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Assessment of Segmentation techniques for skin cancer detection

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Abstract

Skin cancer appears to be the most common among all tumors throughout the globe. The initial finding of skin cancer can be alleviated. Late detection leads to fatal. A human inquiry is thought-provoking. The biopsy procedure is agonizing, so computerized examination of skin cancer turns out to be noteworthy. A prevalent literature survey is carried out to study the State-of-art procedures for skin cancer diagnosis. Segmentation of skin lesion is a crucial task due to several features like the existence of hair, illumination difference, irregular skin color, and multiple unnatural skin regions. This paper recommends a comparison of various segmentation techniques and k-means clustering algorithms to segment the lesion. Several methodologies have been anticipated to determine skin cancer. The features can be resolved by familiarizing an advanced method for segmenting the skin lesion from macroscopic images based on the discrete wavelet transformation.

Keywords: Segmentation, K-Means Clustering, Discrete Wavelet Transform, Gaussian Filter, Artificial Neural Network.

1. Introduction

The most common form of skin cancer and melanoma is the prominent cause of death [1]. Skin cancer spread to the body by blood vessels and the lymphatic system. Cataloging of skin cancer contributes to the chance of being identified early [2]. Thus premature exposure is central for appropriate diagnosis. Each skin disease has dissimilar individualities from other types. For the clinical purposes, dermatologists practice visual examination [3]. Clinical indicative routine is poor compared to Dermoscopy. In clinical preparation, the structure of the skin is not visible. The two categories of skin cancer are melanoma and non-melanoma. Malignant melanoma is a hazard for the developed world [4]. Thus initial diagnosis is recommended for benign and malignant melanoma for reducing morbidity and mortality [5]. For melanoma diagnosis, the input is Dermoscopy

images [6]. Melanoma is the fifth most common malignancy in the US [7]. Thus there is a necessity for an automatic diagnostic melanoma system. Since the invention of computer technology with medical decision support helps dermatologists in distinguishing benign and malignant melanoma. CAD systems of melanoma are advanced which proceeds in less time and accurate diagnosis [8]. Dermoscopy upturns the diagnostic performance associated with the unaided eye [9]. To develop analytical performance, clinicians use the ABCDE rule. Automatic image processing gives improved results as long as the precise info regarding lesion is beneficial for clinicians to identify and catalog automatic skin cancer detection [10]. The four key steps are Pre-processing, Segmentation, Feature Extraction, and Lesion Classification. These steps can quicken the investigative process: pre-processing is essential to increase the image

quality using image cropping, Gaussian filtering, and contrast enhancement [11] [12]. The distinguishing lesion images are removed in the feature extraction stage. Various features used are color, texture feature, GLCM feature, and Discrete Wavelet Transform (DWT) [13]. The most significant feature results inaccurate classification [14]. The classification phase is to identify benign and malignant depending on the mined features [15]. DWT is used to extract the features from the images. The ANN is used to classify the extracted features into benign and malignant melanoma lesions. The rest of the paper is structured as Section 2 briefs the literature survey, Section 3 reviews Existing System, Section 4 presents the Proposed Methodology, Section 5 reports Experimental Results and Section 6 Concludes the paper.

2 Literature Survey

Sabouri et al [1] proposed CAD of medical images that help physicians in early detection and reduce the mortality rate. An interactive object recognition methodology was employed for the border segmentation performance of five classifiers. The results show a sensitivity of 82.6% and specificity of 83% achieved using a single SVM classifier. A cascade classifier with a specificity of 90.05% and a sensitivity of 83.06% attained with tenfold cross-validation is used.

Maurya et al [2] discussed an automatic medical image classification method to classify two major skin cancer types. This work focuses on color and texture features. Use the K-Means clustering algorithm to segment the lesion. The features are extracted by four different color feature extractors. The classification accuracy is evaluated on four types of classifiers and values compared. From the result, SVM outperforms all. Experiment results show that color and texture descriptors provide good classification accuracy. The Gabor features proved to be the best feature.

Margarida Silveria et al [3] propose and evaluate six methods. Results prove the AS and EM-LS are robust and useful for lesion segmentation in a CAD system to assist the clinical diagnosis of dermatologists.

Muthu Senthil et al [4] offer a recent interpretable model (LIPU) Logistic Regression abusing initial variables and product units in terms of binary classification, LIPU performs with an accuracy of

77.6%. The main advantage of the LIPU model is proved as an interpretable model.

Omar Abuzahleh et al [5] propose an innovative smart phone- based application to assist in melanoma detection. Exploits Ph2 dermoscopy images. Experimental results show the proposed system is efficient with an accuracy of 96.3%, 95.7%, and 97.5%.

Yanhui Guo et al [6] projected novel skin detection based on neutrosophic clustering and adaptive region growing algorithms using NCARG. Shearlet transform is used for all the images. For the dataset 50 images are collected and 500 images are used for the training dataset. The proposed NCARG achieves accuracy of 95.3%.

Sinan Kockara et al [7] designed a novel approach of graph spanner based on Soft Kinetic Data Structure (SKDS) for automatic border detection in dermoscopic images. A proximity graph representation is presented. He suggested the insert operation is the most important operation in hierarchy construction. The experimental results show Balls History achieved 97.72% accuracy.

Hengameh Mirza Alian et al [8] suggests artifact removal is considered to be the first step of CAD system of lesion.

Grazyna Kaminska Winciorek et al [9] propose a few diagnostic tricks which are proven to be helpful in achieving diagnostic accuracy. The various types of Dermoscopy devices are used. This paper collects simple dermoscopic tests that can be carried out in case of diagnostic difficulty. The tests are proved to be fast, simple, safe, and cost-effective.

Omar Abuzahleh et al [10] propose two major components, real-time alert to help users and an automated image analysis module. Results conclude the two-level classifier outperforms well.

Amir Reza Sadri et al [11] put forth a method based on the wavelet network. Segmentation is applied to 30 dermoscopic images and evaluated with 11 different metrics. A new approach for segmentation based on Fixed Grid Wavelet Network (FDWN) is proposed. The developed algorithm thus proves to be a useful tool for automatic or semi-automatic analysis of skin lesion images.

Sujaya Saha et al [12] recommended feature extraction to be considered as an essential weapon

to analyze an image properly. Noise reduction is done by median filtering. Based on the border, color, entropy, compactness, radial variance of the mask, and coarseness features, the risk probability factor of the lesion is shown with the help of CAD diagnosis systems.

Damanpreet Kaur et al [13] present the computation of GLCM by image entropy and energy. Analyze the texture of an image. The Multi-class classification serves as a tool in identifying skin diseases.

Emre Celebi et al [14] proposes the most important feature for a melanoma diagnosis is the blue-white veil. The percentage of the blue-white areas detected in a lesion combined yielded a sensitivity and specificity of 69.35% and 89.97% on a set of 545 dermoscopy images. Sensitivity rises to 78.20% for detection of the blue-veil in those cases, which is a primary feature for melanoma recognition.

Yuvaraja et al [15] suggest the morphological filter segmentation to detect skin cancer. The recommended system has higher accuracy, sensitivity, specificity compared to other systems. From the experimental results, the morphological filter along with the neural network is used for segmentation.

Vincy Varghese et al [16] present a survey based on the SVM classifier. Segmentation is based on the Adaptive Snake (AS) method. Results prove that depth is considered an important factor to diagnose skin cancer. The 3D reconstruction method finds the relative depth of the tumor by increasing the efficiency of the tumor.

Khalid M.Hosny et al [17] recommends the transfer learning applied to Alex-Net in various ways. The three well-known data sets MED-NODE, Derm, and ISIC are used in testing and verifying the proposed method. The sensitivity, specificity, accuracy, and precision measures are castoff to estimate the enactment of the proposed method. A pre-trained Deep CNN is used. From the experimental results, the average performance measures with the ISIC dataset are 95.91%, 88.47%, 93.00% and 92.34%. The experimental results show that the proposed method outperforms several states of the art classification method.

Pablo G.Cavalcanti et al [18] gives preliminary

experiment results that provides to be a promising accuracy of 96.71%. Tele dermatology is considered in this work. A new technique to improve processing and analysis of skin images is proposed.

Uzma Jamil et al [19] present the comprehensive study of some classification techniques used in medical imaging. The classification techniques used in this work are well-designed algorithms that provide good results for some selected features.

Konstantin Korotkov et al [20] discuss an overview of microscopic and macroscopic images of pigmented skin lesion. Melanoma screening and imaging techniques are employed here.

Attique Khan et al [21] put forth a method for identification and classification of skin lesion based on probabilistic distribution and the best feature selection is proposed. Results prove the base classifier performs significantly better on the proposed features fusion and selection method.

Uzma Jamil et al [22] emphasize the three stages as segmentation, feature extraction, and classification systems. The model-based techniques of Markov Random fields, Fractals, and Multiresolution auto regression features are used in this work. From the discussion and conclusion for the feature extraction, the more the number of colors, the greater the opportunity of lesion persistence.

Ilias Maglogiannis et al [23] put forth skin lesion classification by AI methods and heuristics such as discriminant analysis, NN, and SVM. Several diagnostic methods are discussed. Concludes the most classical recognition pattern is statistical.

Catarina Barata et al [24] address two different systems for the detection of melanomas. The first system uses global methods to classify skin lesion. The second system uses local features and the bag of features classifier. From the experimental results concludes color features outperform texture features when used alone and both methods achieve better results. The classification results were obtained on a dataset of 176 dermoscopy images. The sensitivity and specificity for global methods are 96% and 80% against the sensitivity of 100% and specificity of 75% for local methods. This work compares two different strategies for the detection of melanomas in Dermoscopy images.

Qaisar Abbas et al [25] put forth the work to demonstrate how effective computerized methods are integrated into a single classification system. The suggested classifier achieved a sensitivity of 88.2% and specificity of 91.3% and AUC of 0.880. Carmen Serrano et al [26] propose a method for detecting patterns. The best classification rate is 86%. The novel classification algorithm is based on Markov Random Field.

Qaisar Abbas et al [27] discussed smoothing constraints. Courant-Friedrichs-Reichs-Lewy (CFL) function is employed. 320 test images are used. The unsupervised border detection system increased the true decision rate to 4.31% and reduced the false positive rate of 5.28%. This segmentation algorithm delivers good results.

Kekre et al [28] propose segmentation using vector quantization technique. Also, use Linde Buzo-Gray (LBG) Algorithm for the segmentation of MRI images. For comparison watershed segmentation and entropy using GLCM are used. LBG shows far better results. The approach does not lead to over-segmentation or under segmentation with less complexity.

Jisha Mariyam John et al [29] recommend a Backpropagation neural network algorithm for texture distinctiveness lesion segmentation which shows higher segmentation accuracy. The segmentation algorithm is required to perform illumination correction and achieves higher segmentation accuracy.

Durga Rao et al [30] presents a survey paper to detect melanoma which plays a major role in image processing tools. The CAD method is employed here. The color space transformation and contrast enhancement are discussed. The pre and post-processing steps are discussed in this work. soft computing techniques yield more accurate results.

Messadi et al [31] recommend an interpretable classification method for skin tumors based on shape descriptors. This work gives a fuzzy rule-based classifier to discriminate against melanoma. An ANFIS is applied to discover fuzzy rules leading to correct classification. The sensitivity of the ABCD rule is reported between 59% and 88%. Contour irregularity is a very crucial factor in the evaluation of malignant melanoma. ANFIS with SVM and ANN is used.

Ali Madooei et al [32] devised an automatic pre-processing method. The entropy minimization method is employed here. Concludes an automatic analysis of dermoscopy images which is prone to error due to its difficulty and the subjectivity of visual interpretation. So a double component pre-processing scheme is used with normalizing intensity falloff and color to grayscale conversion. Ravindran et al [33] put forth a texture feature parameter in segmentation is a vital image analysis technique. The approach attempts to analyze and compare the gray level texture feature techniques, a number of clusters, Fuzzy C-Means and to find which algorithm provides better results.

Paul Wighton et al [34] gives quantitative results for segmentation. The formula is given for the labeling phase.

Shubhangi et al [35] adopted a technique based on Stochastic Region Merging (SRM) and Region Adjacency Graph (RAG). Since the adoption of SRM and RAG, the detection of human skin cancer is improved to a large extent by reducing segmentation and increasing the true detection rate and false -positive rate as compared to other techniques. The future work is made to overcome the mentioned drawbacks with the addition of larger data.

Khalid M.Hosny et al [36] put forward an automated skin lesion classification method with a pre-trained deep learning network and transfer learning. Trained and tested using the Ph2 dataset. Performance compared with existing methods. For constructing a deep NN large count of imageries are labeled. The transfer learning and image segmentation are applied to a pre-trained Alex Net to overcome this major challenge. Four performance measures have been computed and compared. Results proved that the proposed method outperformed. The achieved rates 98.61%,98.33%,98.93%, and 97.73% for accuracy, sensitivity, specificity, and precision.

Munya Arasi et al [37] recommends intelligence approaches such as ANN, Adaptive Network-based Inference Systems (ANFIS) and SVM. The accuracy rate of ANFIS, and SVM is 95.2% while ANN gives a high accuracy rate of 98.8%. An automated diagnosis system shows excellent performance compared to other systems. ANN gives the best results with accuracy improved to 98.8%.

Hengameh Mirzaalian et al [38] suggests hair occlusion is one of the main challenges facing automatic lesion segmentation. Hair tubularness is measured using a quaternion color curvature filter and extract features using Markov random field theory.

Abdulhafid Ali I.Mohamed et al [39] provides an analysis of automatic Dermoscopy images in three stages. The conventional algorithm is compared with the dermatologist like algorithm.

Manish Pawar et al [40] present feed-forward back propagation neural network to classify input texture images into three different classes. Texture analysis is considered as an active area of research in pattern identification. GLCM is taken as a method of texture analysis.

Hitoshi Iyatomi et al [41] talk over a fully automated system for acral volar melanomas. Three pattern detectors are developed such as a parallel ridge, parallel furrow, and fibrillar patterns. Achieved good detection accuracy of 0.985, 0.931, and 0.890 respectively. Matlab 13 was used for analysis and evaluation tools. Incremental stepwise input selection was performed.

Ramya Tamizharasi et al [42] presents a simple, efficient, and automatic skin cancer detection and diagnosis system with the use of commonly available software. The accuracy of classification is measured and presented in the experimental results.

Qaisar Abbas et al [43] recommends a pattern classification of dermoscopic task, aims to classify various patterns using color-texture properties extracted in uniform color space. To design an optimal classifier and to address the problem of multi-component pattern, an adaptive boosting multi-label algorithm (AdaBoost.Mc) is developed. The classification model achieved a sensitivity of 89.28% and specificity of 93.75% and area under the curve (AUC) of 0.986. Results prove that our pattern classifier based on color-texture features agrees with the dermatologist's perception.

Shanu Gaura et al [44] discuss the image acquisition in Dermoscopy images using the hair removal method. Threshold-based segmentation is done and feature extraction followed by ANN and BPNN.

Miciel Zortea et al [45] design a low-cost CAD tool. The dataset is 206 skin lesion images of which 169 are benign images and 37 malignant melanoma. Results show that simple statistical classifiers can be trained to provide a recommended pigmented skin lesion. This system works well in both sensitivity and specificity.

Santhosh Achakanalli et al [46] presents a statistical analysis to determine features for skin cancer. The features are extracted using GLCM. The accuracy of this proposed system is achieved to be 88%. By varying image processing techniques and training algorithms of ANN, the accuracy can be improved for this system.

Maryam Faal et al [47] present a multi-classifier systems. The best multiple classifier system was selected as the system with the highest classification accuracy.

Ilias Maglogiannis et al [48] discuss a report on the statistics and results of the most important implementation. An evaluation state of the art classifier is presented in relation to skin lesion characterization and performance metrics are discussed.

Emre Celebi et al [49] considers border detection as the first step in the analysis. An automated method for detecting lesion borders can be achieved using a fusion of several thresholding methods. Experiments compared with six recent border detection methods.

Hitoshi Iyatomi et al [50] presents an internet - based melanoma screening system. calculates 428 features for the characterization of tumors. Our system achieved a sensitivity of 85.9% and specificity of 86.0% on a set of 1258 dermoscopy images using cross-validation. The result concludes that the ANN classifier achieved a good classification performance.

3 Existing System

Structural methods are available to detect skin cancer [16]. The biopsy method of dermatologists is painful and time-consuming. So CAD systems are developed. The application of Image processing in the medical field has developed drastically. Acquiring digital images for the purpose of the analysis is a perplexing task [17][18]. For the classification of skin lesions, numerous literature exists [19][20].

4 Proposed Methodology

4.1 Preprocessing

Pre-processing is castoff to eliminate the complications of segmentation procedure that may happen due to the existence of hairs on the skin [21]. Gaussian filter is used for removing hairs from imageries [22]. The digital images obtained may contain errors such as air bubbles, hair, and illumination variation effects. Thus pre-processing is vital for any image in order to remove noise and also to improve the image quality [23][24]. The image is pre-processed by the Gaussian filter for this work. Noise is removed in this case. The block diagram of the proposed method is as shown in fig(1). The benign and malignant skin cancer images are in fig(2)(a)(b).

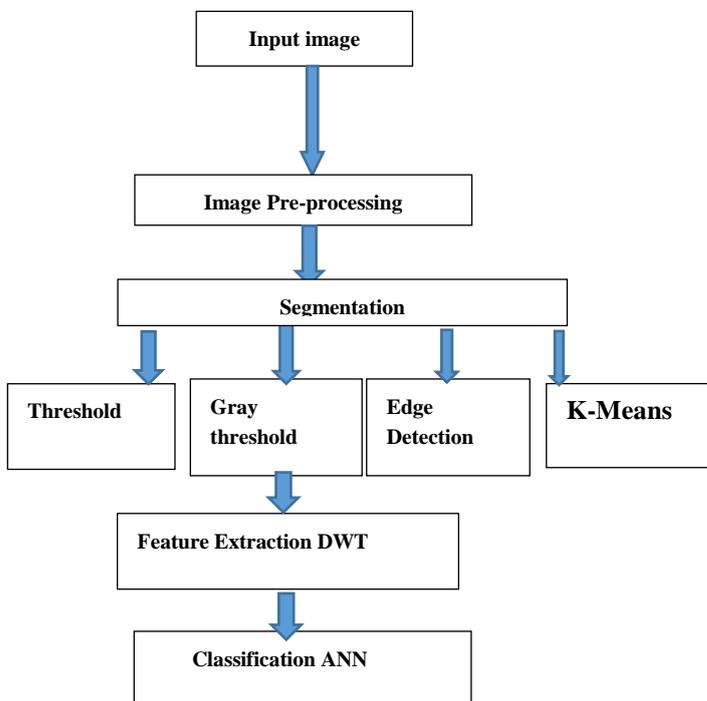


Fig (1) Block Diagram of the proposed system

The following steps are carried out for pre-processing:
 Step 1: The original image is converted to gray scale image.
 Step 2: Any noise in the image is removed.
 Step 3: Images are filtered by Gaussian filter to remove noise. As in fig(3).
 Step 4: Image is enhanced by Contrast enhancement, the process of increasing the pixel values of an image to new standards as in fig(4).

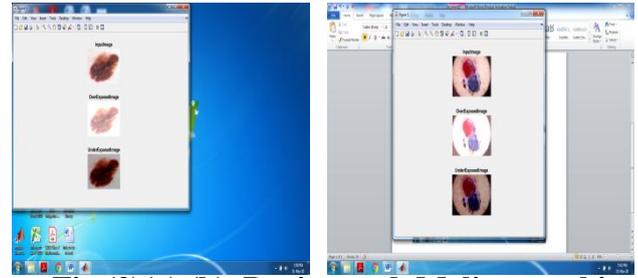
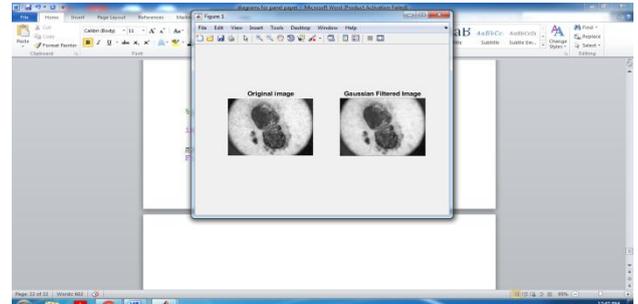


Fig (2)(a) (b) Benign and Malignant skin cancer images



Fig(3) Malignant image by using Gaussian filter



Fig(4) Contrast Enhancement

4.2 Segmentation

The most important process in any image processing application in segmentation [25][26][27]. Segmentation is the partition of an image into its constituent parts [28]. All regions have pixel which has a great relationship like intensity, color, and texture [29][30]. Generally, color images are converted to grayscale. A wide variety of segmentation methods proposed here are threshold, Gray level threshold, Edge detection, K-Means [31].

A Histogram is a graph that indicates the number of times a color appears in an image. Contrast is the change in brightness from one object to another [32].

K-Means clustering is used to segment the color images [33]. It is difficult to distinguish skin cancer visually. Identification and extraction of the affected lesion is a crucial task [34].

Algorithm for K-Means :

- Step 1: Read the image
- Step 2: Convert the image into double
- Step 3: Convert the image matrix into vector
- Step 4: Copy the image to get the matrix dimension
- Step 5: Matrix initialization for making centroid
- Step 6: Assign zeros matrix for first, second and third cluster
- Step 7: If Cond is true
- Step 8: check the centroid
- Step 9: Assign pixel value of the coordinate in order to find which pixel corresponds to which cluster
- Step 10: assign to corresponding clusters based on the condition Go to step 7
- Step 11: Transfer into the vector to find the sum and non-zero element
- Step 12: Fix new center element
- Step 13: if old and new cluster are the same
- Step 14: Start labeling clusters
- Step 15: End

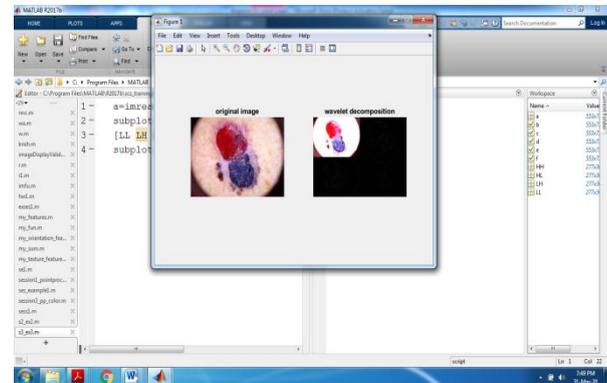
4.3 Feature Extraction

Feature extraction abstracts suitable features from segmented images [35]. These mined features easily categorize the modules of skin cancer. In order to approximately illustrate a lesion, the effectiveness of diagnosis remains increased with the supreme significant features [36]. An extensive image processing application Discrete Wavelet transform (DWT) is used in this work [37].

The images are converted into DWT allocating into accurate detailed images as in fig (5). DWT is a well-organized method for demonstration and examination of images, which overcome the limits of Fourier Transform in frequency domain and time domain.

To acquire a worldwide understanding of the image, the multi-resolution method is employed. It partitions the image into four sub-images with a horizontal band as LL, vertical band as LH, and diagonal as HL and HH modules. The LL module serves for the subsequent 2- dimensional discrete wavelet transform which gives the estimate factor by providing uniqueness to the image. This procedure is iterated for many levels of decomposition, constructing a decomposition tree. The remaining modules signify the complete

segments. The estimated image is used as a substitute for the original one. The various features are used for classification. Color features are mainly algebraic constraints [38][39]. Texture features are mined by transforming to gray-level [40]. Color and texture features are combined as the same feature course for classification accuracy.



Fig(5) DWT on malignant image

4.4 Lesion Classification

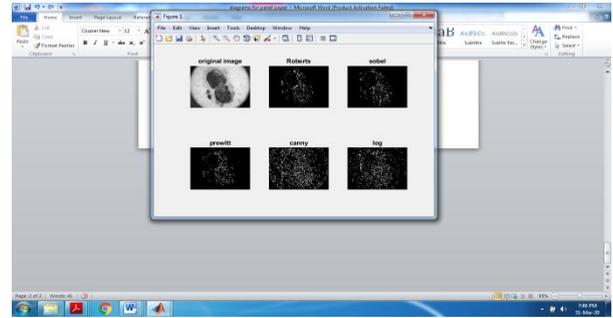
The classification segment is responsible for making the interpretations regarding the evidence mined from previous steps so as to yield problem-solving regarding the input image [41][42]. Based on the color and texture features extracted the segmented image is categorized based on ANN [43][44]. For a medical diagnosis, ANN proves to be the best approach and so it is used [45]. It consists of three layers input layer, the hidden, and output layer. A feed-forward multilayer network is employed [46]. The network is trained with known values [47]. The network performs decision making afterward training [48].

5 Experimental Results

Performance comparison of dissimilar skin cancer detection methods: Previous studies assess the dermatologist-like skin cancer abstraction methods based on a theoretical point of view. In this work, the different segmentation approaches are compared. Initially, the conventional threshold method is provided with histogram [49] as in fig (7). Next, the gray level threshold method is shown followed by the edge detection procedure as shown in fig (8)(9). From the output of edge detection, canny edge detection outperforms others. Then the image segmentation using K-Means is carried out in fig (10)(a-c). Histogram equalization is shown in fig(11). The point to

point operation shown in fig (12).

Histogram Equalization is done on the image as shown in fig (13). The spatial domain is considered in which point operation is performed on the image followed by a mask generated by thresholding in fig (14)(a) (b). All these are carried out for a malignant skin cancer image. The conventional thresholding method is compared with the gold standard method by a dermatologist, the thresholding method in rcb as in fig (15) and Ycber space [50] in fig (16). A table representing the color and texture features of 10 skin cancer images are presented in table(1). The energy of skin benign and malignant is as shown in fig (17) which corresponds to the GLCM feature.



Fig(9) Edge detection methods



(10)(a) K-Means clustering

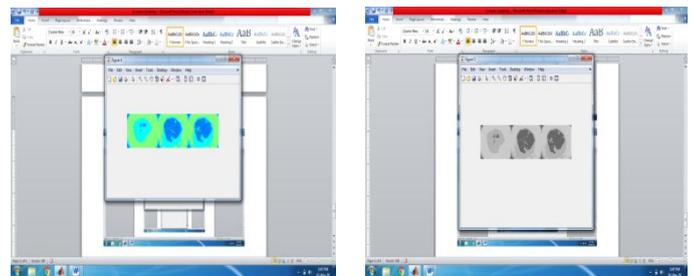


Fig (10) (b) (c) K-Means clustering

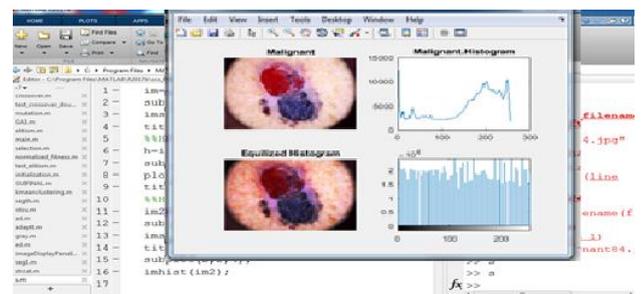
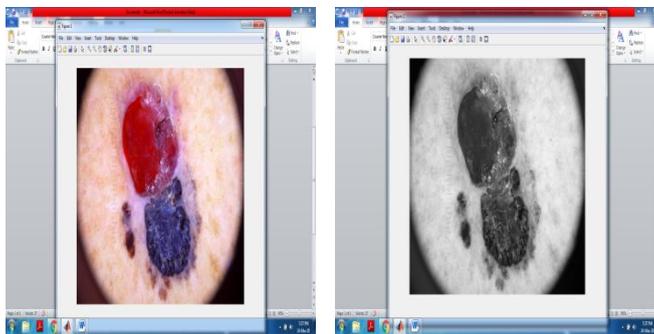
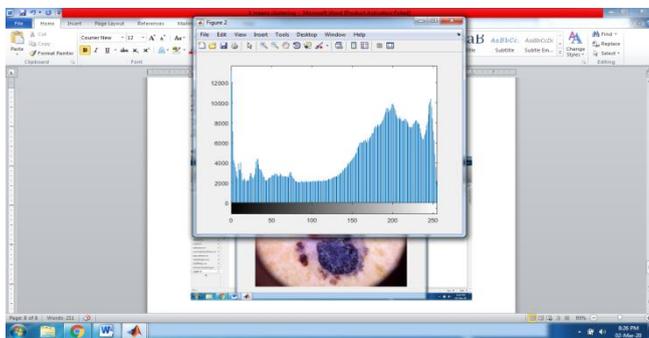


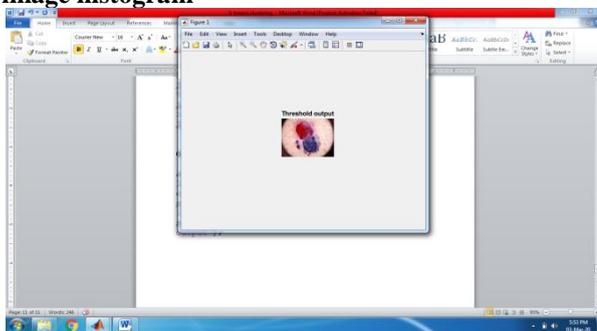
Fig (11) Histogram equalization



Fig(6) Threshold based segmentation Original image and RGB image

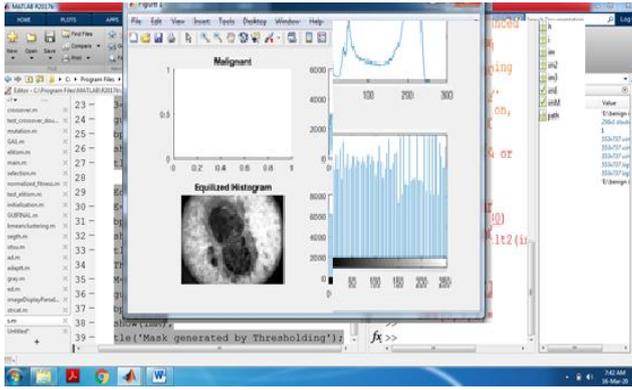


Fig(7) Threshold based segmentation with image histogram

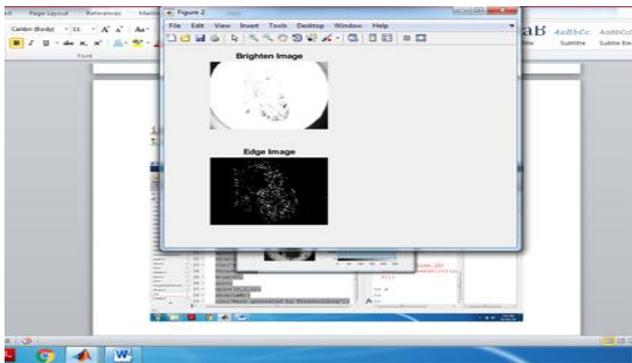


Fig(8) Gray level thresholding

Fig(12) Point operation on the input image



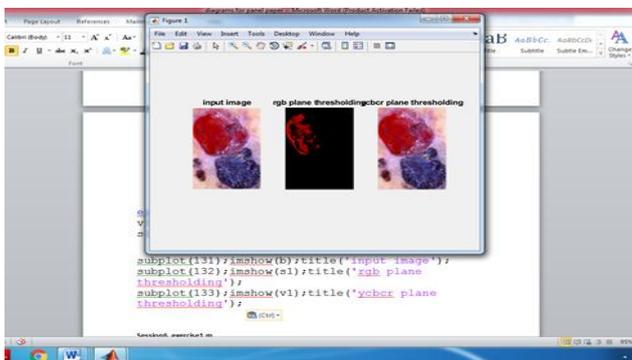
Fig(13) Mask generated by histogram



Fig(14)(a) Mask generated by thresholding



Fig(14)(b) Mask generated by thresholding



Fig(15) Malignant image in rgb and ycbcr plane

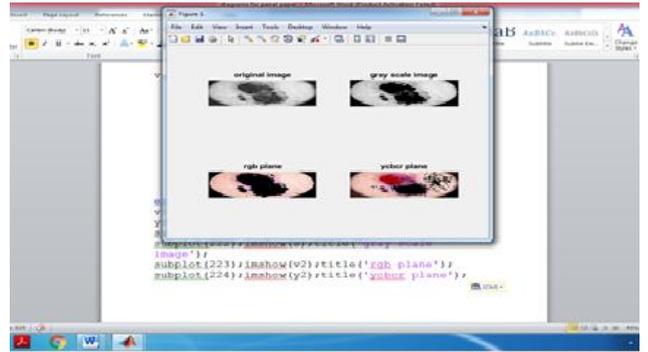


Fig (16) Malignant image in various planes

Table(1) Color and Texture features of skin cancer images

Images	Color Features			Texture Features			
	r1_st at	r3_st at	y_ st at	g_ st at	ske w	kurt	g_ hi gh
Benign1	0.773	0.426	0.976	0.413	0.590	0.508	0.401
Benign2	0.780	0.423	0.816	0.340	0.551	0.487	0.370
Benign3	1.000	0.818	1.000	0.570	0.524	0.453	0.668
Benign4	0.733	0.547	0.666	0.406	0.502	0.473	0.466
Benign5	0.878	0.647	0.898	0.495	0.520	0.473	0.553
Maligna nt1	0.686	0.451	0.706	0.288	0.512	0.459	0.375
Maligna nt2	0.976	0.754	0.890	0.664	0.644	0.500	0.667
Maligna nt3	0.839	0.610	0.796	0.530	0.633	0.537	0.454
Maligna nt4	0.867	0.596	0.867	0.432	0.560	0.462	0.513
Maligna nt5	0.753	0.528	0.525	0.253	0.475	0.440	0.379

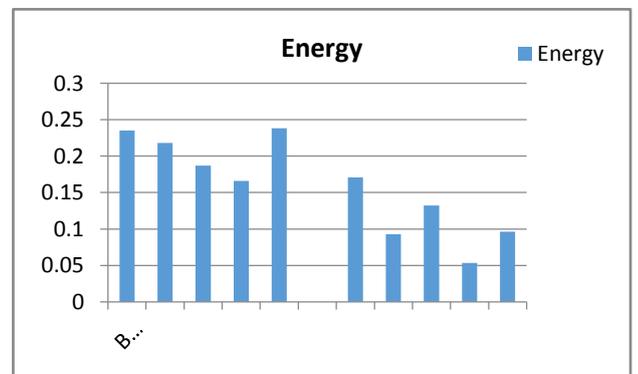


Fig (17) Bar chart depicting energy of GLCM feature

6 Conclusions

Dermoscopy images collected are managed by many image processing techniques. This diagnostic methodology is fast than the usual biopsy method. Different segmentation approaches are compared. The threshold -based segmentation proves to be promising for accurate segmentation of lesion from normal skin. The distinctive features of the resultant images are extracted by GLCM. Depending on the above features the images are categorized as benign or malignant melanoma.

From the experimental results, it is shown that the color and textures factors provide good classification accuracy in skin cancer detection. In varying the techniques of image processing and training algorithms to ANN, the system accuracy is improved. The projected methodology achieves the task proficiently with less time consumption to identify the lesion. Future work extends to adding larger data set for automatic system.

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