Vol. 5(15) Apr. 2015, PP. 2151-2156

Contents list available at IJMEC

International Journal of Mechatronics, Electrical and Computer Technology (IJMEC)

Journal Homepage: www.aeuso.org

PISSN: 2411-6173 - EISSN: 2305-0543

Classification of the Pigmented Skin lesions in Dermoscopic Images by Shape Features Extraction

Neda Razazzadeh[1*] and Mehdi Khalili [2]

[1]*M.S. Student, Dept. Computer and Informatics Engineering, Payame Noor University, Qeshm, Iran*

[2]*Assistant professor, Dept. Computer and Informatics Engineering, Payame Noor University, Tehran, Iran*

***Corresponding Author's E-mail:** n_razazzadeh@yahoo.com*

Abstract

Differentiation of benign and malignant (melanoma) of the pigmented skin lesions is difficult even for the dermatologists thus in this paper a new analysis of the dermatoscopic images have been proposed. Segmentation, feature extraction and classification are the major steps of images analysis. In Segmentation step we use an improved FFCM based segmentation method (our previous work) to achieve to binary segmented image. In feature extraction step, the shape features are extracted from the binary segmented image. After normalizing of the features, in classification step, the feature vectors are classified into two groups (benign and malignant) by SVM classifier. The classification result for the accuracy is 71.39%, specificity is 85.95%, and it has the satisfactory results in sensitivity metrics.

Keywords: *Dermoscopic images, Segmentation, Shape features, SVM classifier.*

1. Introduction

Melanoma is characterized by the most rapidly increasing incidence and causes the majority (75%) of deaths related to skin cancer [1].The most dangerous characteristic of melanoma is that it can spread widely over the body via the lymphatic vessels and blood vessels. Thus, early diagnosis of melanoma is a key factor for the prognosis of the disease. Dermoscopy enables better diagnosis as compared to unaided eye with an improvement in diagnostic sensitivity of 10–30% [2]. Seen the gravity of the melanoma presence and the doubt that reigns about its visual diagnosis, many dermatologists perform a medical procedure (called biopsy), which consists in appropriating a part of patient lesion, in order to ascertain whether the skin lesion is benign or malignant. The problem is that only 10% of these procedures reveal a cancerous pathology. It means that 90 % people undergo a useless surgical intervention. However, this operation which aims to avoid mistakes of diagnosis and it is no valid in most cases, involves some expenses and morbidity [3]. Thus computerized diagnosis of the pigmented skin lesions is proposed in recent years [1]. ABCD is more prone to over classification of atypical melanocytic nevi as melanomas [2].The automatic extraction of characteristics that take into account the rule ABCD is computationally less expensive than the ones that take into account, for example, the one of 7 points or the Menzies method. Furthermore, the reliability in the clinical diagnosis is very high [4]. So in automated diagnosis of skin lesions, feature extraction is based on the ABCD rule of dermatoscopy. ABCD represent the asymmetry, border structure, variegated color, and dermatoscopical structures and define the basis for a diagnosis by a dermatologist [5]. Shape is an important clinical feature in the diagnosis of pigmented skin lesions [6]. In [7] we proposed a method for segmentation of the dermoscopic images in which first the input dermoscopic image is pre-processed by converting the RGB image to YUV color space and selecting

Article History:

Received Date: Dec. 04, 2014

Accepted Date: Mar. 19, 2015

Available Online: Apr. 14, 2015

the U channel of it, denoising the converted image by LPF (low-pass filtering), and contrast enhancement of denoised image . Second the pre-processed image pixels are classified by FFCM clustering that it is statistical histogram based fast version of fuzzy c-mean. After using this method, 2-classes of lesion and skin are attained. Then Otsu thresholding is applied to lesion class for achieving to binary segmented image. Finally the morphological reconstruction algorithms are used to reduce segmentation errors in binary segmented image.

in this paper is done the classification of dermoscopic images. In order to, we implement the previous work in [7] in which the dermoscopic image is segmented by FFCM clustering and Otsu thresholding. In next step shape features are extracted from the binary segmented image. After that the features are normalized. Finally the shape feature vectors are classified with the SVM (RBF).

2. Svm Classifier

Support vector machines (SVMs) have recently drawn considerable attention in the machine learning community due to their solid theoretical foundation and excellent practical performance. They are kernel-based learning algorithms derived from the statistical learning theory [6]. SVMs have several advantages over the more classical classifiers such as decision trees and neural networks. The support vector training mainly involves optimization of a convex cost function. Therefore, there is no risk of getting stuck at local minima as in the case of backpropagation neural networks. Most learning algorithms implement the empirical risk minimization (ERM) principle which minimizes the error on the training data. On the other hand, SVMs are based on the structural risk minimization (SRM) principle which minimizes the upper bound on the generalization error. Therefore, SVMs are less prone to overfitting when compared to the algorithms that implement the ERM principle such as backpropagation neural networks. Another advantage of SVMs is that they provide a unified framework in which different learning machine architectures (e.g., RBF networks, feedforward neural networks) can be generated through an appropriate choice of kernel [6].

3. Proposed Scheme

Block diagram of the proposed scheme is shown in figure 1. This method includes three steps: segmentation, feature extraction and classification.

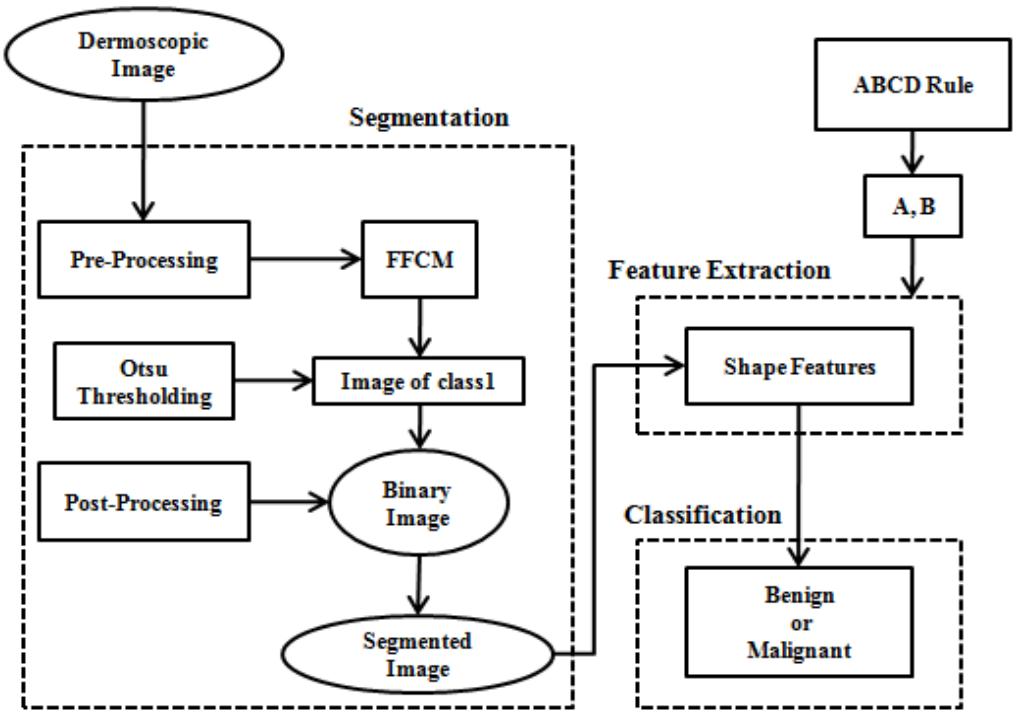

Figure 1: Block diagram of the proposed scheme

1- Segmentation: for image segmentation, we use the our previous work in [7]. As it mentioned before, image is preprocessed by converting the RGB image to YUV color space and selecting the U channel of it, denoising the converted image by LPF (low-pass filtering), and contrast enhancing of the denoised image. Then the FFCM (statistical histogram based fast version of fuzzy c-mean) method is applied on the pre-processed image pixels to get two classes of lesion and skin(background). For achieving to the binary segmented image, the Otsu thresholding is applied to the lesion class. In the post-processing step the morphological reconstruction algorithms are used to improve the segmentation result.

2- Feature extraction: in this step, shape features are extracted from the binary segmented image to satisfy the properties of A and B of ABCD rule. The shape features are explained as follow:

1. Perimeter: the distance around the boundary of the region by calculating the distance between each adjoining pair of pixels around the border of the region.
2. Lesion area: The number of pixels in the lesion region [8].
3. Eccentricity: The eccentricity is the ratio of the minor axis length of the ellipse and its major axis length (1). The value is between 0 and 1. This feature for the melanoma is less than the benign lesion [9].

$$Eccentricity = \frac{MinorAxisLength}{MajorAxisLength} \quad (1)$$

4. Solidity: a measure of border irregularity defined as the ratio between the areas of the object and its convex hull. the Solidity value for the melanoma is less than the benign lesion because the melanoma has more irregular boundary in comparision the benign lesion. It is computed as follows [6]:

$$Solidity = \frac{Area}{convexArea} \quad (2)$$

5. Elongation: bounding box is the smallest rectangle that contains the object and is aligned with the principal axes. Elongation is ratio between the height and width of the bounding box [6, 10]. This value for the benign lesion is more than the melanoma. It is defined as follows:

$$Elongation = \frac{Width}{Lenght} \quad (3)$$

6. Major axis length: Scalar specifying the length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the region [8].
7. Minor axis length: the length (in pixels) of the minor axis of the ellipse that has the same normalized second central moments as the region [8].
8. Compactness: Compactness is usually defined as the ratio of the area of the object to the area of a circle with the same perimeter. It shows the degree of irregularity of the object (lesion) boundary (B in the ABCD) [10]. This feature for the melanoma is less than the benign lesion.

$$Compactness = \frac{4\pi \times Area}{(perimeter)^2} \quad (4)$$

9. Orientation: the angle between the x-axis and the major axis of the ellipse that has the same second-moments as the region. This value for the melanoma is more than the benign lesion [11].
10. Convex area: Convex hull is p-by-2 matrix that specifies the smallest convex polygon that can contain the region. Convex image is binary image (logical) that specifies the convex hull, with all pixels within the hull filled in (i.e., set to on). Convex area is the number of pixels in convex image [11].

11. Equivalent diameter: Scalar that specifies the diameter of a circle with the same area as the region [10].
12. Extent: The ratio between the lesion area and its bounding box area [10].

3- Classification: before classification of feature vectors, the features value should normalize between -1 to 1 because they have various ranges that it can reduce the accuracy of classification. The feature normalization is done as follows:

$$\frac{2(x-\min)}{(\max-\min)}-1 \tag{5}$$

In (5), min and max parameters are respectively the minimum and maximum values in each feature column, and x parameter is a sample feature in the same column. After normalization, the feature vectors that belong to the benign lesion are labeled with 2 value and the feature vectors that belong to the melanoma lesion are labeled with 1 value. Finally they are classified into two groups: benign and melanoma by SVM classifier.

4. Experimental Results

In this study two dermatology atlases that include 120 pigmented skin lesions with 63 melanoma and 57 benign lesions in JPEG format with sizes of 720*480 pixels were used for analysis [12, 13].

After classification, we compute the total accuracy, sensitivity (diagnosis accuracy of melanoma) and specificity (diagnosis accuracy of benign lesions) as the classification metrics. They are defined as follows [14]:

$$Sensitivity = \frac{TP}{TP+FN} \tag{6}$$

$$Specificity = \frac{TN}{TN+FP} \tag{7}$$

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \tag{8}$$

Where, TP, TN, FP and FN are respectively true positives cases, true negative cases, false positives cases, and false negative cases [14].

The classification results for average of 30 executions of the SVM classifier are shown in the table 1 As it can be seen, the SVM are tested with the various kernels. They are the linear, polynomial, MLP and RBF kernels. The experimental results show that the RBF kernel could achieve to the high accuracy about 71.39% and specificity about 85.95% than the other kernels. Also the linear kernel has the highest sensitivity about 66.95%. The results of accuracy and specificity related to the 30 executions of the RBF kernel are shown in figure 2, 3.

Table 1: The SVM classifier results with its various kernels

SVM kernels / Metrics (%)	Linear kernel	Polynomial kernel	MLP kernel	RBF kernel
Sensitivity	**66.95**	64.90	53.15	58.89
Specificity	75.54	70.08	56.42	**85.95**
Accuracy	71.11	67.50	54.72	**71.39**

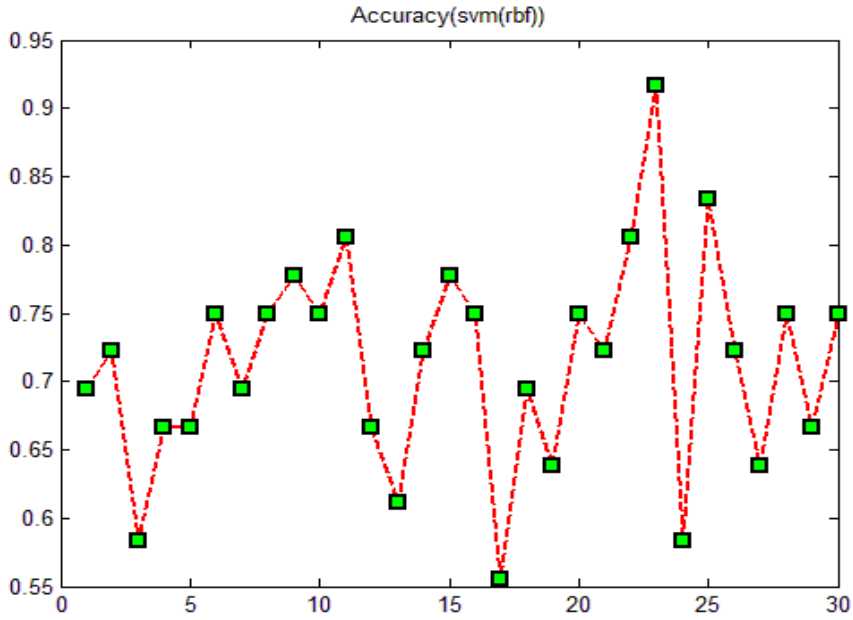

Figure 2: The accuracy related to the 30 implementation of the RBF kernel

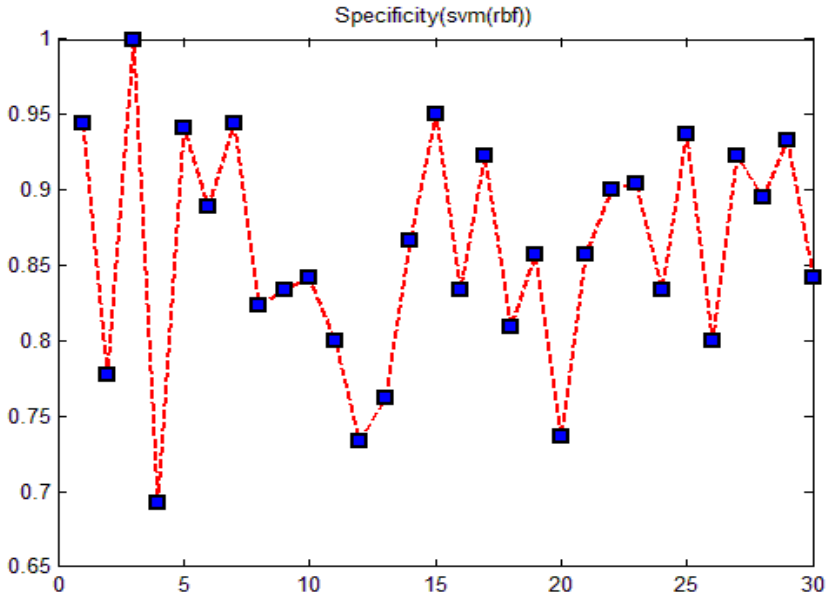

Figure 3: The specificity related to the 30 implementation of the RBF kernel

Conclusion

In this paper, the dermoscopic image segmentation is done by the FFCM and Otsu thresholding based method that we proposed it in [7].The shape features of the lesion (area, eccentricity, perimeter, solidity, elongation, major axis length, minor axis length, compactness, orientation, convex area, equivalent diameter, and extent) are extracted from the binary segmented image. After that they are normalized in the same range. Then the feature vectors contain 12 shape features are classified by SVM (RBF) classifier. The experimental show satisfactory results for accuracy and specificity. They are respectively about: 71.39% and 85.95%.

References

[1] K. Korotkov, R. Garcia, “Computerized analysis of pigmented skin lesions: A review”, Artificial Intelligence in Medicine 56, 2012, pp. 69–90.

[2] A. Masood and A. A. Al-Jumaily, “Computer Aided Diagnostic Support System for Skin Cancer:A Review of Techniques and Algorithms”, International Journal of Biomedical Imaging, 2013, pp. 1-22.

[3] E. Zagrouba and W. Barhoumi, “An Accelerated System for Melanoma Diagnosis Based on Subset Feature Selection”, Journal of Computing and Information Technology - CIT 13, 1, 2005, pp. 69–82.

[4] D. Ruiz, V. Berenguer, A. Soriano, B. Sanchez, “A decision support system for the diagnosis of melanoma: A comparative approach”, Expert Systems with Applications 38, 2011, pp.15217–15223.

[5] H. Ganster, et al., “Automated Melanoma Recognition”, IEEE Trans. Medical Imaging, 20(3), 2001.

[6] M. E. Celebi, et al., “A methodological approach to the classification of dermoscopy images”, Comput Med Imaging Graph 31(6), 2007, pp. 362–373.

[7] N. Razazzadeh and M. Khalili, “An Improved FFCM Based Segmentation Method for Dermoscopic Images”, International Journal of Mechatronics, Electrical and Computer Technology 4(13), 2014, pp. 1637-1649.

[8] V**.** Sridhar, H. S. Sheshadri, M. C**.** Padma (Eds.), “Emerging Research in Electronics Computer Science and Technology”, Proceedings of International Conference, 248, 2014.

[9] M. A. Wirth, “Shape Analysis and Measurement”, Computing and information science Biocomputing Group, University of Guelph, 2002.

[10] P. G. Cavalcanti, J. Scharcanski, “Automated prescreening of pigmented skin lesions using standard cameras”, Computerized Medical Imaging and Graphics 35, 2011, pp. 481– 491.

[11] Gonzalez R.C., Woods R.E. Digital Image Processing, Addison-Welsey, 2002

[12] http://www.dermis.net

[13] http://www.dermnet.com

[14] M. Elgamal, “Automatic Skin Cancer Images Classification”, (IJACSA) International Journal of Advanced Computer Science and Applications 4(3), 2013.