An Efficient 3-class Fuzzy C-Means Clustering algorithm with Thresholding for Skin Lesion Image Segmentation

Babita Ingle[1] , Prof. Anoop Tiwari[2]
[1]M.Tech Scholar, [2]Associate Professor
[1&2]Department of Electronics and Communication Engineering,
[1&2] Sagar Institute of Science and Technology, Bhopal, India.

Abstract: Skin cancer is the most dangerous and a common type of cancer. A skin lesion is an abnormal lump, bump, and ulcer, sore or colored area on the skin. There are many types of skin segmentation. In computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Segmentation has importance to detect skin lesion from images. Different method for segmentation of dermoscopic images of skin cancer and other pigmented lesions is presented. In this paper, C-Means Clustering approach for skin lesion image segmentation is proposed so that detection and recognition of skin decease will easy to understand by patient and biomedical industries.

***IndexTerms* – FCM, Skin, Lesion, Segmentation, Fuzzy.**

I. INTRODUCTION

Customary skin cancer detection techniques implicate image feature investigation to layout the cancerous regions of the typical skin. Thresholding techniques utilize low-level features, including power and color to isolate the ordinary skin and cancerous districts. Garnavi et al. connected Otsu's strategy to distinguish the core-lesion; by and by, such process is arranged to skin tone varieties and lighting. Also, dermoscopic images include a few artifacts because of water bubble, thick hairs, and gel that are an incredible challenge for accurate detection. Silveira et al. assessed six skin lesions segmentation techniques in dermoscopic images, including the slope vector stream (GVF), level set, versatile snake, versatile thresholding, fuzzy-based split and union (FSM), and the expectation–augmentation level set (EMLV) strategies. The outcomes set up that versatile snake and EMLV were considered the prevalent semi-directed techniques, and that FSM achieved the best completely computerized outcomes.

Skin Cancer incidence is increasing at 3.1% every year. Skin cancer spread over the body with the assistance of lymphatic and veins. Along these lines, early detection of skin cancer is significant for appropriate finding of the infection. Melanoma and Non-Melanoma are two noteworthy categories of skin cancers. Harmful melanoma is of a few sub-types. Basal cell carcinoma and Squamous cell carcinomas are two primary sorts of non-melanoma skin cancers. Each kind of skin cancer is unique in relation to the next skin cancers in certain characteristics. Computer supported classification devices are significant in medical imaging for analysis and assessment. Predictive models are utilized in an assortment of medical spaces for diagnostic and prognostic errands. These models are fabricated dependent on experience which constitutes information acquired from actual cases.

Figure 1: Skin cancer

The information can be preprocessed and communicated in a lot of standards, such as that it is frequently the case in information based master frameworks, and consequently can fill in as preparing information for statistical and machine learning models. herefore, numerous researchers are recently becoming keen on creating and utilizing "automfacatic advanced dermatoscopic image examination" techniques to enhance the diagnostic accuracy of melanoma everywhere throughout the world and improve clinical outcomes. Utilizing dermoscopic images alone, the separation of considerate versus threatening lesions won't be a simple errand. Accordingly, a further definite investigation is frantically required.

Dermoscopic Image analysis typically consists of four main steps:

i. image acquisition
ii. lesion segmentation
iii. Feature extraction
iv. Classification

What is increasingly significant in image examination is the segmentation venture as the accuracy of different advances is very reliant on it. In dermoscopic image examination, actualizing the segmentation step is very challenging for some reasons. Instances of factors that may impact the accuracy of this progression are: a low contrast between the lesion and the encompassing skin; sporadic lesion fringes and skin surface; presence air pockets and hair; and finally presence of numerous colors in the lesion.

II. LITERATURE SURVEY

A. Agarwal, A. Issac, M. K. Dutta [1] Melanoma can demonstrate deadly if not analyzed at beginning period. The accuracy of identification of skin cancer from dermoscopic images is directly relative to the accuracy of the skin lesion segmentation. This work proposes a skin lesion segmentation strategy utilizing clustering technique. The utilization of smoothing channel and zone thresholding is competent enough to sufficiently reject the loud pixels from the at last divided image. The aftereffects of skin lesion segmentation acquired from the proposed calculation has been compared with the commented on images. The outcomes have been communicated through covering score and correlation coefficient. The greatest benefits of covering score and correlation coefficient got from the calculation are 96.75% and 97.66% respectively. The outcomes are convincing and recommends that the proposed work can be utilized for some continuous application.

H. Ozkan, R. Gurleyen, E. Usta [2] In the cutting edge world, cancer has increasingly become a medical issue. It has been recorded as the initial three sickness among the 'cause-known passings' in our country. Threatening Melanoma, one of the skin cancer types, is the cause of 75% of all skin cancer related passings despite the fact that it is 4% of all skin cancer cases. The examination of the sicknesses are analyzed through visual inspections by the dermatologists.

S. M. Jaisakthi, P. Mirunalini [3] The proposed strategy comprises two noteworthy advances, to be specific preprocessing and segmentation. In the preprocessing step, commotion such as light, hair and rulers are evacuated utilizing separating techniques and in the segmentation stage, skin lesions are portioned utilizing the GrabCut segmentation calculation. The k-means clustering calculation is then utilized alongside the color features gained from the preparation images to improve the limits of the portions. To assess the creators' proposed strategy, they have utilized ISIC 2017 challenge dataset and PH 2 dataset. They have acquired Dice coefficient estimations of 0.8236 and 0.9139 for ISIC 2017 test dataset and PH 2 dataset, respectively.

P. Kharazmi, M. I. AlJasser, [4] The segmentation affectability and specificity of 90% and 86% were achieved on a lot of 500 000 physically fragmented pixels given by a specialist. To further show the prevalence of the proposed strategy, in view of the segmentation results, we characterized and extracted vascular features toward lesion determination in basal cell carcinoma (BCC). Among a dataset of 659 lesions (299 BCC and 360 non-BCC), a lot of 12 vascular features are extracted from the last vessel images of the lesions and encouraged into an arbitrary woodland classifier. At the point when compared with a couple of other condition of-craftsmanship techniques, the proposed strategy achieves the best performance of 96.5% as far as region under the curve (AUC) in separating BCC from benevolent lesions utilizing just the extracted vascular features.

L. Bi, J. Kim, E. Ahn, A. Kumar, [5] FCNs are a neural system architecture that achieves object detection by hierarchically combining low-level appearance data with abnormal state semantic data. We address the issue of FCN producing coarse segmentation limits for challenging skin lesions (e.g., those with fuzzy limits or potentially low difference in the surfaces between the closer view and the background) through a multistage segmentation approach in which numerous FCNs learn complementary visual characteristics of various skin lesions; beginning time FCNs learn coarse appearance and localization data while late-organize FCNs gain proficiency with the inconspicuous characteristics of the lesion limits. We additionally introduce another parallel joining strategy to combine the complementary data got from individual segmentation stages to achieve a last segmentation result that has accurate localization and well-characterized lesion limits, notwithstanding for the most challenging skin lesions.

Y. Yuan, M. Chao and Y. Lo, [6] Automatic skin lesion segmentation in dermoscopic images is a challenging undertaking because of the low contrast among lesion and the encompassing skin, the unpredictable and fuzzy lesion outskirts, the existence of different artifacts, and different imaging acquisition conditions. In this paper, we present a completely automatic technique for skin lesion segmentation by utilizing 19-layer profound convolutional neural systems that is prepared start to finish and does not depend on earlier learning of the information.

Table 2.1 Summary of Literature Review

Sr. No.	Author Name & Publication year	Proposed work	Result
1	S. M. Jaisakthi 2018	Segmented using the GrabCut segmentation algorithm	Obtained Dice coefficient values of 0.8236 and 0.9139
2	A. Agarwal 2017	Skin lesion segmentation method using clustering technique	Overlapping score and correlation coefficient 96.75% and 97.66% respectively
3	H. Ozkan 2017	Computer based segmentation system is developed to assist the expert	Error rates are reduced
4	P. Kharazmi 2017	k-means clustering	Segmentation sensitivity and specificity of 90% and 86%
5	P. M. Azevedo 2013	Clustering of color components in hue-saturation histograms	Standard deviation of 0.22, low average root-mean-squared error of 4%

III. PROPOSED METHODOLOGY

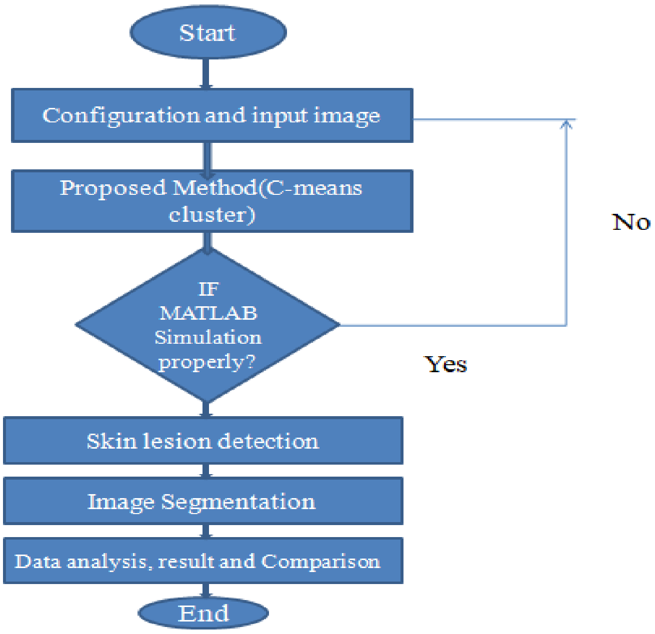

Figure 2: Flow Chart

A. FUZZY C-MEANS CLUSTERING

Fuzzy c-means Clustering Method

- Let *X*={*x1*, *x2*,…, *xn*} be a set of given data. A fuzzy pseudopartition or fuzzy c-partition of *X* is a family of fuzzy subsets of *X*, denoted by *P*={A1, A2,…, Ac}, which satisfies

for all *k*∈*Nn* and

for all *i*∈*Nc*, where c is a positive integer.

- Ex: Given *X*={*x1*, *x2*, *x3*} and A1=0.6/*x1*+1/*x2*+0.1/*x3*
  A2=0.4/*x1*+0/*x2*+0.9/*x3*, then
  {A1, A2} is a fuzzy pseudopartition or fuzzy 2-partition of *X*.
- Given a set of given data ***X***={***x1***, ***x2***,…, ***xn***}, where ***xk***, in general, is a vector
  xk={*xk1*, *xk2*,…, *xkn*}∈*Rp*
  for all *k*∈*Nn*, the problem of fuzzy clustering is to find a fuzzy pseudopartition and the associated cluster centers by which the structure of the data is represented as best as possible. This requires some criterion expressing the general idea that associations be strong within clusters and weak between clusters.
- Given a pseudopartition *P*={A1, A2,…, Ac}, the c clusters, ***v1***, ***v2***,…, ***vn*** associated with the partition are calculated by the formula

$$v_i = \frac{\sum_{k=1}^{n} [A_i(x_k)]^m x_k}{\sum_{k=1}^{n} [A_i(x_k)]^m}$$

for all *i*∈*Nc*, where *m*>1 is a real number that governs the influence of membership grades.

- Observe that the vector ***vi*** calculated above, which is viewed as the cluster center of the fuzzy class *Ai*, is actually the weighted average of data in *Ai*.
- The weight of a datum ***xk*** is the *m*th power of the membership grade of ***xk*** in the fuzzy set *Ai*.
- The performance index of a fuzzy pseudopartition P, Jm(P), is then defined in terms of the cluster centers by the formula

$$J_m(P) = \sum_{k=1}^{n} \sum_{i=1}^{c} [A_i(x_k)]^m \| x_k - v_i \|^2$$

where ||·|| is some inner prod ||2 represents the distance between ***xk*** and ***vi***.

- This performance index measures the weighted sum of distances between cluster centers and elements in the corresponding fuzzy clusters.

IV. SIMULATION RESULT

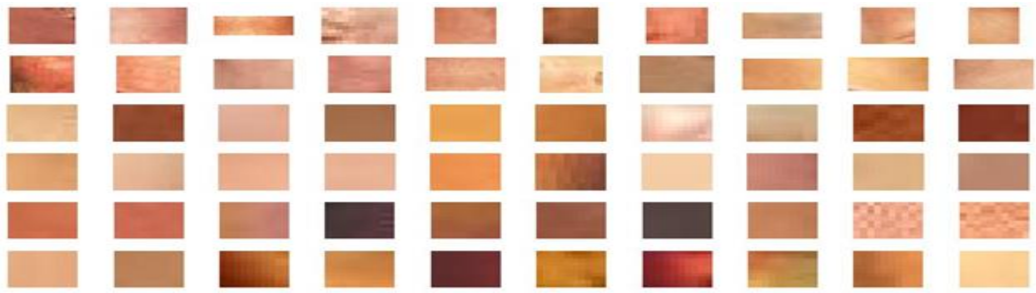

Figure 3: Skin pixel database

Results of Original Skin Lesion Image (1):

(a) Original Image

(b) Otsu Approach Image

(c) FCM 0(Fuzzy C-means class 0)

(d) FCM 1(Fuzzy C-means class 1)

(e) FCM 2(Fuzzy C-means class 2)

Figure 4: Results of Segmentation of Original Lesion Image 1
(a) Original image (b) Otsu approach (c) FCM 0 (Fuzzy C-means class 0)
(d) FCM1 (Fuzzy C-means class 1) (e) FCM2 (Fuzzy C-means class 2)

Results of Enhanced Skin Lesion Image (1):

(a) Original Image

(b) Otsu Approach

(c) FCM 0 (Fuzzy C-means)

(d) FCM 1(Fuzzy C-means)

(e) FCM 2 (Fuzzy C-means)

Figure 5: Results of Segmentation of Enhanced Lesion Image1
(a) Enhanced image (b) Otsu approach (c) FCM 0 (Fuzzy C-means class 0)
(d) FCM 1 (Fuzzy C-means class 1) (e) FCM 2 (Fuzzy C-means class 2)

Table 1: Simulation Result Summary

sr. no	**Tested Input Images**		**Otsu's Method Threshold**	**Class 3 Fuzzy C-Means Clustering**			**No. of Iteration**	**Elapsed time**
				FCM 0 level Threshold	**FCM 1 level Threshold**	**FCM 2 level Threshold**		
1	Image 1	Original	0.674510	0.357550	0.471510	0.357550	36	21.08Sec
		Enhanced	0.739216	0.383007	0.538562	0.383007	26	11.45sec
2	Image 2	Original	0.46860	0.227336	0.458802	0.22773	28	12.88Sec
		Enhanced	0.45884	0.23398	0.52679	0.23398	35	6.603 sec

Table 2: Comparison of proposed method with previous method

Sr. No.	Parameter	Previous Work	Proposed Work
1	Methodology	K-Means	C-Means (FCM)
2	Threshold Level	0.421569	0.25491
3	Simulation Time (Min)	3.88 Sec	1.79 Sec
4	Simulation Count	10	3
5	No of Iteration(Min)	29	22
6	Class	FCM-1	FCM-2

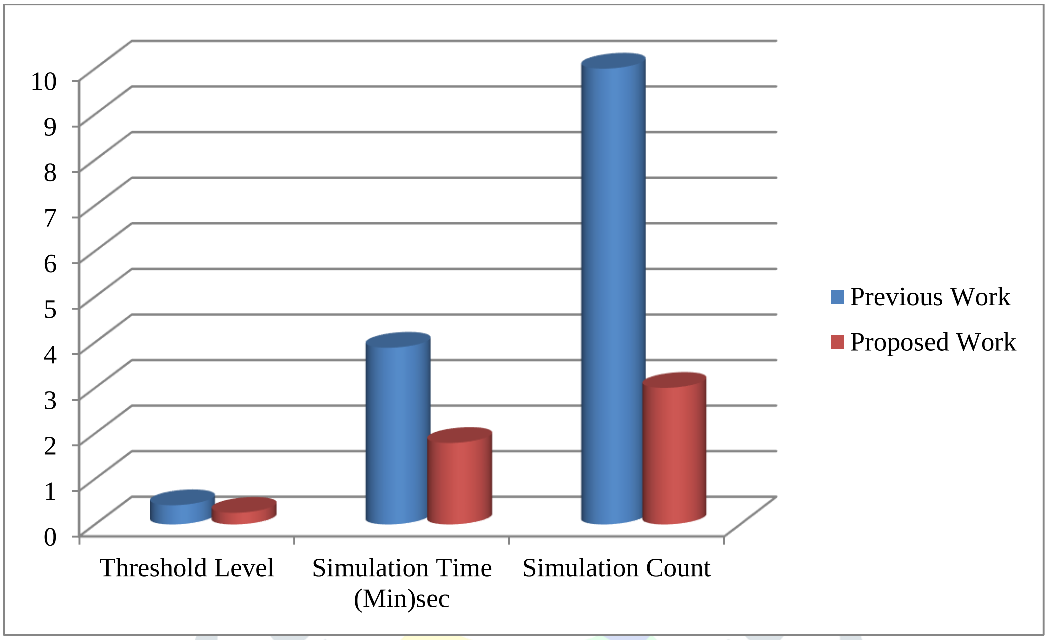

Figure 6: Comparison Chart

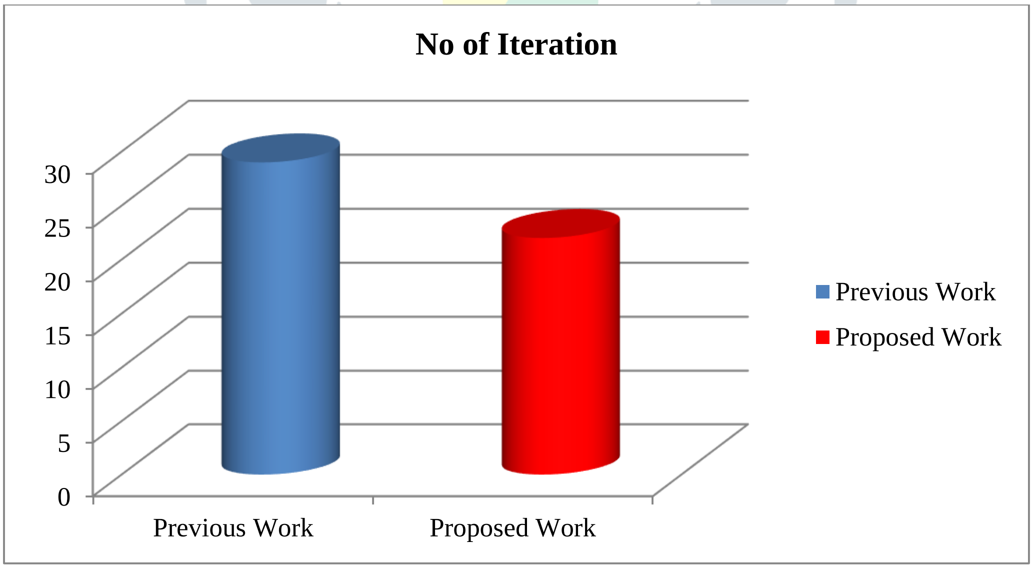

Figure 7: Iteration Count

Figure 6 and 7 shows comparison of parameters of previous and proposed work. It is clear that proposed approach gives significant achievement than previous work.

V. CONCLUSION

In this paper we have exhibited FCM approaches to build up a framework for automatic classification of skin cancer. According to results on color and surface examination, we are utilizing color and surface descriptors for skin cancer classification which give great classification accuracy on various classification rate. Legitimate selection of extraction strategy and classifier in combination is constantly significant for classification of skin cancer images. Image contrast and lesion direction directly affect the performance of the framework. In our investigation, we accept that contrast is equivalent and lesion direction is same. A model for human skin lesion circulation is manufactured utilizing a database of marked skin pixels. A clustering calculation dependent on fuzzy C-means has been prepared utilizing a similar database of skin pixels. A skin model, alongside a FCM for skin background pixels, is utilized to compute the likelihood of each pixel in an info color image to speak to skin.

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