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Effective Approach of Learning based Classifiers for Skin Cancer Diagnosis from Dermoscopy Images

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Abstract:
Skin cancers encase basal cell and squamous cell and melanoma. First two are not dangerous but malignant melanoma is very dangerous and it is very difficult to treat if it goes at higher stages. Early identification of dangerous melanoma can possibly diminish destructiveness and exhaustion. Two grouping approaches for the recognition of skin cancer using learning based classifier are presented. Support vector machine and bag of visual words classifiers have been used based on Laws Texture Energy Measures to classify the skin cancer images into cancerous and non cancerous. The proposed cancer detection methods extract Laws Textures from the Malignant Melanoma and classify the suspicious regions by applying the machine learning classifier. These methods have been tested for 100 skin cancer images and from the performance analysis, the accuracy of support vector machine is 93.57% and Bag of visual words is 95.67%. This experimental result shows the performance of Bag of visual words is better than support vector machine for the recognition of melanoma disease.

***Keywords**: Malignant Melanoma, Laws Texture Energy Measures, Support Vector Machine, Bag of visual words.*

1. INTRODUCTION

Malignant Melanoma (MM) is universally expanding, deadliest and most hazardous kind of skin disease. Early location of MM is most important for preventing deaths due to skin cancer. In the previous not many decades, the clinical analyses of MM were for the most part done dependent on visual examinations, their interpretation is complicated and time consuming. This issue was overcome by Computer-Aided Diagnosis (CAD) frameworks that are utilized for clinical assessment by dermatologists. These systems undergo several processes such as segmentation feature extraction and classification.

Segmentation is the way toward isolating the lesion from the encompassing skin. Highlight Extraction is utilized to remove the highlights, for example, shading, surface, and so forth, In grouping the separated highlights are utilized to decide malignant. Segmentation is troublesome in light of the incredible variety of sore shapes, sizes, colours, skin types, textures and dark hairs. In the earlier period, a big number of researches have spotlighted on image segmentation for the reason that precise segmentation of biomedical images can give to simplified diagnosis, surgical planning and prognosis. Many segmentation methods histogram thresholding pursued by locale developing [1], JSEG calculation dependent on shading quantization and spatial division [2], worldwide thresholding on enhanced shading channels pursued by morphological activities [3], and mixture thresholding [4], segmentation of digitize dermatoscopic images by a shading based division plot [5], division utilizing Fuzzy C-implies bunching systems [6], a robotized strategy for lesion border identification in dermoscopy images utilizing gatherings of three holding strategies [7], an iterative

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stochastic district converging for portioning skin injuries in camera images [8], thresholding based division approach [9], mean move based fluffy C-implies calculation [10], wavelet arrange approach [11] and a lot of techniques inclination vector stream, adaptive thresholding, adaptive snake, EH level set and fluffy based part and consolidation calculation and their comparision [12] for the division of dermoscopy images have been exhibited.

The feature extraction technique is fundamental so as to decide malignant. In future extraction the first information is diminished by estimating positive properties, or highlights, that separate one information test from another example. Additionally it figures include based on which image can be effectively delegated kindhearted or dangerous. The significant clinical component in the finding of pigmented skin sores are shape highlights (territory, perspective proportion, asymmetry and smallness), shading highlights (mean and standard deviation, shading asymmetry, centroidal separations and histogram separations), outskirt highlights and surface highlights. The regular element extraction strategy depends on ABCD (Asymmetry, Border abnormality, Color and Dimension) rule [13]. The surface based component extraction is accomplished by applying wavelet decay on red, blue, green and shade of images [14]. In wavelet include extraction strategy [15] the texture and border feature are removed. The attributes of the extricated highlights give input by thinking about portrayal of noteworthy properties. In our trials, Laws Texture highlights are separated from the malignant growth influenced and non influenced regions for characterization stage.

The most general order strategies that have been utilized to PC based skin malignant growth location frameworks in various medicinal imaging techniques contain artificial neural system [16], k-nearest neighbourhood [17], support vector machine [16], [18], decision trees [16], [19], Bays networks [16], and logistic regression [20]. The support vector machine is a competent classifier, which employed in several image processing areas. It is a parametrically kernel-based technique to deal with supervised classification problems. Single kernel SVM has been commonly applied in data analysis domains

Among the existing CAD methods, the fundamental issue of building up a satisfactory CAD framework is conflicting and low arrangement precision, affectability and explicitness. So as to improve the learning procedure and precision, this paper presents machine classifiers that utilization surface data as contribution to group the typical and unusual tissues in skin malignancy image.

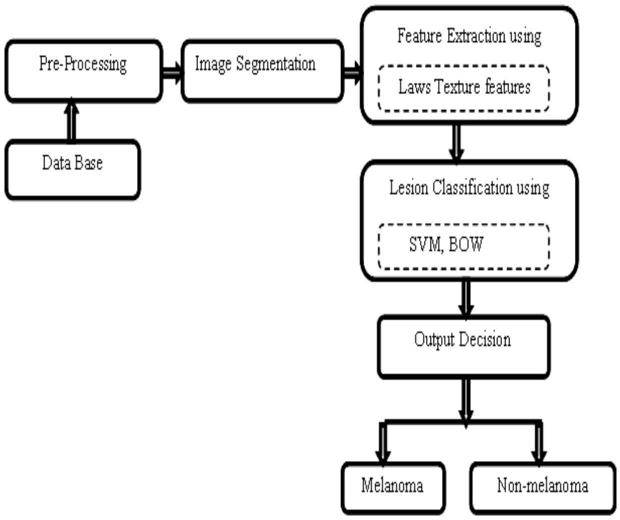

Fig.1 Proposed methodology for location of variation in Malignant Melanoma

Fig.1 shows the proposed a methodology for location of variation in Malignant Melanoma. The main contribution of this research is to classify benign/malignant from skin cancer images. This paper proposed the support vector machine and Bag of visual words for classification of MM images. In this work to generate texture features Laws Texture Energy Measures is used to extract various types of textures. Kernel process is designed and applied to do the non-linear classification via support vector machine and Bag of visual words.

II. MATERIALS AND METHODS

A. Laws Texture Energy Measures

The Laws Algorithm includes

- *Filtering*
- *Computing texture energy*
- *Combining features*

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The sketch map of Laws process and Laws filter is outlined in Fig. 2.

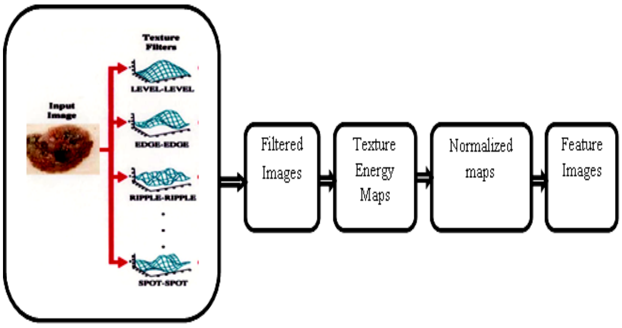

Fig.2 Laws Feature Extraction Process

Laws texture energu measures (TEM) are gotten from three basic vectors of length 3, which represent to neighborhood averaging, edge recognition and spot detection. On the off chance that these vectors are convolved with themselves or with one another, at that point acquire five vectors of length 5, *L5 = (1 4 6 4 1), E5=(- 1 - 2 0 2 1), S5 = (- 1 0 2 0 - 1), W5 = [- 1 2 0 - 2 1] and R5 = (1 - 4 6 - 4 1),* where L5 again performs neighborhood averaging, S5 and E5 are, individually, spot and edge locators, and R5 and W5 can be viewed as "ripple" and "ripple" identifiers.

Convolution veils of 5x5 are utilized to process the vitality of surface which is then spoken to by a nine component vector for every pixel. The covers are created from the accompanying vectors:

1-D convolution kernels

L5	=	*[1 4 6 4 1]*	*Level*
E5	=	*[-1 -2 0 2 1]*	*Edge*
S5	=	*[-1 0 2 0 -1]*	*Spot*
W5	=	*[-1 2 0 -2 1]*	*Wave*
R5	=	*[1 -4 6 -4 1]*	*Ripple*

Where

L5 - Gaussian gives a centre- weighted local average

E5 - Gradient responds to row or column step edges

S5 - LOG detects spots

R5 - Gabor detects ripples

1-D Masks are multiplied to construct 2D masks:

The product of E5 and L5 is the mask E5L5

$$\begin{bmatrix} -1 \\ -2 \\ 0 \\ 2 \\ 1 \end{bmatrix} \times \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \end{bmatrix} \quad \begin{bmatrix} -1 & -4 & -6 & -4 & -1 \\ -2 & -8 & -12 & -8 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 8 & 12 & 8 & 2 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$

2-D convolution kernels

L5 L5 = L5' * L5; E5 L5 = E5' * L5; S5 L5 = S5' * L5;

W5 L5 = W5' * L5; R5 L5 = R5'* L5;

L5 E5 = L5' * E5; E 5E5 = E5' * E5; S5 E5 = S5' * E5;

W5 E5 = W5' * E5; R5 E5 = R5' * E5;

L5 S5 = L5' * S5; E5 S5 = E5' * S5; S5 = S5' * S5;

W5 S5 = W5' * S5; R5 S5 = R5' * S5;

L5 W5 = L5'* W5; E5W5 = E5' * W5;

S5 W5 =S5' * W5; W5W5 = W5'*W5; R5 W5=R5'* W5;

L5 R5 = L5' * R5 ; E5 R5= E5' * R5 ; S5 R5 = S5' * R5 ;

W5 R5 = W5' *R5 ; R5 R5 = R5' * R5;

B. Classification Methods

Once the required features are removed through element extraction stage, skin disease order is finished using support vector machine and bag of visual words classifiers. The classification process mainly depend the features carry out and the classifier selected.

C. Support Vector Machine Classifiers

Support vector machine (SVM) is a learning machine utilized for grouping of information. Fig.3 shows the SVM classifier. SVM has a preferred position of programmed model determination. The exhibition of SVM to a great extent relies upon the part. SVM is an AI strategy that characterizes paired classes by finding and utilizing a class limit the hyper plane augmenting the edge in the given preparing information. The preparation information tests along the hyper planes close to the class limit are called support vectors, and the edge is the separation between the help vectors and the class limit hyper plane.

SVM ascertain isolating hyper planes that augment the edge between two arrangements of information focuses by utilizing Lagrange multipliers, the issue can be planned so that the main tasks on the information focuses are the figuring of scalar items. While the essential preparing calculation can just build direct separators, piece capacities can be utilized to figure scalar items in higher dimensional spaces. The bit limit in the first space will be non direct. Since there are a wide range of piece capacities, there is a wide assortment of conceivable SVM models. In this paper, the radial basis function (RBF) bit was adjusted. The RBF piece has less hyper parameters (γ)which should be resolved when contrasted with the polynomial (γ,r,d) and sigmoid kernels(γ,r).

When the highlights are separated through element extraction stage, tumour order is finished utilizing support vector machine (SVM). SVM utilized here is a supervised learning strategy and it can tackle straight and non-direct issues. Utilizing a parallel classifier for each classification prompts the accompanying sort of directed learning issue. The key ideas we need to utilize are definite as pursues. There are two classes, $v_i \in \{-1,+1\}$, $(u_1,v_1),(u_2,v_2),...(u_n,v_n)$, $u \in R^d$ where d is the dimensionality of the vector.

On the off chance that the two classes are directly distinct, at that point we can estimate a best weight vector w_0 such that $\|w_0\|^2$ is least; and

$$w_0 \bullet u_i - b \geq 1 \text{ If } v_i = 1, \quad (1)$$

$$w_0 \bullet u_i - b \leq 1 \text{ If } v_i = -1 \quad (2)$$

Where, w_0 is the ordinary to the hyper plane accomplished a direct blend of a subset of the direction information. Information are then classified by

$$w_0 \bullet u_i + b = 0 \quad (3)$$

The information can be verifiably changed to a high-dimensional component space to apply SVM into non-direct information dispersions, where a partition may get conceivable. The upsides of SVM are: I) It is utilized to get ideal answer for useful issue; ii) It guarantees to locate the worldwide instead of nearby ideal arrangement. iii) Generalization capacity of SVM is awesome with moderately less computational multifaceted nature. One significant issue is that the calculation is mind boggling; this trouble is understood by bit work. By an appropriately chosen bit work, the hour of preparing is decreased without lost of any accuracy. The bit capacity records the information of the information space to a prevalent dimensional space called highlight space by a non-straight redesign. The ideal hyper plane is from that point made in the component space, delivering a non-direct breaking point in the information space.

This paper proposes a various part procedure to improve the classifier execution which broadens the help vector machine with a different bit picking up setting. Different parts naturally modify the bit loads, SVM is increasingly noteworthy to ineffectual portions and superfluous highlights, this prompts the selection of pieces less significant. The proposed methodology utilizes three portions, for example, polynomial, quadratic and direct are utilized.

The coefficients are determined by settling a significant quadratic programming riddle for which capable calculations are incorporated that guarantee widespread best ends, and v_i is target, and $\sum_{i=1}^{N} \alpha_i v_i = 0$.

The support vectors choose the ideal isolating hyper plane and identify with the abutting purposes of each class and $0 \leq \alpha_i \leq C$, where C allows certain versatility in isolating the gatherings and deals with the swap between allowing direction inaccuracies, pushing solid edges and produces an adaptable edge that permits certain off-base groupings. The goal is to evaluate minimal estimation of with which an insignificant error order is accomplished.

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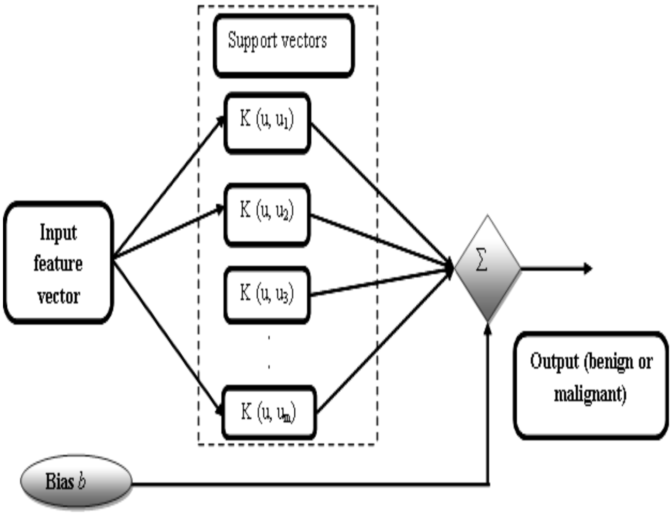

Fig.3 Support vector machine architecture

The model consolidates loads to get a solitary yield result. Bolster vector machine is utilized to skin disease analytic procedure. From the outset, the SVM prepare help vectors, utilizing the preparation datasets. The preparation skin disease datasets can be generous or threatening picture. From the data of help vectors, the test skin disease informational index is arranged appropriately. Our test datasets go about as non-straight or non-distinct case. In this tests, utilize three distinct portions which are: direct, polynomial and quadratic.

D. Bag-of-visual-words (BOW) classification

In computer vision and image analysis, the bag-of-words (BOW) model applied to accomplish image arrangement, by treating image includes as words. In BOW, image arrangement is the way toward relegating a classification name to a picture under test. It was developed to create a vocabulary that can describe the image in terms of their features.

The construction of bag of visual words includes several processes such as feature extraction and vocabulary construction. Figure 4 represents the BOW construction. The first step in building a bag of visual words from the dataset. In the next step vocabulary of possible visual words is constructed from each image in the dataset. Vocabulary construction is normally accomplished by clustering.

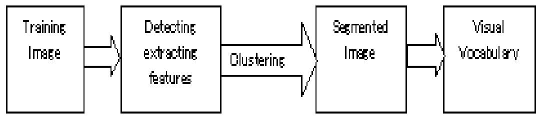

Fig. 4 BOW Construction

The classification of image using bag of visual words follows 3 simple steps.

Step 1: In this step, the image is divided into training and test subjects; and the images are stored for training. It is easy to handle large set of data

Step 2: In this step, a visual vocabulary or bag of features, is made by removing highlight descriptors from delegate pictures of every class

Step 3: In this method, multiclass classifier is used to train using error correcting output code with binary support vector machine.

III. EXPERIMENTAL ANALYSIS

A. Melanoma Database

From diagnosis centres the images were collected and severity analysis has been done. This image dataset encloses 100 images with 67 benign, 33 malignant. All images were digitized with 24- bit RGB color, 485 X 716 sizes. For this study, 75 images are used for the training purpose and 25 images are used for testing purpose.

B. Results

Fig. 5(a) shows the skin cancer input images that is studied in this research. The output skin cancer image after application of SVM is shown in Fig. 5(b). The output skin cancer image after application of BOW is shown in Fig. 5(c). In the output image, the blackish area identifies the skin cancer area. The

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SVM and BOW separated the cancer cell and non cancer cell.

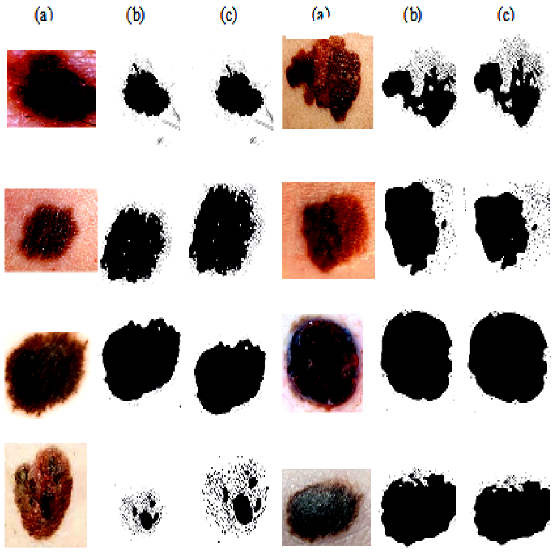

Fig.5 Skin cancer images a) Original Images b) SVM- Output Images c) BOW- Output Images

D. Performance Measures

This segment depicts about the different presentation estimates used to investigate the capability of different characterization approaches utilized for skin malignant growth identification. There are three significant estimates. Affectability, Explicitness, Precision of SVM and BOW classifier is depicted as from the estimation of (Total number of dangerous cases effectively delegated positive), (Total number of favourable cases really named negative), (Total number of kind hearted cases dishonestly perceived as positive) and (Total number of threatening erroneously perceived as negative). The grouping execution of the SVM and BOW imager classifier is dissected utilizing exactness, affectability and particularity appeared in Table 1.

$$Sensitivity = \frac{T_P}{T_P + F_N} * 100 \qquad (4)$$

$$Specificity = \frac{T_N}{T_N + F_P} * 100 \qquad (5)$$

$$Accuracy = \frac{T_P + T_N}{T_P + F_N + T_N + F_P} * 100 \qquad (6)$$

Table 1: Performance measure of classifier models

Classifier	SVM	BOW
Accuracy (%)	0.93571	0.9567
Sensitivity (%)	94.167	96.183
Specificity (%)	92.105	92.593
AUC (%)	0.97588	0.97809

The (Receiver Operating Characteristics) ROC examination is a broadly utilized technique in the medicinal region, for assessing the precision, Sensitivity and Specificity. A ROC bend is a two-dimensional proportion of order execution and the plot of the True Positive Fraction (TPF) versus its False Positive Fraction (FPF). Fig.6 shows the exchange off between affectability against–explicitness to make the ROC bend for a grouping. Fig.6 shows that the BOW is better more prominent ROC region

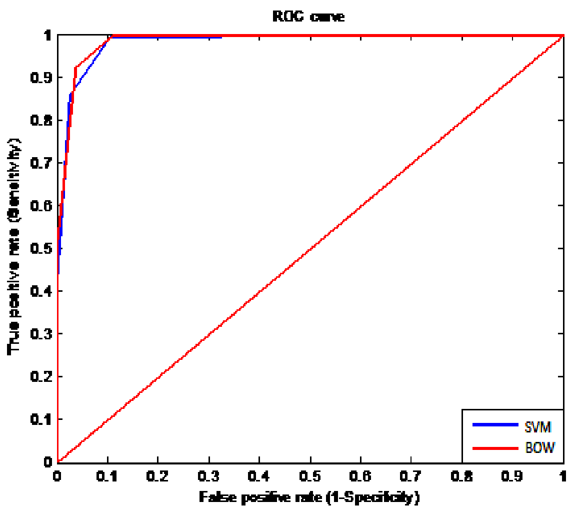

Fig.6 ROC curve for skin cancer

V. CONCLUSION

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This paper gives a technique for classification of benign and malignant nodules utilizing Support Vector Machine and Bag of visual words. The features are extracted from the skin cancer images. At that point, diagnosis rules are framed for the extracted Laws texture energy measures features. At long last with the got analysis administers, the characterization is performed to distinguish the event of malignancy. BOW based proposed approach achieves the accuracy of 95.67%, which is higher than the SVM classifier which achieves the accuracy of 93.57%. The experiment shows that the usage of BOW with RBF Kernel results in better accuracy of classification with accuracy 95.67%, sensitivity 96.18% and Specificity 92.59%.

REFERENCES

1. H. Iyatomi, H. Oka, M. Saito, A. Miyake, M. Kimoto, J. Yamagami, S. Kobayashi, A. Tanikawa, M. Hagiwara, K. Ogawa, G. Argenziano, H. P. Soyer, and M. Tanaka, “Quantitative assessment of tumour extraction from dermoscopy images and evaluation of computer-based extraction methods for an automatic melanoma diagnostic system, “Melanoma Res., vol. 16, no. 2, pp. 183–190, 2006.
2. M. E. Celebi, Y. A. Aslandogan, W. V. Stoecker, H. Iyatomi, H. Oka, and X. Chen, “Unsupervised border detection in dermoscopy images,” Skin Res. Technol., vol. 13, pp. 454–462, 2007.
3. R. Garnavi, M. Aldeen, M. E. Celebi, A. Bhuiyan, C. Dolianitis, and G. Varigos, “Automatic segmentation of dermoscopy images using histogram thresholding on optimal color channels,” Int. J. Med. Sci.,vol.1, no. 2, pp. 126–134, 2010.
4. R. Garnavi, M. Aldeen, M. E. Celebi, S. Finch, and G. Varigos, “Border detection in dermoscopy images using hybrid thresholding on optimized color channels,” Comput. Med. Imag., vol. 35, pp. 105–115, 2011.
5. P. Schmid, “Segmentation of digitized dermatoscopic images by twodimensional color clustering,” IEEE Trans. Med. Imag., vol. 18, pp. 164–171, 1999.
6. K. Chuang, S. Tzeng, H. Chen, J. Wu, and T. Chen, “Fuzzy c-means clustering with spatial information for image segmentation,” Comput.Med. Imag. Graph., vol. 30, pp. 9–15, 2006.
7. M.E. Celebi.H.Iyatomi,G.Schaefer, and W.V.Stoecker,” Lesion border detection in dermoscopy images”, Comp.Med.Imag. Graph., vol. 33, no. 2, pp. 148–153, 2009.
8. Alexander Wong, Jacob Scharcanski and Paul Fieguth,” Automatic skin lesion segmentation via iterative stochastic region merging”, IEEE Trans. Inf. Technol. Biomed., vol. 15, no. 6, pp. 721–733, Nov. 2011.
9. M.Emin Yuksel and Murat Borlu,” Accurate Segmentation of Dermoscopic Images by Image Thresholding Based on type-2 Fuzzy Logic”, IEEE Trans. Fuzzy Systems, vol. 17, no. 4, pp. 976–982, Aug. 2009.
10. Huiyu Zhou, Gerald Schaefer,Abdul h.Sadka and m.Emre Celebi,” Anisotropic Mean Shift Based Fuzzy C-means Segmentation of Dermoscopy Images”, IEEE Journal of selected topics in signal processing, vol. 3, no. 1, pp. 26–34, Feb. 2009.
11. Sadri AR, Zekri M, Sadri S, Gheissari N, Mokhtari M, and Kolahdouzan F, ” Segmentation of dermoscopy images using wavelet networks ”, IEEE Trans.Biomed., vol. 60, no. 4, pp. 1134–41, Apr. 2013.
12. Margarida Silveira, Jacinto C. Nascimento , Jorge S. Marques, André R. S. Marçal, Teresa Mendonça, Syogo Yamauchi, Junji Maeda, and Jorge Rozeir, ” Comparison of Segmentation Methods for Melanoma Diagnosis in Dermoscopy Images ”, IEEE Journal of selected topics in signal processing, vol. 3, no. 1, pp. 35–45, Feb. 2009.

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ISSN: 0193-4120 Page No. 3089 - 3096

13. W.Stolz, A.Riemann, and A.Cognetta, “ABCD rule of dermatoscopy: A new practical method for early recognition and malignant melanoma,” Eur. J. Dermatol.,, vol. 4, pp. 521–527, 1994.
14. Aadd Alexander Wong, , Jacob Scharcanski, and Paul Fieguth, “Automatic Skin Lesion Segmentation via Iterative Stochastic Region Merging”, IEEE Trans. Inf. Technol. Biomed., vol. 15, no. 6, pp. 929–936, Nov. 2011.
15. Rahil Garnavi, Mohammad Aldeen and James Bailey,” Classification of Melanoma Lesions Using Wavelet-Based Texture Analysis”, Digital Image Computing: Techniques and Applications, pp. 75–81, Dec. 2010.
16. Maglogiannis and C. Doukas, “Overview of advanced computer vision systems for skin lesions characterization,” IEEE Trans. Inf. Technol. Biomed., vol. 13, no. 5, pp. 721–733, Sep. 2009.
17. R. Walvick, K. Patel, S. Patwardhan, and A. Dhawan, “Classification of melanoma using wavelet-transform-based optimal feature set,” inProc. SPIE Med. Imag.: Image Process, 2004, vol. 5370, pp. 944–951.
18. H. Ganster, P. Pinz, R. Rohrer, E. Wildling, M. Binder, and H. Kittler, “Automated melanoma recognition,”IEEE Trans. Med. Imaging, vol. 20, pp. 233–239, Mar. 2001.
19. M. Wiltgen, A. Gergerb, and J. Smolle, “Tissue counter analysis of benign common nevi and malignant melanoma,”Int. J. Med. Inf., vol. 69, pp. 17– 28, 2003.
20. S. Dreiseitl, L. Ohno-Machado, and H. Kittler, “A comparison of machine learning methods for the diagnosis of pigmented skin lesions,” J. Biomed. Inf., vol. 34, pp. 28–36, 2001.