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Skin Lesion Classification Using GLCM Based Feature Extraction in Probabilistic Neural Network

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Abstract:-- **Melanoma is the deadliest form of skin cancer. Incidence rates of melanoma have been increasing, especially among non-Hispanic white males and females, but survival rates are high if detected early. Due to the costs for dermatologists to screen every patient, there is a need for an automated system to assess a patient's risk of melanoma using images of their skin lesions captured using a standard digital camera. One challenge in implementing such a system is locating the skin lesion in the digital image. In Proposed method a novel texture-based skin lesion segmentation algorithm is proposed. And classify the stages of skin cancer using Probabilistic neural network. Because in skin lesions lots of stages are there so probabilistic neural network will give better performance in this system. The proposed framework has higher segmentation accuracy compared to all other tested algorithms.**

Keywords: **Segmentation, TD Algorithm, TDLS Algorithm, K-nearest neighbour, PNN.**

I. INTRODUCTION

There are a considerable number of published studies on classification Methods related to the diagnosis of cutaneous malignancies. Since 1987 the number of published papers has and the significant progress that has occurred in this field is demonstrated by the recent journal special issue those summaries the state of the art in Computerize analysis of skin cancer images and provides future directions for this exciting subfield of medical image analysis. Different techniques for segmentation, feature extraction and classification have been reported by several authors. Numerous features have been extracted from skin images, including shape, color, and texture and border properties. Classification methods range from discriminate analysis to neural networks and support vector machines.

Examples of skin lesion images used in this work is undeniably important (as malignant melanoma is the form of skin cancer with the highest mortality), in the "real-world" the majority of lesions presenting to dermatologists for assessment covered by this narrow domain. Most systems ignore other benign lesions and crucially the two most common type of skin cancer (Squamous Cell Carcinomas and Basal Cell Carcinomas).Our key contribution is to focus on 5 common classes of skin lesions: Actinic Keratosis (AK), Basal Cell Carcinoma(BCC), Melanocytic Nevus / Mole (ML), Squamous Cell Carcinoma(SCC), Seborrhoeic Keratosis (SK). Moreover, we use only high resolution colour images acquired using standard camera (non-dermoscopy).A large number of classifier combinations have been proposed in the literature [3]. The schemes for combining multi pleto their architecture:

1) Parallel

2) Cascading

3) Hierarchical

In the hierarchical architecture, individual classifier is combined into a structure, which is similar to a decision tree classifier. The advantage of this architecture is the high efficiency and flexibility in exploiting the discriminant power of different types of features and therefore improving the recognition accuracy .The approach used in our research falls within the hierarchical model. Our approach divides the classification task into a set of smaller classification problems corresponding to the splits in the classification hierarchy. Each of these subtasks is significantly simpler than the original task, since the classifier at a node in the hierarchy only distinguish between a smaller number of classes .Therefore, it may be possible to separate the smaller number of classes with higher accuracy. Moreover, it may beta make this determination based on a smaller set features. The reduction in the feature space avoids many problems related to high dimensional feature spaces, such as the "curse of dimensionality" problem .The main idea of feature selection is to choose a subset of input features by eliminating features with little or no predictive information.

It is important to note that the key here is not merely the use of feature selection, but its integration with the hierarchical structure. In practice we build different classifiers using different sets of training images (according to the set of classification made at the higher levels of the hierarchy). So each classifier uses a different set of features optimized for those images. This forces the individual classifiers to contain potentially independent information. Hierarchical classifiers are well known and commonly used for document and text classification, including a hierarchical K-NN classifier.

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While we found papers describing applications of hierarchical systems to medical image classification tasks, to best of our knowledge only a hierarchical neural network model has been applied to skin.

II. LITERATURE SURVEY

The challenge in implementing such a system is locating the skin lesion in the digital image. Melanoma is the deadliest form of skin cancer. Incidence rate of melanoma have been increasing especially among non-Hispanic white males and females but survival rates are high if detected early. Due to the costs for dermatologists to screen every patient, there is a need for an automated system to access the patient risk of melanoma using images of skin lesion captured using the standard digital camera.

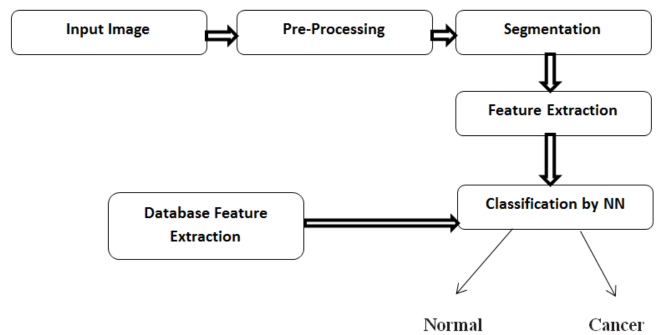
In august 2009, HU Zhilan , WANG Guijin , LIN Xing gang, YAN Hong, proposed a Skin Segmentation Based on Graph Cuts. This paper presents a graph cuts algorithm to segment arbitrary skin regions from images. The detected face is used to determine the foreground skin seeds and the background non-skin seeds with the color probability distributions for the foreground represented by a single Gaussian model and for the background by a Gaussian mixture model.

M. Portes de Albuquerque, I. A. Esquef, e Marcelo Portes de Albuquerque proposed Image Segmentation using non extensive relative in 2008. This approach uses the Shannon entropy from the information theory considering the gray level image histogram as a probability distribution. In this work, it was applied the Tsallis entropy as a generalized entropy formalism for information theory.

In March 2001 Harald Ganster, Axel pinz, Reinard Rohrer, Ernst Wilding, Michael Binder and Harald Kittler proposed a Automated melanoma Recognition . In this paper as a intial stepm the binary mask of the skin lesion is determined by several basic segmentation algorithms together with a fusion strategy. A set of features containing shape and radiometric feature as well as local and global parameter is calculated to describe the malignancy of a lesion.

Estimating the effectiveness and cost effectiveness of melanoma screening was proposed by K. A. Freedberg, A. C. Geller, D. R. Miller, R. A. Lew, and H. K. Koh . The purpose of this study was to estimate the cost-effectiveness of melanoma screening programs. A decision analysis model was used to estimate the cost effectiveness of a hypothetical melanoma screening program by dermatologists in 1998 in a self-selected (higher-than-average-risk) population by comparing data on melanomas diagnosed in screenings by the American Academy of Dermatology (AAD) screenings with data on melanomas diagnosed by current care (largely without special screenings) as reported to the Surveillance, Epidemiology, and End Results (SEER) program.

III. METHODOLOGY



IV. EXPERIMENTAL RESULT

Two experiments are performed to compare the TDLS algorithm to other state-of-the-art algorithms. In the first experiment, the first step of the TDLS step, calculating the TD metric, is compared to a similar algorithm. The compared algorithm calculates a TD metric, but does not include statistical information. The second experiment compares the segmentation results obtained using the TDLS algorithm with four other segmentation algorithms designed for skin lesion images. The TDLS algorithm is implemented in MATLAB on a computer with an Intel Core i5-2400s CPU (2.5 GHz, 6-GB RAM). To segment a skin lesion in a 1640 × 1043 image, the algorithm has an average runtime of 62.45 s.

A. TD Comparison

The first step of the TDLS algorithm is compared to the results from the algorithm by Scharfenberger et al. [32], which calculates a similar TD metric and is referred to as the TD algorithm. The difference between the two algorithms is that the TDLS algorithm introduces the use of probabilistic information to determine representative texture distributions and to measure TD. To determine if incorporating this information is useful, TD maps produced using the first step of the TDLS algorithm are compared to distinctiveness maps produced using the TD algorithm. The TD algorithm only uses the k-means clustering algorithm to find the representative texture distributions. Furthermore, the TD algorithm does not take into account the covariance corresponding to each cluster when calculating the distinctiveness metric. Finally, because the TD algorithm is designed to compute saliency maps, the distinctiveness metric includes an additional term based on the distance

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between a pixel and the center of the image. Since we are interested in understanding the effect of the additional probabilistic information, this term was omitted in the comparisons.

The TD maps are compared visually. Select skin lesion images from the Dermquest database [40] are used for comparison, after being corrected for illumination variation using the MSIM algorithm [14]. These examples are selected because they highlight cases with significant differences between the TD and TDLS algorithms and are shown in Fig. 5. Also, the dynamic range of pixels is scaled to the maximum pixel intensity and minimum pixel intensity, resulting in a different dynamic range for each TD map. For example, in figure, the presence of shading on the left side of the image is highlighted when using the TDLS algorithm, but not when using the TD algorithm. This motivates use of the texture-based segmentation step in the TDLS algorithm, rather than using the textural distinctiveness maps directly.

B. Segmentation Comparison

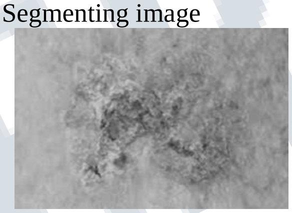
The TDLS algorithm is compared to four state-of-the-art lesion segmentation algorithms. The first algorithm (L-SRM) is designed for dermatological images, but can be applied to lesion photographs as well. It applies the SRM algorithm outlined in Section III-A and uses the normal skin color to find the regions corresponding to the lesion. The three other algorithms are proposed by Cavalcanti et al. and are designed specifically for lesion photographs. One algorithm (Otsu-R) finds the Otsu threshold using the red color channel. The second (Otsu-RGB) uses all three RGB color channels and finds Otsu thresholds for each channel. The final algorithm (Otsu-PCA) processes the RGB color channels to find three more efficient channels to threshold. A texture channel is obtained using Gaussian filtering, a color channel is obtained using the inverse of the red color channel, and the third channel is found using PCA. A set of 126 images from the Dermquest database [40] are used to test the segmentation algorithms. There are 66 photographs with lesions diagnosed as melanoma and 60brk photographs with lesions diagnosed as nonmelanoma. These images are selected because they satisfy the stated assumptions and can be adequately corrected for illumination variation. All tested photographs were first corrected using the MSIM algorithm [14]. The segmentation algorithms are compared to manually segmented ground truth. The algorithms are compared visually and by calculating sensitivity, specificity, and accuracy of the algorithm to properly classify each pixel as normal skin or lesion.

C. Segmentation Accuracy Comparison: The objective of this experiment is to measure sensitivity, specificity, and accuracy of each segmentation algorithm after the algorithms classify each pixel as belonging to the normal skin class or lesion class. Each algorithm is applied to the corrected images and the resulting segmentation is compared to the manually drawn segmentation acting as ground truth. The metrics used to compare to the ground truth are sensitivity, specificity, and accuracy.

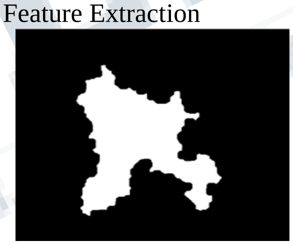
4.4 Experimental result:

Figure 4.4.1:
Input image
Preprocessing image (512X512)

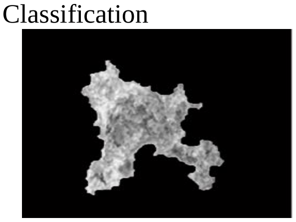
Segmenting image



Feature Extraction



Classification



Warning Dialog

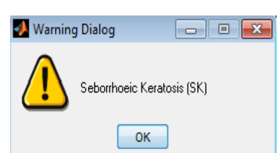


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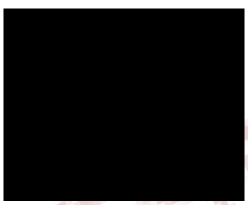
Figure 4.4.2:
Input image

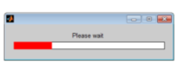
Preprocessing image(512X512)

Segmenting image

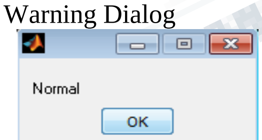
Feature Extraction



Classification



Warning Dialog



5.1 PERFORMANCE METRICS

Performance metrics is to evaluate an image quality and its performance. The objective of this experiment is to measure sensitivity, specificity, and accuracy of each segmentation algorithm after the algorithms classify each pixel as belonging to the normal skin class or lesion class. Each algorithm is applied to the corrected images and the resulting segmentation is compared to the manually drawn segmentation acting as ground truth. The metrics used to compare to the ground truth are sensitivity, specificity, and accuracy. Their formulas are given below, where TP is the pixels, TF is the number of true negative pixels, and FN is the number of false negative pixels,

Sensitivity = TP / (TP + FN)
Specificity = TN / (TN + FP)
Accuracy= (TP + TN) / (TP + TN + FP + FN)

5.2 PERFORMANCE EVALUATION

In order to evaluate the performance metrics, it is plotted in the table to identity the values of the proposed system. The tables are shown below.

TABLE 5.2.1 Experimental result for all non melanoma lesion photographs.

METRICS / TECHNIQUE	Sensitivity	Specificity	Accuracy
L-SRM	89.4%	92.7%	92.3%
Otsu-R	87.3%	85.4%	84.9%
Otsu-RGB	93.6%	80.3%	80.2%
Otsu-PCA	79.6%	99.6%	98.1%
TDLS	91.2%	99.0%	98.3%
Texture	84.5%	78.8%	85.7%

Table 5.2.1 show the average sensitivity specificity, and accuracy across the entire set of images or for just melanoma or non-melanoma photographs.

6.1 CONCLUSION

In summary, a novel lesion segmentation algorithm using the concept of Texture filters. A probabilistic texture metric is introduced based on a learned model of normal skin and lesion textures. Here the measuring metrics such as sensitivity, specificity, accuracy were used to find their performance factor.

6.2 FUTURE SCOPE

The entire framework is tested by using the illumination corrected images as the input to the texture-based segmentation algorithm. It is compared to state-of-art lesion segmentation algorithms, including three algorithms designed

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for lesion images. The proposed framework produces the highest segmentation accuracy using manually segmented images as ground truth. A larger data collection and annotation process, including additional testing on a wide range of images, will be undertaken as future work. While the experimental results show that the proposed method is able to segment the lesion in images of different scales and levels of quality, it is worth conducting a more comprehensive analysis on the impact of image quality and scale on the proposed method.

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