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Prescreening of Skin Lesions from Digital Images

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Abstract: ***Melanoma is one of the deadliest form of skin cancer. Incidence rates of melanoma have been increasing, especially white males and females, but survival rates are high if detected early. The automated systems assess a patient's risk of melanoma using images of their skin lesions which is taken using a standard digital camera. Locating the skin lesion in the digital image is a big challenge. A set of texture distributions were learned from an illumination-corrected photograph. Texture distinctiveness metric is calculated for each texture distribution. Later regions in the image are classified as normal or cancerous based on representative texture distributions. Texture filter based skin lesion segmentation is proposed. Based on this method the region of lesion is segmented without noise. Features are extracted from the segment and fed to classifier. The proposed work has higher segmentation accuracy compared to all other tested algorithms.***

Keywords: Dermatologists, Melanoma, Skin Cancer, Segmentation, Feature Extraction, Classification

1. Introduction

It is the need of the hour to have a better automated system for dermatoscopic identification of skin cancer. A good number of segmentation algorithms are only applicable to dermoscopy images. An algorithm compared in the summary includes the simple thresholding, active contours, and region merging. The current algorithms usually use features derived from pixel color to drive the segmentation. This includes the blue channel from the RGB color space, the luminance channel from the CIELUV or CIELAB color spaces. To accurately segment lesions with fuzzy edges is difficult when relying solely on color features. The method derives segmented lesion from digital images and its further feature extraction and diagnosis. The diagnosis method incorporated the classifiers like Neural Network, SVM and Decision tree.

2. Related Works

Hongmin Cai et.al proposed Iterative Triclass Thresholding Technique for Image Segmentation in IEEE 2014 march, which address the problem of image segmentation [2].This is based on Otsu's method but iteratively searches for sub-regions of the image for segmentation. Jeffrey Glaister et.al proposed Multistage Illumination Modeling of Dermatological Photographs for Illumination-Corrected Skin Lesion Analysis in IEEE 2013, which address the problem illumination variation in digital images [7]. Illumination variation in the photographs can have a adverse impact on lesion segmentation and classification performance. The MSIM algorithm corrects the illumination variation problems in skin lesion photographs.

This was proposed by Alexander Wong, Jacob Scharcanski, and Paul Fieguth, in IEEE Trans. Jan 2012 [8]. Due to factors such as illumination variations, irregular color variations and the presence of hair and the occurrence of multiple unhealthy skin regions automatic segmentation of skin lesions from macroscopic images is a very challenging problem [8]. For this an iterative stochastic region-merging approach is employed to segment the skin lesions regions from the macroscopic images. The regions formed in the initial phase are then merged using the same stochastic region merging process to yield the final segmentation result.

Pablo G. Cavalcanti et.al proposed An ICA-Based Method for the Segmentation of Pigmented Skin Lesions in Macroscopic Images in the year 2011 in IEEE proceedings of annual international conference, which introduces the concept of Independent Component Analysis based method for the segmentation pigmented skin lesions [11]. Using ICA method shading effects are neutralized to get a more error free segmented lesion. Lesion localization is obtained and Level-set method is used to determine the lesion boundary.

Hina Sood et.al proposed Segmentation of Skin Lesions from Digital Images using an Optimized Approach in the year 2014, which presents an optimized approach for image segmentation [3]. Genetic Algorithm is used to rectify the problems in under and over segmentation. Here R, G and B components of the digital image are extracted to represent the respective components of the lesion more clearly. In the next step Genetic Algorithm add best thresholds using the fitness function and generates a GA segmented lesion. Further operations like binarization of R, G and B components, Morphological operations and filtration is performed in the third step.

Robert Amelard, Jeffrey Glaister et.al proposed High-Level Intuitive Features (HLIFs) in IEEE March 2014 which addresses the problem of image lesion feature extraction [4]. This is based on ABCD rule method. High-Level Intuitive Feature (HLIF) is a mathematical model that describe some human-observable characteristic, and its results are intuited in a natural (e.g., visual) way [4]. Advantages include an HLIF captures a specific characteristic (e.g., complexity of the color distribution), making intuitive feedback possible. Less HLIFs may be needed to accurately describe the data. Disadvantages include issues with availability of database and insufficient data leads to sub-optimal results.

Jeffrey Glaister et.al proposed High-Level Intuitive Features (HLIF) extraction for Classifying Skin Lesions [9] in IEEE

March 2012, which introduces the concept of extracting high-level intuitive features (HLIF) for classifying skin lesions. Here least number of features are considered. Rahil Garnavi et.al proposed the Diagnosis of Melanoma Using Border and Wavelet-based Texture Analysis in the year 2012, includes 1) Use of four level of wavelet decomposition 2) Boundary-series analysis in spatial domains and frequency domain. 3) Gain Ratio feature selection method 4) Combining different types of features in an optimized way [10]. Disadvantages include that the technique is employed for dermoscopy images only and creates more expensive coding.

Paul Wighton et.al proposed paper on Common Tasks in Automated Skin Lesion Diagnosis [12] in IEEE Jul. 2011 which introduces a model using supervised learning and MAP estimation. Here a model is applied to segment skin lesions, detect unwanted hair, and identify the dermoscopic pigment network. Catarina Barata et.al proposed Two Systems for the Detection of Melanomas in Dermoscopy [6] in IEEE March 2013, which addresses two different systems for the detection of melanomas in dermoscopy images. In the two system, the first system uses global methods to classify skin lesions. The second system uses local features and the bag-of-features classiffier[6].Ajeesh S S and Indu M S evaluate the performance of the selected algorithms for a particular database [5]. Insight for using multiple classifiers was derived from the proposed work.

3. Methods

Texture Based Lesion Segmentation (TBLS) algorithm has been implemented by taking both images, the segmented one using texture distinctiveness and using SRM technique[1]. Texture distinctiveness is taken by considering the different intensity values of the image pixels. Then coarse and fine segmentation is performed. Coarse segmentation segments the image region. In fine segmentation each pixel values are considered for segmentation. Later the resultant is fed to k-means cluster for creating the cluster mask. The output will be represented in different classes. Here 6 classes are used for improvement in accuracy.TD segmentation map is obtained as the result. This is combined with the SRM result to obtain the final segmented image which is suitable for feature extraction. The whole process is illustrated in the given figure 1.

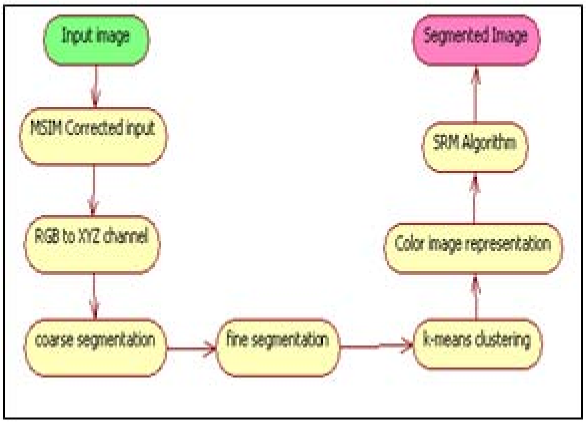

Figure 1: Segmentation Process

3.1 Texture Distinctiveness

If the pixel is brighter it corresponds to a higher TD metric. Fig. 2 and 3 give illustrative examples of the TD metric corresponding to each pixel in the image. In both figures, the lesion is predominately white, meaning that the lesion texture distributions have higher TD metrics, as expected. In Fig. 3, there are two texture distributions that correspond to the lesion class and have high distinctive measure. However, some normal skin pixels to the left of the lesion also have high TD due to unique texture patterns in normal skin areas. This commonly occurs, motivating the region classification step of the TDLS algorithm. The region classification step allows the algorithm to be more robust and minimize misclassification of pixels.

Figure 2: Skin Lesion Input Image

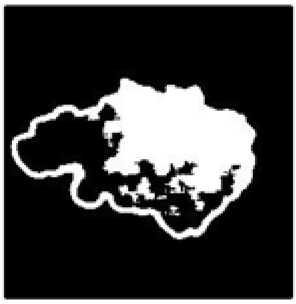

Figure 3: Segmented Image

3.2 Region Segmentation

The second main step in the TDLS algorithm is to classify regions in the input image as lesion based on the texture distributions and their related TD metric. First, the image is over-segmented. This divides the image into a large number of regions. Then the region is classified as normal skin or lesion based on the textural contents. Finally, post-processing steps refine the lesion segmentation. Then the corrected lesion image is divided into a number of regions. This initial over-segmentation step is added to increase the TDLS algorithm's robustness to noise. Dividing into different regions allows for the use of an efficient and fast classification algorithm to find which regions belong to the skin or lesion class. Statistical region merging (SRM) algorithm is adapted as the initial over-segmentation algorithm. The SRM algorithm uses the image in the RGB color space, while the algorithm converts the photograph to the XYZ color space. The advantages of using the SRM algorithm as the initial over-segmentation algorithm are that it considers pixel location, it is computationally efficient and simple.

The result of the initial over-segmentation step is a map which correspond to the normal or lesion classes. To reduce the number of regions, a single region is created by merging all segments that touch the edges of the photograph. Photographs are taken in controlled clinical environment. Hence regions touching the edges are all likely to be part of the normal skin class. Result of SRM algorithm for the input image in figure 2 is illustrated in figure 4.

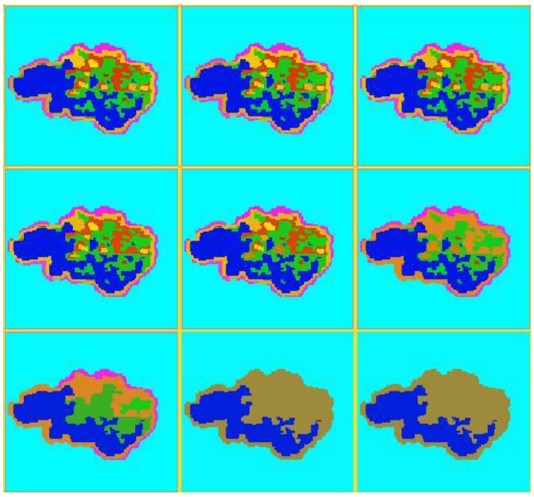

Figure 4: SRM Segmentation Result

3.3 Segmentation Refinement

After the regions are classified as being normal skin or lesion, the following post processing steps are applied to refine the lesion border. This includes the mathematical operator morphological dilation and region selection. Initially morphological dilation operator is applied to all holes and smoothing the border. Morphological dilation expands binary masks to all small holes. The shape and amount that the binary mask is expanded which is controlled by a disc, the structuring element with a radius of 5 pixels in the TDLS algorithm. Next, since multiple non-contiguous regions may have been identified as part of the lesion class the number of regions is reduced to one. The framework assumes that only a single lesion is being analyzed in the image. The number of pixels in each contiguous region is counted to eliminate the small regions. The contiguous region with the largest number of pixels is assumed to be the lesion class and other regions to the normal skin class. This extracts the final lesion segmentation. Final resultant segmented image is given below. It can be identified that the resultant image has been less accurate for the classifier. Half portion of the image is blackened due to intensity variations. This malfunction has been taken into consideration while modifying the method. See figure 5 for the segmented image.

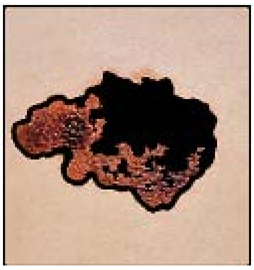

Figure 5: Noisy Segmented Image

3.4 Modified Skin Lesion Segmentation Method

The modified skin lesion segmentation algorithm takes less computational load than the previous algorithm implemented. Different filters like range filter standard fillter and entropy filter are checked with the input image. The result shows that entropy filter gives better result in case of skin lesion segmentation. This is due to the consideration of different intensity threshold vales of the input image. Grayscale of the resultant image is taken initially. The grayscale image is converted to binary and along with applying intensity threshold. Unwanted features are removed and the lesion region is extracted. Smoothing is performed using neighborhood method. Holes in the lesion are filled for segmenting the region of interest and stored in a rough mask. The mask is combined with the original image providing lesion segmented area. The resultant lesion area segmentation for the input image 2 is shown in figure 6.

Figure 6: Noise free segmented image

3.5 Feature Extraction and Classification

The system is intended to diagnose a skin lesion image as benign or malignant. Benign means the lesion is non-cancerous or harmless. Malignant lesion is cancerous lesion. Here the proposal intends to create an automatic skin lesion classification system. This includes modules like skin lesion segmentation, feature extraction, classifier training and diagnosis of the input image. At segmentation the regions in the image are classified as being part of the lesion or normal skin. This region classification algorithm incorporates the texture information captured by the texture distinctiveness. The classification is performed using Support Vector Machine, Neural network and classification tree which are robust classifiers that are available. Many features (low level and high level features) are extracted. Same features are taken for classifier training. This ensures the credibility of best classifier for skin lesion evaluation. The flowchart for the process is illustrated in the given figure 7.

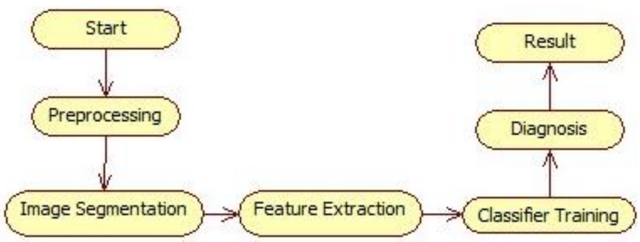

Figure 7: Flowchart

In feature extraction features derived are intended to be informative facilitating the subsequent learning. Features such as shape, texture, color, border, histogram gradient etc.

are used to describe the content of the image. As an experimental modal fisher feature selection is employed here. This gave shorter training times, improved model interpretability and enhanced generalization by reducing over fitting. Total 132 features have been extracted out of the segmented skin lesion and in trial 100 features are selected.

The extracted features from 206 images are used for training the classifier. The classifiers used are Support Vector Machine (SVM), Neural Network (NN) and Classification tree. While classifying data points each belonging to one of two classes -melanoma or non-melanoma, and the goal is to decide which class a new data point belongs to. The experimented result showed considerable improved classification performance that that of neural network.

4. Performance Evaluation

Analysis of the segmented image is done based on visual evaluation and histogram analysis. Histogram is the graphical representation of intensity parameters of the image. The intensity parameter of segmented image with noise shows more peaks in the histogram. The segmented image without noise shows smoothed curve. Figure 8 shows segmented image with noise. This is obtained by taking the histogram of segmented lesion as per the base work. Figure 9 shows segmented image without noise which is obtained after the modified work. This work included use of entropy texture. The characteristic histogram has smoothened curves. This is because the texture filter used takes care of the texture details more efficiently. Figure 10 compares the effectiveness of new texture filter based method.

The segmentation of skin lesion image has been carried out as the initial work. Base work implementation yielded 9.47 seconds for full execution. The modified algorithm yielded the result with 3.05 seconds. The cited time varies slightly according to the images selected for segmentation. The results favored more fast and accurate result with the proposed method than the same with TD measure. The segmented result is used for feature extraction and there by classification and diagnosis of melanoma.

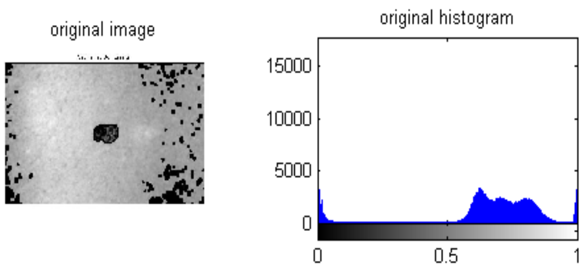

Figure 8: Histogram for base work

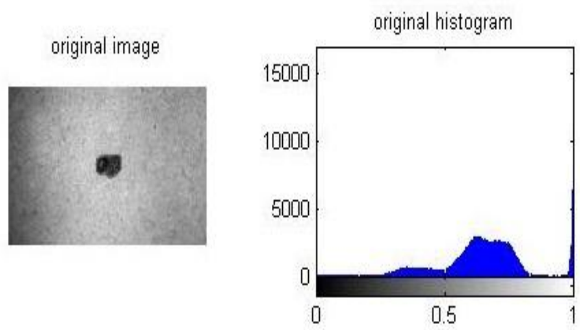

Figure 9: Histogram for modified method

In feature extraction phase 132 features are extracted and are used for training the classifiers. Upon training the classifiers SVM and classification tree yielded better accuracy and specificity than that of neural network. see figure 11,12 and 13 for accuracy, sensitivity specificity measure respectively. Also it was found that neural network takes 2/3 time period than the other two classifiers. Classification tree showed fast response than SVM. Hence a combined system (CSM) with Support Vector Machine (SVM) and Classification Tree (CTree) was experimented in which accuracy outperformed for the one which used selected feature set. This is illustrated in the figure 14 and 15. Accuracy, Sensitivity and specificity for the classifiers SVM, Neural network ant classification tree for total and full feature set is illustrated in the graphical figure 11, 12 and 13 respectively.

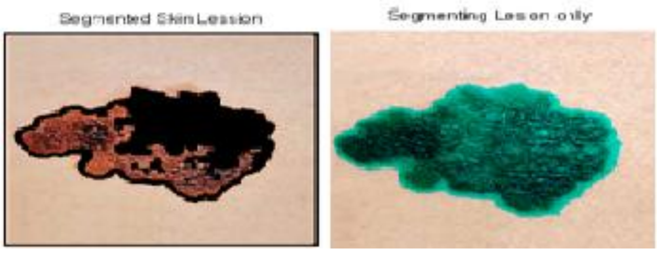

Figure 10: Result set comparison

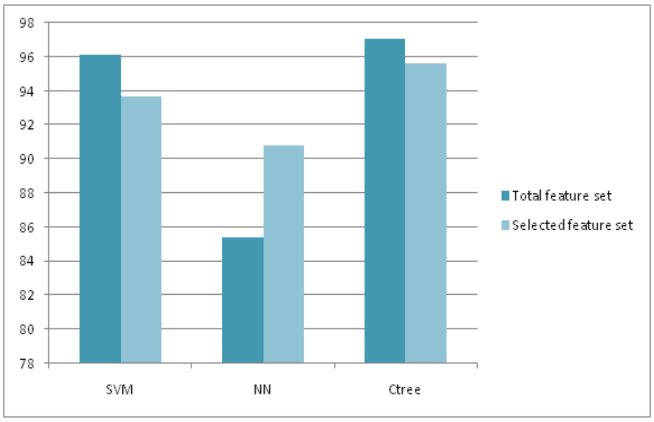

Figure 11 : Accuracy measure for skin lesion classifiers

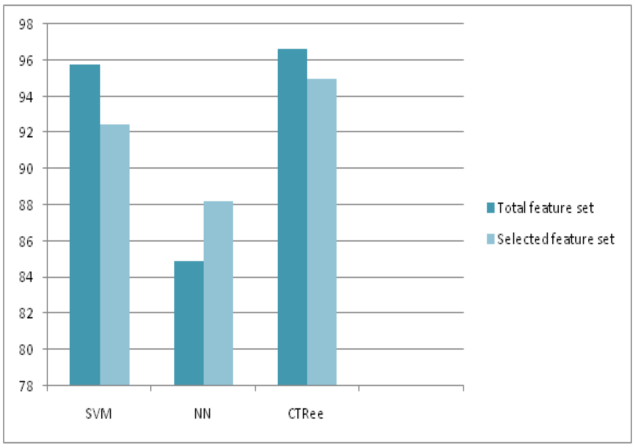

Figure 12 : Sensitivity measure for skin lesion classifiers

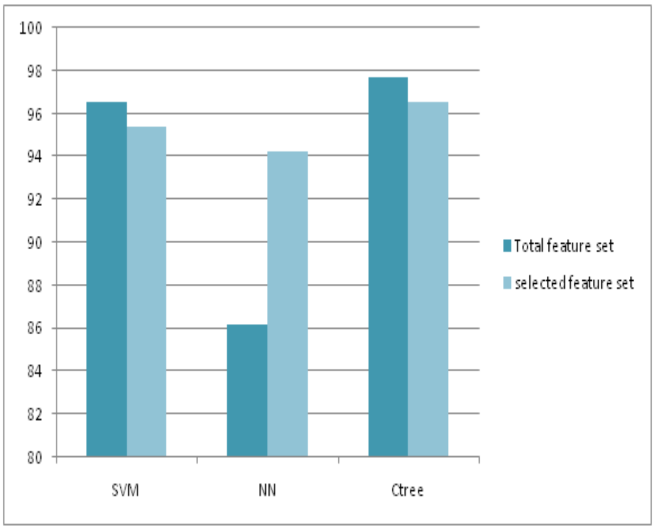

Figure 13 : Specificity measure for skin lesion classifiers

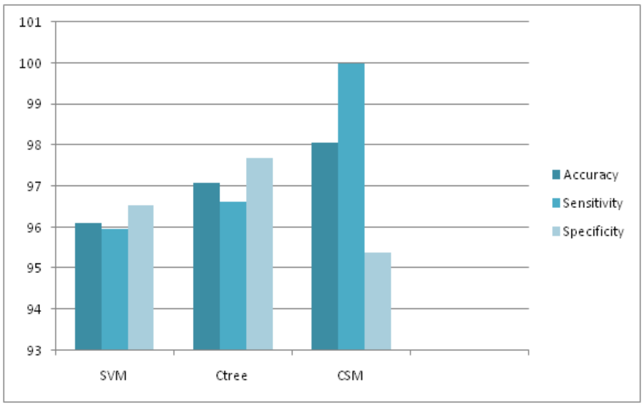

Figure 14 : Efficiency for full feature set

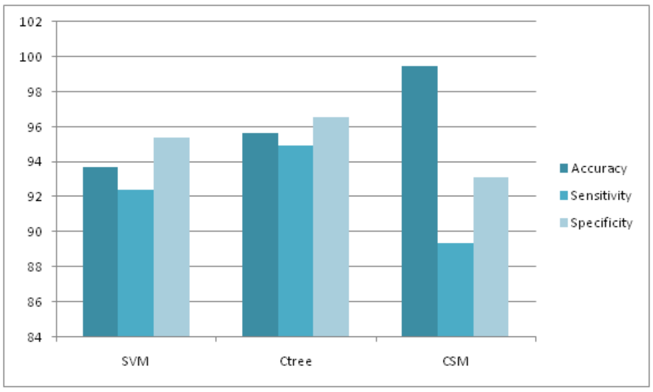

Figure 15 : Efficiency for selected feature set

5. Conclusion

The Proposed skin lesion segmentation algorithm segments the skin lesion region separately. While converting the grayscale image to binary image particular threshold is mentioned accordingly for each image. The segmentation algorithm shows an extra advantage in removing the noise and region of interest segmentation. The extra outliers in the image can be removed via applying gray threshold and a rough mask. TDLS algorithm has been taken as the base work for the proposed method. Implemented work includes segmentation using Texture Distinctiveness measure and Statistical Region Merging (SRM) algorithm. The accuracy of the method depends on the threshold taken for each image. The method uses different methods for obtaining different segmentation of the image. This proved to be computationally cost effective, resistant to noises and most importantly full lesion region segmentation is possible. Feature Extraction using ABCD characteristics of lesion images includes A for asymmetry, B for boundary, C for color variation and D for diameter of the lesion. A skin lesion with asymmetrical shape, irregular boundary, color variation and diameter greater than 0.7 mm is considered as a suspicious one for cancer. These features are found out for the classification. Classification can be carried out using different classifiers. The features extracted are fed into the classier for diagnosis.

The initial work of skin lesion segmentation has been carried out and the next phase includes feature extraction for classifier training and diagnosis. The features set extracted are based on ABCD rule set. The extracted features are used for classifier training. The system that used SVM and Classification Tree showed 98.05% accuracy when used with full feature set for training and the system showed 99.62% accuracy for selected feature set training. Using better feature selection methods would improve the automatic error free working of the process. Classification can be carried out using different classifiers and combination of different classifiers. The resultant weight from each classifier can be added to gain more reliable result. Another future work includes image mining from big database. The image mined can be based on different types of skin cancer nodular melanoma, basal cell cancer etc.

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