A Comparative Study between Content-Adaptive Superpixel and Semantic Segmentation for *Skin Cancer*

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Abstract:- Medical imaging techniques play a vital role in identifying skin cancer. The detection of skin cancer in its early stage is very crucial and important. This project shows a comparative study of two different segmentation method for segmenting skin cancer region from dermoscopic image. Content-Adaptive Superpixel (CAS) segmentation is based on Clustering and Semantic segmentation is based on Artificial Neural Network (ANN). The goal is to find an efficient method for detection of skin cancer from a dermoscopic image. The proposed model comprise of Preprocessing, Segmentation using CAS and Semantic segmentation. The Fully Convolutional Network and RGB conversion is used for semantic segmentation. CIELAB conversion and modified linear clustering algorithm for CAS segmentation. The experimental results confirm that performance on semantic segmentation is better than CAS.

***Keywords**:- Skin Cancer, Segmentation, Dermoscopic image, Preprocessing, Segmentation, Content-adaptation, K-Nearest Neighbor Classifier.*

I. INTRODUCTION

Digital Image Processing (DIP) [1] deals with processing digital image through digital computer using efficient computer vision algorithms. Digital images are the two- dimensional representation of image as finite values called pixels. The goal of image processing is to extract informationfrom digital images. The components of DIP are image acquisition, image enhancement, image restoring, color image processing, wavelets and multi resolution processing, image compression, morphological processing, segmentation, representation and object recognition. The scope of Digital Image Processing are widely recognized in image forensics, agriculture medical imaging, remote sensing, and so on.

Carcinoma has a tremendous impact on human lifespan globally. There are different types of cancer including Skin cancer [2], Lung cancer [3], Brain cancer [4] and so on. Skin cancer occurs due to the abnormal growth of skin cells. Mutation occurs in the DNA of skin cells and it grows inan uncontrollable fashion to form a mass of cancer cell. The top most layer on skin is called Epidermis layer. It contains Basal Cell, Squamous Cell and Melanocytes. The Melanocytes produce a pigment called melanin; it gives normal color to the skin. Skin cancer can be divided into two categories: Melanoma and Non-melanoma. Non-melanoma isclassified into two types: Basal Cell Carcinoma (BCC) [5] and Squamous Cell Carcinoma (SCC) [6]. Melanoma [7] is most dangerous than Non-melanoma because it has a tendency to spread. The main cause of Melanoma is due to exposure of skin to ultraviolet rays. So early detection and identification of melanoma is crucial and important.

Segmentation [8] is the process of dividing image into multiple segments, to extract information easily. It enhances representation of image and used for identifying objects and boundaries. Hence image segmentation can be used for detecting tumor regions. Different type of segmentation are Threshold based [9], Edge based [10], Clustering based [11], Fuzzy theory based [12], Watershed based [13], Partial Differential equation (PDE)based [14], Artificial Neural Network (ANN) based [15] and region- based segmentation [16].

In this work, two segmentation methods are used for identifying skin cancer region in dermoscopic image. Dermoscopy [17] is a hardware device that helps in acquiring the surface of the skin using skin surface microscopy for the detection of skin cancer. The reports show that dermoscopy based cancer detection has higher accuracy compared with other methods. The input image contains noise, artifact, ink markings etc. So, to enhance the region, prepossessing is done to the raw data. Preprocessing is followed by a clustering based Content- Adaptive Superpixel (CAS) segmentation [18] and ANN based Semantic segmentation [19] methods.

Superpixel segmentation [20] is a type of segmentation aims to grouping of pixels into atomic regions that are consistent. Compared with the traditional rigid segmentation it has low computational cost. Superpixel segmentation does not include adequate feature representation and discriminability measure. Existing methods use fixed parameter and features are taken manually. So, to overcome these problem CAS is proposed that use a modified linear clustering algorithm. CAS integrates a new feature representation and Clustering based discriminability

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measure. Semantic segmentation classifies each pixel in an image using Fully Convolutional Network (FCN) [21]. The objective of this paper is to determine which segmentation perform well in detecting skin cancer more efficiently.

The rest of this paper is organized as follows: Section 2 discusses various related works in connection with skin cancer segmentation. Section 3 presents a method for skin cancer segmentation based on Content adaptive superpixel segmentation and Semantic segmentation. Section 4 presents result and discussion., Section 5 discuss conclusion andfuture works.

II. RELATED WORKS

In paper [18] a novel Content-Adaptive Superpixel (CAS) segmentation algorithm is proposed. The advantage of using this algorithm is that it automatically and iteratively updates weights of different features. The new feature representation includes color, texture, spatial and contour feature from images and discriminability measure is calculated using cluster variance from different cluster. This algorithm is tested with four different data set and result shows that algorithm accurately segments the image.

In paper [21] Fully Convolutional Network (FCN) for semantic segmentation is proposed. FCN can classify each pixel in an image into predefined classes. FCN is built on “convolutional layers”, t hat take input of any sizeand perform extraction of global and local features. The importance of feature is identified and a subsequent recursive feature elimination is carried out. Local feature is taken from isolated regions while grouping meaningful and informative pixel to form super pixel atomic regions. Then morphological and statistical texture features are extracted from superpixel region and is classified using Support Vector Machine (SVM) classifier.

In paper [22] proposed a color consistency algorithm on skin cancer segmentation using FCN. The image is preprocessed in the first stage. The data set is taken from ISIC challenge data set 2017. Apply different color constancy algorithm on data set and analyze the result using deep learning algorithm, that is FCN. The experimental resultshows that segmentation is more accurate using color consistancy algorithm.

In paper [23] a new algorithm is proposed called “Super Hierarchy”. This algorithm focus on efficiently segment all scale of super pixels. This algorithm can integrate with different edge detector algorithm hence improve accuracy forsegmentation.

In paper [24] proposed an end-to-end solution using FCN for multi-class semantic segmentation. In single-class semantic segmentation cannot distinguish between the type of skin cancer. This paper includes transfer learning and a hybrid loss function to improve segmentation. The two-tier transfer learning is used to overcome the data deficiency. Then train FCN by extracting features from skin lesion. A hybrid loss function is introduced to handle class imbalance. This method can used for other medical imaging task.

In paper [25] proposed a super pixel based method for extracting color feature for classification of skin lesion. This method is used for identifying melanoma and common nevus. Here, classification technique using computer-aided skin lesion extraction of different global and local features is detailed. The importance of feature is identified and a subsequent recursive feature elimination is carried out. Local feature is taken from isolated regions while grouping meaningful and informative pixel to form super pixel atomic regions. Then morphological and statistical texture features are extracted from super pixel region and classified using Support Vector Machine (SVM) classifier.

There is a need for computation effective segmentation methods for detection of cancerous region. Content-adaptive super pixel (CAS) segmentation has low computational cost compared with other super pixel segmentation. To our knowledge CAS is not used in melanoma skin cancer detection. Efficiently training a deep network is a challenging task for skin lesion segmentation. Automatic identification of Melanoma skin cancer in its early stage is crucial [26]. So most efficient algorithm for segmentation is necessary. Therefore, the goals of this study are to compare two different type of segmentation methods and find out which one is better. Aim is to segment Melanoma skin cancer region from dermoscopic images using Content-adaptive super pixel segmentation (CAS) and Semantic segmentation methods, then compare which segmentation is more efficient.

III. PROPOSED METHODOLOGY

The proposed system consists of Preprocessing, CAS segmentation and Semantic Segmentation. Figure 1 shows ourproposed architecture.

A. Dataset

To evaluate, the data set can be taken from Kaggle skin cancer. It contains images and its ground truth. Train, test and validation are included separately. In the train data set contains 50 images of melanoma skin cancer images and folder name as trainx. The ground truth of training image is store in trainy and image has name as trainx. The test image contains 50 different images and store in testx folder, itsground truth is stored in testy. The validation x and y have 150 images. So total of 250 image and its ground truth contain asdata set.

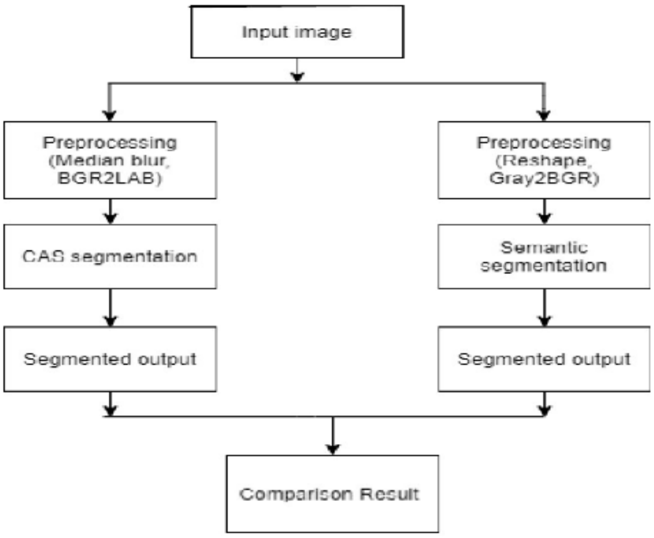

Fig. 1 Proposed Architecture

B. Preprocessing

Preprocessing [27] is to improve the data by suppressing the distortion. Dermoscopic images of skin cancer contains noise, artifacts, hair, dark mark, pen inking etc. So, it is essential to remove and enhance the information for easy detection. Pre processing is done for enhancing the representation of data.

Skin cancer may differ in its size, color, texture and features. In CAS segmentation pre processing the input image is done by applying Gamma correction [28]. In gamma correction it applies gamma value to the input image so that it makes image into human perceptive bias on brightness. Then image is converted to CIELAB. The image is represented in CIELAB color space because superpixel segmentation calculate the color difference in CIELAB color space. The median blur isapplied to image for removing noise and make edge more sharpened. In semantic segmentation, firstly it reshapes theimage without changing its data. So, to give a new shape to array of input image. Then image is converted to RGB colorspace. It contains red, green and blue channels. After thatimage is ready for segmentation.

C. Content adaptive superpixel segmentation

The existing super pixel algorithms has different drawbacks such as inadequate feature representation and do not include feature discriminability measure. To overcome these issues Content Adaptive Superpixel (CAS) is proposed that utilizes the local characteristics in images. The CAS integrate feature representation and clustering based discriminability measure. The feature representation embrace color, spatial, texture and contour features. The color and spatial along cannot distinguish different objects in an image. So, CAS has advantage over other super pixel segmentation. In clustering based feature discriminability measure, calculate sum within the cluster is small has more discriminative and larger sum within the cluster variance has less discriminative. That's how it evaluates the importance of different features and take features with good discriminability. In CAS algorithm, number of super pixels are identified andassign each cluster center. In each iteration pixels are assigned to its nearest center. The Euclidean distance [29] is measuredto calculate the distance between cluster center and pixel. After that generate partition of image instance. Then based onpartition, discriminability is calculated and weight is updated in next iteration. After fixed number of iterations this process stops. Then CAS merge the unconnected super pixels to its nearest neighbors.

D. FCN for Semantic Segmentation

Semantic segmentation performs fine-grained inference by predicting each pixel in an image to predefined class. Each pixel is labeled with class of its region. Semantic segmentationis different from classification because it does not bound any rectangle over the object. One more important thing is that it cannot distinguish between different instance of same object.FCN is used for Semantic segmentation. The aim of FCN is to perform "semantic segmentation". FCN can take any arbitrary size of image. FCN use convolutional layers for segmenting region. It extracts features from the image, create a model and then train the model for prediction. FCN contains convolutional layer, max-pooling, batch normalization, activation function. FCN has convolution and deconvolution process. In convolution layers get smaller and smaller because of striding and pooling, it reduces the dimension of tensor. So, FCN use deconvolution to up-sample the intermediate tensor and get the output as original image size. FCN reduce the number of parameter and computation time [30].

IV. RESULTS AND DISCUSSION

Different preprocessing technique are applied to the data set. preprocessed image is given to CAS segmentation. It finds outsuper pixels and generate connectivity. Semantic segmentation is used to gets the preprocessed image and FCN method to identify the tumor region. Both segmentation methods are compared. We compare performance by Dice similarity score and time taken for segmenting tumor region. The input image to CAS and Semantic segmentation is shown in Figure 2.

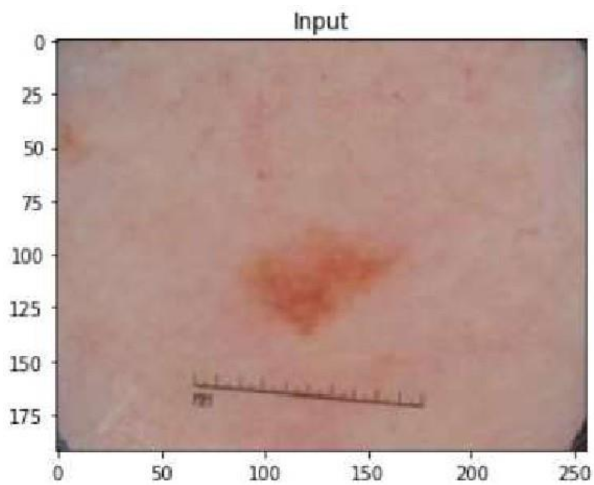

Fig. 2 The input image for segmentation

The ground truth of input image is shown in Figure 3.

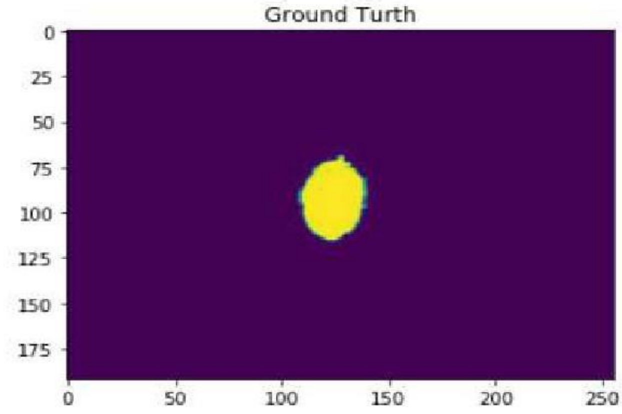

Fig. 3 The Ground truth image of input

The data set consists of the dermoscopic images and its ground truth corresponding to the images.T he steps involved in CAS segmentation is shown in Figure 4.


```
Initiating Segment Attributes...
[[  0   0   0 ... 338 338 338]
 [  0   0   0 ... 338 338 338]
 [  0   0   0 ... 338 338 338]
 ...
 [ 14  14  14 ... 344 344 344]
 [ 14  14  14 ... 344 344 344]
 [ 14  14  14 ... 344 344 344]]
Merging Segments...
segments merged - final
```

Fig. 4 CAS segmentation

Firstly, gamma correction is applied to input image. After that image is converted to CIELAB color space. Then extract the features and iteratively find the clusters. Superpixel are generated and segments are created. The merged segments are shown in Figure 5.

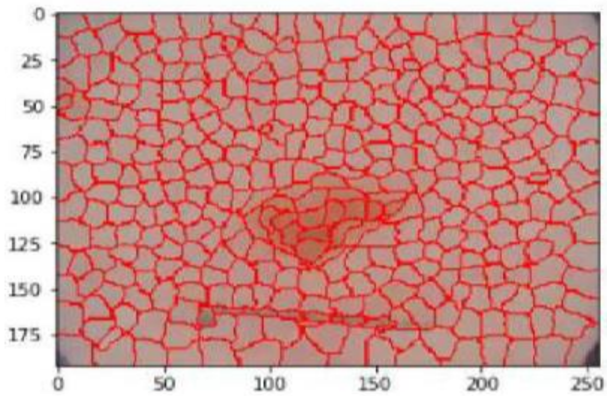

Fig. 5 Merged segments

After generating segments, the unconnected segments are merged and final result of super pixel segmentation is obtained. It is shown in Figure 6.

```
(192, 256) (192, 256)
Dice similarity score is 0.7096150716145834
Time taken : 34.357577323913574
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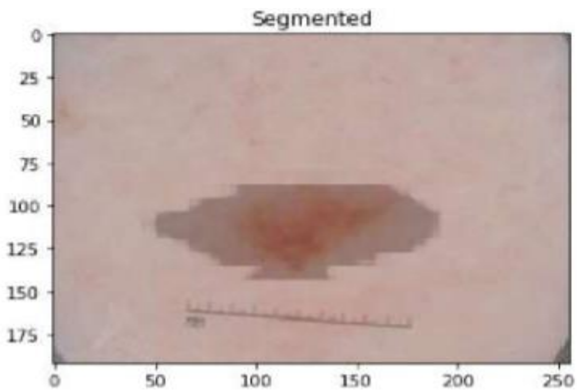
Fig. 6 Output of CAS segmentation

The region marked in yellow color shows the tumor region. The metric used for calculation is Dice similarity score and time taken. For the given input dice similarity score is 70.96% and time taken is 34.35 seconds. Figure 7, shows the output of Semantic segmentation after segmenting input image.

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Dice similarity score is 0.8930257161458334
Time taken : 0.8846347332000732
```

Fig. 7 Output of Semantic Segmentation

The marked region shows the tumor present in the dermoscopic image. For the given input, dice similarity score is 89.30% and time taken is 0.88 seconds. So, comparing both results, it is clearly evident that semantic segmentation perform better than CAS. The dice similarity score of semantic segmentation is more than CAS and time taken for semantic segmentation is less than CAS. In the Table 1, shows a comparison between Semantic and CAS segmentation for same input image. The performance evaluation of FCN for semantic segmentation is better than CAS. FCN efficiently detect the tumor region but CAS result shows that it alsomarks the artifact in the images.

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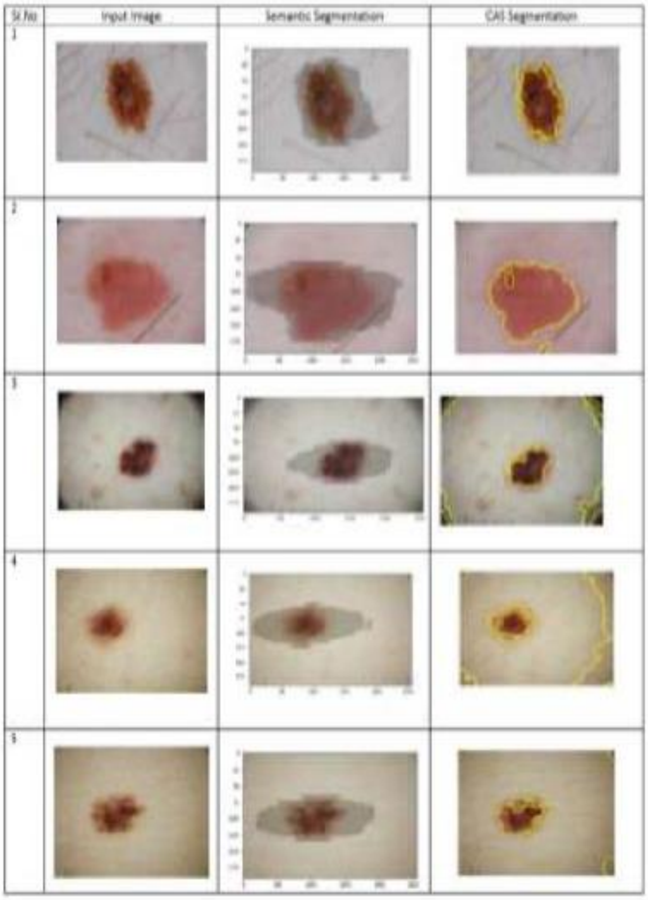

Table. 1 Comparison between Semantic and CAS

V. CONCLUSIONS AND FUTURE WORKS

Segmentation is the process of separating the lesion from the surrounding skin in order to form the region of interest. In this work, we compare two different segmentation methods. Various preprocessing techniques are used for enhancing the input data. CAS algorithm has gamma correction and converting RGB to CIELAB color space as preprocessing and semantic segmentation has reshape and converting the Gray scale image into RGB. First, CAS segmentation is applied to input images and get the desired segmented output. Then Semantic segmentation is applied to same input image. The FCN is used for semantic segmentation. Experimental results demonstrated that semantic segmentation is better than CAS. The dice similarity score and total time taken for each image segmentation is used as metric for evaluation. The dice similarity score of semantic segmentation is higher than CAS. The time taken for segmentation using CAS is less than Semantic segmentation. So, we conclude that Semantic segmentation is better for segmenting melanoma skin cancer from dermoscopic images. In Future, this comparison can apply to other medical image segmentation and find out which segmentation is better for identifying region.

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