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A Linear Filtering on Automatic Decomposition and Reconstruction of Dermoscopy Images using Global Thresholding

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Abstract: *One of the fastest growing cancers in human cell is skin cancer. Initially starts from the outer layer of human body and spreads unevenly all over by increasing in diameter. The formation of skin cancer depends on the weakness of skin cell. To find the perfect diagnosis, dermatologist should use the computational method. The identification of skin cancer is not easy on the first stage by the dermatologist but the computational method describes out perfectly. The proposed work describes in extracting the skin lesion using Otsu Thresholding with inverse discrete 2D wavelet transform. The proposed work initiated by pre-processing is to enhance the image, followed by segmentation to extract skin lesion with decomposition of fore ground and background image and terminates with post processing to extract feature like uneven boundary. The performance measure between proposed segmentation and ground truth image, described with accuracy up to 96.69% for ISIC 2016 dataset.*

Keywords *: Gaussian Filter, 2D Discrete Wavelet Transform, Otsu Threshold, 2D Inverse Wavelet Transform, Canny Edge Detection, Morphological Open, Principal Component Analysis.*

I. INTRODUCTION

Skin cancer is a very dangerous infection, which easily spreads out on the layers of the skin, which is called as melanoma. The melanoma can be easily identified with some properties like change in mole shape, color and irregular border. If the size of mole is more than 6mm in diameter, it is melanoma. It is hard to differentiate mole and melanoma in initial stage, even by the dermatologist. A computational methodology is required to differentiate it easily. The computational method, converts the disease into an image, which can be incorporated into multiple technological aspects, and further identification of property is easy.

Jose Fernandez Alcon et al. [1] have proposed to identify pigment skin lesion, an automatic system for segmentation and classification by decision system was given. The segmentation process is done with edge detection and active contours. The segmentation deals with separation of foreground and background, where the histogram of background is represented by quasi-Gaussian distribution. The segmentation is sequenced with the threshold value of foreground image.Further Otsu segmentation is used to minimize relies happen between foreground and background. ABCD features are extracted with segmentation contour image. The segmented contour image is compared with the ground truth image and some components are derived, 86% of accuracy, 94% of sensitivity and 68% of specificity.

B. Bozorgtabar et al. [2] have developed an initial segmentation with FCN based and fine turning with super pixel for deep convolution learning. The segmentation is on each pixel on the image by fine tuning method to extract the lesion border. The formation of fuzzy boundary is done with certain condition and complex textures. These extract some local contextual information of boundary. The research took on ISBI 2016 dataset. To organise each pixel, feed forward computation and back propagation technique are used in semantic segmentation.

FaouziAdjed et al. [3] have developed a fusion of structured features like wavelet and curvelet transform and texture features like local binary pattern operator. The features are segmented with svm classifier. The research work is done on public dataset PH2. The performance measures are given with a sensitivity of 78.93%, specificity of 93.25% and accuracy up to 86.07%. Even after identifying the structure and texture, some feature like stream, dots and borders are also identified.

N. C. F. Codella et al. [4] have proposed the separation with completely convolutional UNet architecture. The segmentation splits the job into 2 methods the preliminary portion deals with the foreground shape and finishing portion extract shape in back ground. The Gaussian filter is used to remove the artifacts in the lesion image. The performance measure is calculated which determines accuracy up to 94%, specificity up to 96.3% and sensitivity up to 91.4%. HaraldGanster et al. [5] have developed an automated system for recognizing melanoma disease by segmenting the image using fusion strategy. There are some set of feature extracted to describe about the correctness of segmentation. The breakdown is advance continued with Global Thresholding and Vibrant Thresholding. The threshold images are clustered based upon the colour. Shape, radiometric, line, area, perimeter features are extracted from the segmented image. The performance measure of the algorithm is 87% of sensitivity and 92% of specificity. Saptarshi Chatterjee et al. [6] have developed a 2D wavelet packet decomposition to extract fractal texture analysis. The border in the skin lesion are always irregular, to analyse the irregularity, the irregular texture pattern are extracted by organizing the boundary on basis of colour and texture.

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The elimination of other colour is done with recursive feature and with SVM classifier. The elimination of pixels is done automatically by selecting the Correlation Thresholding, equating each pixels and eliminating precise bias. The unsolicited pixels or artifacts are detached using median filter and morphological bottom filtering. Some features like area, eccentricity, and perimeter are extracted.

II. MATERIALS AND METHOD

A. Filter unsolicited pixels

The response of Gaussian filter is impulse to its function. There is a less group delay in Gaussian filter due to close connection of pixels [7]. The filter modifies the given signal by convolution matrix to Gaussian function [8]. There is an integral transformation of kernel function that reacts with Gaussian filter and generates sampling points to reduce noise [9]. It is a linear filtering technique, which is discrete. The Gaussian function is transformed by fast Fourier transform (FFT) with high impulse response in 2D Gaussian function, expressed as [10, 11].

$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (1)$$

B. Image Enhancement

When the image is converted in to Grayscale or binary image, the image intensity is insufficient to overcome the segmentation process. Hence to strength the image intensity, the image is taken into double precision and the image is scaled in an identical order. LAB is a non-linear transformation of RGB. Euclidian distance between two color is equal to their perception distance [12]. During the color conversion for perfect segmentation, there could be some problem in identification of a particular data. To overcome such problem, PCA introduces a matrix methodology [13]. The image has to be structured in such a manner that the large matrix, where row matrix corresponds to the human observation and column matrix represents the variable. The PCA segments the row and column using singular value decomposition algorithm. For perfect segmentation, the quality of pixels are noted by flat morphological structuring element, which is invited after a smooth morphological dilation [19, 20]. The flat structure is meant with the property of pixel present in the image. If the image pixels are true alone they are taken into consideration. Otherwise they are left unknown. This segmentation is implemented only if the image is in binary or grayscale in color [21, 22].

This segmentation arranges the row and column from PCA, identifies the center value of matrix and maintains its origin from the center of the matrix. From the identification of true pixels and from the flat structuring element, the morphological closing is called for eroding the pixel. Later the image is complemented to remove fine details or noise.

C. Image Enhancement

The wavelet transformation is executed in 2D discrete single level of data. The decomposition of image with respect to wavelet filters by discrete 2D transformation [14, 16]. The outcome of DWT gives the coefficient matrix, formed in horizontal, vertical and diagonal. In the Otsu Thresholding, images are clustered using the threshold basis [23].

The automatic process on deriving the threshold minimum level and maximum level is finished. The main process of using Otsu is to reduce Gray scale to binary image. The image is divided into 2 classes with bimodal histogram that derives the fore ground image and background image [24, 25]. The processing methodology of Otsu is to search threshold that minimizes the intra class variance, which defines as sum of variance given as

$$\sigma_w^2(t) = w_0(t)\sigma_0^2(t) + w_1(t)\sigma_1^2(t) \qquad (2)$$

W0, W1 → probability of 2 classes separated by threshold t.

σ_0^2, σ_1^2 → Variance of 2 classes.

The filters are used to reconstruct particular wavelet using single level 2D wavelet. The filters are low pass and high pass that should be of same length [16, 17].

III. PROPOSED SYSTEM

The requirements for constructing the computational method are described with following stages shown in Figure 1. The image dataset is obtained from ISIC dataset, which contains 400 Bengin, 300 Melanoma images. The image is in the format of RGB, processed with simple filtering techniques and Component analysis in preprocessing stage, followed by decomposition of region with respect to the intensity by 2D Wavelet Transformation. The regions are reconstructed with inverse 2D wavelet and Otsu Thresholding. The negative pixels are removed with morphological operation and a sharp edge is formed with canny edge detection, provides out the segmented image. The final stage of transformation is completed by identifying regional properties to extract uneven border. The borders are marked to describe its irregular border.

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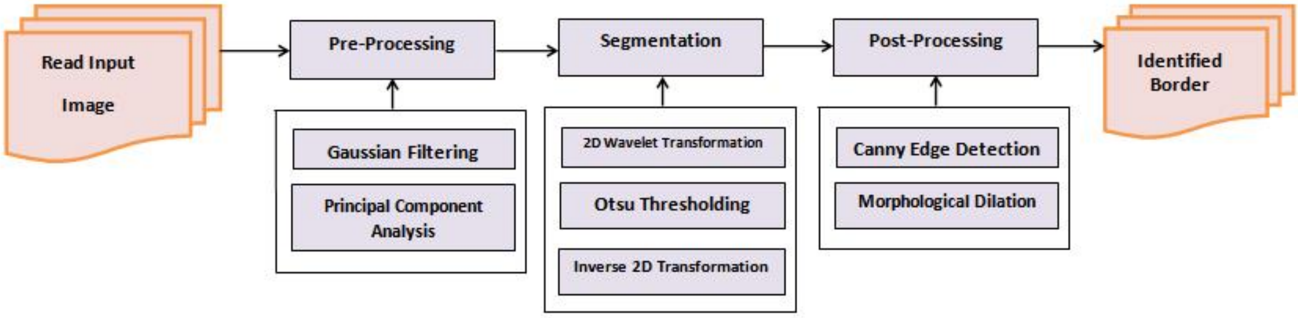

Fig. (1). Graphical Abstract of Proposed System

A.Architecture

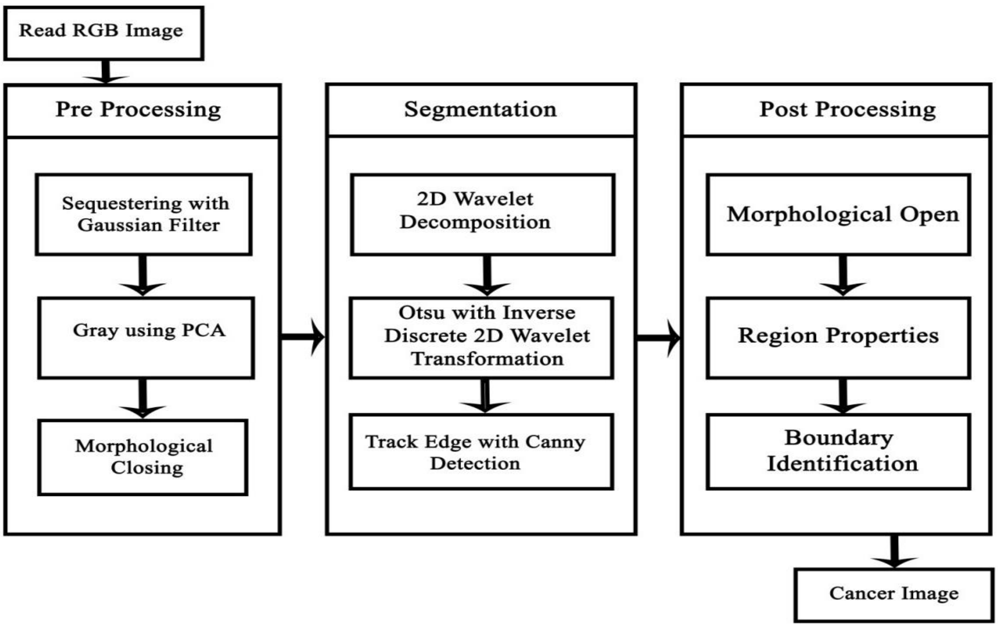

Fig. (2). Architecture diagram of Proposed System

B. Algorithm: Inverse Otsu (IO)

Step 1: Input RGB image J and Ground truth image G.

Step 2: Generate RGB histogram His(I) to examine the series, depth and complexity of intensity.

Step 3: Confiscating the artifacts from input image using Gaussian filter to smooth image Gau(I).

Step 4: Double the blurred smoothed image Gau(I) into Dbl(I).

Step 5: Assimilate Dbl(I) using morphological task to sieve true pixels Mor(I).

Step 6: Decompose Mor(I) using 2D Wavelet into D(I).

Step 7: Fragment D(I) using Otsu Threshold and Inverse Wavelet Transform as Seg(I).

Step 8: Quantize Seg(I) and Discovery boundary using canny.

Step 9: Identify specific Region Properties to Mark uneven boundary.

IV. RESULTS AND DISCUSSIONS

The pre-processing stage starts with the input RGB image with the ground truth image. The input RGB image is emphasized with the histogram to prove the thickness of colour intensity of R,G and B.

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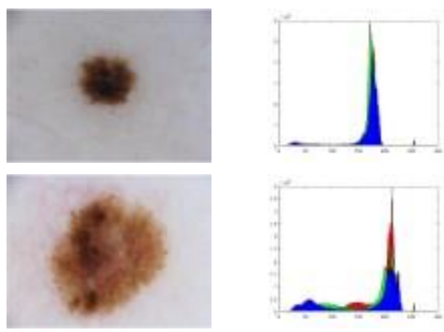

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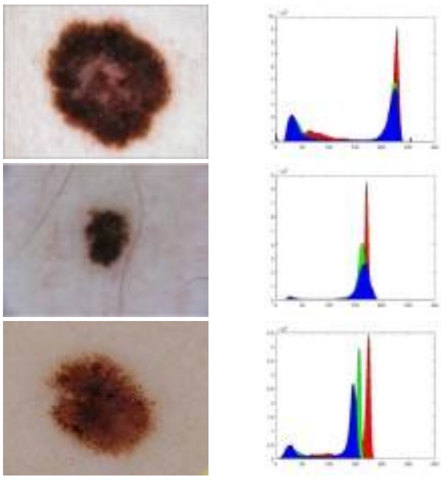

(a) (b) (c)

Fig.(3).Input Test Image with RGB Histogram. (a) Pseudo name, (b) Sample image, (c) RGB threshold

The ground truth image is given in black and white colour where the affected region are given in white colour and the remaining pixels are filled with black as shown in Figure **3**.The input image contains plenty of noise, which is formed by hair and artifacts.

There is no need to worry about such kind of noises because, we use linear noise filtering like Gaussian filter. After filtering the fine details of noise in RGB, histogram is constructed to emphasize the filtered image shown in Figure**4**. To prove the quality of smoothened image, noise ratio between the input image and smoothened image are identified.

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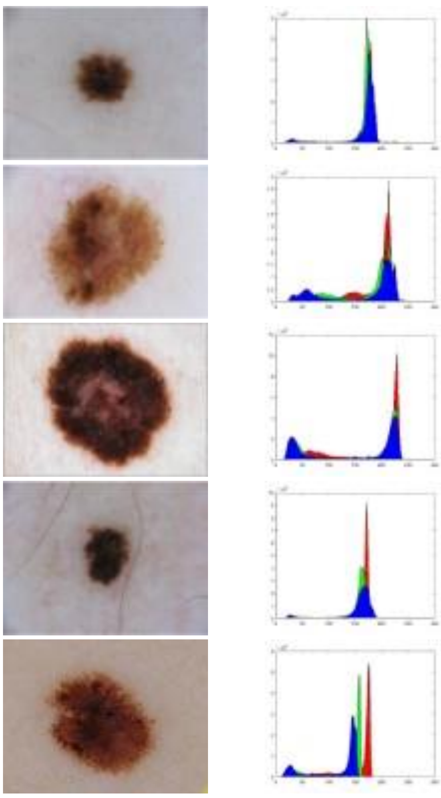

(a) (b) (c)

Fig. (4).Noise Filtered Image with RGB Histogram. (a) Pseudo name, (b) Gaussian filtered image, (c) RGB threshold

In the pre-processing stage, the Gaussian filtered image is converted into grayscale image for structural element retrieval in the form of a disk. The noise ratio is identified to prove that the dustless image is taken for segmentation process. The noise ratios PSNR, SNR and MSE, are expressed as

$$\text{SEI} = ((\text{Input Image}) - (\text{Noisy Image}))^{2} \qquad (16)$$

$$\text{MSE} = \text{sum}(\text{SEI}) / (\text{Rows} * \text{Columns}) \qquad (17)$$

$$\text{PSNR} = 10 * \log10(256^2 / \text{MSE}) \qquad (18)$$

$$\text{SNR} = 20 * \log10((\text{Max Intensity} - \text{MinIntensity}) / \text{MSE}) \qquad (19)$$

The identification of noise ratio is tabulated in Table **1**.

Table 1.Noise Ratio after Filtering

Dataset	PSNR	SNR	MSE
0000001	36.7978	33.1657	13.592
0000008	39.9966	37.0346	6.5076
0000029	25.7233	22.5657	174.078
0000256	41.2942	37.1668	4.8268
0000544	38.7016	33.5078	8.7683

The outcomes of the structural element are taken into morphological dilation to remove the false pixels out and use true pixels for segmentation shown in Figure **5**.

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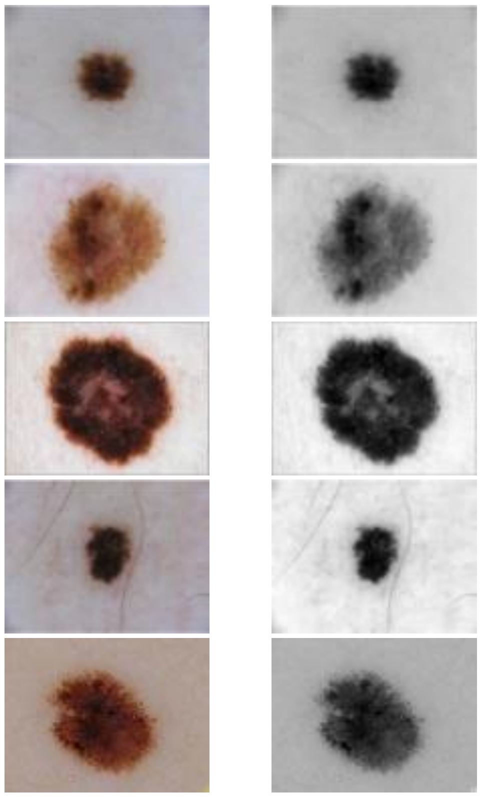

(a) (b) (c)

Fig.(5).Test Image to Morphological Dilation. (a) Pseudo name, (b) Sample image, (c) Morphological Dilation

The segmentation stage starts with 2D wavelet decomposition, by generating a matrix format.

The requirement of data is formed as horizontal, vertical and diagonal coefficient. The threshold value of horizontal, vertical and diagonal regions is found out and passed into Otsu threshold.

The mid level of threshold is identified by taking the sum of all thresholds of matrix format and dividing by two. This continues until the final value of threshold. Further each threshold is taken into inverse discrete 2D wavelet transformation to reach the column and rows to enhance the image that lies between the low pass filter and high pass filter as shown in Figure **6**.

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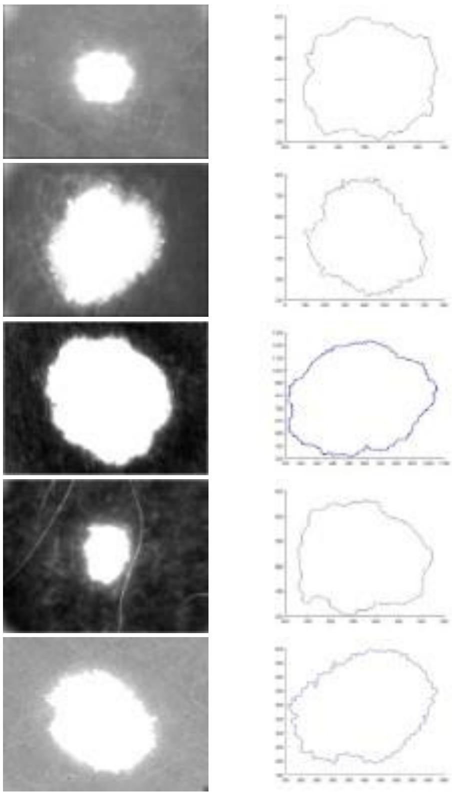

(a) (b) (c)

Fig.(6).Wavelet Transformation with Streamline. (a) Pseudo name, (b) 2D Wavelet Image, (c) Streamline.

Further the filters are quantized to bring the image in perfect matrix setup. The final process in segmentation stage is canny edge detection. Canny edge detection is used here to compare the boundary consisting of white pixels. Each pixel threshold is taken out and compared with all the pixels, so that the weak pixels and strong pixels are identified to average the moderate pixel to fix a perfect boundary and remove black pixel inside the boundary. After finding a perfect boundary, the segmented image is compared with ground truth image as shown in Figure **7**.

Finally the feature extraction is carried out to find uneven borders. Calculate the area of the infected region in the segmented image by finding major and minor axis on the white region. From axis, borders can be fixed by calculating radius of the region. Further the ROI is set from a point and moved according to the color intensity to frame the border. The centroid is identified to locate the mid value of the segmented region. The radius can be calculated from major axis and minor axis, further a circular index can be calculated to find the boundary regions. The area and perimeter of the segmented image can be calculated from axis point.

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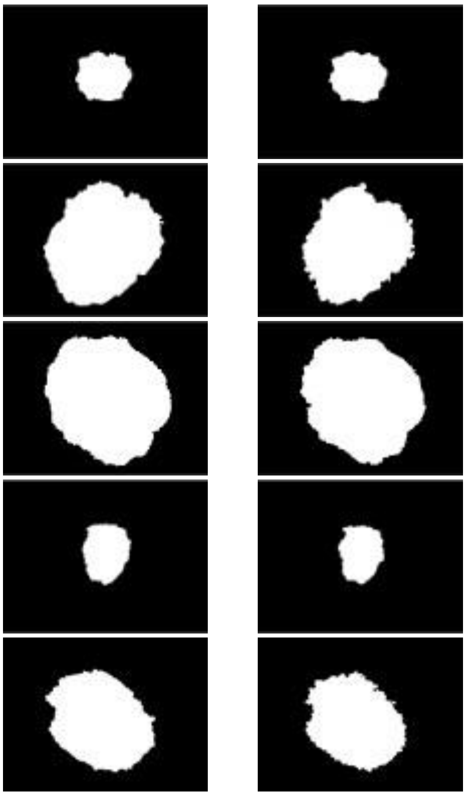

(a) (b) (c)

Fig.(7).Comparing Ground Truth with Segmented Image.(a) Pseudo name, (b) Ground Truth Image, (c) Segmented Image.

Each pixel is compared to all the other pixels nearby to extend the border shown in Figure **8**. The borders are identified by intensity values, there are many problems in identifying the perfect intensity because the values will not be equal to the neighboring intensity values but more or less, it will be equivalent to neighboring pixel. Both the pixels should be taken into the average intensity and fix a new pixel. The weak edge is compared with the strong edge to enhance the border strong strength. We make a green boundary along the borders of the segmented region. This region clearly proves the uneven structure of lesion. The lesion that can be of any shape, this computational tool easily extracts the border.

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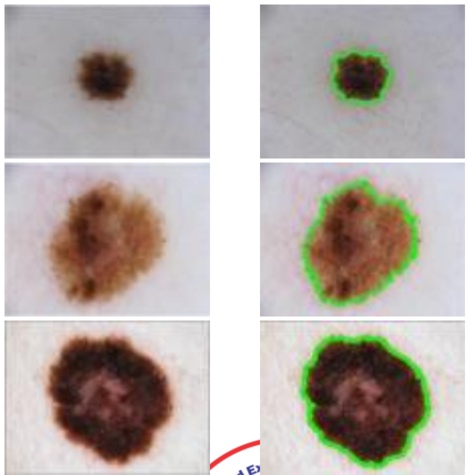

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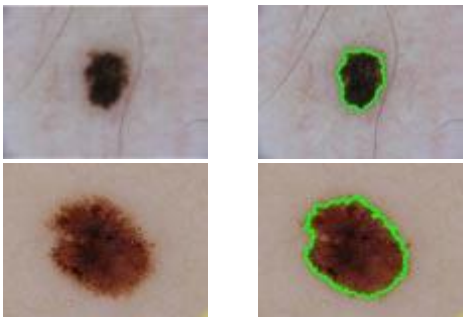

(a) (b) (c)

Fig.(8).Attained Uneven Boundary.(a) Pseudo name, (b) Sample Image, (c) Border Extracted Image.

The performance measure [29, 30]iscalculated to prove the efficiency of segmentation tabulated in Table **2**, expressed as

$$JI = TP / (FP+TP+FN) \quad (20)$$

$$Di=2*TP/ ((FP+TP) + (TP+FN)) \quad (21)$$

$$Sen = TP/P \quad (22)$$

$$Spe=TN/N \quad (23)$$

$$Acc = (TP+TN)/ (P+N) \quad (24)$$

$$ER= (FP+FN)/ (TP+FN+FP+TN) \quad (25)$$

JI = Jaccard Index, Di = Dice Coefficient, Sen = Sensitivity, Spe = Specificity, Acc = Accuracy, ER = Error Rate.

Table 2. Performance Measure of Proposed Methodology

Performances	0000001	0000008	0000029	0000256	0000544
Accuracy (%)	99.64	95.99	97.02	99.32	91.48
Dice	97.39	93.61	96.47	94.99	89.42
Jaccard Index (%)	94.91	87.99	83.51	90.47	87.67
Sensitivity (%)	99.64	87.99	83.58	90.56	86.43
Specificity (%)	99.63	100	99.99	99.99	100
Error Rate (%)	0.36	4	2.97	0.67	1.85

V.CONCLUSION

The computational method using Otsu and inverse wavelet has been perfectly designed to segment the skin lesion from the dermoscopy image. The input image is enhanced with Gaussian filtering and the color conversion is required for segmentation that is supported by PCA and the true pixels are selected by morphological operation is described in the pre-processing. The next stage, segmentation was perfectly completed using Otsu Thresholding with a fine decomposition of wavelet filtering. The final stage of feature extraction describes the uneven set of the boundary. The components of performance measures are identified by comparing the segmenting image and ground truth image with an average accuracy of 96.69%, sensitivity of 89.64%, higher specificity of 99.92% and very less error rate up to 1.97%.

REFERENCES

1. Jose Fernandez Alcon, calinaCiuhu, Warner ten Kate, Adrienne Heinrich, NatalliaUzunbajakava, GertruudKrekels, Denny Siem, and Gerard de Haan, “Automatic Imaging System with Decision Support for Inspection of Pigmented Skin Lesions and Melanoma Diagnosis”, IEEE Journal Of Selected Topics In Signal Processing, 3(1), 2009.
2. B. Bozorgtabar, S. Sedai, P. Kanti Roy, R. Garnavi , “Skin lesion segmentation using deep convolution networks guided by local unsupervised learning”, IBM J. RES. & DEV.61(5), 2017.
3. FaouziAdjed, Syed Jamal SafdarGardezi, FakhreddineAbabsa, IbrahimaFaye ,Sarat Chandra Dass , “Fusion of structural and textural features for melanoma recognition”, IET Computer Vision 2018,12(2).
4. N C F. Codella, Q.-B. Nguyen, S. Pankanti, D. A. Gutman, B. Helba, A. C. Halpern, J. R. Smith, “Deep learning ensembles for melanoma recognition in dermoscopy images”, IBM J. RES. & DEV.61(5), 2017.
5. HaraldGanster, Axel Pinz, ReinhardRöhrer, Ernst Wildling, Michael Binder, and HaraldKittler,”Automated Melanoma Recognition, IEEE Transactions On Medical Imaging,20(3), 2001.
6. SaptarshiChatterjee, DebangshuDey, SugataMunshi , “Optimal selection of features using wavelet fractal descriptors and automatic correlation bias reduction for classifying skin lesions.”, Biomedical Signal Processing and Control 2018.
7. Jingyun Liang, JinlinGuo ,Xin Liu , SongyangLao,”Fine-Grained Image Classification With Gaussian Mixture Layer”, IEEE Access(6).
8. Steven Schoenecker ,TodLuginbuhl,”Characteristic Functions of the Product of Two Gaussian Random Variables and the Product of a Gaussian and a Gamma Random Variable”, IEEE Signal Processing Letters, 23(5), 2016.
9. Peng-Lang Shui , Li-Xiang Shi , Han Yu , Yu-Ting Huang,”Iterative Maximum Likelihood and Outlier-robust Bipercentile Estimation of Parameters of Compound-Gaussian Clutter With Inverse Gaussian Texture”, IEEE Signal Processing Letters, 23(11), 2016.
10. MiladNiknejad, Isfahan, HosseinRabbani ,MassoudBabaie-Zadeh,”Image Restoration Using Gaussian Mixture Models With Spatially Constrained Patch Clustering”, IEEE Transactions on Image Processing, 24(11),2015.
11. Lucas P. Queiroz , Francisco Caio M. Rodrigues , Joao Paulo P. Gomes , Felipe T. Brito , Iago C. Chaves , “A Fault Detection Method for Hard Disk Drives Based on Mixture of Gaussians and Nonparametric Statistics”, IEEE Transactions on Industrial Informatics, 13(2), 2017.
12. EwedaEweda , Neil J. Bershad , José Carlos M. Bermudez,”Stochastic Analysis of the LMS and NLMS Algorithms for Cyclostationary White Gaussian and Non-Gaussian Inputs”, IEEE Transactions on Signal Processing, 66(18), 2018.Wen Wang , Ruiping Wang , Zhiwu Huang , Shiguang Shan , Xilin Chen,” Discriminant Analysis on Riemannian Manifold of Gaussian Distributions for Face Recognition With Image Sets”, IEEE Transactions on Image Processing , 27(1), 2018.
13. M. Yusaf , R. Nawaz , J. Iqbal,”Robust seizure detection in EEG using 2D DWT of time-frequency distributions”, Electronics Letters, 52(11),2016.
14. ThamizharasiAyyavoo, Jayasudha John Suseela,” Illumination pre-processing method for face recognition using 2D DWT and CLAHE”,IET Biometrics , 7(4), 2018.
15. Changkun Wu , Wei Zhang , Qi Jia , YanyanLiu,”Hardware efficient multiplier-less multi-level 2D DWT architecture without off-chip RAM”, IET Image Processing , 11(6), 2017.
16. AmanGhasemzadeh, Hasan Demirel,”3D discrete wavelet transform-based feature extraction for hyperspectral face recognition”, IET Biometrics, 7(1), 2018.
17. Wolfgang Schnurrer , NiklasPallast , Thomas Richter , Andre Kaup,”Temporal Scalability of Dynamic Volume Data Using Mesh Compensated Wavelet Lifting”, IEEE Transactions on Image Processing, 27(1), 2018.
18. Y. Zhang , T. Y. Ji , M. S. Li , Q. H. Wu,”Identification of Power Disturbances Using Generalized Morphological Open-Closing and Close-Opening”, IEEE Transactions on Industrial Electronics,63(4), 2016.
19. Sung-JeaKo , A. Morales , Kyung-HoonLee,”Block basis matrix implementation of the morphological open-closing and close-opening”, IEEE Signal Processing Letters, 2(1),1995.
20. Sung-JeaKo , A. Morales , Kyung-Hoon Lee,” A fast implementation algorithm and a bit-serial realization method for grayscale morphological opening and closing”, IEEE Transactions on Signal Processing,43(12), 1995.
21. Kyung-HoonLee , A. Morales , Sung-JeaKo,”Adaptive basis matrix for the morphological function processing opening and closing”, IEEE Transactions on Image Processing (Volume: 6 , Issue: 5 , May 1997), Page(s): 769 – 774.
22. NingMa ,JianxinWang,”Dynamic threshold for SPWVD parameter estimation based on Otsu algorithm”, Journal of Systems Engineering and Electronics 24(6),2013.

23. G.Y. Zhang , G.Z. Liu , H. Zhu , B. Qiu," Ore image thresholding using bi-neighbourhood Otsu's approach", Electronics Letters46(25), 2010.
24. Jing-HaoXue , D. Michael Titterington," t-Tests,F-Tests and Otsu's Methods for Image Thresholding", IEEE Transactions on Image Processing , 20(8), 2011.
25. A.K. Khambampati , D. Liu , S. K. Konki , K. Y. Kim," An Automatic Detection of the ROI Using Otsu Thresholding in Nonlinear Difference EIT Imaging", IEEE Sensors Journal, 18(12), 2018.
26. P. Bao , Lei Zhang , XiaolinWu,"Canny edge detection enhancement by scale multiplication", IEEE Transactions on Pattern Analysis and Machine Intelligence , 27(9), 2005.
27. Dey N, Rajinikanth V, Ashour AS, Tavares JMRS. Social group optimization supported segmentation and evaluation of skin melanoma images. Symmetry.2018; 10(2):51.
28. Rajinikanth V, Satapathy SC, Dey N, Fernandes SL, Manic KS. Smart Innovation, Systems and Technologies. 2019; 104:193-202.
29. Kowsalya N, Kalyani A, Shree TDV, Raja NSM, Rajinikanth V. Skin-Melanoma Evaluation with Tsallis's Thresholding and Chan-Vese Approach. In. International Conference on System, Computation, Automation and Networking.IEEE.2018; 1-5. Doi: 10.1109/ICSCAN.2018.8541178.
30. Y. Zhang , P.I. Rockett," The Bayesian Operating Point of the Canny Edge Detector", IEEE Transactions on Image Processing, 15(11), 2016.

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