

C3 Skin Lesion Based Melanoma Disease Detection Approach for Efficient Classification of Medical Images

^{1*}K.Muthukumar, ²P.Gowthaman, ³M.Venkatachalam, ³M. Saroja, ¹N. Pradheep

¹Research Scholar, Department of Electronics, Erode Arts and Science College, Erode

²Assistant Professor, Department of Electronics, Erode Arts and Science College, Erode

³Associate Professor, Department of Electronics, Erode Arts and Science College, Erode

Corresponding author's E-mail : kmuthukumar.easc@gmail.com

Abstract:

The problem of image classification and skin tumor detection has been well studied. There are number of approaches available for the detection of skin lesion but suffer with the classification accuracy. To improve the performance of skin lesion detection and classification, an efficient Color Coverage Correlation based classification approach is presented in this paper. The method reads the human skin image and improves the image quality with Gabor Filter and histogram equalization. Then with enhanced image, the method computes the color quantization value based on the intensity values of pixels of different skin region. Based on the color quantization, the image has been segmented. The segmented region has been identified and the features are extracted. Using the segmented region and features, the method compute the C3 lesion correlation measure with available patterns of tumors. Based on the correlation measure, the lesion detection and classification has been performed. The proposed algorithm improves the performance of classification and reduces false ratio.

Index Terms: Skin Lesion, Image Processing, Skin Tumor, Classification, C3 Approach, Segmentation.

Introduction:

The human society has facing various life threatening diseases. Among them, the cancer is the most deadly disease being faced by the human society independent of age. The disease can be appearing in any part of the body. The human skin has the major threat to the skin lesion. The skin lesion is a kind of tumor being considered which can spread to other part of the body. It looks like a ulcer initially. The skin has all the supporting features for the tumor due to the melanin. As the melanin gets malfunctioned the melanoma could appear on the skin of human. When the melanin gets reduced due to the shortage of iron and blood of

human sample, the melanoma would appear. It can be identified by any experienced medical practitioner but the accuracy of detection is highly questionable. To solve this issue number of automatic systems has been developed.

However, the prediction of the disease requires certain strategic approaches. Image processing techniques can be used to solve this issues. Earlier for the detection of mammogram and cancer in other parts like lungs, various image processing techniques has been adapted. Similarly the same approaches have been proposed for the detection of skin lesion from skin images. The skin tumors cannot be identified at the initial stage with the medical practitioner but with the help of automated systems the presence of the tumor can be identified or classified efficiently.

The classification is the process of identifying the class of input image. As the skin image becomes the input data, the classification process identifies the class of image between normal and malign. To perform this, the sample images of various victims of skin lesion has been collected and organized. Using the samples available with the image processing technique, the similarity between them can be measured. Number of measures and approaches available for the classification. The color based approaches are using only the color values of the skin images. This would introduce higher false classification and time complexity. Similarly, the gray values have been used in different approaches which produce same set of results on classification. This increases the necessity of considering different other features and combines them to produce higher classification ratio.

To support the classification process, the input images has to be segmented. Either using the color value or the contrast, they can be segmented to identify the suspected region. Because of the skin region of the human has particular color value according to the nature of the person. By considering this, the region which looks different from other part of the body could be identified and segmented. For segmentation, different approaches available but we use our own way of segmenting the image pixels to different groups.

C3 represent the terms Color Contrast and Correlation. The above mentioned features of the image can be used to perform segmentation and lesion detection. The color value represent the intensity of the skin region and contrast represent the gray scale value of the pixel. Using these two, the segmentation can be performed. The correlation measure represent the similarity of both of them. Based on these two, the problem of skin lesion

detection can be approached efficiently. The detailed approach is discussed in the next section.

Related Works:

There are number of approaches available for the detection of skin lesion and this section discuss different methods available for the problem identified.

Skin lesion classification from dermoscopic images using deep learning techniques [1], focus on the problem of skin lesion classification, particularly early melanoma detection, and present a deep-learning based approach to solve the problem of classifying a dermoscopic image containing a skin lesion as malignant or benign. The proposed solution is built around the VGGNet convolutional neural network architecture and uses the transfer learning paradigm.

Detection and Analysis of Skin Cancer from Skin Lesions [2], skin images are filtered to remove unwanted particles, then a new method for automatic segmentation of lesion area is carried out based on Markov and Laplace filter to detect lesion edge, followed by convert image to YUV color space, U channel will be processed to remove thick hair and extract lesion area. Diagnosis of melanoma achieved by using ABCD rules with new method for determine asymmetry based on rotation of lesion and divide lesion to two parts horizontally and vertically then count the number of pixels mismatched between the two parts based on union and intersection between the two parts.

Automatic Detection of Melanoma Skin Cancer using Texture Analysis [3], presents an automated method for melanoma diagnosis applied on a set of dermoscopy images. Features extracted are based on gray level Co-occurrence matrix (GLCM) and Using Multilayer perceptron classifier (MLP) to classify between Melanocytic Nevi and Malignant melanoma. MLP classifier was proposed with two different techniques in training and testing process: Automatic MLP and Traditional MLP. Results indicated that texture analysis is a useful method for discrimination of melanocytic skin tumors with high accuracy.

Very deep convolutional networks for large-scale image recognition [4], nvestigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Our main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3x3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth

to 16-19 weight layers. These findings were the basis of our ImageNet Challenge 2014 submission, where our team secured the first and the second places in the localisation and classification tracks respectively. We also show that our representations generalise well to other datasets, where they achieve state-of-the-art results.

Imagenet large scale visual recognition challenge [5], evaluates algorithms for object detection and image classification at large scale. One high level motivation is to allow researchers to compare progress in detection across a wider variety of objects -- taking advantage of the quite expensive labeling effort. Another motivation is to measure the progress of computer vision for large scale image indexing for retrieval and annotation.

Deep learning ensembles for melanoma recognition in dermoscopy images [6], propose a system that combines recent developments in deep learning with established machine learning approaches, creating ensembles of methods that are capable of segmenting skin lesions, as well as analyzing the detected area and surrounding tissue for melanoma detection.

Two systems for the detection of melanomas in dermoscopy images using texture and color features [7], addresses two different systems for the detection of melanomas in dermoscopy images. The first system uses global methods to classify skin lesions, whereas the second system uses local features and the bag-of-features classifier. This paper aims at determining the best system for skin lesion classification. The other objective is to compare the role of color and texture features in lesion classification and determine which set of features is more discriminative.

Skin Lesion Analysis Towards Melanoma Detection [8], Preprocessing To prepare the images for the network, each of the training images was resized to 192 pixels by 192 pixels. To create additional training images, each of the training images was elastically distorted. For each of the original training images, four randomly generated elastic distorted images were generated and then resized down to 192 by 192 pixels. In addition, each training image was also rotated 90 degrees and additional elastic distortions were applied to the rotated images.

Detection of Melanoma Skin Cancer in Dermoscopy Images [9], present a novel method for the detection of melanoma skin cancer. To detect the hair and several noises from images, pre-processing step is carried out by applying a bank of directional filters. And therefore, Image inpainting method is implemented to fill in the unknown regions. Fuzzy C-Means and

Markov Random Field methods are used to delineate the border of the lesion area in the images. The method was evaluated on a dataset of 200 dermoscopic images, and superior results were produced compared to alternative methods.

Computer Aided Melanoma Skin Cancer Detection Using Image Processing [10], present a computer aided method for the detection of Melanoma Skin Cancer using Image Processing tools. The input to the system is the skin lesion image and then by applying novel image processing techniques, it analyses it to conclude about the presence of skin cancer. The Lesion Image analysis tools checks for the various Melanoma parameters Like Asymmetry, Border, Colour, Diameter,(ABCD) etc. by texture, size and shape analysis for image segmentation and feature stages. The extracted feature parameters are used to classify the image as Normal skin and Melanoma cancer lesion.

Skin Lesion Detection using Automatic Neural Network Segmentation [11], image is subjected to pre-processing for removing the noise and enhancing the image. Brightness Preserving Dynamic Fuzzy Histogram Equalisation is an attractive method to enhance the image considering the local histogram method. This method is employed to provide crisper image by increasing the number of pixels between the interval. Then the image is segmented using Artificial Neural Network.

Border detection in dermoscopy images using statistical region merging [12], present a fast and unsupervised approach to border detection in dermoscopy images of pigmented skin lesions based on the statistical region merging algorithm. Pigmented skin lesion segmentation on macroscopic images [13], proposes a new method for segmenting pigmented skin lesions on macroscopic images acquired with standard cameras. Our method is simpler than comparable methods proposed for dermoscopy, and our experiments based on publicly available datasets of pigmented skin lesion images show promising results.

An ICAbased method for the segmentation of pigmented skin lesions in macroscopic images [14], a new skin lesion segmentation method is proposed. This method uses Independent Component Analysis to locate skin lesions in the image, and this location information is further refined by a Level-set segmentation method.

Comparison of segmentation methods for melanoma diagnosis in dermoscopy images [15], propose and evaluate six methods for the segmentation of skin lesions in dermoscopic images. This set includes some state of the art techniques which have been successfully used

in many medical imaging problems (gradient vector flow (GVF) and the level set method of Chan et al. [(C-LS)]. It also includes a set of methods developed by the authors which were tailored to this particular application (adaptive thresholding (AT), adaptive snake (AS), EM level set (EM-LS), and fuzzy-based split-and-merge algorithm (FBSM)]. The segmentation methods were applied to 100 dermoscopic images and evaluated with four different metrics, using the segmentation result obtained by an experienced dermatologist as the ground truth.

All the methods introduce higher false classification ratio and time complexity.

C3V Based Skin Lesion Detection Scheme:

The proposed skin lesion detection algorithm reads the input image and perform noise removal with Gabor filter. Then the image has been segmented based on various features considered. Using the segmented image, the method estimates different lesion support measure. Finally a C3 lesion support measure has been estimated to perform lesion detection.

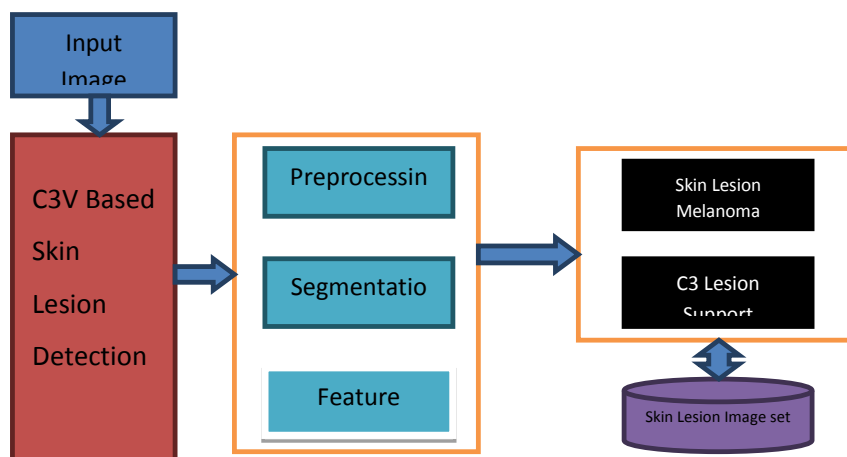


Figure 1: Architecture of proposed C3 Approach

The Figure shows the architecture of proposed C3 Approach for lesion detection. The Figure also shows the various components of the proposed algorithm.

Preprocessing:

The preprocessing is the process of preparing the image for the required format. In this stage, first the input image has been applied with Gabor filter to remove the noise present in the image. Then the image has been adjusted for its quality using the histogram equalization technique. This improves the quality of the image and the contrast of the image has been adjusted. The quality improved image has been used to perform rest of the process.

Algorithm:*Input: Image I**Output: Prepared Image PI**Start**Read input image I.**Initialize Gabor Filter GF.*

$$GF = \int_{i=1}^{Level} GF(i) < Gradient >$$

Perform noise removal.

$$PI = GF(I)$$

Initialize Value Set Vs.

Identify unique color values $Vs = Vs \cup (\int_{i=1}^{size(PI)} \sum PI(i).Value \notin Vs)$

*For each value v from Vs**Pd = compute probability of distribution(v)**Reset all the pixels with the value Pd.*

$$PI = \int_{i=1}^{size(PI)} (PI(i) = pd) ? PI(i) == v$$

*End**Stop*

The above discussed algorithm reads the input image and performs noise removal. Using the noise removed image, the quality has been adjusted based on the histogram equalization technique.

Segmentation:

The preprocessed image has been read, and unique color values of the image have been identified. Based on the color values, they have been grouped into two classes based on standard deviation. For each pixel, the method estimates the distance measure and based on that the group of the pixel has been identified. The image pixels are segmented based on the distance with the standard deviation measure. The segmented image has been used to perform feature extraction and to estimate other measures.

Algorithm:*Input: Preprocessed Image PI*

Output: Segmented Image SI

Start

Read preprocessed image PI.

Identify unique valued pixels $Uvp = Uvp \cup (\sum_{i=1}^{size(PI)} PI(i).Value) \notin Uvp$

Compute minimum value $Min-v = Min(Uvp)$

Compute maximum value $Max-v = Max(Uvp)$

Compute total no of pixels $Tn = size(PI)$.

Initialize Groups G1,G2.

For each pixel p

Estimate distance with min as $Mind = Dist(Minv, P. value)$

Estimate distance with max as $Maxd = Dist(Maxv, P. value)$

If $Mind < Maxd$ then

Assign to Group G2

Add to segmented image $SI = \sum(pi \in SI) \cup p$

Else

Assign to Group G1

Add to segmented image $SI = \sum(pi \in SI) \cup p$

End

End

Stop

The segmentation algorithm estimates the distance measures with the pixels of different range and performs segmentation.

Feature Extraction:

In this stage, the preprocessed and segmented images are read. Using both, for each pixel coordinate, the lesion region value has been compared. If it is similar to the lesion region value, then it has been considered as interest one. For the pixel being identified, the method extracts the coordinates, color value. The same has been converted into gray scale and from that the gray scale value has been taken. All the extracted values has converted into feature set. Generated Feature set has been used to estimate the C3 lesion support measure.

Algorithm:

Input: Segmented Image SI, Preprocessed Image PI, Value Set Vs

Output: Coordinate set Cs, Color set Cos, Contrast Set cns.

Start

Read SI,PI,Vs.

Convert segmented image SI to gray scale GI.

For each pixel of SI

If Group 2 then

Extract coordinate $Cn = (SI(p).X, SI(p).Y)$.

Add to coordinate set $Cs = \sum(Cn(Cs)) \cup Cn$

Extract color value $Cv = SI(p).value$

Add to color value set $Cvs = \sum(Cv(Cvs)) \cup Cv$

Extract contrast value $Con=GI(p).value$

Add to contrast value set $Cns = \sum(Con(Cns)) \cup Con$

End

End

Stop

The above discussed algorithm extracts various features and adds to different feature set. The generated feature set has been used to estimate different measures for the classification.

C3 Lesion Support Estimation:

The lesion support represents the closure of the image for the disease. It has been measured based on the features of the pixels present. If the particular region looks more close to the samples available in terms of color, contrast and area being covered, then it can be termed as positive. To estimate that different support measures are estimated in this stage. First, color lesion support measure, contrast lesion support measure and coverage lesion support measures are estimated. Using all these, the method computes the C3 lesion support measure to perform classification.

Algorithm:

Input: Data set Ds, Feature Set Fs, Feature Vector set Fvs.

Output: C3Ls

Start

Read Ds.

Initialize Fvs

For each image I from Ds

PI = perform preprocessing (I).

SI = perform segmentation(PI)

Fvs = $\sum(Fv \in Fvs) \cup FeatureExtraction(SI)$

End

For each feature f from Fvs

$$\text{Compute color lesion support } Cls = \frac{\sum_{i=1}^{\text{size}(Fvs)} \text{Dist}(f.Cv, Fv.CV)}{\text{size}(Fvs)}$$

$$\text{Compute contrast lesion support } Conls = \frac{\sum_{i=1}^{\text{size}(Fvs)} \text{Dist}(f.Con, Fv.Con)}{\text{size}(Fvs)}$$

$$\text{Compute coverage lesion support } covls = \frac{\sum_{i=1}^{\text{size}(Fvs)} \text{Dist}(f.Area, Fv.Area)}{\text{size}(Fvs)}$$

$$\text{Compute C3 lesion support } C3ls = \frac{Cls}{Conls} \times Covls$$

End

$$\text{Compute cumulative } C3ls = \frac{\sum C3ls}{\text{size}(Fvs)}$$

Stop

The above discussed algorithm estimates various support measures and finally a cumulative C3 lesion support measure has been estimated.

Skin Lesion Melanoma Detection:

The presence of skin lesion disease from the medical image has been identified using C3 lesion support measure being estimated. To perform this, first the method reads the input image and perform preprocessing. [16] In the second stage, the segmentation is performed with feature extraction. The extracted features has been used to compute the C3 lesion support value. Based on the value of C3ls the detection process is performed.

Algorithm:*Input: Image I, Data Set Ds**Output: Boolean**Start**Read I, Ds**PI = Perform preprocessing(I)**SI = Segmentation(PI)**Feature Set Fs = Feature Extraction (PI,SI)**C3ls = Estimate C3lesion support (Fs, Ds)**If C3ls > Th then**Return true**Else**Return false**End**Stop*

The above discussed algorithm performs lesion detection based on the results of different stages involved.

Results and Discussion:

The proposed C3ls based skin lesion based melanoma disease detection has been implemented using Matlab and the performance in detection has been analyzed. The method has produced efficient results on skin lesion detection and produced less time complexity.

Table 1: Details of implementation

Property	Value
Tool	Matlab
Data Set	ISIC
No of lesion Images	13786
No of classes	Belign or Malignant

The Table 1, shows the details of implementation and evaluation being used to evaluate the performance of the proposed algorithm.



Figure 2: Comparison on lesion detection performance

The Figure 2, shows the comparative result on lesion detection performance produced by different methods. The proposed algorithm has produced higher detection accuracy than other methods.

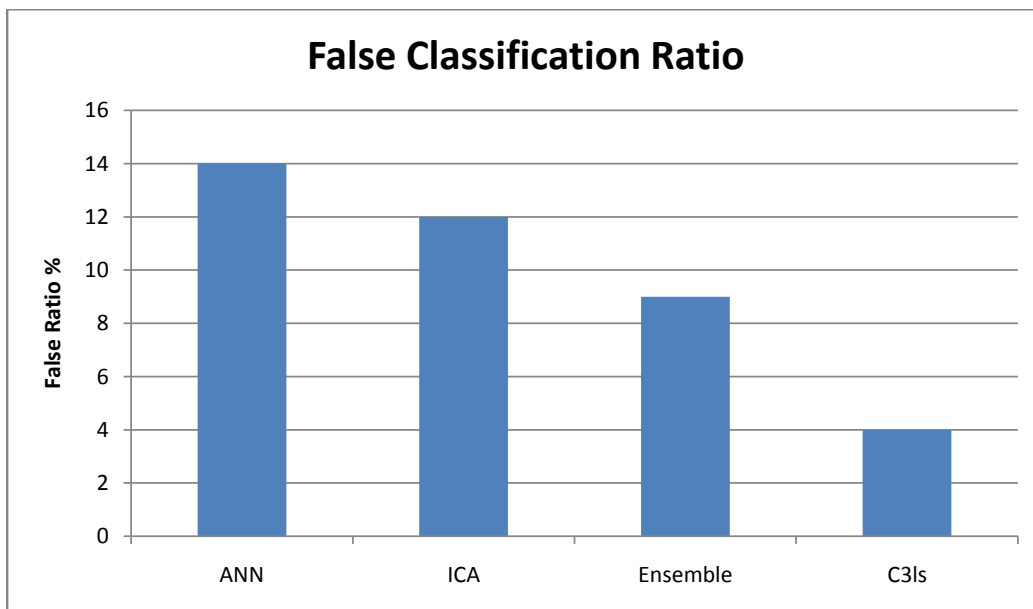


Figure 3: Comparison on false classification ratio

The Figure 3, shows the comparative result on false classification ratio being produced by various methods. The proposed algorithm has produced higher lower false ratio than other methods.

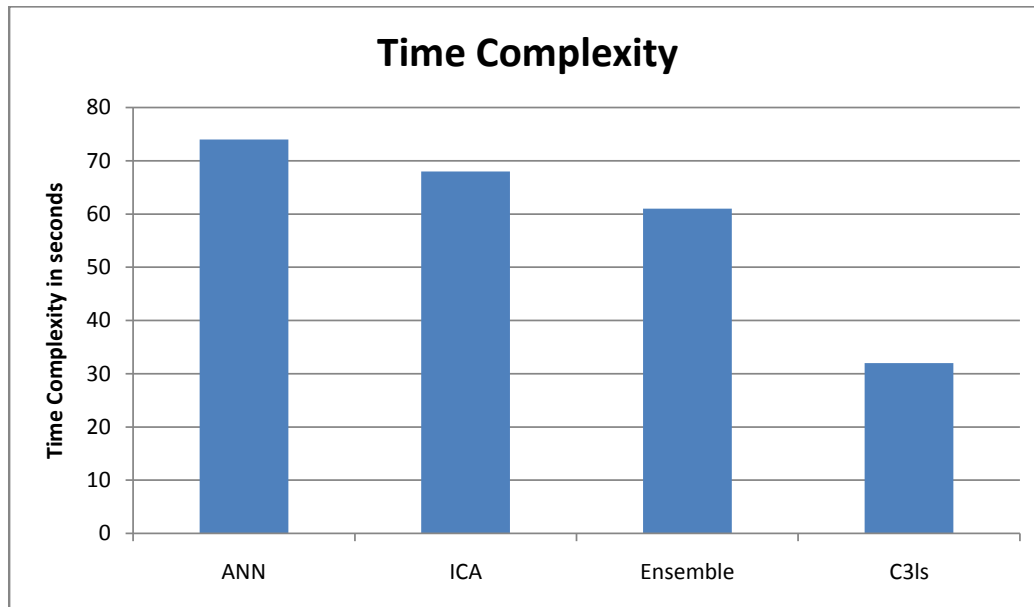


Figure 4: Comparison on time complexity

The Figure 4, shows the comparative result on time complexity produced by different methods. The proposed algorithm has produced less time complexity than other methods.

Conclusion:

The problem of skin lesion based melanoma disease detection has been approached with different methods but suffers to achieve higher performance. To improve the performance, an C3ls approach is presented in this paper. The method enhances the image and performs segmentation. From the segmented image the features of color, contrast and coverage measures are extracted. Then using the features extracted, the method computes different support measures to compute C3 lesion support measure. Based on the value of C3ls, the detection is performed. The method produces higher detection accuracy and reduces the false ratio with time complexity.

References:

- [1]. Adria Romero Lopez ; Xavier Giro-i-Nieto ; Jack Burdick ; Oge Marques, Skin lesion classification from dermoscopic images using deep learning techniques, IEEE Conference on Biomedical Engineering, 2017.
- [2]. Nidhal K. EL Abbadi and Zahraa Faisal Detection and Analysis of Skin Cancer from Skin Lesions, International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 19 (2017) pp. 9046-9052.

- [3]. M. A. Sheha, M.S.Mabrouk, A. Sharawy, "Automatic Detection of Melanoma Skin Cancer using Texture Analysis," International Journal of Computer Applications, vol. 42, no. 20, pp. 22–26, 2012.
- [4]. K. Simonyan, A. Zisserman, "Very deep convolutional networks for large-scale image recognition", arXiv preprint arXiv:1409.1556, 2014.
- [5]. O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein et al., "Imagenet large scale visual recognition challenge", International Journal of Computer Vision, vol. 115, no. 3, pp. 211-252, 2015.
- [6]. N. Codella, Q.-B. Nguyen, S. Pankanti, D. Gutman, B. Helba, A. Halpern, J. R. Smith, "Deep learning ensembles for melanoma recognition in dermoscopy images", arXiv preprint arXiv:1610.04662, 2016.
- [7]. C. Barata, M. Ruela, M. Francisco, T. Mendonça, J. S. Marques, "Two systems for the detection of melanomas in dermoscopy images using texture and color features", IEEE Systems Journal, vol. 8, no. 3, pp. 965-979, 2014.
- [8]. Matt Berseth, Skin Lesion Analysis Towards Melanoma Detection, Seantic Scholar, ISIC 2017.
- [9]. Khalid Eltayef, Yongmin Li and Xiaohui Liu, Detection of Melanoma Skin Cancer in Dermoscopy Images,IOP, Journal of Physics, Vol 787, 2017.
- [10]. Shivangi Jain, Vandana jagtap Nitin Pise, Computer Aided Melanoma Skin Cancer Detection Using Image Processing, Elsevier, vol.28, pp:735-740, 2015.
- [11]. D. Ramya1 , G. Sri Lakshmi2 and S. Prithi, Skin Lesion Detection using Automatic Neural Network Segmentation, SSRG International Journal of Electronics and Communication Engineering, 2017.
- [12]. A. Marghoob, H. S. Rabinovitz, and S. W. Menzies, "Border detection in dermoscopy images using statistical region merging," Skin Res. Technol., vol. 14, no. 3, pp. 347–353, 2008.
- [13]. P. Cavalcanti, Y. Yari, and J. Scharcanski, "Pigmented skin lesion segmentation on macroscopic images," in Proc. 25th Int. Conf. Image Vision Comput. New Zealand., 2010, pp. 1–7.
- [14]. P. Cavalcanti, J. Scharcanski, L. Di Persia, and D.Milone, "An ICAbased method for the segmentation of pigmented skin lesions in macroscopic images," in Proc. IEEE Annu. Int. Conf. Eng. Med. Biol. Soc., 2011,pp. 5993–5996.

- [15]. M. Silveira, J. C. Nascimento, J. S. Marques, A. R. S. Marcal, T. Mendonca, S. Yamauchi, J. Maeda, and J. Rozeira, "Comparison of segmentation methods for melanoma diagnosis in dermoscopy images," *IEEE J. Sel. Top. Signa.*, vol. 3, no. 1, pp: 35-45, 2009.
- [16]. N. Pradheep, M. Venkatachalam, M. Saroja, S. Prakasam, "A Cloud Computing Solution for Securely Storing and Accessing Patients Medical Data", *Jour of Adv Research in Dynamical & Control Systems*, 12-Special Issue, August 2017.

