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Segmentation and Classification of Skin Cancer Images

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Abstract—This paper proposes a novel approach for detection and classification of skin cancer images. The proposed work comprises of Pre-Processing, Segmentation, Feature extraction and Classification. In the Pre-Processing stage, Weiner Filter is implemented to remove noise and undesired structures from the images. In the Segmentation stage Distance Regularized Level Set (DRLS) method is implemented in order to acquire a contour by means of the gradient flow that minimizes an energy function with a distance regularization term and an external energy that drives the motion of the zero level set toward desired locations. Support vector machine(SVM) classifier is employed for the classification task, utilizing feature vectors derived from gray level co-occurrence(GLCM) features. The classification results are evaluated with the use of accuracy, sensitivity and specificity. It is derived that SVM classifier is more capable than any other classifier for discriminating benign and malignant melanoma lesions, obtaining accuracy 91.66%, sensitivity 93.33% and specificity 90.00%.

Keywords— Skin Cancer, Weiner filter, DRLS Segmentation, GLCM, SVM.

I. INTRODUCTION

Skin cancer - a malignant tumour that grows in skin cells is one of the most common of all human cancer and in the present-days, accounts for more than 50% of all types of cancers around the world. Skin cancer (also known as "skin neoplasm") is skin's unwanted growth with differing causes and varying degrees of malignancies. It can spread very fast to all organs/parts of human body through lymphatic system or blood. The incidences of "melanoma - the deadliest form of skin cancer has been on rise at an alarming rate of 3% per year [1]. Detection of malignant melanoma in its early stages considerably reduces morbidity and mortality. Skin cancer can be cured at very high rates with simple and economical treatments. For the benefit of human race, there is a need of diagnosis of skin cancer at an early stage and lots of researchers already working in that direction by means of hardware and software development using different techniques. In this regards, we are suppose to use images of cancer affected skin of patients frequently.

Cancer can be defines as a diseases in which there is uncontrollable growth of cells aggressively, invasively and metastatically. Cancer can be classified based on tissues from which the cancerous cell originates. Skin cancer is by far the most common of all cancer and it usually begins with skin lesions. So based on the nature of these skin lesions, skin cancer can be majorly divided into melanoma and nonmelanoma. The malignant non-melanoma lesions are further divided into basal cell carcinoma (BCC) and squamous cell carcinoma (SCC) [2]. BCC is the most common type of skin cancer. It originates from the basal keratinocytes of the epidermis. The most common example of such cancer is a pink, pearly papule or plaque all sun -exposed skin [2]. BCC can occur in fair complexion, chronic sun exposure and ionizing radiation. BCC can be seen on the human face, particularly the nose. BCC tends to grow slowly. Proper lighting is most important in detecting BCC at their earliest stages.

SCC is second most common type, arises from the epidermal keratinocytes. The common example of SCC represents a scaly papule, plaque or nodule on sun-exposed skin. In addition to BCC, SCC can occur because of cigarette smoking. The skin of the head and neck are the most common location for SCC. SCC can grow rapidly and has an increased risk of metastasis, especially in chronically immunosuppressed patients, such as organ transplant recipients.

Malignant melanoma, the third most common and the leading cause of death is the second type of skin cancer. Although Melanoma can occur in many organs, the most common form, cutaneous melanoma arises from the melanocytes that are found in basal layer of the epidermis, hair follicles, sebaceous glands and other adnexal structure. Melanoma often presents as an irregularly bordered, pigmented macule. A melanoma presents numerous shades of colour, ranging from tan to brown to jet-black, but they also be evenly colored. Popular or nodular lesions are worrisome for deeper, more invasive disease. Melanoma is the leading cause of skin cancer-related deaths and early detection and diagnosis is the need of present day.

Most of the times, the patches of darker colour on the skin represents pigmented skin lesions and is the result of excessive melanin concentration. In benign lesions (e.g., common nevi), melanin deposits are normally found in the epidermis. In malignant lesions (i.e., melanoma), the melanocytes reproduce melanin at a high, abnormal rate. Due to the penetration of

malignant melanocytes into the dermis, they leave melanin deposits there and thus changing the nature of skin coloration. The presence of melanin in the dermis is the most significant sign of melanoma. Melanoma typically grows horizontally within the epidermis. It then penetrates into the dermis. Therefore, accurate diagnosis of malignant melanoma at an early stage, leading to earlier treatment is crucial to successful cancer management and is a crucial issue for dermatologists. Earlier detection and therapy also lead to less morbidity and decreased cost of therapy. The standard method to evaluate a skin growth to rule out melanoma is by biopsy followed by histopathological examination. The challenge lies in identifying the lesions that have the highest probability for being melanoma.

In the present study, a new computer based approach has been developed towards skin cancer lesions automatic classification, in terms of benign or malignant. The proposed method comprises at first Pre-Processing the images to remove the noise using Weiner filter. Secondly extract the lesion from the Digital Image by DRLS segmentation method. Thirdly, extracting second order statistical textural GLCM features from the segmented skin lesion. Finally classify the lesion as benign or malignant by using SVM classifier. The performance of the proposed method is evaluated with the help of some terminologies, such as accuracy, sensitivity and specificity.

The rest of this paper is organized as follows. The next section elaborates on the proposed method. Section II presents the image database. Section III elaborates the proposed method. And the results of this study are summarized in section IV.

II. IMAGE DATABASE

The database is composed of 60 Skin Cancer images: 30 cases are benign, 30 cases are malignant. The digital images were collected by the doctors of the Hospital (Karnataka, India) and some of the benchmark images are collected from the internet. Every lesion is manually outlined by an experienced Doctor. The images are classified into Benign and Malignant by the experienced doctors of the recognized hospital.

III. PROPOSED METHOD

A. Pre-Processing

The Digital Images are degraded by optical lens in a digital camera. This leads to difficulties in the diagnosis done by visual evaluation, as the information contents of digital images are very complex. Efficient image processing techniques must therefore be developed to help physicians to making a correct and accurate diagnosis. Image pre-processing makes an acquired-prepared image suitable for a particular application. It basically involves improvement or enhancement of image, which includes noise removal, edge highlighting, sharpening, deblurring, brightening, change in image contrast, masking, hair removal, cropping or resizing. The pre-processing step removes the undesirable parts, enhances the image, corrects the image skew and removes noise from the image.

The approach of reducing one degradation at a time allows us to develop a restoration algorithm for each type of degradation and simply combine them. The Wiener filtering executes an optimal trade-off between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously. The Weiner Filter exploits correlation information between signal and noise to enhance SNR or reduce distortion.

Let $s[n]$ be the original image and $y[n]$ be the noisy image.

The noise is given by:

$$\eta[n] = y[n] - s[n] \tag{1}$$

Mean square error (MSE) sense means minimizing the expected value of:

$$\mathrm{E}\left[\eta^2[n]\right] = \mathrm{E}\left[\left|y[n] - s[n]\right|^2\right] \tag{2}$$

This is equivalent to maximizing the SNR:

$$\mathrm{E}\left[\eta^2[n]\right] = \frac{\mathrm{E}\left[\left|s[n]\right|^2\right]}{\mathrm{E}\left[\left|y[n] - s[n]\right|^2\right]} = \frac{\mathrm{E}\left[\left|s[n]\right|^2\right]}{\mathrm{E}\left[\eta^2[n]\right]} \tag{3}$$

We examine the mean square error and Peak Signal to Noise Ratio (PSNR) in which the parameters are determined.

. Segmentation

1) *Distance Regularized Level Set Evolution Method*: In level set methods, a contour (or more generally a hyper surface) of interest is embedded as the zero level set of an LSF. Although the final result of a level set method is the zero level set of the LSF, it is necessary to maintain the LSF in a good condition, so that the level set evolution is stable and the numerical computation is accurate. This requires that the LSF is smooth and not too steep or too flat (at least in a vicinity of its zero level set) during the level set evolution. Level set methods have been widely used in image processing and computer vision. The level set evolution is derived as the gradient flow that minimizes an energy functional with a distance regularization term and an external energy that drives the motion of the zero level set toward desired locations. Signed distance functions have been widely used as level set functions in level set methods. In conventional level set formulations, the LSF is typically initialized and periodically reinitialized as a signed distance function. In this section, we propose a level set formulation that has an intrinsic mechanism of maintaining this desirable property of the LSF.

The distance regularization effect eliminates the need for reinitialization and thereby avoids its induced numerical errors. The Edge-Based Active Contour Model in Distance Regularized Level Set Formulation is implemented.

Let I be an image on a domain Ω, we define an edge indicator function *g* by

$$g \equiv \frac{1}{1+\left|\nabla G_\sigma * I\right|^2} \tag{4}$$

Where G_σ is a Gaussian kernel with a standard deviation **σ**

This function *g* usually takes smaller values at object boundaries than at other locations

For an LSF $\emptyset: \Omega \to \Re$ we define an energy function $\epsilon(\phi)$ by

$$\epsilon(\phi) = \mu R_{p(\phi)} + \lambda L_{g(\phi)} + \alpha A_{g(\phi)} \tag{5}$$

Where $\lambda > 0$ and $\alpha \epsilon \Re$ are the coefficients of the energy functions $L_{g(\phi)}$ and $Ag_{(\phi)}$ which are defined by

$$L_g(\phi) \equiv \int_\Omega g\delta(\phi)\,|\nabla\phi|\,dx \tag{6}$$

$$A_g(\phi) \equiv \int_\Omega gH(-\phi)dx \tag{7}$$

Where δ and H are the Dirac delta function and the Heaviside function, respectively

In this case, if the initial contour is placed outside the object, the coefficient α in the weighted area term should be positive, so that the zero level contour can shrink in the level set evolution. If the initial contour is placed inside the object, the coefficient α should take negative value to expand the contour. We can see that the role of in this energy term Ag is to slow down the shrinking or expanding of the zero level contour when it arrives at object boundaries where g takes smaller values.

In practice, the Dirac delta function and Heaviside function H in the functional Lg and Ag are approximated by the following smooth functions δϵ and Hϵ as in many level set methods defined by:

$$\delta_\varepsilon(x) = \begin{cases} (1/2\varepsilon)\left[1+\cos\left(\frac{\pi x}{\varepsilon}\right)\right] & |x| \le \varepsilon \\ 0 & |x| > \varepsilon \end{cases} \tag{8}$$

$$H_\varepsilon(x) = \begin{cases} (1/2)\left(1+\frac{x}{\varepsilon}+\frac{1}{\pi}\sin\left(\frac{\pi x}{\varepsilon}\right)\right) & |x| \le \varepsilon \\ 1 & |x| > \varepsilon \\ 0 & |x| < -\varepsilon \end{cases} \tag{9}$$

The DIRAC Delta Function is the first derivative of Heaviside Function

C. Feature Extraction

Feature extraction is an important step in skin cancer detection and classification. An optimum feature set should have effective and discriminating features, feature vectors highly affects the performance of the classification Thus, how to extract useful features and make a good selection of the features is a crucial task for CAD systems. The Textural features are Energy, Correlation, Contrast and Entropy. Extraction of effective features is a necessary step. The goal of feature extraction is to maximize the discriminating performance of the feature group. In this work, extracted 32 GLCM features [8], all the features are extracted with all angles and with a distance 1 and 2; they show discrimination between malignant and benign lesions.

The extracted GLCM feature equations are;

Energy:

$$Ene = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)^2 \tag{10}$$

Correlation:

$$Cor = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(i-\mu_x)(j-\mu_y)\,p(i,j)}{\sigma_x\sigma_y} \tag{11}$$

Contrast:

$$Con = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} |i-j|^2\, p(i,j) \tag{12}$$

Entropy:

$$Ent = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)\log(p(i,j)) \tag{13}$$

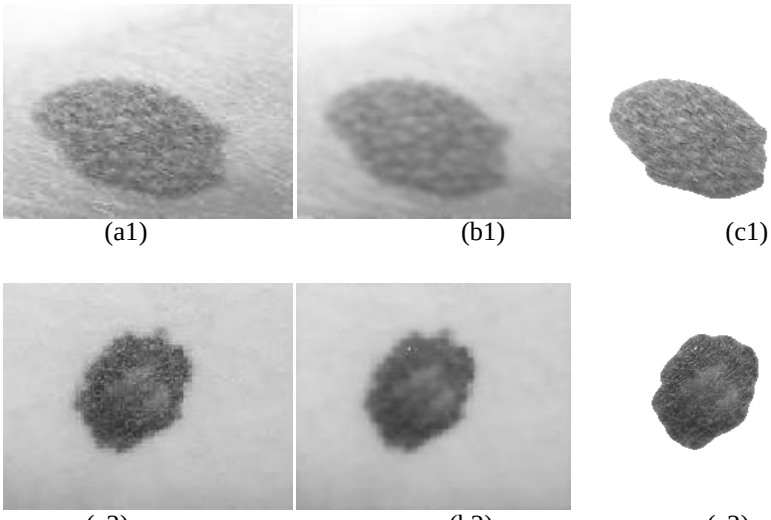

Fig 1 Results of the proposed method: (a1-a2) original image; (b1-b2) pre-processed image; (c1-c2) final segmented image

D. Classification

Support vector machine [9], is a supervised learning technique that seeks an optimal hyper plane to separate two classes of samples. Kernel functions are used to map the input data into a higher dimension space where the data are supposed to have a better distribution, and then an optimal separating hyper plane in the high dimensional feature space is chosen. The database is organized equally for Training set (Benign-10, Malignant-10) and Testing set (Benign-20, Malignant-20).

IV. RESULTS

The test images used in this work are taken from skin cancer image database and the lesion's boundary is manually outlined by experienced dermatologist. Fig. 1 shows the original skin image used as input to our algorithm and it shows output after pre-processing. The final segmented images are also shown in Fig.1.The performance of the Classifier for different parameters are shown in table 1.

TABLE 1. Performance of the Classifier

PARAMETERS	SVM CLASSIFIER
TRUE POSITIVE(TP)	28
TRUE NEGATIVE(TN)	27
FALSE POSITIVE(FP)	3
FALSE NEGATIVE(FN)	2
ACCURACY	91.66%
SPECIFICITY	90%
SENSITIVITY	93.33%

V. CONCLUSION

This work presents a segmentation and classification method for skin lesions in digital images. This technique pre-processes the image with Weiner filtering, in order to preserve and enhance useful information in the lesion boundaries, unlike from other filtering techniques that blur the image. The distance regularized level set method is used to segment the skin lesion from the original skin image. The DRLS transformation is defined as a robust and flexible method for segmenting objects with closed contours such as skin lesions. One advantage of our method is its simplicity to be implemented, because it

does not require large computational cost to solve complex mathematical models, such as snake-deformation. SVM classifier efficiently classifies the Benign from Malignant and also works faster than other classifiers.

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