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# Survey on Melanoma Skin Cancer Detection Methods

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**ABSTRACT**

Skin cancers are generally grouped into either melanoma or non-melanoma skin cancers. Melanoma skin cancers comprise a higher rate of mortality, while non-melanoma skin cancers have a higher frequency rate. This paper describes different methods for the detection and classification of melanoma and non-melanoma skin cancer.

**Keywords:** Dermoscopy, Rankpot, Segmentation, Clustering, CAD, ROI, FCM

## I. INTRODUCTION

The cancer treatment varies based on cancer type. Different cancer has different treatment so early detection is necessary for better treatment. As melanoma has a higher death rate than non-melanoma skin cancer, characteristic between cancer and non canucerous melanoma skin images has engrossed significant research [10].

Dermoscopy is measured as the widely common practice used to detect cancer. But it is time consuming and need trained dermatologists. Therefore, the need to build a system which help dermatologist for right decision [12].

Computer Aided Diagnosis (CAD) systems have been proposed by many different researchers to identify malignant melanomas. Image segmentation is the main part of diagnosis. Separation of skin lesion from background is a difficult task because of the presence of hair, air bubbles and reflection of light. This paper comprises some methods which is used for melanoma detection. Fig 1 is the image representation of the skin lesion [21].

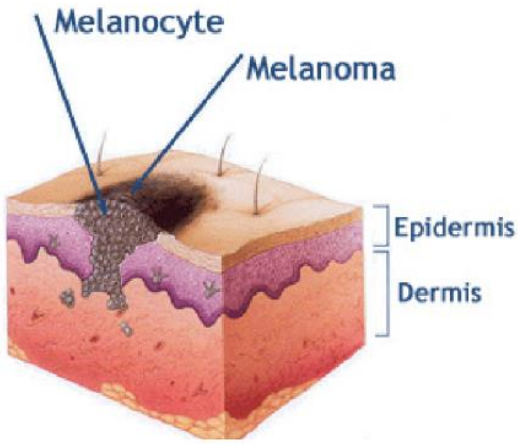



Fig.1 Melanoma skin cancer

## II. MELANOMA

Melanoma, a type of skin cancer that naturally starts in pigment cells, is one of the deadliest forms of cancer . According to American Cancer Society regarding 87110 new belongings of melanoma are projected to be diagnosed and about 9730 victims are predictable in United States in 2017. The most significant way to increase the endurance rate is to distinguish melanoma in its early stages and indulgence it properly. The development of dermoscopy method can significantly give to improving the diagnostic accuracy of melanoma, and thus humanizing the survival rate of patients [10]. Dermoscopy is a noninvasive skin imaging method, which uses polarized light to make the contact area transparent, and can expose the subsurface skin composition. However, manual analysis of the dermoscopy image is typically time-consuming, pragmatic, and slanted. Therefore, computer-aided diagnosis (CAD) has been developed to supply fast, quantitative, and purpose assessment for dermatologists.

## III. MELANOMA SKIN CANCER DETECTION METHODS

### A. Bow Method

This method transforms input image texture to a feature vector. It contains texture properties which simplify classification of texture. A texture contain group of pictures [11]. Fig 2 shows the Bow Method.

**Algorithm:**

Step1. Local patch extraction for a specified image

Step2. Represent it in to N patches.

Step3. Code book production is to generate K codeword's based on training data.

Step4. Feature encoding represent each local feature xi with the codebook,

Step 5. Feature Pooling is a global feature representation

Step 6. SVM is used for the classification based on the training data [5].

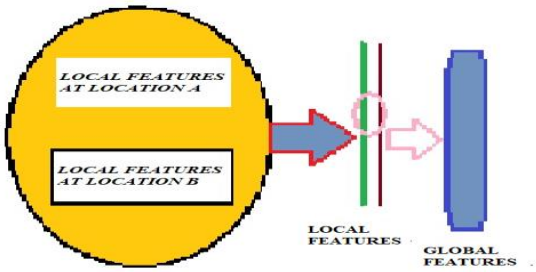



Fig.2 Bow Method

### B. FCM METHOD

The pixels of an input image are divided into two clusters: cancerous pixels as the front position (ROI) and ordinary skin pixels as the surroundings. The major drawback with the FCM method is that it deals with pixels in separation by their intensity values only, so lacks the capability to model the taken as a whole look of a local neighborhood region. In order to deal with this issue, The MRF method is implemented to improve the prior segmentation of the image. In this method the FCM deals with the single pixel at a time. It is a drawback of this method [5].

#### 1) Reflection Detection

Reflection artifacts and air bubbles develop into observable like noise in dermoscopy images. A threshold value is designed and then the intensity of every pixel is premeditated and compare with the surrounding pixel value. If the assessment value is greater than the threshold value then it is classify as artifacts.

#### 2) Hair Detection and Inpainting

In this step hairs should be extracted and removed. The directional Gabor filters are apply to extract the hairs from dermoscopy images. However, the parameter used in the Gaussian filters at every stage is different. [7].

3) Hair Detection and Inpainting

In this step hairs should be extracted and removed. The directional Gabor filters are apply to extract the hairs from dermoscopy images. However, the parameter used in the Gaussian filters at every stage is different [20].

4) Skin Lesion Segmentation:

The segmentation period is one of the most significant and demanding steps in dermoscopic image processing. It is a difficult step because the low contrast between the lesion and healthy skin. The variance in color also depend segmentation. Useful information can be obtained by applying suitable segmentation method. FCM and MRF were integrated to carry out the final segmentation of the images [20].

5) Feature Extraction :

Extracting features from the segmented images. The algorithm used for feature extraction is given below

**Algorithm:**

Step 1: Initialize first fuzzy cluster, $C1$ = Unknown $\cup$ Foreground

Step 2: Calculate the mean, $\mu 1$, and the covariance matrix $\Sigma 1$of the variable $C1$

Step 3 For $i = 2$ to K do

Step 4: Find the variables, Cn, with the largest eigen value and its associate eigenvector en

Step 5: Split Cn into two sets along the mean values projection on the eigenvector

Step 6: Compute $\mu n*$, $\Sigma n*\mu i$ and $\Sigma i$

6) Classification:

The segmentation outcome are used to classify the main contour to obtain its skin texture. Classification is done by finding a threshold value. Each features are taken as each coutours. The size of contours which is less than the threshold value is eliminated. And compare with the dataset image and classified as melanoma or non-melanoma Fig.3 shows the output of the FCM classification method.

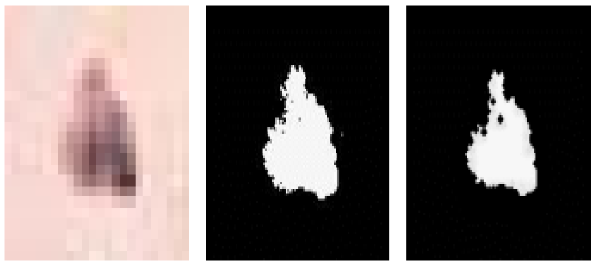
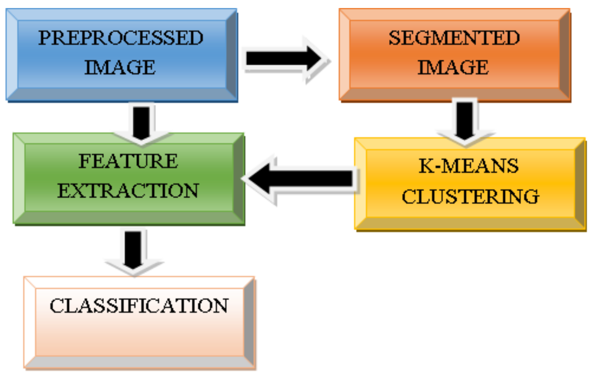


Fig.3 Result of FCM Method [5].

## C. MRF MODEL

The MRF technique is a numerical model, but can be used for segmentation methods. It was introduced in image investigation by Geman and Geman. The image pixels are indexed by a rectangular scrap S. It works based on the bayes theorem.Fig 4 describes the basic steps in MRF method [11].




to K do

Fig.4 Melanoma detection using MRF method

**Algorithm:**

Step 1: At first split the image I into M×N blocks where each block is consisting of single pixel
Step 2: Each block is assigned a unique number and termed as regions.
Step 3: Construct an initial region adjacency graph where every region r is compared with its Neighbors.
Step 4: Repeat step 3
Step 5: Begin design of feature from the block bi of image I, Queue= ri (I) $n$ $i$=0
Step 6: Then terminate feature mining and repair all the neighboring region pairs.
Step 7: Place all contiguous region pairs into a major concern queue based on rising regional possibility differences.
Step 8: Repeat step 7.
Step 9: Reduce region pairs Ra and Rb from priority queue. Restore with a probability α (Ra ,Rb) based on the projected region merging likelihood function.
Step 10: After restoring the image modernize the adjacency graph.
Step 11: until priority queue is empty.
Step 12: Decrease Q by half.
Step 13: until convergence [11].

## D. CLASSIFICATION FOR DERMOSCOPY IMAGES USING CONVOLUTIONAL NEURAL NETWORKS

It uses region average pooling for feature extraction and using the extracted feature and segmented lesion feature classification is done. Linear classifier RankOpt based on the area below the ROC curve (AUC) is used to optimize and obtain the final sorting result. This method integrates segmentation sequence into the organization task, and in addition, by the optimization of RankOpt, a better association routine for unnecessary dermoscopy image dataset is obtained [21,1]. Fig.5 explains about the region based method which is mostly used for feature mining in convolutional neural network.

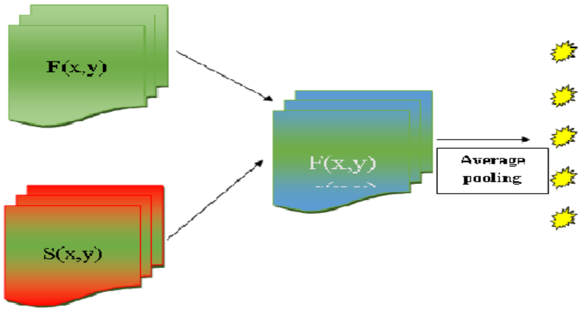



Fig.5 Region Based Method

1) Designed classification framework based on the region average pooling

CNN structure for melanoma categorization based on the region average pooling is shown in Fig. 5, which includes a ResNet50 [8] structure, and followed by two branches: segmentation branch and classification branch.

**Algorithm:**

Step1: The weights of layers are all initialized with the weights in the pretrained network.
Step2: To create the network easier to join,
Step3: Reduce the influence of segmentation training on the classification performance
Step4: Combines the classification task with the segmentation task. The loss in joint training Ljoint is formulated as:
Ljoint = Lclass + λLseg [8].

2) Classification using rankopt

Due to the separation in morbidity, there are often merciless problems of class imbalance in the dermoscopy image dataset, which may cause the classifier to carry out sub optimally, and the trained classifier is tending to classify samples into non-melanomas to improve the overall accuracy [1]. In this framework, use the softmax classifier and the bad-tempered entropy loss function to train the network [1].

**E. CLASSIFICATION FOR DERMOSCOPY IMAGES USING AGGREGATED DEEP CONVOLUTIONAL FEATURES**

It is an original framework for dermoscopy image recognition via both a deep learning method and a local descriptor encoding strategy. Specifically, the deep representations of a rescaled dermoscopy image are first take out via a very deep lasting neural network (ResNet) pre-trained on a large natural image dataset. Then these local deep descriptors are arranged by unorganize image statistic skin texture based on fisher vector (FV) encoding to make a international image representation. Finally, the FV encoded representations are used to categorize melanoma images using a support vector machine (SVM) with a Chi-squared kernel [21]. This method is capable of generating more discriminative features to deal with large variations within melanoma classes as well as. Fig.6 describes the feature extraction and classification using convulutional neural network.

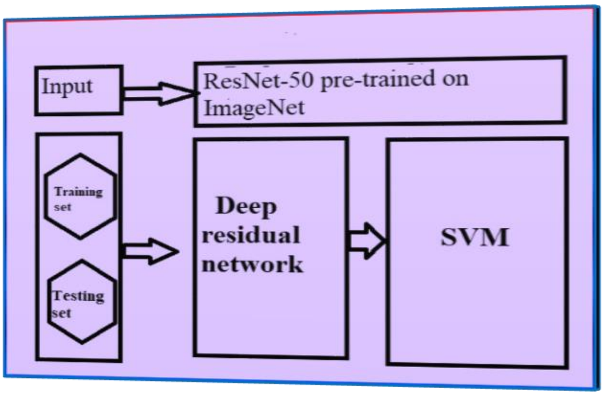



Fig.6 Melanoma detection using DCNN

1) Deep Residual Neural Network

The deep hierarchy architecture of CNN models is of crucial outcome for its powerful education capability [21,10]. It adopt the latest production of the convolutional neural.

2) Image Preprocessing and Data Augmentation

2.1) Image size:

There is a huge dissimilarity in image resolution of the skin lesion dermoscopy dataset provided by ISBI 2016 challenge ranging from the main scale (4288×2848) to the smallest scale (722×542). Resizing and cropping these descriptions directly into required size introduce object distortion and substantial in sequence loss .It take relatively large (compared with 224×224) as inputs. For the skin lesion dataset, resize these images along the shortest side to a uniform scale while maintain the aspect ratio.

2.2) Image normalization and augmentation:

Before processing by CNN, images are normalized by subtracting the mean pixel value, which is designed over the entire use dataset. As a result, the RGB values are centered at zero (denoted as all-img-mean). However, the lighting, skin tone and view point of the skin lesion images vary greatly across the dataset, subtracting a uniform mean value does not well normalize the illumination of individual images [9].

3) Extraction of Local Convolutional features:

Features Given a pre-trained network. Deep image representations are extracted at the final layer of a pre-trained CNN model after removing the softmax layer (classifier layer).

4) Fisher Vector Encoding Strategy:

Each local deep convolutional feature extracted from layer refers to a small region (receptive field) in the input image, and reflects the local distinction of that region. This is similar to established local descriptors. Since each image contains a set of deep features.

5) Kernel-based Classification:

For the classification of the FV representations, we train an SVM classifier with Chi-squared (chi2) kernel. Although linear kernel are efficient for the categorization, non-linear kernels tend to yield better performance and empirical study have recognized the control of the chi2 kernel for image classification [10].

## IV. COMPARATIVE STUDY

Comparison between different methods for detection of melanoma skin cancer is shown in Table 1.

**Table 1:** Comparison metrics of melanoma detection method

| Metrics / Method | Sensitivity | Specificity | Accuracy |
|---|---|---|---|
| BOW | 93% | 85% | 95% |
| FCM | 97.81% | 94.17% | 94.8% |
| MRF | 98.74% | 85% | 95.97% |
| CNN | 96.3% | 89.5% | 97.8% |
| DCNN | 97.89% | 97.17% | 98.8% |

## V. CONCLUSION

In this survey, the overview of dissimilar skin cancer technique is explained briefly. The study also reviews the different techniques used in each method and compare its efficiency. The skin lesion image is segmented, enhanced and pre-processed for the detection of melanoma in each method. Detection using deep convolutional neural network has high accuracy than all other methods. In some system uses combined form of bow method and mrf method for better results.

## VI. REFERENCES


[1] W. Stolz, A. Rieman A.Cognetta, L. Pillet, W. Abmayr, D. Holzel, et al.,"Abcd rule of dermatoscopy-a new practical method for early recognition of malignant-melanoma," Eur. J. Dermatol., vol. 4, pp. 521-527, 1994

[2] S. W. Menzies, C. Ingvar, K. A. Crotty, and W. H. McCarthy, "Frequency and morphologic characteristics of invasive melanomas lacking specific surface microscopic features," Arch. Dermatol., vol. 132, pp. 1178-1182, 1996.

[3] T. Lee, V. Ng, R. Gallagher, A. Coldman, and D. McLean, "Dullrazor®: A software approach to hair removal from images," Comput. Biol. Med., vol. 27, pp. 533-543, 1997.

[4] E.deVries,L.V.vandePollFranse,W.J.Louwman,F. R.deGruijl, and J. W. Coebergh, "Predictions of skin cancer incidence in the Netherlands up to 2015," Brit. J. Dermatol., vol. 152, no. 3, pp. 481–488, Mar. 2005

[5] S. Annadurai, and R. Shanmugalakshmi, Fundamentals of Digital Image Processing, Dorling Kindersley, Delhi, 2006.

[6] J. S. Henning, S. W. Dusza, S. Q. Wang, A. A. Marghoob, H. S. Rabinovitz, D. Polsky, et al., "The CASH (color, architecture, symmetry, and homogeneity) algorithm for dermoscopy," J. Amer. Acad. Dermatol., vol. 56, pp. 45-52, 2007.

[7] H. Iyatomi, M. E. Celebi, G. Schaefer, and M. Tanaka, "Automated color calibration method for dermoscopy images," Comput. Med. Imag. Graph., vol. 35, pp. 89-98, 2011.

[8] G. Schaefer, M. I. Rajab, M. Emre Celebi, and H. Iyatomi, "Colour and contrast enhancement for improved skin lesion segmentation," Comput. Med. Imag. Graph., vol. 35, pp. 99-104, 2011.

[9] G. Capdehourat, A. Corez, A. Bazzano, R. Alonso, and P. Mus´e, "Toward a combined tool to assist dermatologists in melanoma detection from dermoscopic images of pigmented skin lesions," Pattern Recognition Letters, vol. 32, no. 16, pp. 2187–2196, 2011.

[10] A. R. A. Ali and T. M. Deserno, "A systematic review of automated melanoma detection in dermatoscopic images and its ground truth data," Proc. SPIE Med. Imag., vol. 8318, pp. 83181I-1-83181I-11, 2012

[11] Smaoui N and Bessassi s," Detection of Melanoma Skin Cancer in Dermoscopy Images",International Journal of Computer Vision and Signal Processing 3 10-17,2013.

[12] U. Jamil and S. Khalid, "Comparative study of classification techniques used in skin lesion detection systems," presented at the IEEE Int. Multitopic Conf., 2014.

[13] A. Sáez, C. Serrano, and B. Acha, "Model-Based Classification Methods of Global Patterns in Dermoscopic Images," IEEE Trans. Med. Imag., vol. 33, pp. 1137-1147, 2014.

[14] N. Codella, J. Cai, M. Abedini, R. Garnavi, A. Halpern, and J. R. Smith, "Deep Learning, Sparse Coding, and SVM for Melanoma Recognition in Dermoscopy Images," presented at the Proc. Med. Imag. Comput. Comput. Assist. Interv., 2015.

[15] M. Rastgoo, R. Garcia, O. Morel, and F. Marzani, "Automatic differentiation of melanoma from dysplastic nevi," Comput. Med. Imag. Graph., vol. 43, pp. 44-52, 2015.

[16] K. Shimizu, H. Iyatomi, M. E. Celebi, K. A. Norton, and M. Tanaka, "Four-Class Classification of Skin Lesions With Task Decomposition Strategy," IEEE Trans. Biomed. Eng., vol. 62, pp. 274-283, 2015.

[17] R. Kasmi and K. Mokrani, "Classification of malignant melanoma and benign skin lesions: implementation of automatic ABCD rule," IET Image Processing, vol. 10, pp. 448-455, 2016.

[18] D. Gutman, N. C. Codella, E. Celebi, B. Helba, M. Marchetti, N. Mishra, et al. (2016, Skin Lesion Analysis toward Melanoma Detection: A Challenge at the International Symposium on Biomedical Imaging (ISBI) 2016

[19] L. Bi, J. Kim, E. Ahn, D. Feng, and M. Fulham, "Automatic melanoma detection via multi-scale lesion-biased representation and joint reverse classification," presented at the Proc. IEEE 13th Int. Symp. Biomed. Imag, 2016.

[20] Khalid Eltayef1, Yongmin Li1, Bashir I. Dodo1, and Xiaohui Liu1, " Skin Cancer Detection in Dermoscopy Images Using Sub-Region Features," Conference Paper , October 2017.

[21] Zhen Yu, Xudong Jiang, Senior Member, IEEE, Feng Zhou, Jing Qin, Member, IEEE, Dong Ni, Member, IEEE, Siping Chen, Baiying Lei*, Senior Member, IEEE, and Tianfu Wang*, " Melanoma Recognition in Dermoscopy Images via Aggregated Deep Convolutional Features," IEEE Transactions on Biomedical Engineering., 2018.

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