

Novel Segmentation Method to Diagnose Breast Cancer in Thermography Using Deep Convolutional Neural Network

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ABSTRACT

Based on the recent analysis it is more evident that in India breast cancer has become the most common type of cancer among women. There is an increase in the number of patients suffering from breast cancer especially in rural areas. Another fact is the patients with young age groups are increasing more when compared earlier. The only remedy is prior detection leading to more survival rate. Research is in progress for latest diagnosis method employing machine learning and deep learning techniques. One such deep learning method discussed in this paper is the convolutional neural network model used for thermal image segmentation. Spatial pyramid pooling method is combined with modified U-Net Architecture to give accurate results. Thermography images are used for diagnosis which is more innovative compared with other screening methods. Using the proposed method, the segmented images when tested for classification produces an accuracy of 96.13% trained with Residual network model with loss of 0.40%.

KEYWORDS: Deep learning, convolutional neural network, spatial pyramid pooling, U-Net, screening method.

1. INTRODUCTION

According to the report of "The Indian Council for Medical Research", the number of fresh cancer cases is expanding in cities and in rural areas also. Statistics of Breast cancer in India reveals that the figure may raise to 17.3 lakhs patients in 2020. The threat continues even in post cancer period because cancer treatment becomes more challenging during advance stage and more than half of the affected Indian women diagnosed with breast cancer suffer from progressive stages of this disease [1]. Another alarming truth is that women of age group, 25-50 are suffering from breast cancer. Especially in India, the danger of being detected with breast cancer is more due to the lack of alertness and poor diagnosing and prevention rates. So exposure of the disease becomes late and women become victims of this syndrome. Breast cancer is a curable disease when treated in time and survival rate increases if accurately diagnosed earlier. [1] Unique methods for diagnosing cancer are surveyed for precise results like mammography, MRI, ultra sound and thermo gram. Early detection is a blessing and prevention is a step away from cure.

Breast cancer forms in the cells of the breast from normal cells due to a modification of DNA or RNA because of many reasons like nuclear radiation, electromagnetic viruses, heat, chemicals in air, water, food

and aging of DNA. Breast is composed of two main tissues termed glandular and the supporting tissue, stromal. Glandular tissue contains the lobules, the milk producing glands and the ducts, milk passages. Ducts, lobules and the tissue in between the cells that line the ducts are the areas where breast cancer primarily affects. Different stages of breast cancer are portrayed in the Table.1.1 below.

Table 1.1 Different breast cancer stages

| STAGES | DESCRIPTION | TYPE |
|-----------|---|--------------|
| Stage 0 | Pre-cancerous or marker condition Ductal carcinoma-cancerous lesion Lobular carcinoma –unusual cells in the lobules | Non-invasive |
| Stage 1-3 | Lymph within the breast or regional lymph nodes | Invasive |
| Stage 4 | Metastatic cancer-spread beyond the breast and regional lymph nodes | Metastatic |

A method is needed to diagnose breast cancer without any symptom for accurate treatment and the suggested method is thermography which provides exact results earlier compared with other approaches. A painless method with no harmful radiation and no pressure mode while diagnosing is thermography which belongs to non-invasive and non-ionizing technique. Thermal image depicts various colours based on the heat distribution of the image categorizing whether the image belongs to normal or abnormal class. Segmentation is the method which divides the image into similar regions where the necessary area is segmented for identifying purpose. The image is divided using advanced methods like deep learning using convolutional neural network and algorithms to make the work faster and accurate.

2. RELATED WORK

For past many years the research is performed on various types of images to detect breast cancer using different models and architectures. The problem varies due to diverse methods used for segmentation which is the basic step for accurate diagnosing of the disease. Pixel wise segmentation is performed using FCNN model with LBP feature-based and texton pixel wise method. Other segmentation methods using Gaussian Mixture model, hidden Markov model with expectation maximization algorithm are proposed with good accuracy explained by Hai Su et.al. Foran et al. proposed to segment out the tumour region using texton features and logistic boosting.

Various methods like fuzzy C-means and K-means clustering are adopted for hottest region in thermal images and in the mammogram images where the selected region is segmented, but these images are unsuitable for repeated mass screening measurements. Other methods, such as photo acoustic, diffuse optical

tomography (DOT) imaging methods proposed by Qiwen Xu et.al. Showing 88% accuracy are implemented with the use of artificial neural networks, fuzzy logic, Bayesian networks and decision trees. A breast cancer detection algorithm was proposed based on texture feature extraction, a Markov random field and a modified local binary pattern. Fractal analysis of breast thermal images with bi-spectral invariant features was evaluated and classification was done using AdaBoost algorithm.

2.1. Contribution and Outline of the work

Deep convolutional neural network model is used to segment cancerous region in thermal images for detecting whether the image is normal or abnormal. The segmented image if abnormal is used for classification to find whether the patient is in starting, middle or advanced stage of cancer. The image is segmented using U-Net architecture which is well known for its fast and accurate output with small datasets also. This paper first concentrates in traditional methods namely K-means clustering and compares with fuzzy C-Means segmentation method also. Both the results are compared with the proposed model, DCNN segmentation where transfer learning model is implemented with U-Net architecture. Automatic segmentation of thermal images with binary

segmentation mask is used for cropping cancer region only with the background in the image. Feed forward function is used and different feature maps are produced to combine the result to produce final output segmented image.

The rest of the paper is organized as follows. The basic concept of deep convolutional neural network is defined along with description about the layers and parameters which are used in the proposed model. The following section explains the two traditional methods for segmentation with results. The next section consists of the proposed algorithm with U-Net architecture and implementation. Following section describes the block diagram of segmentation. The last section gives the experimental result and justification along with conclusion.

3. OVERVIEW OF DEEP CONVOLUTIONAL NETWORK

Especially in medical image processing, neural network plays an important role in segmenting the region of interest to identify particular areas. To extract the features for detection of similarities, the modified version of neural network called convolutional model is used. This model receives image as input performs a dot product with weights encoding some properties into the model implementing forward function more efficiently by reducing parameters finally producing the required output. Activation function is included to provide accurate values. Convolutional model has more advantages compared with neural network.

Deep convolutional neural network is constructed with multiple layers, each having their own functions independent of other layers. These layers are the building blocks of the convolutional networks

which are the basics for the architecture constructed for the proposed model. Hidden layers are also used in this model for more accuracy in segmenting the images. The following section describes the layers and parameters used in the model and architecture of the proposed model.

3.1. Building Blocks of CNN

The basic building blocks of a Convolutional Neural Network are the arrangement of layers and every layer converts one layer purposes to another through a differentiable function. There are three main types of layers to build CNN architectures: They are **Convolutional Layer**, **Pooling Layer** and **Fully-Connected Layer** arranged one on top of the other to form the **architecture**.

In our proposed algorithm, CNN model is constructed with four layers. In each hidden layer, one convolutional layer and one pooling layer are present followed by one fully connected layer. All the layer functions are explained in brief. The important components used in these layers are

- (i) Input image- image to be used for segmentation
- (ii) Feature Detector- Matrix referred as kernel or filter.
- (iii) Feature Map- matrix representation of the image multiplied element wise to produce feature maps called convolved feature or an activation map using filter.

3.1.1. Convolutional Layer

Convolution is the mathematical operation on two functions that produces a third function expressing the modification of one function by another. If f and g are two functions then the result function is given by the formula

$$\begin{aligned} (\mathbf{f} * \mathbf{g})(t) &= \int_{-\alpha}^{+\alpha} \mathbf{f}(T) \mathbf{g}(t - T) dT \\ &= \int_{-\alpha}^{+\alpha} \mathbf{f}(t - T) \mathbf{g}(T) dT \end{aligned}$$

The first layer that receives an input image is called convolution layer. Convolution is a process where the network tries to identify the input image by referring to what it has learned in the past. The resulting output image is then passed on to the next layer.

Convolution layer functions in the following way. The layer's parameters consist of a number of weights or filters. Every filter is a small matrix with equal rows and columns with the filter traversing the entire depth of the input image. During the forward pass, each filter is scanned throughout the width and height of the input image and calculates dot products between the filter values and the input at any position to produce an activation map called feature map. In this algorithm 5x5 filters are used for convolution layer with stride 2. Thus the convolution operation extracts needed spots from its input feature map and applies the same

$$\text{Size} = (\mathbf{I} - \mathbf{F} + 2\mathbf{P}) / \mathbf{S} + 1$$

conversion to all of these areas, producing the new output feature map [3]. The feature map size is calculated using the formula

Where I stands for Input image size, F stands for filter size, P stands for padding and S stands for stride.

3.1.2. Pooling Layer

The next layer is the Pooling layer inserted between the convolution layers to reduce the enlarged size of the image illustration and reduce the amount of parameters to control over fitting. The Pooling Layer operates independently on every complexity layer of the input image and resizes it, using the MAX operation. The Spatial Pyramid pooling layer with filters of size 3x3 is applied with a stride of 2 in this algorithm to handle multi scale images effectively and address problems like classification. Up sampling method is used in this algorithm to increase the number of features in the image. Similar versions of the same network principles are used to train inputs at different sizes and combine the structures to get the required output. [4]. The pooling (POOL) layer reduces the height and width of the input image. It reduces the complexity of computation and makes feature detectors more suitable to the corresponding position in the input. These pooling layers have no parameters for back propagation to train. However, they have hyper parameters such as the window size ff.

3.1.3. Activation Function

Two important functions used in the proposed algorithm are

- (i) Feed Forward Function- Information flows in only one direction forward from the input nodes through the hidden nodes and to output nodes.
- (ii) Rectilinear Activation Function- Linear function that output the input values directly if it is positive otherwise generates zero. The function is defined by
Where x is the input to a function.

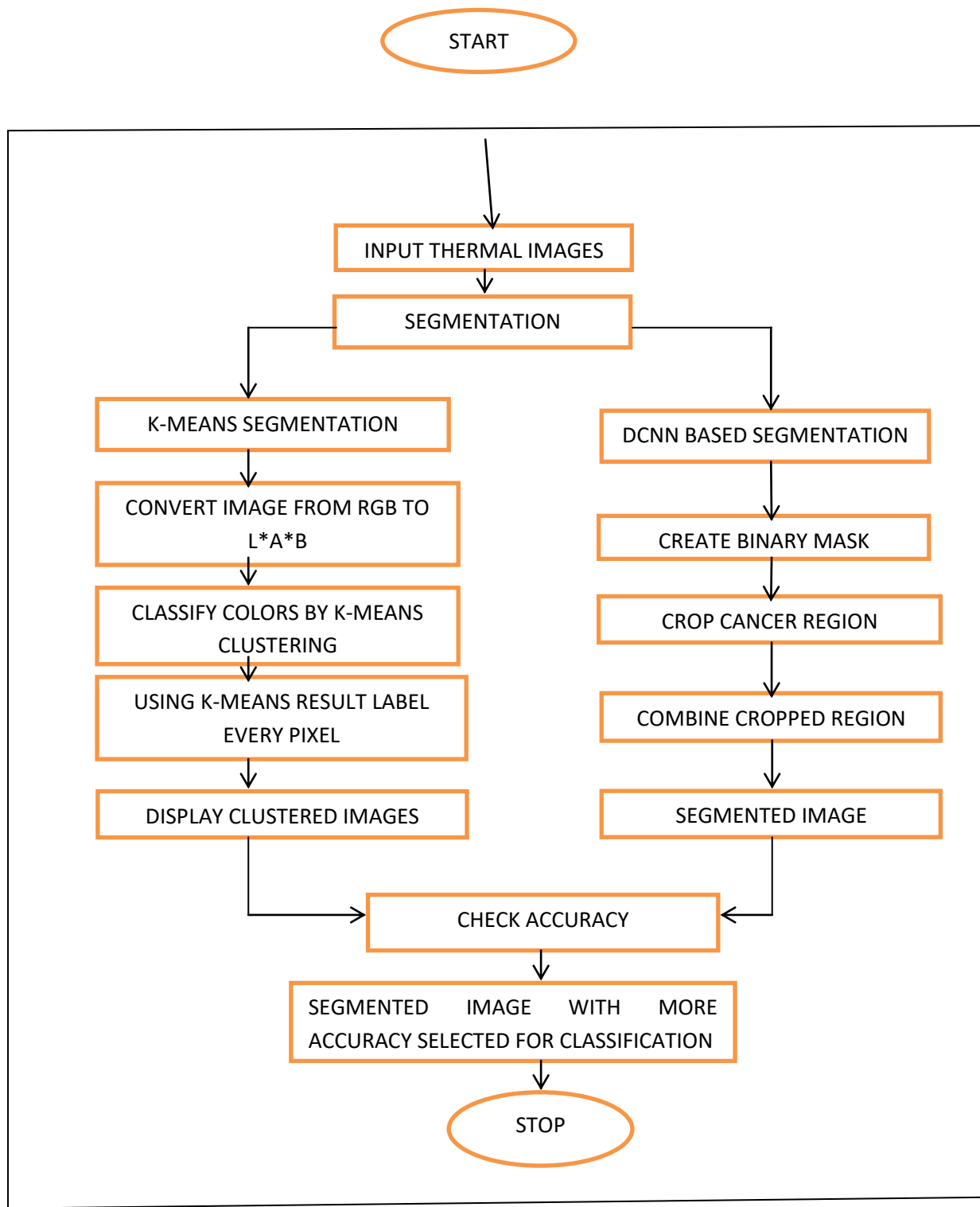
Rectifier is used as a solution to the vanishing gradient problem and allows the network to obtain sparse representation.

3.1.4. Fully Connected Layer

The last layers in the network are fully connected, meaning that all features of the preceding layers are connected to every unique feature in the succeeding layers. This shows the high level possibility where all available pathways from input to output image are computed to produce the desired image.

$$F(X) = X = \max(0, X)$$

4. BLOCK DIAGRAM OF SEGMENTATION METHODS



5. OVERVIEW OF TRADITIONAL METHODS

The general segmentation process manually done in the early days were replaced by automated approach using various colour analyses in thermography for checking temperature abnormalities in human body. The two basic methods used for checking any difference in temperature are K-Means clustering and fuzzy C-means method which are analysed using the dataset collected for comparison purpose with the DCNN segmentation to find accuracy.

In K-means clustering method colours are segmented automatically using the technique explained. The input image transformed from RGB color space to L^*a^*b color space where L is luminosity layer and 'a' and 'b' are chromaticity layers which contains all colour information. Euclidean distance metric is used to find the difference between two colours. Based on this concept initial data points are randomly assigned to clusters which are divisions of the input image. Next Euclidean distance is calculated for every point to the cluster and if it is close to the cluster it is included in the same cluster. This idea is used to segment thermal images where the colours present in the image form different clusters. The sample images considered for segmentation both normal and abnormal, 3 clusters are produced in the output image segmenting blue, green and yellow colours in normal image whereas red, orange and green colours are clustered in abnormal image to show the difference.

The same concept is tried in fuzzy C-means segmentation also with slight modification. The number of clusters and the exponent weight are chosen. Cluster center is calculated based on minimisation function and exponent weight factor is used to control the fuzziness of the membership functions. First membership is initialised to find cluster centers and later updated until distortion is minimised. Based on this idea the method is implemented to segment cancer region in thermal images. The output is displayed as clusters including empty clusters in the image. The clusters are more in number when compared to K-means clustering.

6. PROPOSED ALGORITHM

Based on the functions of convolutional neural network layers, thermal images both normal and abnormal are taken as input image for segmentation of cancer affected region. The proposed model transform the original image layer by layer from the original pixel values to the desired output image displaying affected area only in the abnormal image. To segment affected part in the thermal image, mask is created first and using the mask, cancer affected portion is segmented.

6.1. Steps for Proposed Method

There are two phases in the algorithm. They are training phase and testing phase used to train the images first and using the training method, test the data to correctly segment the affected portion. The basic steps are

- (i) Begin. Input the thermal image
- (ii) Image is converted into matrix format automatically. Filter or weight is chosen and added with input image in convolution layer to produce feature maps.
- (iii) To reduce dimensionalities of the image perform pooling using spatial pyramid pooling operation. The image is shrunk into feature map by removing unwanted regions.
- (iv) Stride 2 will move the filter two pixels at a time producing many feature maps. Rectilinear Activation function is activated to avoid negative values. Using Feed Forward Function data flows forward in one direction only.
- (v) Stochastic gradient is an iterative method used to update the weight.

- (vi) The step is repeated until the difference between observed output and targeted output is minimised. Calculate the error found in the first layer, adjust the weight and calculate to find error in next layer. This process continues until required feature map is obtained.
- (vii) Using normalization method weight is adjusted to produce feature maps. If accuracy is converged stop the iteration.
- (viii) Exit.

6.2. U-NET Architecture

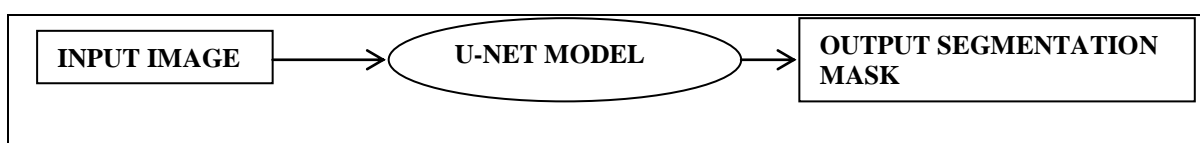
The architecture consists of a contracting path (left side) and an expansive path (right side). The contracting path follows the typical architecture of a convolutional network. [5]. It consists of the repeated presentation of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2. In the proposed architecture, following the convolution and pooling operations, up sampling method is used. The basic idea of U-Net model is to produce the output with low resolution first and using up-sample method produce required segmentation image. Up-sampling is used to raise the feature volume whenever the image size is reduced to minimum. Both up-sampling and concatenation trains the network to learn accurate segmentation. Finally the input features are retained in the output image also. In total the network has 24 convolutional layers. The image size is 128X128 for both input and output images. The block diagram below is the U-Net architecture depicting the layers and mask and their functions.

The block diagram of modified U-Net architecture for the proposed model is given below.. First the input image is fed to the model followed by convolution layers and max-pooling layers. Up-sampling layers are also added with concatenation and drop-out layer is also added to get the final output.

Figure 6.2 is the modified U-Net model block diagram given in the end of this paper.

6.2.1. Implementation of U-Net Architecture

The segmentation method used in this paper is semantic segmentation, which produces accurate results applied using modified U-Net architecture. In this method each pixel in the image will have unique label for identification so similar pixels share same label. The basic idea applied for U-Net method is



The mask is called binary segmentation mask where there are only two values based, one is background value and other is affected region pixel value. The input used in this model is thermal images and U-Net produces a binary mask of 1 s and 0 s. Here 1 indicates cancer cell and 0 indicates background. Based on the conditions, the mask is created with white colour representing background and blue colour indicating cancer cells. Colour based

Segmentation is combined in this method to indicate cancer cells as red in colour that should be considered alone for creating mask to separate the background from the cancer affected region. Thus the model is trained with the mask given directions so that the mask crops red colour pixels indicating cancer that should be segmented from the background which is the input image. Individual masks are created for each input image and based on this Mask the cancer cells are segmented to produce output image. The U-Net architecture is given below

| 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, 128) | 73856 |
| 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 |
| Concatenate_4 (Concatenate) | (None, 128,128,128) | 0 |
| Conv2d_21 (conv2D) | (None, 128, 128, 64) | 73792 |
| Conv2d_22 (conv2D) | (None, 128, 128, 64) | 36928 |
| Conv2d_23 (conv2D) | (None, 128, 128 3) | 1731 |
| Conv2d_24 (conv2D) | (None, 128, 128, 3) | 12 |

| |
|----------------------------------|
| Total Parameters: 31,033,432 |
| Trainable Parameters: 31,033,432 |
| Non trainable parameters: 0 |

7. JUSTIFICATION

The proposed algorithm is segmenting thermal images for identifying cancer regions using U-Net architecture by deep convolutional neural networks. Among many methods, U-net model is chosen because of its various merits. Some of them are

- U-net is modified version of Fully Convolutional Network especially used for segmentation in medical images for accurate results.
- U-Net has a symmetric shape with up-sampling which is not provided in other FCN models and skip-connections with down-sampling to produce concatenations operations. All provides more feature maps which offers precise results.
- Images of various sizes are allowed in this model. This model predicts good results even if the size of dataset is small especially in medical images. Data augmentation method is used with transfer learning to give high resolution results.
- Though similar to Encoder-Decoder model in the field of biomedical image processing, U-net is more suitable for its fast and correct processing.
- In U-net model, the layers transfer information from low to next high layer so many feature maps can be reconstructed to converge the result.

8. ASSESSMENT OF SEGMENTATION METHODS

To find out the accuracy of proposed algorithm, the methodology is compared with the traditional methods like K-means clustering and fuzzy C-means segmentation method to segment cancer areas in the thermal image. Compared with these earlier methods, the proposed method shows more accuracy nearly 93.5% because all the input images of variable sizes which were tested for segmentation showed precise result. The demerits of the traditional methods when analysed are only fixed size images were segmented accurately and more empty clusters were displayed in the output. Moreover different results were the out comings of these methods when tried for many times. So more accuracy cannot be achieved from the sample dataset provided.

8.1. Experimental Result for Proposed Method

Based on the proposed algorithm the data set is trained using the DCNN model with modified U-Net architecture. Normal and abnormal images are verified and confirmed using segmentation. CNN mask is created for each image where blue and white colours are used for colour variation of intensities. Built on the mask, affected portions are differentiated by red colour with yellow border.

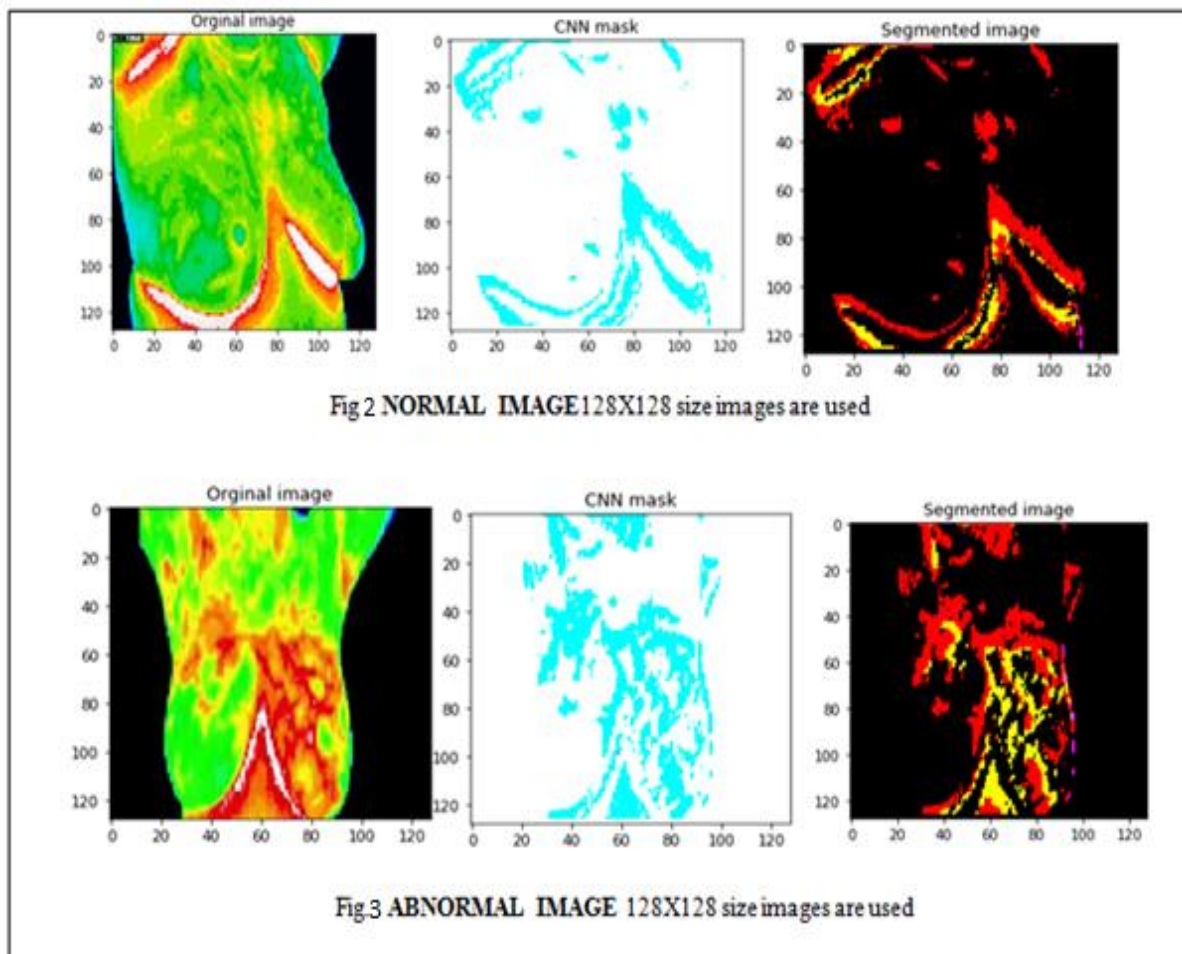


Figure 8.1 Outputs for Proposed Method

8.2. Experimental Result for Traditional Method

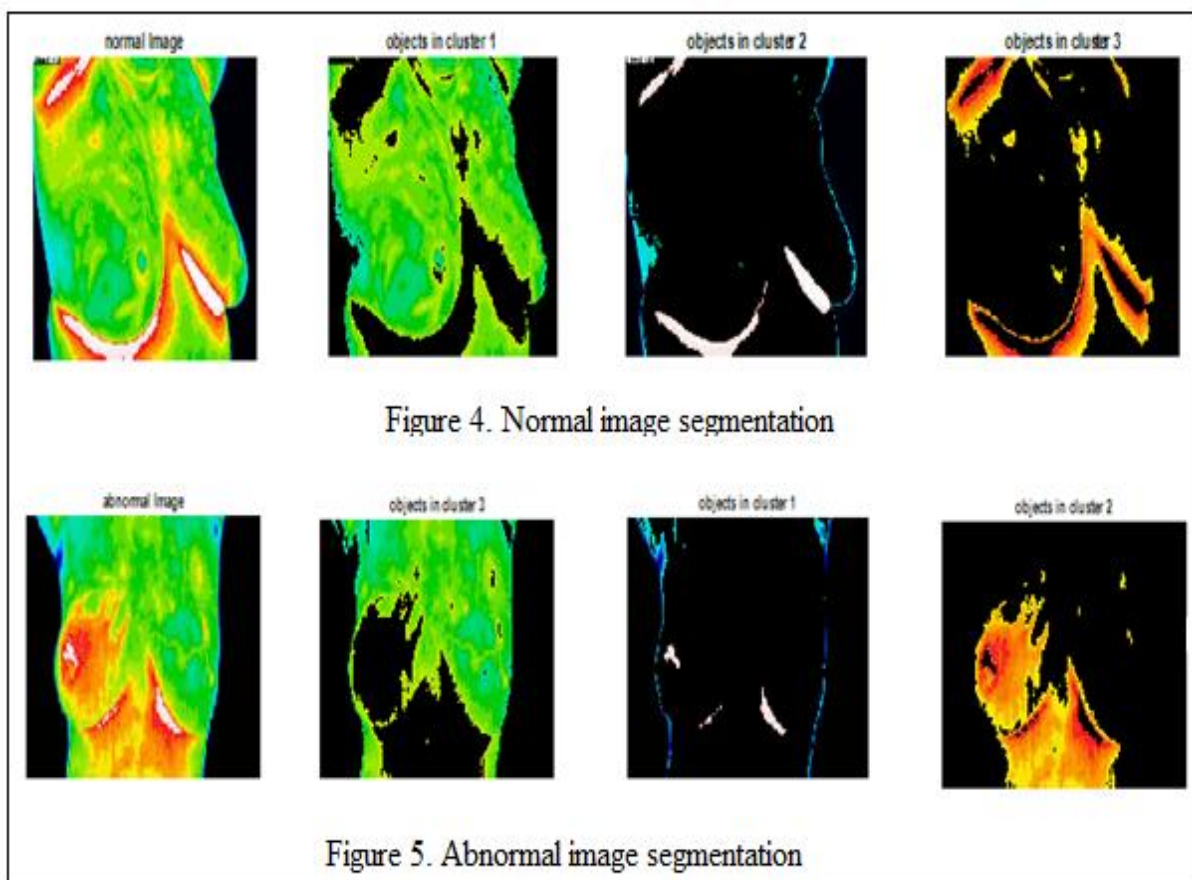


Figure 8.2 Outputs for Traditional Method

9. EVALUATION OF PROPOSED SEGMENTATION METHOD

The performance of proposed segmentation method is considered by comparing its accuracy with other basic methods discussed earlier in this paper. The obtained results are shown in the table below along with bar chart. DCNN method shows better accuracy up to 93% compared with other methods like K-Means and fuzzy C-means.

| SEGMENTATION METHODS | ACCURACY RATIO |
|----------------------|----------------|
| K-MEANS | 90% |
| FUZZY C-MEANS | 91.5% |
| DCNN | 93% |

Table 9.1 Performance Analysis

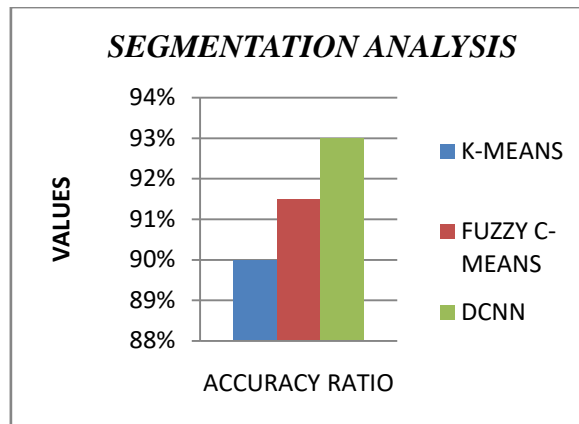


Figure 9.1 Bar Chart of Accuracy ratio

10. CONCLUSION

The basic step for diagnosis of breast cancer using thermal images is the segmentation method, which is achieved using Deep Convolutional Neural Network model. The concepts used for segmentation is transfer learning with modified U-Net architecture. Based on the segmentation method the thermal images can be divided as normal and abnormal class. The next step is classification where the abnormal images are divided using the data set into three modules namely starting, middle and advanced stages of breast cancer. The work is further extended for comparison with traditional method like mammogram.

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Figure 6.2. U-Net model

