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Classification of Melanoma on Dermoscopy Images using SVM Classifier

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Abstract: ***By analyzing the dermoscopy pictures, a unique technique is developed for classifying melanocytic tumors as benign or malignant. The algorithm contains the following steps: first, lesions extracted using k-means method; then second, features are extracted; and third, lesion classification by using a classifier based on a Support Vector Machine (SVM) model. Lesions occur that are overlarge to be entirely contained among the dermoscopy image. To influence this tough presentation, new features are proposed, and which are able to characterize border irregularities on both complete and incomplete lesions. In this model, to achieve improved performance a SVM classifier is intended. Experiments are administered on two numerous dermoscopy databases that embrace images of both the xanthous and caucasian races. The results show that classification accuracy is greatly enhanced by the employment of the new features and also the proposed classifier model.***
Keywords: Melanoma; Dermoscopy; K-means; SVM

I. INTRODUCTION

Malignant melanoma is the foremost malignant cancers and this is the third most frequent form of melanocytic tumors [2][3]. Dermoscopy may be a non-invasive skin imaging technique. Dermoscopy allows an exaggerated visualization of the skin surface and subdermal structures [6]. Dermoscopy pictures have contended a significant role in the early identification of malignant melanoma. However, diagnoses that are created by human consultants are nonetheless subjective. Once conducted by inexperienced dermatologists, dermoscopy may actually lower diagnostic accuracy [7].

Computer-Aided Diagnosis (CAD) systems aren't subjective, will assist the physician once creating selections via quantifying diagnostic features, lesion border detection, classifying lesions by type, etc [3].

Cancer begins with uncontrolled division of one cell, which results in a visible mass named tumor. Tumor can be of two forms benign or malignant. MM tumor grows speedily and invades its surrounding tissues causing their damage. By providing the better treatment, the earlier the cancers are detected. The, early detection requires an accurate diagnosis which should be able to distinguish benign and malignant tumors. A better detection approach is producing both low false positive rate and false negative rate. Conventional methods of diagnosing the diseases rely on detecting the presence of signal features by a human observer. Due to large number of patients in intensive care units, several CAD approaches for automated diagnostic systems have been developed to solve this problem. A number of CAD approaches have been proposed to improving the accuracy of diagnosis and evaluate the prognostic risk [50].

II. RELATED WORK

Most of the prevailing literature relating to computer assisted lesion classification has targeted on feature extraction and classifier style on pictures that are either explicitly, or implicitly, assumed to contain a whole lesion object. Also, images might not forever capture entire lesions, as shown in Fig. 1. [1]. To deal with such difficult situations local features are often used. Situ et al. [16] used wavelets and Gabor-like filters to extract the local features, and then analyzed the responses to recognize malignant melanoma by employing a Bag-of-Features (BoF) model. In [17], to code the extracted texture and color features, Barata et al. used a BoF model to classify lesions. By imposing a color constancy constraint [18] they then improved classification performance.

In [1], Xie et al. used a neural network ensemble model for lesion classification. This is complex relative to some other common classifier models, such as standard Back Propagation (BP), Adaboost, KNN and Support Vector Machine (SVM), and needs more storage space and computation time. Here, we proposed a dermoscopy tumor classification model Support Vector Machine (SVM) that aims to handle incomplete tumor presentations. The model utilizes a collection of tumor border features along with other tumor-descriptive features that are fed to a SVM model that's trained to differentiate malignant lesions from benign lesions. Our main aim was to find a better border irregularity description method and to design a good classifier model for the classification of lesion.

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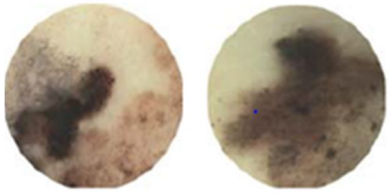


Fig. 1. Dermoscopy images of incomplete lesion objects.

III. ARTIFACTS REMOVAL AND BOUNDARY DETECTION

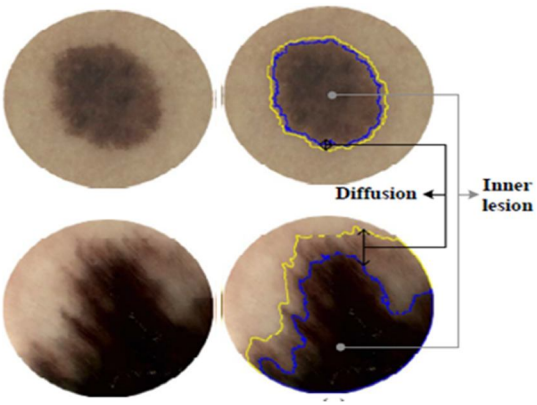
The purpose of artifacts removal stage is that the hair removal. Due to the presence of hairs dermoscopy image analysis is greatly difficult. Hairs are detected for these pictures and then removed using the median filter based technique presented in [48]. The accuracy of subsequent feature extraction and classification depends on the accuracy of the segmentation process. Although projected a number of automatic segmentation ways for dermoscopy images. In the earlier work [20], to segment the dermoscopy pictures, an automatic technique based on k-means model was developed, and it was able to acquire a lot of correct results under complicated conditions than Otsu's threshold [21], fuzzy c-means and Statistical Region Merging (SRM) [22].

Fig. 2. Segmentation instances on dermoscopy image (yellow line: k-means).

Here, we use a k-means model to segment the images as a proxy for absolutely automatic segmentation. Fig. 2. shows segmentation result obtained by using the k-means model of [20].

IV. FEATURE EXTRACTION

The color, texture, and shape [14][23][24] are the most common features mentioned within the literature on lesion classification and border features are less well-described [13][25]. Since we handling pictures of incomplete lesion objects, shape features are abandoned in this model. Within the following, describe a collection of widely used color and texture features yet as a collection of lesion border features [1] that are effective on incomplete lesions. These features are utilized in this classification methodology.



(a) (b)

Fig. 3. Generation of two lesion regions. (a) Original lesion image. (b) Segmentation result on (a) using k-means.

Before feature extraction we need to perform region division [20]. Therefore, the lesion object instead divides into a diffusion region and an inner lesion region and features are extracted on both individual regions, as well as over the entire lesion region. As delineated in Section II, every lesion object is separated from the background skin by employing the k-means technique. Then, this technique also employed to automatically segment the lesion into these two region types. Fig. 3. is an example showing generation of these two regions.

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A. Description of Color, Texture and Border Features

The color and texture features utilized in this model are the same as those delineate by Celebi et al. in [14]. Here, briefly summarize these features.

1) *Color features:* Total 30 color features are extracted. That are, 24 RGB features, two LUV histogram distances, one color diversity feature and three centroidal distances feature.
2) *Texture features:* In this paper, several statistical texture descriptors are calculated from the Gray-Level Co-occurrence Matrix (GLCM) [26] based texture descriptor: the regional energy, entropy, contrast, inverse difference moment, and correlation [1]. Then we propose some additional statistical texture descriptors from GLCM: the autocorrelation, cluster prominence, cluster shade, dissimilarity, homogeneity, maximum probability, sum of squares, sum average, sum variance, sum entropy, difference variance, difference entropy, inverse difference moment normalized, information measure of correlation1, and information measure of correlation2. These statistics also are calculated over every of the three segmented regions. Again, the ratios of these statistics on the diffusion and inner lesion regions are also calculated. Total 114 texture features are extracted.
3) *Border features:* Border features [1] that are wont to characterize the degree of border irregularity of lesions are typically supported measurements of color, texture or brightness gradient. Total 7 border features are extracted.

B. Feature Dimensionality Reduction

A careful method of feature reduction will eliminate redundant, irrelevant and unnecessary features whereas also rising classification performance. Here, to separate out redundant, irrelevant and unnecessary features the feature reduction is accomplished by using Principal Components Analysis (PCA) [27] method. This is the better technique for the dimensionality reduction.

V. CLASSIFICATION USING SVM CLASSIFIER

Artificial neural network ensemble [1], Adaboost [15], ANN [11] and KNN [13] have been widely used for lesion classification. Many factors influence classification performance, such as parameter settings, extracted features or feature combinations, and the quality of the experimental samples. On highly representative benign or malignant lesions, correct classification is easily achieved, yet on non-representative lesions, incorrect classifications often happen. Therefore, the difficult task is to achieve correct classification on non-representative lesions. Here, we describe a Support Vector Machine (SVM) classifier to achieve more accurate lesion classification results. SVM proposed by Vapnik [47] and Michal Antkowiak [49] was originally designed for classification and regression tasks, however later has expanded in another directions. Essence of SVM method is construction of optimal hyperplane, which can separate data from opposite classes using the biggest possible margin. Margin is a distance between optimal hyper-plane and a vector which lies closest to it. There can be many hyperplanes which can separate two classes, but with regard to optimal choice, the most interesting solution can be obtained by gaining the biggest possible margin. Optimal hyperplane should satisfy,

$$\frac{Y_N F(X_N)}{\|W\|} \geq M \quad N= 1,2,\ldots..n, [49] \qquad (1)$$

where M is a margin and F(X) is defined as:

$$F(X) = W^M X + b \ [49] \qquad (2)$$

This function is not suitable for solving more complicated, linearly non-separable problems.

Kernel functions: Possibility of occurrence of the linearly non-separability in the input space consist the cause why the idea of SVM is not optimal for hyperplane construction in the input space but rather in high-dimensional so called feature space Z. The feature space is usually defined as a non-linear product of base functions $\emptyset_i(X)$ defined in the input space. Function of the optimal hyperplane is now:

$$F(X) = \sum_{i=1}^{n} \propto_i y_i N(X_i, X) + b \ [49] \qquad (3)$$

Where $N(X_i, X)$ is the inner product kernel of base functions $\emptyset_j(X)$, j=1,2,….m Inner product may be defined as:

$$N(X,X') = \emptyset_i(X)^{\,M}\, \emptyset_i(X') \ [49] \qquad (4)$$

It is more effective, even if the problem was linearly non-separable in the input space.

VI. EXPERIMENTAL RESULTS AND ANALYSIS

Two dermoscopy datasets are deployed in our experiments: a xanthous race dataset and a caucasian race dataset. In order to judge the effectiveness of the proposed method, the experiments were performed with reference to assessing the performance dependence on three aspects of the model: novel border features, the generalization ability of the designed SVM model, and the performance of the proposed classification framework. Three metrics together with sensitivity, specificity and accuracy are used. Sensitivity is that the probability of correct detection of disease. Specificity is that the probability that a benign lesion would not be diagnosed as malignant. And accuracy defines the ratio of the number of properly classified samples to the total number of cases. The higher the values of the accuracy, the better the classification performance of the algorithm.

A. Experiment 1: Effectiveness of Border Features

In the projected classification framework, to separate malignant melanoma from benign lesions, new border features [1] are combined with 144 color and texture features. So as to evaluating the proposed border features, compared them with different border features extracted in [13], [25] and [42], as shown in Table I. Shape/geometric features were extracted in these different studies, which implies that their border features were calculated on the whole lesions. Invalid border areas are excluded once extracting border features from incomplete lesions using the compared strategies to avoid unfair comparisons.

TABLE I
Four Border Feature Sets Used For Comparisons

Featureset	Dimension	Reference	Detail
Featureset1	8	[13]	Maximum,Minimum, Average and variance of the normalized intensity and the gradient values in the border band.
Featureset2	12	[25]	Mean and variance of the gradient magnitude along lesion border as well as over 8 symmetric regions around the border in three separate channels: color, texture and local skin darkness.
Featureset3	5	[42]	Mean and deviation of the gradient magnitude for the entire border band.
Featureset4	7	[1]	Mean and standard deviation of length, depth, thickness and separation between inner and outer borders

We evaluated the classification efficiency of the border features on the xanthous race dataset and caucasian race dataset. The classifier used was a SVM classifier model.

It can be seen that incomplete lesions indeed decreased the classification performance. When classifying the lesions using color, texture and proposed border features, our features achieved the most effective classification accuracy for each incomplete lesions and complete lesions. It may be seen that, once combining C&T features with these border features, the classification accuracy is improved, and also the increase from using our border features is the most obvious. Therefore, our border features outperform the other border features.

B. Experiment 2: Performance Analysis of Lesion Classification

In this experiment, our SVM classifier model was compared with artificial neural network ensemble classifier model [1], to verify the performance of the proposed classifier model. Table II provides the classification results of the two methods (our methodology and artificial neural network ensemble classifier model). It can be seen that artificial neural network ensemble classifier model

delivered the very best specificity however their sensitivity was low, whereas our methodology obtained the most effective sensitivity. With regards to sensitivity, the performance of our model was at least 8% more than that of the compared classifier models. Therefore, with the highest accuracy and the best balance between sensitivity and specificity, our SVM model greatly outperforms the compared classifier model. In [1] wherever features are extracted on patch regions, the models are in a position to cope with incomplete lesion objects. In our methodology, new border features are proposed and on that SVM classifier model is designed. As could be seen in Table II, once compared with the system in [1], by using our methodology the sensitivity and accuracy were greatly improved, that could be a terribly positive outcome. With the most effective accuracy, our methodology is superior to the compared ways. Therefore, our proposed features and designed classifier are additionally highly effective on the datasets.

TABLE II
Classification Results Using Different Classifier Models

Classifiers	Sen(%)	Spec(%)	Acc(%)
ANN	89.13	78.12	84.61
Proposed classifier	97.82	75	88.46

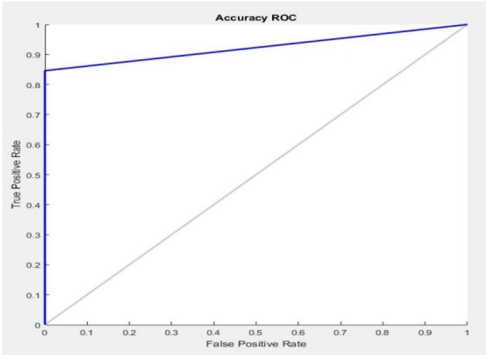

Fig. 6. ROC curve of ANN classification model

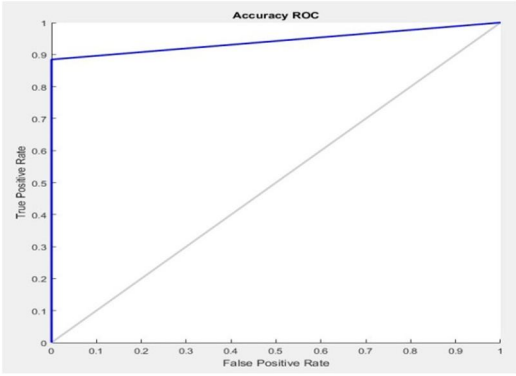

Fig. 7. ROC curve of proposed classification model

Fig. 6. shows the Receiver Operating Characteristic (ROC) curve of the artificial neural network ensemble classification model and Fig. 7. shows the ROC curve of proposed SVM classification model. The closer to the top-left corner the ROC curve, the better the method. It can be seen that the proposed classification model greatly outperforms the compared ANN classification model.

VII. DISCUSSION

In this paper, a framework was projected for lesion classification, wherever new texture and border [1] features were proposed and a SVM classification model was designed. Concerning the proposed method, having the subsequent observations.

Although the proposed border features are ready to describe border irregularities more efficiently than the compared strategies, incomplete lesions still present a larger risk of incorrect classification than complete lesions. When a border irregularity is well preserved, this risk is lowered.

The main design strategies for SVM classification model: the main goal was to construct an optimal hyperplane, which can separate data from opposite classes using the biggest possible margin; and find an honest border irregularity description technique and to design an appropriate classifier model for lesion classification. Therefore, within the SVM classification model, some parameters were set supported the prevailing literature. This designed model is advanced relative to another common classifier models, like normal Back Propagation (BP), Adaboost, KNN and needs a less compute time and storage space.

VIII.CONCLUSION

For classifying skin lesion objects as malignant or benign we have described a unique methodology. 151 descriptive features are used, including 144 color and new texture features and 7 novel lesion border features [1]. In clinical observe, images containing large and incomplete lesion objects are typically obtained by dermoscopy, leading to the failure of systems that depends on common shape features. For the incomplete lesion objects the proposed border features delineate here were insensitive. To deal with this difficult classification problem a SVM classifier can be used in a very robust and efficient approach. In the experiments, feature extraction were verified and classification performance was tested using artificial neural network ensemble model, and the proposed SVM classification model on two datasets that respectively include xanthous race data and caucacian race data. The experimental results powerfully suggest that the proposed lesion features are significantly useful for differentiating malignant from benign skin lesions. The classification results delivered by the designed model were shown to be more accurate than those by the compared methods.

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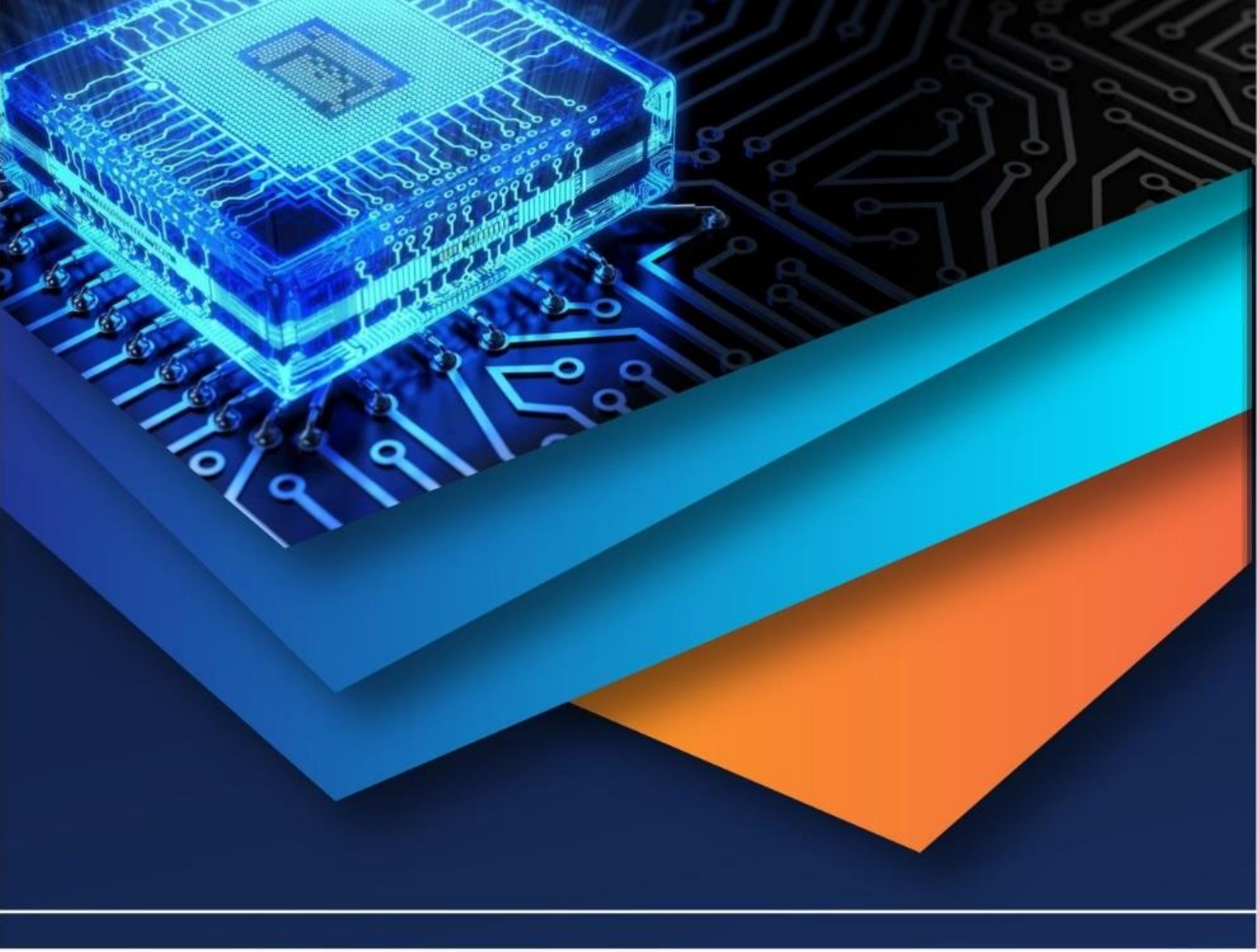

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