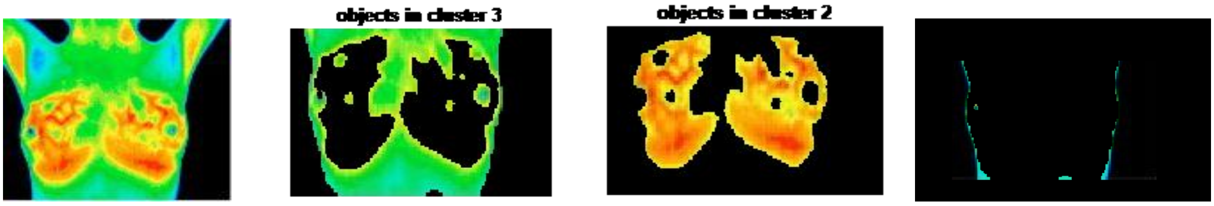

Fig2a. segmentation of normal image

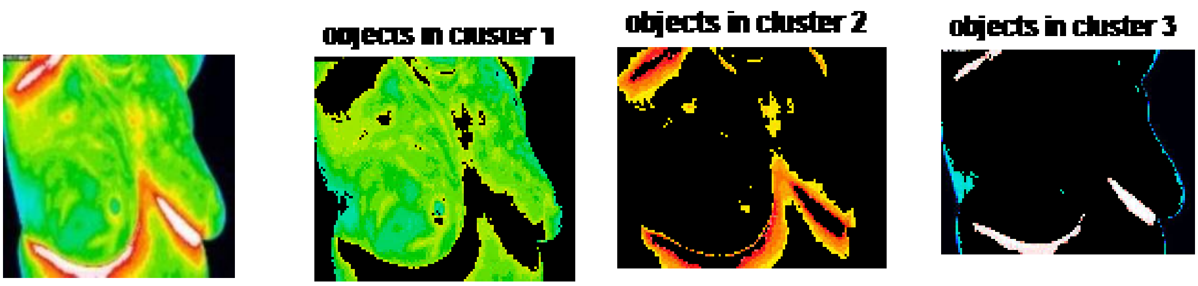

Fig.2b. Segmentation of abnormal images

Both normal and abnormal images are segmented using region based segmentation based on code book generation method. There are three clusters formed by code vectors selected like red, green and blue. Red cluster predicts the cancer affected regions clearly shown in second figure. In first picture there is no red region indicating the image is normal.

(ii) **DCNN Segmentation using U-Net Model**

Thermal images are segmented using this proposed model and output for both normal and abnormal images are given as Fig.3a and 3b.

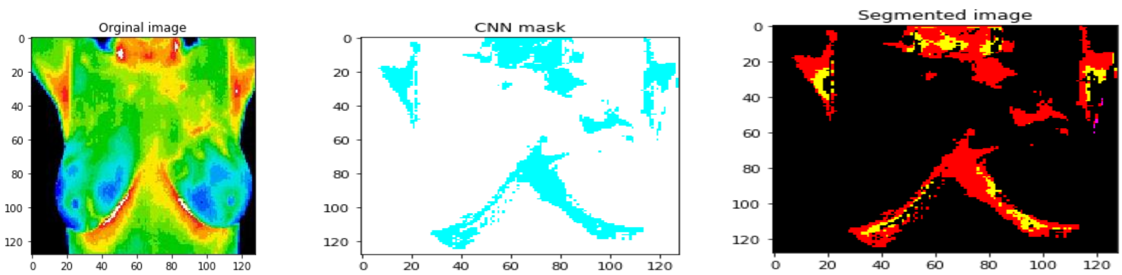

Fig.3a. Segmentation of abnormal image

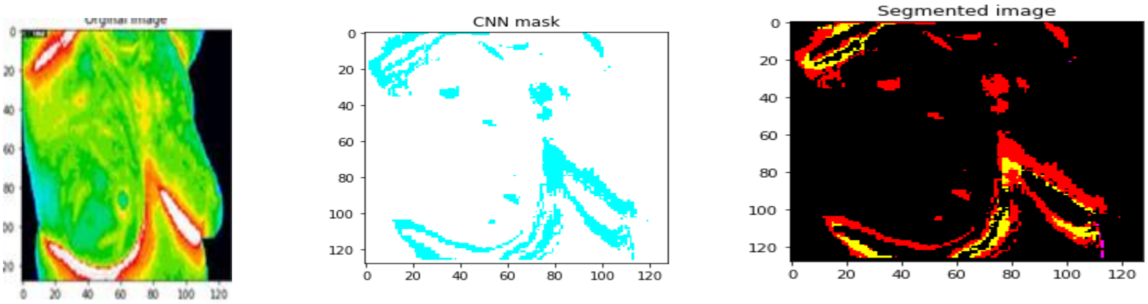

Fig.3b. Segmentation of normal image

First picture shows the segmentation of abnormal image with the mask depicting cancer affected regions clearly in the segmented image. Second image gives the segmentation of normal image where there is no red patch in the segmented image along with corresponding mask. Both normal and abnormal images are segmented accurately using the proposed model.

(iii) **Segmentation using enhanced U-net model**

Thermal images are segmented using improved U-Net architecture with RME optimizer and the output images are given as Fig.4a and 4b.

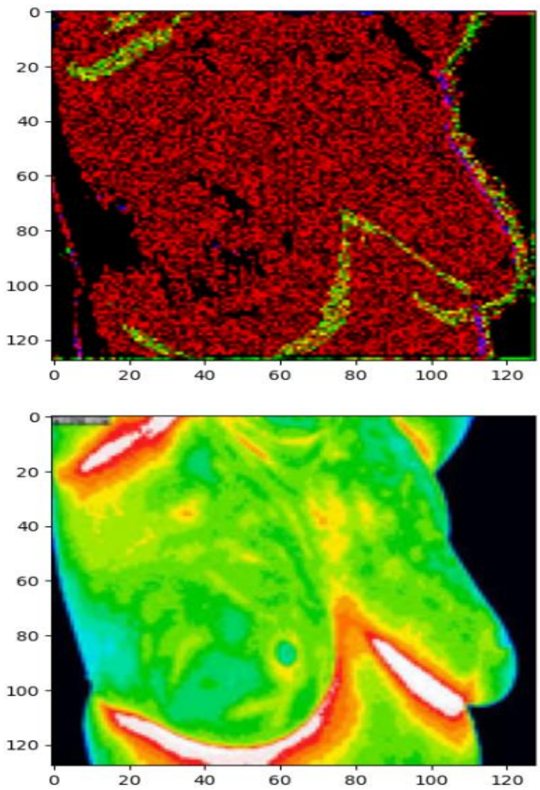

Fig.4a. Segmentation of normal image

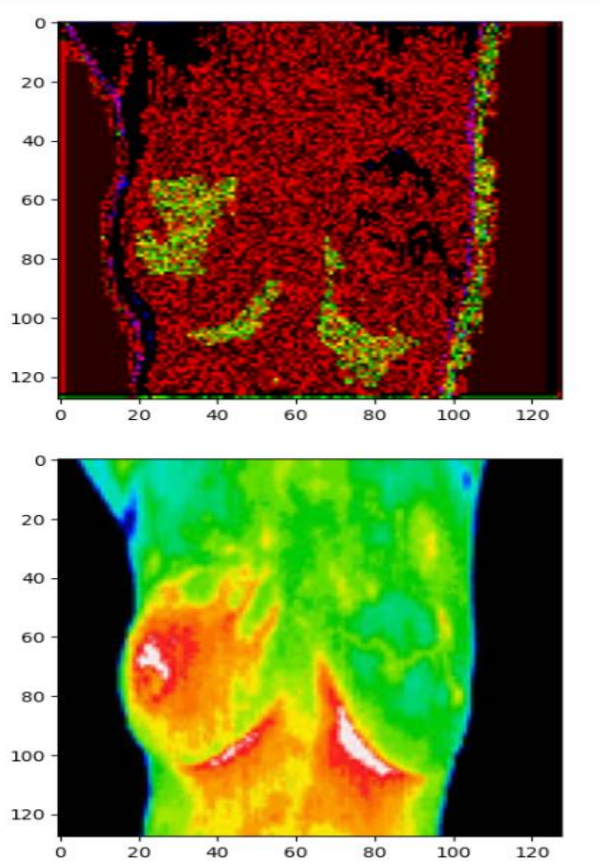

Fig.4b. Segmentation of abnormal image

The output clearly sorts the normal image from the abnormal one by accurate segmentation with fine boundaries and the cancer affected regions are separated using different color from the remaining parts of the image.

All segmentation results are given as clear images in the above figures and thermal images are segmented in three different methods using novel algorithms.

Conclusion

In the proposed work thermal images are processed for detecting the presence of breast cancer using both machine and deep learning procedures. For this purpose thermal images are retrieved from data bases and pre-processed using traditional methods. Once the images are ready for processing they are segmented using three innovative methods. Region based method is used with super voxel as criteria and the images are segmented accurately. Next using deep learning models the images are segmented using U-Net architecture with mask produced to collect the output image. Finally enhanced U-Net model is used for segmenting the images accurately to obtain the region of interest. All models provide clear images and the final model shows best accurate images when compared with other two models. The final images are further used for classification purpose to find the three stages of cancer affected in the patients.

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