IJCSE International Journal of Computer Sciences and Engineering Open Access
Review Paper Volume-5, Issue-10 E-ISSN: 2347-2693

A Comparative Review of Various Approaches for Skin Cancer Detection

R. Maurya[1*], A. Singh[2], V. Srivastava [3], R. Yadav[4]

[1*] Computer Science and Engineering, Shri Ramswaroop Memorial University, Barabanki, India
[2] Computer Science and Engineering, Shri Ramswaroop Memorial University, Barabanki, India
[3] Computer Science and Engineering, Shri Ramswaroop Memorial University, Barabanki, India
[4] Computer Science and Engineering, Shri Ramswaroop Memorial University, Barabanki, India

[*]Corresponding Author: maurya123ritesh47@gmail.com, Tel.: +91-7379255085

Available online at: www.ijcseonline.org

Received: 19/Sep/2017, Revised: 02/Oct/2017, Accepted: 20/Oct/2017, Published: 30/Oct/2017

***Abstract*—** Classification of skin cancer gives the best chance of being diagnosed early. Biopsy method for skin cancer detection is much painful. Human interpretation contains difficulty and subjectivity therefore automated analysis of skin cancer affected images has become important. This paper proposes an automatic medical image classification method to classify two major type skin cancers: Melanoma and Non-melanoma. In this paper, we have used the color and texture features in combination which give better results than using color or gray level information alone. We have used k-means clustering algorithm to segment the lesion. The features are extracted by four different color-texture feature extractors from the segmented images. DullRazor technique is used to eliminate surrounding hairs. Classification accuracy of our proposed system is evaluated on four different types of classifiers and their values are compared with one another. The results of the proposed system are computed on five different classification rates in order to perform better analysis of our proposed system. SVM outperforms among all other classifiers with accuracy of 76.69%.

***Keywords*—**Grey Level Co-occurrence Matrices, Support Vector Ma-chine, Local Binary Patterns, Texture features, color percentiles, K-means clustering, Cooccurence Matrix, Color Features, Integrative Cooccurence Matrix, Gabor Features, Linear Classifier, NN Classifiers, NMC Classifiers, Cross-validation.

I. INTRODUCTION

Skin Cancer incidence is increasing at 3.1% per year [1]. Skin cancer spread over the body with the help of lymphatic and blood vessels. Thus, early detection of skin cancer is very important for proper diagnosis of the disease.

Melanoma and Non-Melanoma are two major categories of skin cancers. Malignant melanoma is of several sub-types. Basal cell carcinoma and Squamous-cell carcinomas are two main types of non-melanoma skin cancers.

Each type of skin cancers has different characteristics from other skin cancers.

In clinical detection of skin cancer diagnosis, dermatologist uses a visual inspection. Clinical diagnostic performance is very poor in comparison to dermoscopy and automatic diagno-sis. Dermoscopy is a non-invasive diagnostic technique. It uses clinical dermatology and dermatopathology in combination to inspect the morphological features which is not possible in clinical detection. Dermoscopy increases the performance of diagnosis with 10-30% compared to unaided eye [2]. To differentiate skin cancer images needs much more experience with dermoscopy technique. Less experienced clinicians use ABCD-E rule [3] to improve the diagnostic performance [3].

Automatic image processing of skin cancer gives better results by providing the exact information about lesion, which can be useful for the clinician to detect and classify skin automatic skin cancer detection has four main stages: (1) Preprocessing (2) Segmentation of lesion (3) Feature extraction and feature selection (4) Lesion classification.

Preprocessing is used to remove the difficulties of segmentation process that may occur due to presence of hairs on skin. DullRazor technique is used to remove hairs from images.

Segmentation is an important process in image processing applications and computer vision because doctors are always interested in meaningful regions of the dermoscopic image. Segmentation divides an image into a number of separate regions. Pixels, in each region have high similarity such as color, intensity, and texture. Many Researchers use only gray-level for image segmentation [23]. But, in our proposed system, we use color information of the image for lesion segmentation.

In general, we convert the color image in gray-level image therefore color information does not use. There is a wide variety of segmentation methods used in dermoscopy images [4]. Recent advancements include thresholding [5, 6], k-means clustering [7], fuzzy c-means clustering [8, 9], density-based clustering [10], mean shift clustering [11], gradient vector flow snakes [12, 13, 14], color quantization followed by spatial segmentation [15], statistical region merging [16], watershed transformation [17], dynamic programming [18, 19], and supervised learning [20, 21]. Clustering is an unsupervised learning technique, where one can give the number of clusters in advance to classify pixels [22]. A similarity measure is defined between pixels and similar pixels are then grouped into a cluster. We use k-means clustering for segmentation of color images.

It is very hard to differentiate skin cancer visually. Identification and extraction of most effective features from cancer affected lesion is very important. Each class of skin cancer has some different features than others. We use these different features for classification. Feature extraction extracts useful features or properties from segmented images. These extracted features easily classify the classes of skin cancer.

Color features are mainly statistical parameters. These are calculated from inter and intra-channel of an image, like average value and standard deviation of the RGB [24, 25, 26, 27, 28] or HSV color channels [29]. Here, we use ”Local Binary Patterns + Color percentiles”, ”Integrative co-occurrence matrices”, ”Gray level co-occurrence matrices + color percentiles”, ”Gabor features + Chromatic features”, ”Gabor Features”, ”Opponent Color LBP”, ”Color Ranklets” [30]. These methods are based on texture and disjoint color analysis. Textural features are extracted from images by converting into gray-level and color features are computed with the help of three color component of an image. Textural and color features are concatenated into the same feature vector to improve the classification accuracy.

The main aim of feature selection is to select the maximum number of features to achieve high performance in cancer classification [31]. Feature selection is important when anyone works on gray-level features. In our proposed system, there is no need of feature selection algorithms.

Classification phase of the diagnostic system is the one in charge of making the inferences about the extracted information in the previous phases in order to be able to produce a diagnostic about the input image. In our experiment, we have used four well-established classifiers: Support Vector Classifier (SVC), Nearest Neighborhood (NN), Linear classifier, and Nearest Mean Classifier (NMC).

The rest of the paper is organized as follows. Section 2 briefly reviews segmentation, feature extraction techniques, and classification methods which are used in proposed frame work. Section 3 reports extensive experimental results and Section 4 concludes the paper.

II. METHODOLOGY

Proposed framework is a compiled abstraction of digital image classification. Fig.1 describes the steps in image classification.

In this paper, we propose this framework with Preprocessing by DullRazor technique, K-means clustering segmentation and color a texture feature extraction technique which is a new approach to classify the skin cancer images. For validation purpose fivefold cross validation is used.

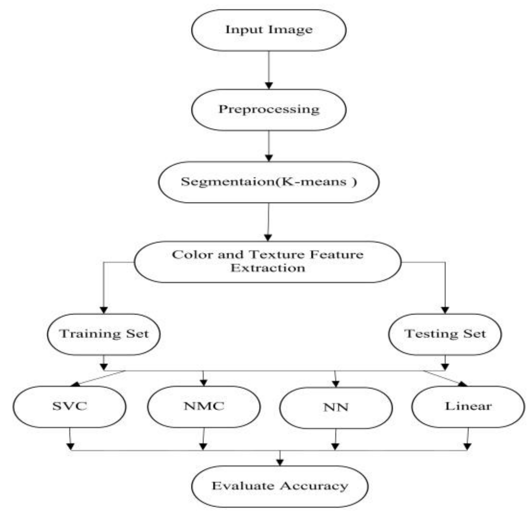

Fig. 1: Proposed Method

A. Preprocessing

Skin surface of human is accumulated by hairs, scars and skin tone differences. Hence, the images should be preprocessed to accurately access the affected skin lesions. For this we use DullRazor software technique, this removes the black and thick hairs present on the images.

B. Segmentation

Segmentation is a process to partitioning an image into disjoint regions that are homogeneous with respect to a chosen property such as luminance, color, and texture. The aim of segmentation is to change the representation of an image into something that is more meaningful and easier to analyze [31].

K-means Clustering Segmentation:

K-means clustering method is one of the simplest unsupervised learning methods and this method is nondeterministic, numerical and iterative. In this experiment, color images are used as input hence this technique is used for segmentation. K-means clustering is partitioning method.

This method group objects in the way that within group variance is minimized. If within group variance is minimized then it gives high featured segmented image. The working of this method is as follows [23]:

1) Select K pixels for centers randomly. Initially, Center represents group centroids.
2) For grouping the sample data, calculate histogram bin value distance between pixels and selected centroids and assign the group on the basis of nearest distance.
3) Calculate the histogram bin value for new group to find the new position of centroids.

4) If the value of centroids changes then repeat steps 2 and 3.

Fig. 2: Input Image and Segmented Image

C. Feature Extraction

It is important to identify the most effective features to extract from skin cancer lesions and to find the most effective pattern classification criteria and algorithms for differentiating those lesions.

1) Local Binary Patterns + Color Percentiles: The LBP feature vector is created in the following way:

1. Divide the window size into cells in the form of n*n matrix (i.e. 16*16).

2. If the center pixel value (Threshold Value) is less than the selected pixel then write 1 otherwise write 0. For rotational invariant features move in one direction either clockwise or anti-clockwise. This step gives 8 digit binary number. Convert it into decimal number for further processing.
3. Compute the histogram of the frequency of each “number” occurring over the given cell.
4. Apply normalization on histograms.

5. Concatenate the histograms of all divided cells

The combination of LBP+CP presented by Niskanen et al. [33]. In this method, we calculate local binary patterns in a gray scale image.

For better results we reduce the calculated features into rotationally invariant features. Rotational invariance is necessary because when image is rotated, the gray values also rotated in a circular form where origin is same. Then calculation of feature vector is changes with the rotation. We apply Discrete Fourier Transformation Function (DFT) to make features rotationally invariant. There are always 36 rotationally invariant features in a gray scale image. Now we calculate the color percentiles of first, second, and third quartile (three points that divide the each channel into four parts) of three channels. Total features from color percentiles are 9. When we concatenate features of these two methods the final resulting feature vector dimension is 36.

2) Integrative Co-occurrence Matrices: Integrative co-occurrence matrix [34, 35] is a new approach for calculating the inter-channel and intra-channel features. In inter-channel feature calculation, we calculate the co-occurrence matrix features from each of three channel and in intra-channel, we calculate the features from combination of color channels ((r, g), (r, b), (g, b)). In our experiment, we use five co-occurrence features: Energy, Contrast, Correlation, Homogeneity, and Inertia. Final resulting feature vector dimension is 30.

3) Co-occurrence Matrices + Color Percentiles: The combination of Co-occurrence matrices and color percentiles is presented by Niskanen et al. [33]. This method is first used for applications in wood inspection. Out of 14 features we computed 5 important co-occurrence features for classification. Color percentile is calculated as discussed in LBPnCP method. So, the dimension of final resulting feature vector is 14.

4) Gabor Features: Gabor features are used to extract scale and orientation information from different channels. We calculate Gabor features for inter-channel of an image with above mentioned configuration. One channel gives 36 rotationally variant features. So, the resulting feature vector is of 32+32+32=96 dimension when we apply DFT normalization to achieve rotationally invariant features.

5) Gabor Features + Chromatic Features: Different frequencies and orientations are used in Gabor filters for extracting features from an image. The tuning of Gabor filters with these parameters: Number of orientations (n_o) = 6, Number of frequencies(n_F)= 4, Frequency ratio(F_r) = half-octave, Standard deviation of gaussian envelope (longitudinal) (η) = 0.5, Standard deviation of gaussian envelop (trasversal) (Υ) = 0.5, Max frequency (F_m) = 0.327. This tuning is same in overall experiment.

6) Opponent Color LBP: The Processing of Opponent color LBP feature extraction method is same as LBP method. In Opponent Color LBP method we calculate features from inter-channel and intra-channel but in LBP method we calculate features from gray-scale image. Separate channels give 108 (36+36+36) features and paired channels give 108 features. The dimension of resulting feature vector is 216.

7) Color Ranklets: Ranklet transform is an image processing technique which considers the relative rank of neighboring pixels instead of their values. Invariance against rotation is achieved by computing the discrete Fourier transform (DFT) of a set of ranklet features computed from circular neighborhoods at different rotation angles.

D. Classifier

1) Nearest Neighbor and Nearest Mean Classifier: An input pattern is classified in the class of the nearest training pattern (NN) or that of the nearest centroid (NMC). Absence of parameter tuning makes these classifiers advantageous and easy to implement. In NN, sensitivity to outliers makes it poor performer In Nearest Mean Classifier, misclassifications arise because probably centroids are not representative.

2) Linear Classifier: Linear classifiers classify features by making a classification decision which is based on linear combination of the feature values. Linear classifier is originally developed for binary classification it requires a predefined linear function (hyper-plane) that best separates the required classes in the feature space. If the two classes are linearly separable then perfect separation between classes exists.

3) Support Vector Classifier: Support Vector Machine is highly effective classifier, and is currently has a great importance in pattern recognition and artificial intelligence. The tuning of a SVC is very important and need very careful analysis. In our experiment, we are using RBF kernel function in SVM classifier then we have to tune two parameters: C and gamma (the radius of RBF).
C is used during the training phase and says how much outliers are taken into account in calculating support vector. C is a trade-off between training error and the flatness of the solution. If the value of C is larger, then the final training error will be less. But if we increase value of C too much then the risk of losing the generalization properties of the classifier is high. Large C is increases the time needed for training and small C makes classifier flat. We have to find a C that keeps the training error small and generalizes well. In SVC processing, we choose a kernal function which mapped patterns into a high dimensional space [39]. According to Hsu et al. [40], if the number of features is not large then RBF kernel is a reasonable choice.

Fig. 3: Four images set of melanoma and Non melanoma skin cancer

III. Results and Discussion

A. Database Preparation

In our experiment we use database of skin cancer images (Melanoma and Non-melanoma) have been collected from University of Waterloo University. Collection of 150 images is used in this experiment. 75 images are of melanoma and non-melanoma types each respectively. Size of image is always an important aspect of image processing experiments. In this experiment input image is resized in 128*128. We observe that this size of images speedup the computational performance. Matlab is easy to implement and computationally cheap than other simulation softwares. Therefore we use Matlab to implement our project.

Resized images further go through the segmentation process. Segmented images are deal separately for feature extraction process. Seven Dataset created by seven different feature extraction techniques described in section II. We used five folds of cross validation. In which five different partitions (60, 15), (55, 20), (50, 25), (45, 30), (40, 35) are used. When partition (60, 15) is chosen, then 60 randomly selected images are used for training purpose and another 15 images, chosen randomly are used for testing from each dataset.

B. Result Analysis

Our experimental results, based on combination of color and texture features, are showing better performance than results based on gray-level features [41, 42]. Table 1 to Table 7 contains classification accuracy at different partitions on different classifiers.

TABLE I: Accuracy of LBPnCP Feature Extraction Technique on Different Classifiers with given training and testing ratio.

Partition /Testing	NN	NMC	Linear	SVC
(60, 15)	65.56	50.00	63.33	62.00
(55, 20)	57.14	61.43	51.43	57.14
(50, 25)	68.00	58.00	62.00	66.00
(45, 30)	80.00	66.67	80.00	83.33
(40, 35)	80.00	70.00	93.36	89.14

TABLE II: Accuracy of Gabor+CF Feature Extraction Technique on Different Classifiers with given training and testing ratio

Partition /Testing	NN	NMC	Linear	SVC
(60, 15)	62.00	66.67	63.33	68.89
(55, 20)	70.00	77.14	70.00	68.57
(50, 25)	76.00	80.00	70.00	82.00
(45, 30)	86.67	46.67	86.67	80.00

Partition /Testing	NN	NMC	Linear	SVC
(40, 35)	90.00	80.00	80.00	90.00

TABLE III: Accuracy of Integ.CM Feature Extraction Technique on Different classifiers with given training and testing ratio

Partition/Testing	NN	NMC	Linear	SVC
(60, 15)	70.00	66.67	53.33	66.67
(55, 20)	64.29	62.86	67.14	70.00
(50, 25)	84.00	80.00	74.00	72.00
(45, 30)	86.67	83.33	83.33	86.67
(40, 35)	90.00	70.00	80.00	87.76

TABLE IV: Accuracy of GLCM+CP Feature Extraction Technique on Different Classifiers with given training and testing ratio

Partition /Testing	NN	NMC	Linear	SVC
(60, 15)	60.00	57.78	58.89	64.44
(55, 20)	61.43	47.14	68.57	64.29
(50, 25)	74.00	84.00	82.00	82.00
(45, 30)	80.00	76.67	83.33	83.33
(40, 35)	91.24	60.00	88.65	93.94

TABLE V: Accuracy of Gabor Feature Extraction Technique on Different Classifiers with given training and testing ratio

Partition /Testing	NN	NMC	Linear	SVC
(60, 15)	71.11	74.44	74.44	76.67
(55, 20)	64.29	71.43	54.29	67.14
(50, 25)	78.00	74.00	78.00	78.00
(45, 30)	90.00	83.33	76.67	90.00
(40, 35)	90.00	80.00	60.00	96.57

TABLE VI: Accuracy of Opponent Color LBP Feature Ex-traction Technique on Different Classifiers with given training and testing ratio

Partition /Testing	NN	NMC	Linear	SVC
(60, 15)	55.56	65.56	60.00	63.33
(55, 20)	67.14	68.57	64.29	68.57
(50, 25)	76.00	66.00	68.00	80.00
(45, 30)	86.67	76.67	90.00	86.67
(40, 35)	92.29	50.00	80.00	95.11

TABLE VII: Accuracy of Color Ranklets Feature Extraction Technique on Different Classifiers with given training and testing ratio

Partition /Testing	NN	NMC	Linear	SVC
(60, 15)	68.89	57.78	60.00	63.33
(55, 20)	72.86	55.71	61.43	70.00
(50, 25)	74.00	56.00	72.00	74.00
(45, 30)	76.67	60.00	70.00	76.67
(40, 35)	80.00	70.00	78.00	80.00

IV. CONCLUSION AND FUTURE SCOPE

Experimental results show that color and texture descriptors for skin cancer classification provide good classification accuracy. We have also evaluated the performance of four different classifiers on these extracted features. SVC (Support Vector Classifier) outperform among all others with the same features set then comes Linear classifier, whose classification accuracy is nearly same as the SVC. 1-NN performs poorly on the given feature sets. Gabor features proved to be the best features that can be used for this particular application. Other more suitable methods are LBPnCP. Integrated GLCM which are also giving the promising results. Opponent and color ranklets are the methods which are not advisable to be used for the particular application because of their large dimensions and less prediction accuracy as well.

REFERENCES

[1] E. Linos, S.M. Swetter, M.G. Cockburn, G.A. Colditz, and C.A. Clarke, "*Increasing burden of melanoma in the United States*," Journal of Investigative Dermatology, vol. 129, no. 7, pp. 1666–1674, 2009.

[2] J. Mayer, "*Systematic review of the diagnostic accuracy of dermatoscopy in detecting malignant melanoma,"* Medical Journal of Australia, vol. 167, no. 4, pp. 206–210, 1997.

[3] J. K. Robinson and R. Turrisi, "*Skills training to learn discrimination of ABCDE criteria by those at risk of developing melanoma,"* Archives of Dermatology, vol. 142, no. 4, pp. 447–452, 2006.

[4] M. E. Celebi, H. Iyatomi, G. Schaefer, and W.V. Stoecker, *"Lesion Border Detection in Dermoscopy Images,"* Computerized Medical Imaging and Graphics, vol. 33, no. 2, pp. 148-153, 2009.

[5] H. Iyatomi, et al., "*An Improved Internet-based Melanoma Screening System with Dermatologist-like Tumor Area Extraction Algorithm*," Computerized Medical Imaging and Graphics, vol. 32, no. 7, pp. 566-579, 2008.

[6] R. Garnavi, M. Aldeen, M.E. Celebi, G. Varigos, and S. Finch, "*Border Detection in Dermoscopy Images Using Hybrid Thresholding on Optimized Color Channels,"* Computerized Medical Imaging and Graphics, vol. 35, no. 2, pp. 105-115, 2011.

[7] H. Zhou, et al., "*Spatially Constrained Seg- mentation of Dermoscopy Images*," in Proceedings of the 5th IEEE International Symposium on Biomedical Imaging, pp. 800-803, 2008.

[8] P. Schmid, “*Segmentation of Digitized Dermatoscopic Images by Two-Dimensional Color Clustering*," IEEE Transactions on Medical Imaging, vol. 18, no. 2, pp. 164-171, 1999.

[9] H. Zhou, G. Schaefer, A. Sadka, and M. E. 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, 2009.

[10] M. Mete, S. Kockara, and K. Aydin, “*Fast Density-Based Lesion Detection in Der-moscopy Images,*" Computerized Medical Imaging and Graphics, vol. 35, no. 2, pp. 128-136, 2011.

[11] R. Melli, C. Grana, and R. Cucchiara, “*Comparison of Color Clustering Algorithms for Segmentation of Dermatological Images,*" in Proceedings of the SPIE Medical Imaging Conference, pp. 1211-1219, 2006.

[12] B. Erkol, R. H. Moss, R. J. Stanley, W. V. Stoecker, and E. Hvatum, “*Automatic Lesion Boundary Detection in Dermoscopy Images Using Gradient Vector Flow Snakes,*" Skin Research and Technology, vol. 11, no. 1, pp. 17-26, 2005.

[13] H. Zhou, et al., “*Gradient Vector Flow with Mean Shift for Skin Lesion Segmentation,"* Computerized Medical Imaging and Graphics, vol. 35, no. 2, pp. 121-127, 2011.

[14] Q. Abbas, M. E. Celebi, and I. F. Garcia, “*A Novel Perceptually-Oriented Approach for Skin Tumor Segmentation,"* International Journal of Innovative Computing, In-formation and Control, vol. 8, no. 3, pp. 1837-1848, 2012.

[15] M. E. Celebi, et al., “*Unsupervised Border Detection in Dermoscopy Images,"* Skin Research and Technology, vol. 13, no. 4, pp. 454-462, 2007.

[16] M. E. Celebi, et al., “*Border detection in Dermoscopy Images Using Statistical Region Merging*”, Kins Research and Technology, vol. 14,no. 3, pp. 347-353, 2008.

[17] T. Wang, et al., “*Modified Watershed Technique and Post-Processing for Segmentation of Skin Lesions in Dermoscopy Images,*" Computerized Medical Imaging and Graphics, vol. 35, no. 2, pp. 116-120, 2011.

[18] Q. Abbas, M. E. Celebi, I. F. Garcia, and M. Rashid, ”*Lesion Border Detection in Dermoscopy Images Using Dynamic Programming,*" Skin Research and Technology, vol. 17, no. 1, pp. 91-100, 2011.

[19] Q. Abbas, M. E. Celebi, and I. F. Garcia, “*Skin Tumor Area Extraction Using an Improved Dynamic Programming Approach,*" Skin Research and Technology, vol. 18, no. 2, pp. 133-142, 2012.

[20] G. Schaefer, M.I. Rajab, M.E. Celebi, and H. Iyatomi, “*Colour and Contrast En-hancement for Improved Skin Lesion Segmentation,*" Computerized Medical Imag-ing and Graphics, vol. 35, no. 2, pp. 99-104, 2011.

[21] P. Wighton, T. K. Lee, H. Lui, D. I. McLean, and M. S. Atkins, “*Generalizing Common Tasks in Automated Skin Lesion Diagnosis,*" IEEE Transactions on Infor-mation Technology in Biomedicine, vol. 15, no. 4, pp. 622-629, 2011.

[22] V. K. Dehariya, S. K. Shrivastava, R. C. Jain,“*Clustering of Image Data Set Using K-Means and Fuzzy K-Means Algorithms* ” , International conference on CICN, pp. 386- 391, 2010.

[23] Vijay Jumb, Mandar Sohani, Avinash Shrivas, “*Color Image Segmentation Using K-Means Clustering and Otsu’s Adaptive Thresholding,*” International Journal of Innovative Technology and Exploring Engineering (IJITEE), February 2014.

[24] J. F. Aitken, et al., *“Reliability of computer image analysis of Pigmented skin lesions of Australian adolescents*,” Journal of Cancer, vol. 78, no. 2, pp. 252–257, 1996.

[25] A.Green, N. Martin, J. Pfitzner, M. O’Rourke, and N.Knight, “*Computer image analysis in the diagnosis of melanoma*,” Journal of the American Academy of Dermatology, vol. 31, no. 6, pp. 958–964, 1994.

[26] H. C. Lee, *Skin Cancer Diagnosis Using Hierarchical Neural Networks and Fuzzy Logic*, Department of Computer Science, University of Missouri, Rolla, Mo, USA, 1994.

[27] S. Seidenari, M. Burroni, G. Dell’Éva, P.Pepe, and B.Belletti, “*Computerized evaluation of pigmented skin lesion images recorded by a videomicroscope: comparison between polarizing mode observation and oil/slide mode observation*,” Skin Research and Technology, vol. 1, no. 4, pp. 187–191, 1995.

[28] K. Ramlakhan and Y. Shang, “*A mobile automated skin lesion classification sys-tem,”* in Proceedings of the 23rd IEEE International Conference on Tools with Artificial Intelligence (ICTAI ’11), pp. 138–141, November 2011.

[29] N. Cascinelli, et al., “*Results obtained by using a com-puterized image analysis system designed as an aid to diagnosis of cutaneous melanoma,”* Melanoma Research, vol. 2, no. 3, pp. 163–170, 1992.

[30] Francesco Bianconia, et al., “*Automatic classification of granite tiles through colour and texture features*”, Preprint submitted to Expert Systems with Applications, February 20, 2012.

[31] Ammara Masood and Adel Ali Al-Jumaily, “*Computer Aided Diagnostic Support System for Skin Cancer: A Review of Techniques and Algorithms*” Hindawi Pub-lishing Corporation International Journal of Biomedical Imaging, Volume 2013.

[32] T. Ojala, M. Pietikainen, and T. Maenpaa, *"Multiresolution gray-scale and rotation invariant texture classification with Local Binary Pattern*s". IEEE Transactions on Pattern Analysis and Machine Intelligence, 24:971-987, 2002.

[33] Niskanen, M., Silven, O., Kauppinen, H., June 2001. “*Color and texture based wood inspection with non-supervised clustering*”, Proceedings of the 12th Scandivanian Conference on Image Analysis. Bergen, Norway, pp. 336–342, 2001 .

[34] Arvis, V., et al., *Generalization of the cooccurrence matrix for colour images: application to colour texture classification*. Image Analysis and Stereology 23 (3), 63–72, 2004.

[35] Palm, C., “*Colour texture classification by integrative co-occurrence matrices*”, Pat-tern Recognition 37 (5), 965–976, 2004.

[36] F. Bianconi and A. Fernandez., "*Evaluation of the eﬀects of Gabor filter parameters on texture classification*". Pattern Recognition, 40:3325-3335, 2007.

[37] F. Bianconi, et al., *Robust color texture features based on ranklets and discrete Fourier transform.* Journal of Electronic Imaging, 18:043012-1-8, 2009.

[38] M. Masotti and R. Campanini., "*Texture classification using invariant ranklet fea-tures",* Pattern Recognition Letters, 29:1980-1986, 2008.

[39] Scholkopf, B., Smola, A., “*Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond*”, MIT Press, 2002.

[40] Hsu, et al., “*A Practical Guide to Support Vector Classification*”, Tech. rep., Department of Computer Science National Taiwan University, 2010.

[41] B.Gohila vani, A. Selvaraj, M. Vijayapriya, N.Anandh, “*Segmentation and Classification of Skin Lesions Based on Texture Features*”, Int. Journal of Engineering Research and Applications, December 2014

[42] R. Maurya ,S.K. Singh, A. K. Maurya, A. Kumar, "*GLCM and Multi Class Support vector machine based automated skin cancer classification* IEEE Con-ference", Page(s):444 - 447Print ISBN:978-93-80544-10-6 INSPEC Accession Num-ber:14382783, 5-7 March 2014

Authors Profile

Mr. R. Maurya Assistant Professor in Computer Science & Engineering Department at Shri Ramswaroop Memorial University, Lucknow-Deva Road, Uttar Pradesh, India. His main research work focuses on Medical Image Processing and Artifical Intelligence.

Mr. A. Singh Assistant Professor in Computer Science & Engineering Department at Shri Ramswaroop Memorial University, Lucknow-Deva Road, Uttar Pradesh, India. His main research work focuses on Medical Image Processing, Computer Vision & Pattern Recognition.

Ms. V. Srivastava M.Tech Computer Science & Engineering Student at Shri Ramswaroop Memorial University, Lucknow-Deva Road, Uttar Pradesh, India. Her main research work focuses on Medical Image Processing, Computer Vision & Pattern Recognition.

Ms. R. Yadav M.Tech Computer Science & Engineering Student at Shri Ramswaroop Memorial University, Lucknow-Deva Road, Uttar Pradesh, India. Her main research work focuses on Medical Image Processing, Computer Vision & Pattern Recognition.

