Skin Cancer Diagnosis Using an Improved Ensemble Machine Learning model

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***Abstract*— In recent years skin cancer is becoming more and more threatening because of its fast and significant spread worldwide. This evidence has increased interest and efforts in the development of automatic diagnostic computational systems to assist early diagnosis. Several approaches have been proposed to assist in skin lesion diagnosis which used machine learning and ensemble learning. In some cases, a classifier can correctly predict the output class while others fail and vice versa. So the idea is to use different machine learning and ensemble learning to classify skin cancer. In this paper, we propose an improved ensemble learning method to classify skin cancer. Features used are the best combination of extracted features from different characteristics, i.e., shape, color, texture, and skeleton of the lesion, then we classify these features using different algorithms to predict the classes. Globally, the experimented results show a promoting result.**

***Keywords*— Skin cancer, features extraction and selection, ensemble learning.**

I. Introduction

Various computational systems have been proposed to help dermatologists to achieve an accurate diagnosis. The computer-aided diagnosis (CAD) is one of the invented systems, which help dermatologists to classify the skin cancer types figure 1. Generally, the extracted features from skin lesion images should describe the lesion and help to distinguish melanoma and non-melanoma skin cancer lesion. Thus, several methods have been applied to extract relevant features from skin cancer images. These characteristics are based on the ABCD rules (Asymmetry, Border, Color and Diameter), which can better classify the properties of skin lesions. From our previous work [1],[2], we noticed that the skeleton lesion got from the segmented image, texture, and color can be a great descriptor to analyse skin cancer. Several approaches has been proposed to assist in skin lesion diagnosis which use machine learning and ensemble learning. In some cases, a classifier can correctly predict the output class while others fail and vice versa. So the idea is to compare each classifier and see the impact of features selection to improve the classification rate. Furthermore, the features are extracted from the skeleton, shape, texture, and color skin lesion. Behind the total number of extracted features are 37 features extracted from each characteristic. A features selection is used to keep only the most useful one. Next, the final features vector will be an input of distinct machine learning classifiers, e.g., Support Vector Machine(SVM), K-nearest neighbor and Multilayer perceptron (MLP) and Adaboost to compare the impact of using different techniques of machine learning classifiers. The rest of the paper is organized as follows: section one, will contain a skin cancer review of segmentation, features extraction, and classification. Section two, contains our proposed approach. Next, the result will be in the third section, followed by a conclusion.

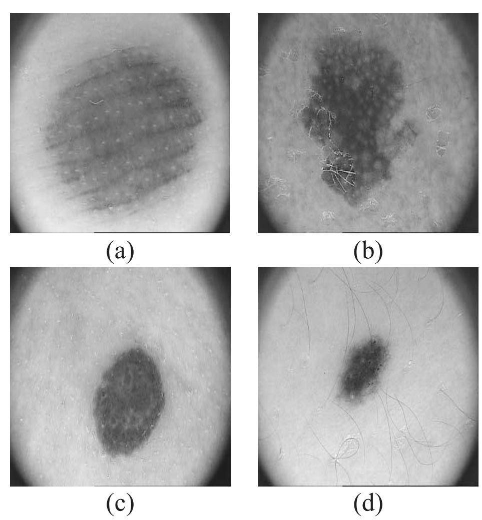

Fig. 1. Example of skin cancer; (a) and (b) melanoma skin cancer, (c) and (d) non-melanoma skin cancer

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II. STATE OF ART

The classification of cancer as melanoma and non-melanoma is the biggest challenge in skin cancer. Computer aided diagnosis (CADs) is an early prediction of this disease. Typically these systems focus on 4 steps: pre-processing, segmentation, feature extraction, and classification. The first step is focused at reducing and eliminating noise and artefacts found in the lesion. The Pre-processing has an impact on the result of segmentation, due to the various information contained in the lesion, which may be destroyed with the object. The next step is segmentation; a poor segmentation would certainly result in the extraction of bad features and could misidentify the lesion. Nevertheless, k-means, active contour, Otsu threshold are examples of the segmentation algorithms that have been applied in skin cancer.

Using the segmentation, we can extract the features from the region of interest that can better identify skin cancer. Most researchers in the literature used to identify the skin cancer as the dermatologist like the ABCD rules (Asymmetry, Border, Color and Diameter). Authors also used Gray level co-occurrence matrix, GLCM, Local Binary Pattern, (LBP), and Histogram of Oriented Gradient HOG, and Gabor filter to extract textural features that can well represent the lesion [1][3]. Furthermore, the color containing the lesion is an important feature that can help to achieve a good classification result. The final step is the classification, these classifier performs typically depend on the accuracy of the segmentation and the abstraction and selection features; SVM, decision tree, KNN and logistic regression are an example of the classifier used in the classification of skin cancer[4][5]. Deep learning methodology has also been used for functions of detection and diagnosis of skin cancer. The accuracy of this method has demonstrated its efficacy. The CNN is a kind of deep learning model where series of filtering and pooling operations are performed to extract the raw data and automatically identify the images [6][7].

III. THE PROPOSED APPROACH

The figure 2 describes our suggested approach to classify skin cancer, which include three major steps:

1-Pre-processing and image segmentation: the input image is decomposed using the multi-scale decomposition into object and texture components, the segmentation is done only on the object component.

2-Features engineering: features are derived from, shape, skeleton, texture and color separately. The shape is extracted from the segmented image, and skeleton form the transformation of the segmented images into skeleton. Texture characteristics are extracted from the texture component, and color features are extracted from the original image. We compare different combinations of all these features emerged through a range of features and then we select the relevant features.

3- Classification: we compare different machine learning classifiers and we provide the best accuracy rate.

A. *Pre-processing and segmentation*

One of the most common problems with skin cancer is the elimination of noise found in skin cancer. The effect of the lesion containing artefact can be seen on the next steps "segmentation, extracted features and the classification outcome". From our previous work [8], [9] we used a multi-scale decomposition that proved the efficiency in the case of skin cancer. This decomposition gives two components, the first will only contain the object, and the second will contain the texture and noise of the lesion. The object component is structured and gives a good description of the lesion, therefore only a threshold algorithm is robust to have a good segmentation result.

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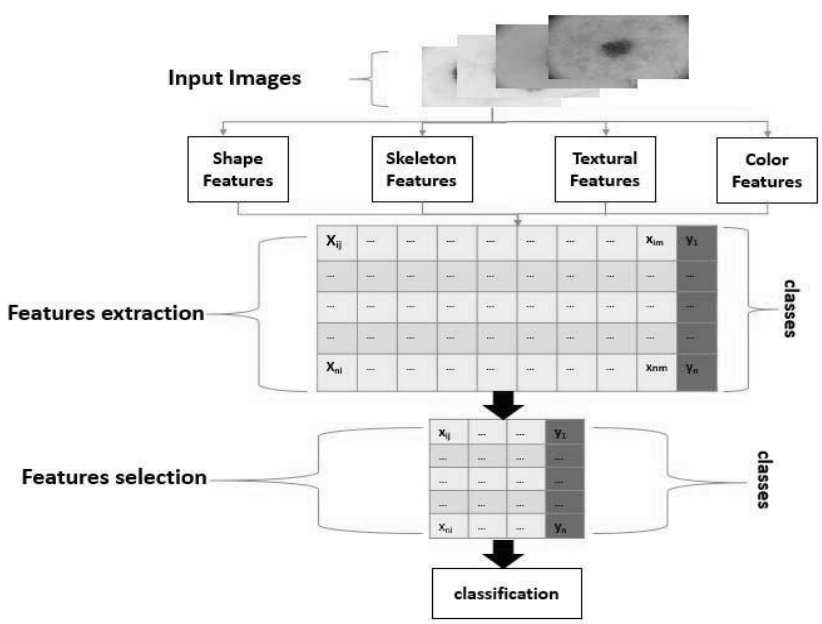

Fig. 2. Flowchart of the proposed approach

B. Features engineering

The features extracted from the lesion are composed of skeleton, texture, shape and color features.

- Skeleton: The segmented lesion can also be transformed into skeletonization, which is just a wired lesion representation. The skeletonization will increase the identification and classification rate. We notice from previous work, the melanoma and non-melanoma form of the skeleton is very different, in terms of number of branches and endpoints. Nine features are extracted from the skeleton lesion [2].

- Texture: A set of mathematical texture descriptors have been used to measure the texture present in a lesion. The 10 features extracted are: Contrast; correlation; Energy; Homogeneity; Entropy; inverse difference Moment; Smoothness; Standard Derivation; Kurtosis; Root Mean Square[1].

- Color: The objective is to quantify the lesion's color variation. The derived characteristics are: maximum, minimum mean and variance of the pixel intensity within the R, G and B plan, a total of 12 features[1].

- Shape: The form of the lesion plays an important role in determining the type of lesion as the dermatologist uses in their diagnosis. The 6 features extracted from the lesion are: area; maximum and minimum diameter; extent ;perimeter; and eccentricity[10].

C. Features selection

All these features will firstly, will be normalized and selected using Info gain algorithm A total of 37 features are extracted from all the characteristics.

Feature selection based on information gain: This algorithm calculates a feature's efficiency, based on its class knowledge value. Based on the information theory criteria, the information gain between each feature F and the class C is determined by entropy. The features with high information gain are considered to be the most important.

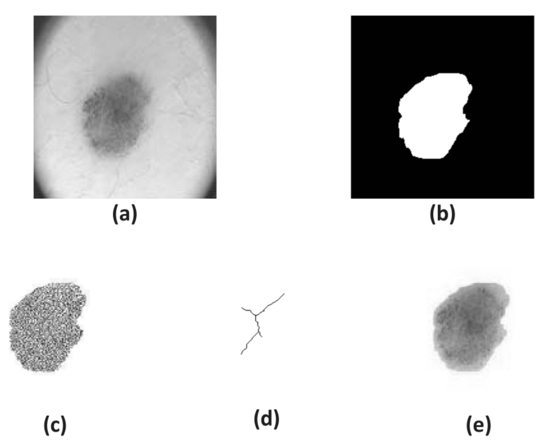

Fig. 3. Result of the proposed approach of non-melanoma cancer from the PH2 dataset; (a) the original images; (b) shape lesion; (c) texture lesion; (d) skeleton lesion; (e) color lesion.

D. Classifier

The classifiers used to measure the classification rate of our proposed approach are: Support Vector Machine (SVM), Multilayer perceptron (MLP), and k-nearest neighbors and the Adaboost[11][12].

1) Multilayer perceptron (MLP): This algorithm is one of the most widely used Artificial Neural Network (ANNs) architectures that are parallel distributed systems composed of layers of input and output components connected by weighted connections. The weights were modified during the learning phase to determine the right class depending on the input samples. The MLP algorithm has good ability and versatility to solve diverse non-separable classes.

2) Support vector machine (SVM): Based on the specified categories, this classifier is used to construct a hyper-plane to separate data, this type of classifier was widely used to identify skin lesions. In addition, kernel functions simplify the process of extracting non-linear data in a high-dimensional feature space using a basic hyper-plane.

*3) K nearest neighbors (KNN)***:** K nearest neighbors is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions). this algorithm does not implement a decision boundary. The density estimation uses a distance measure: the Euclidean distance. The only parameters in the algorithms is k, the number of neighbors, so a larger value of the parameter k considers a larger number of neighbors, and a smaller value considers a limited number of neighbors.

4) Adaboost: ADABOOST is one of the famous algorithms that demonstrate the capacity to essentially increase the accuracy of the algorithms that got a weak learner. It is a replacement of the boosting calculation that consolidates a lot of feeble learning calculations to build a model with better prediction results. ADABOOST gathering strategy has increased a great deal of consideration among the AI methods because of its low mistake rate and performing perfectly in noise data set [13]. The extra advantage of ADABOOST is that it requires less info parameters and little or no prior knowledge of the weak learner.
Several researchers have effectively used the ADABOOST algorithm to give solutions to classification problems such as skin cancer classification.

IV. EXPERIMENTATION

A. Dataset and metrics:

In this part, the given result for the features extraction, features section and classification are presented and discussed. The dataset used to evaluate the proposed approach contain 200 images of the pigmented skin lesion taken from PH2 [14]. The dataset also contains the ground truth of the segmented lesions validated by experts.
For the evaluation of the classification results we will use the Sensitivity (TP rate), Specificity (TN rate) and Accuracy measures.

Sensitivity=TP/(TP+FN) (1)

Specificity =TN/(FP + TN) (2)

Accuracy=(TP+TN)/(TP+TN+FP+FN) (3)

with TP is number of true positives; TN is number of true negatives; FP is number of false positives; FN is number of false negatives.

B. Result:

In order to remove the artefacts that the lesion contains, the input image was decomposed into texture and object components using PDE decomposition.

The decomposition leads us to have a good recognition of the object that makes a better segmentation result (see fig. 2).

In figure 2.(b, c, d , e) we can see the features that will be extracted from each image. From the skeleton lesion, we will extract the nine features to describe the skin cancer [2], the segmented image will give a description in terms of shape [10]. The textural features will be extracted from the projection of the texture component on the segmented images, and the color from the projection of the original images on the segmented images [10].

The K-Cross-validation is a way of predicting the efficacy of a model, for that we use the 5-Cross-validation in the classification step in our proposed approach.

Table 1 shows the result of using different classifiers “support vector machine, MLP and KNN and Adaboost” on the Ph2 database. The classification is done on the fusion of the extracted features using and without selection. The features selection using the Info gain algorithm keep only 5 features that are the most relevant.

Table 1: Classification results of the PH2 database with metrics measure

Classifier		Fusion of all the features	Fusion with features selection
MLP	*Se*	86	96
	Sp	46	48
	Acc	**78.9**	**87**
SVM	*Se*	87	90
	Sp	49	60
	Acc	79.5	84
KNN	*Se*	88	88
	Sp	44	50
	Acc	**77**	**81**
Adaboost	*Se*	87	93
	Sp	49	63
	Acc	**79**	**93**

With: Se is sensitivity, Sp is specificity and Acc is accuracy.

Table 2: Results of the proposed approach compared with literature

Classifier	[13]	[14]	Proposed approach
Se	85	87	93
Sp	87	93	63
Acc	**87**	**92**	**93**

Table 2 presents the classification accuracy of our proposed approach in comparison with recent approaches proposed by Barata [15] and Bi Li[16].

In [15], authors described the importance of color features for detection of skin lesions. The color sampling method was utilized with Harris detector and compared their performance with grayscale sampling and got 87 as the accuracy rate. [16] used multiple closely related histograms derived from different rotations and scales to represent skin lesions using a single-scale histogram, and got 92 as the accuracy rate. Our proposed approach got a high score with **93** accuracy rate.

V. Conclusion

To help dermatologists in their diagnosis, many solutions in image processing and analysis have been proposed. The work that we performed in this paper is to use many features extracted that can describe the lesion, which are skeleton, shape, texture and color features of the lesion. The input of the Machine learning classifier are the selected features using the Info gain. The Adaboost classifier got the best score. The proposed approach achieved a promising classification rate. In future work, we will try to implement the proposed approach in an embedded FPGA system.

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