Advanced Processing Techniques for Detection and Classification of Skin Lesions

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***Abstract*—The paper presents how the skin cancer in forms of melanoma can be identified based on the digital image processing of the lesion. The solution is based on the extraction of seven features (deterministic and statistic type) from the image of a skin lesion: perimeter, area, diameter, fractal dimension, lacunarity, histogram of oriented gradients, and local binary patterns. Each feature has attached a specific classifier and the diagnosis is obtained by using a voting scheme in the final classifier. The experimental results on a free database demonstrate that the method provides a high accuracy.**

Keywords—image processing, feature extraction, medical diagnosis, melanoma detection

I. INTRODUCTION

Melanoma is the most severe form of skin cancer, being curable only in the incipient phase because the malignant melanocytes multiply uncontrollably invading surrounding tissues and even other organs and so endangering the individual's life. For this reason, it is necessary to remove the melanoma in a very short time after its appearance, without giving it the possibility of spreading. Thus, it is necessary to be developed an easy-to-use diagnosis method available to the general public in order to reduce the mortality caused by skin cancer. Initially, the melanoma has the appearance of nevi, but, unlike them, the malignant tumor develops rapidly and has irregular shape and non-uniform coloring (Fig. 1).

The diagnosis of melanoma is based on the examination of the suspected lesion with a dermatoscope, which determines a number of features like:

- Asymmetry of the lesion: a malignant lesion does not support any axis of symmetry;
- Irregularity of the edges of the lesion: a malignant lesion has irregular edges;
- Uniformity of the color of the lesion: a malignant lesion has a non-uniform color, usually varying from light brown to black, but may also contain red, white or blue shades;
- Diameter of the lesion: a malignant lesion has a diameter much larger than that of common nevi.

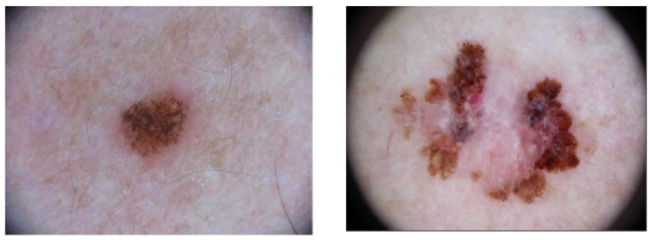


Fig. 1. Visual comparison between a benign lesion (left) and a malignant lesion (right).

The informational approaches of the proposed problem are different, some are more complex, some simpler, some are more performing, others weaker, some are faster, others more computationally intensive. Some of the best algorithms developed by the researchers are the following.

In 2016 it was developed an automated segmentation system for the segmentation of skin lesions by Bloisi et al. [1]. The system was based on the extraction of two masks from the same image: healthy skin removal and lesion detection. By overlapping both of them, the final mask of segmentation is obtained. It was used a 200 images database consisting of 160 benign lesions and 40 melanomas for testing this approach and the accuracy obtained was 89.66%.

Later, S. Bakheet [2] studied the use of histogram of oriented gradients to classify skin lesions. The process of classification was done by using a support vector machine which had as input an array formed by concatenating the optimized set of histograms of oriented gradients obtained from every block of the image. The experiments were done on a 224 images database having half images of benign lesions and half images of malignant lesions. The accuracy obtained was 97.32%.

A study by Abuzaghleh et al. [3] proposed a discriminatory algorithm which is composed of three classifiers. The first of them has only a level, being capable of classifying the image in one of three classes: benign, malignant and atypical. The other two are more complex by having two levels of classification. The first level classifies the image into benign or abnormal, malignant or benign and atypical respectively, and the second level discriminates between atypical or melanoma, benign or atypical respectively. This approach was validated on a 200 images database composed of 80 images of malignant skin lesions, 80 images of benign skin lesions and 40 images of atypical skin lesions. The accuracy obtained was 94.3% for the first classifier, 97.5% for the second one and 100% for the last one.

Deep learning neural network was used by Jafari et al. [4] to perform the automated classification of skin lesions. The digital image is firstly preprocessed to reduce the noise and illumination effects. And then the image is fed to a convolutional neural network to classify it as benign or malignant. After the experimental testing the accuracy obtained was 81%.

The solution proposed in this paper is based on the extraction of seven features from skin lesion images: three geometric features (perimeter, area and radius of the lesion), two fractal characteristics (fractal dimension and lacunarity) and two visual descriptors (histograms of oriented gradients and local binary patterns). Regarding the classification system, a polling system is proposed in which, on the basis of the diagnosis obtained for each characteristic, a decision is made as to the malignity of the respective lesion.

II. Methodology

The first step in developing an information system capable of correctly diagnosing melanoma is to extract a series of supposed useful features in the process of discrimination between a malignant and a benign lesion and subsequently determine the utility of their integration into the decision-making system. Each feature (perimeter, area, diameter, fractal dimension, lacunarity, LBP, and HOG) has attached a specific classifier and the diagnosis is obtained by using a voting scheme in the final classifier (Fig 2).

A. Geometric Features

In order to extract the geometric features: perimeter, area and diameter of the lesion, a MATLAB program was developed to automatically segment a skin lesion image based on the *Adaptive Thresholding* method. The segmentation mask is extracted by comparing the value of each pixel with the threshold value. The pixel is considered part of the lesion if its value is greater than the threshold. At the output of this program a binary image is obtained, on which several morphological operations are applied in order to eliminate the artifacts.

The appropriate color channel for the current image segmentation is automatically determined by calculating the entropy of all three color channels using the formula (1):

$$S(i) = -\sum_{j=0}^{L} h_i(j) log h_i(j) \quad (1)$$

where $S(i)$ represents the entropy of the color channel *i*, $h_i(j)$ represents the histogram of the color channel i and L represents the number of color levels.

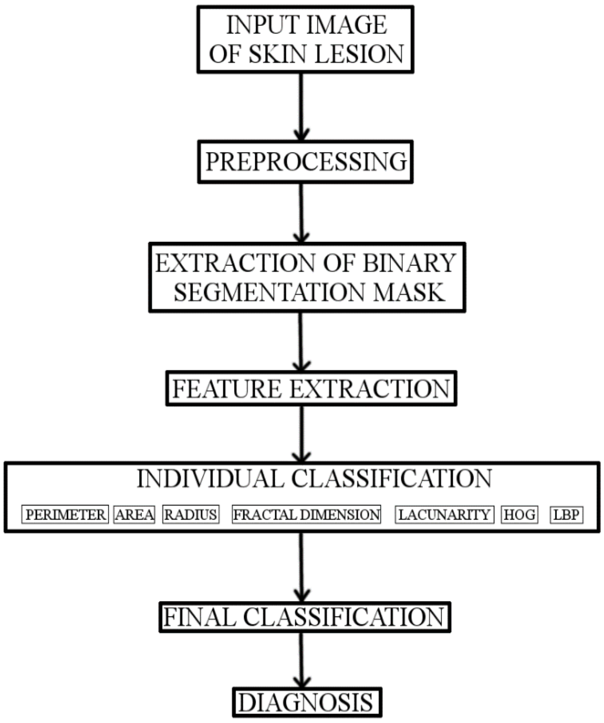


Fig. 2. Flow chart of the proposed system.

After making the calculations on the three channels, it is selected the one with the highest entropy value (2):

$$k = \arg(max(S(i))) \quad (2)$$

The segmentation algorithm is the following:

Algorithm 1

Input: img = RGB image of the skin lesion

Output: mask = binary image of the lesion

for each color channel i

for each histogram value

$S(i) = S(i) - h_i/sum(h_i) * log(h_i/sum(h_i))$

$k = arg(max(S(i)))$

$threshold = min(h_k)$

for each pixel at the coordinates (i, j) of the color channel k

if(pixel(i, j) > threshold)

mask(i, j) = 0

else

mask(i, j) = 1

Based on the obtained mask, the perimeter of the lesion, its area, as well as its radius is calculated using MATLAB.

B. Fractal Features

According to [5] fractal analysis is a way of studying the forms that cannot easily be described by the usual geometry. More precisely, fractal analysis allows describing how objects or structures occupy a certain space.

The *fractal dimension* is used as a quantitative descriptor of a structure's morphology and can provide information about how a particular structure has been formed. In this paper the fractal dimension will be determined by the Differential box counting method (DBC), which implies that in each block the maximum value and the minimum value are determined and based on them the number of copies is calculated as follows (3):

$$n_r(i, j) = l - k + 1, \tag{3}$$

where l and k represent the box numbers containing the highest and the smallest value of the gray level in the block.

Taking into account all the blocks N_r (4):

$$N_r = \sum_{i,j} n_r(i, j), \tag{4}$$

DBC provides information on how an object occupies space and can be used to quantify the roughness or fineness of a curve in space, such as the edge of a skin tumor. The edge of a benign tumor can be seen as a smooth curve, like a circle, of a small fractal dimension, while melanoma, due to uneven development, will have a larger fractal dimension.

The lacunarity (L) allows describe the texture of an object by determining the degree of heterogeneity. The homogeneity of color or texture is equivalent to low L values, whereas heterogeneity of colors or texture leads to high L values. Thus, the irregularity of the pigment distribution at the surface of the lesion can be estimated and expressed numerically by the lacunarity (5) [6, 7]:

$$\lambda_{\varepsilon,g} = \left(\frac{\sigma_{\varepsilon,g}}{\mu_{\varepsilon,g}}\right)^2, \tag{5}$$

where $\lambda_{\varepsilon,g}$ represents the value for a square whose side has a length of ε and his orientation is g, $\sigma_{\varepsilon,g}$ represents the standard deviation and $\mu_{\varepsilon,g}$ represents the average of the pixels [8].

Lacunarity and fractal dimension have been extracted using the FracLac plug-in developed for the ImageJ image analysis program.

C. Histogram - Based Descriptors

a) Histograms of Oriented Gradients

Histogram of oriented gradients (HOG) is a feature used in image processing and in computer vision that allows the identification of objects in a digital image. HOG were constructed by imitating how the brain processes visual information, and the data extracted with them has been shown to be an effective way of describing the local appearance of an object of a form by determining the distribution of intensity gradients of direction edges.

The main steps of the HOG extraction algorithm are [9]:

1. Splitting the image in smaller regions called cells, and for each cell it is calculated the histogram of oriented gradient directions for the pixels contained in the cell;
2. Each cell is discretized in several angular bins depending on the gradient orientation;
3. Weighting the values in each individual bin based on the number of pixels present in the cell;
4. Grouping the adjacent cells in space regions called blocks. This is required to normalize the histogram;
5. Normalized histogram is the histogram of the entire block. The histogram set of all the blocks in the image form the HOG descriptor.

b) Local Binary Patterns

Local Binary Patterns (LBP) is one of the visual descriptors used in the artificial view that allows the analysis of an image in terms of its texture. They combine the structural and statistical information of the texture based on a histogram, compiling a pattern for each pixel of the image by thresholding its neighbors with the value of the central pixel and concatenating the binomial result in the form of a number [10].

Extracting the LBP descriptor from an image is done as follows:

1. Divide the image into cells, as with the HOG descriptor;
2. For each pixel of a cell compare its value with the value of the central pixel;
3. When the value of the central pixel is higher than the current pixel value, the value 0 is retained, otherwise the value 1 is retained. On this basis a binary number, written on 8 bits, is obtained;
4. Compile the histogram based on the number of occurrences of the values of 1 and 0;
5. Normalize the histogram;
6. The histograms of all cells are concatenated, thus obtaining the feature vector.

HOG and LBP histograms were calculated using MATLAB routines extractHOGFeatures and extractLBPFeatures respectively for each RGB color channel.

D. Proposed Classifier

Regarding the classification of images with skin lesions, it is proposed to use seven individual classifiers, one for each extracted characteristic, and the final classification to be made on the vote given by each classifier. A diagnosis is considered certain if at least five of the seven votes are in his favor.

The individual classifiers are based on determining the Euclidian distance from the feature extracted to the model of both classes. The vote is chosen as the closest model to feature extracted.

The algorithm for determining the diagnosis has been implemented in MATLAB by creating an array of results that contains all the outputs of the individual classifiers which is then iterated over for generating the output.

The pseudocode for it is as follows:

Algorithm 2

Input: results = array of votes given by individual classifiers

Output: Displays result on screen

```
noBenign = 0;
noMalignant = 0;
for i from 1 to 11
    if(results(i) == 'B')
        noBenign++;
    else
        noMalignant++;
if(noBenign > noMalignant)
    if(noBenign >= 5)
        disp("Diagnosis certain. Benign Lesion")
    else
        disp("Diagnosis uncertain. Benign Lesion");
else
    if(noMalignant >= 5)
        disp("Diagnosis certain. Malignant Lesion")
else
```

III. Experimental Results

In the experiments, there were used 100 images: 50 images of benign tumors and 50 images of malignant tumors which were extracted from the International Skin Imaging Collaboration and PH_2 databases [11].

Initially, the mask of the lesion is extracted using the MATLAB program presented earlier, mask over which several algorithms have been applied to obtain the geometric features previously exposed. In order to favor the correct extractions of the lesion outline a smoothing filtration was performed to reduce the variations within the lesion.

Experimentally, as specified in [12], it was observed that the blue color channel was preferred by the algorithm to segment the majority of the images used in the experiments.

The geometric features results obtained for the two classes are presented in the Table I.

The use of geometric features should be done cautiously because images must be taken at the same distance from the patient's skin. If such data is not known these features should not be taken into account, or if the database is known to be non-homogenous, images can be resized correspondingly so that a correct correlation of the image with the class model can be made.

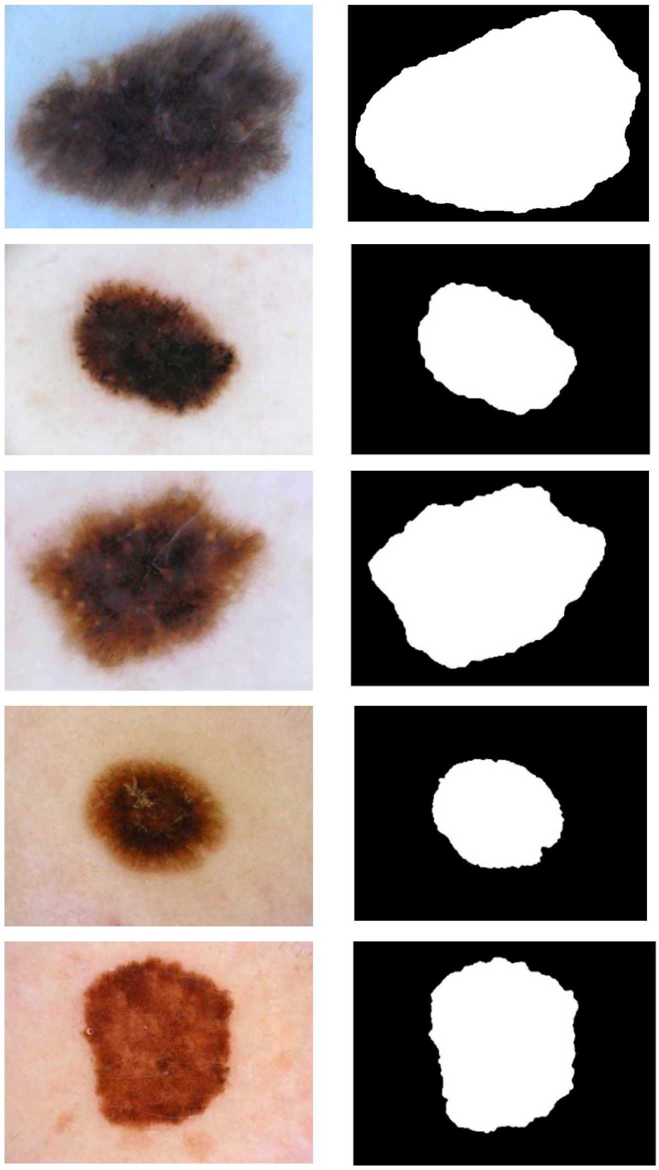


Fig. 3. Result of the segmentation algorithm.

TABLE I. Interval Values of the Geometric Features Extracted from the Image Set

Geometric feature	Intervals	
	Benign	**Malignant**
Perimeter [pixels]	1224 ÷ 1656	1763 ÷ 3759
Area [pixels]	47763 ÷ 115151	126795 ÷ 255133
Diameter [pixels]	311 ÷ 427	456 ÷ 726

In terms of fractal analysis, the results are as follows (Table II):

TABLE II. Interval Values of the Fractal Features Extracted from the Image Set

Fractal feature	Intervals	
	Benign	**Malignant**
Fractal dimension	2.69 ÷ 2.71	2.58 ÷ 2.66
Lacunarity	0.025 ÷ 0.045	0.108 ÷ 0.228

The fractal analysis features have led to the best results, giving an easy way to distinguish between the two classes with a small overlapping area, as can be seen in the Fig. 4.

For HOG and LBP, the mean histograms were used as class representatives (Table III).

TABLE III. HOG AND LBP MEAN HISTOGRAMS

HOG		LBP	
Benign	**Malignant**	**Benign**	**Malignant**
0.175	0.178	0.271	0.250
0.160	0.192	0.350	0.252
0.150	0.199	0.198	0.247
0.150	0.190	0.223	0.322
0.160	0.164	0.225	0.337
0.154	0.128	0.224	0.334
0.158	0.110	0.222	0.228
0.163	0.117	0.335	0.229
0.165	0.121	0.336	0.299
0.177	0.140	0.581	0.501

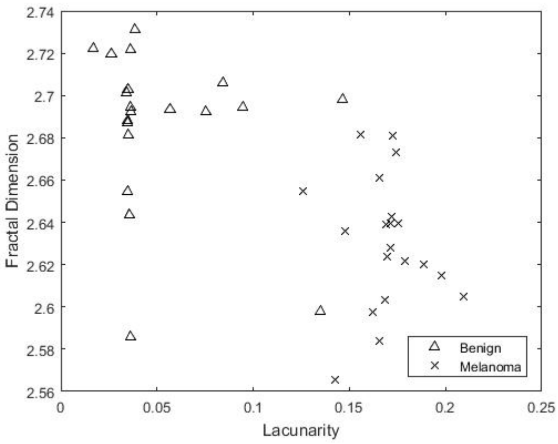


Fig. 4. Graphic representation of fractal features extracted from the image set.

It can be noticed that the fractal dimension does not lead to good results in terms of discrimination between the two classes, unlike lacunarity, in which two accumulation regions can be distinguished.

For HOG and LBP analyzes, some of the results are shown in Fig. 5 and Fig. 6.

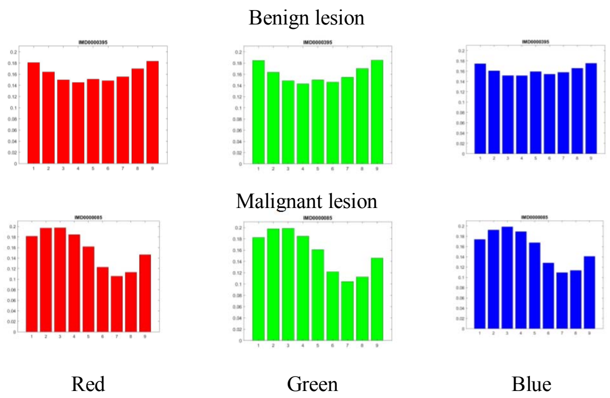


Fig. 5. HOG histograms calculated on RGB channels.

In the case of HOG and LBP histograms, it was observed that the best differentiation between classes is performed on the blue color channel, whereas the histograms of the red and green color channels are of similar values.

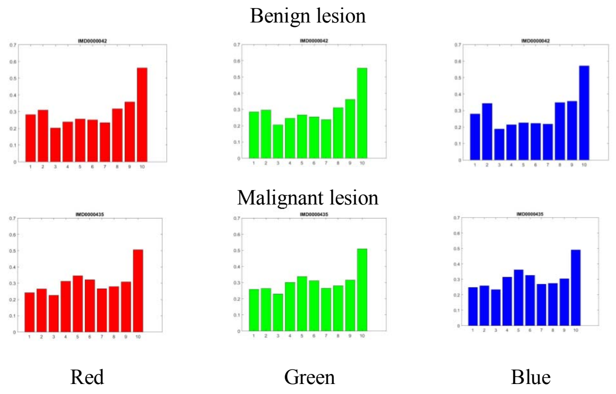


Fig. 6. LBP histograms calculated on RGB channels.

For some images the histograms obtained were very similar to the histograms of the opposite class and that there is also a very high variability within the same class. These results were attempted to be corrected by applying a median filter, but no significantly better results were obtained. A complete classification for two test images, containing all 7 features is presented in Fig. 7. For the perimeter, area, diameter, fractal dimension and lacunarity, corresponding thresholds were used for classification as benign or malignant. These thresholds are established as the half distance between the intervals for benign and, respectively, malignant cases. The decision of malignant diagnosis was "greater than the thresholds" for perimeter, area, diameter, and lacunarity, on grey level. For fractal dimension, also on grey level, the decision of malignant diagnosis was "less than the thresholds". For example, in the case of the perimeter, from the Table I result that the threshold value is of 1709.5. The local classifiers for HOG and LBP, on blue channel, are considered as minimum distances (Minkowski order 1) between the measured histogram and class representatives histograms (the mean histograms – Table III).

The decision of classification as benign or malignant is taken as a vote between all classifiers (minimum 4 from 7).

Regarding the classifier, the results obtained were quantitatively assessed by the accuracy ACC (6). 100 images were tested, including 50 with benign tumors and 50 with malignant tumors from the PH^2 database. In our case the ACC for malignant detection was 85%.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} 100 \quad [\%] , \qquad (6)$$

where TP means the number of true positive cases (correctly classified positive cases), TN means the number of true negative cases (correctly classified negative cases), FP means the number of false positive cases (incorrectly classified negative cases), and FN means the number of false negative cases (incorrectly classified positive cases).

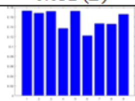
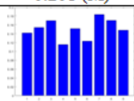
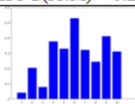
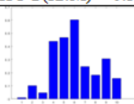
Features	I1	I2
Initial images/masks		
Perimeter	1390 (B)	1763 (M)
Area	78486 (B)	101055 (B)
Diameter	354 (B)	420 (B)
Fractal dimension	2.71 (B)	2.65 (M)
Lacunarity	0.032 (B)	0.201 (M)
HOG histogram		
HOG distance	**dHOG(I1.B) = 0.170** (B) dHOG(I1.M) = 0.227	**dHOG(I2.B) = 0.175** (B) dHOG(I2.M) = 0.345
LBP histogram		
LBP distance	dLBP(I1.B) = 2.051 **dLBP(I1.M) = 1.062** (M)	dLBP(I2.B) = 2.065 **dLBP(I2.M) = 1.542** (M)
Feature number Benign/Malignant	6B / 1M	3B / 4M
Decision (Diagnostic)	B	M

Fig. 7. Example of lesion classification.

IV. CONCLUSION

In this paper work several features were extracted from images of both benign and malignant skin lesions and their utility in the automated classification process was analyzed. The best results were obtained based on the lacunarity of the lesions, as it is known that a benign lesion is uniform and a malignant one is heterogeneous. Based on the extracted features. a classification system has been developed which takes into account the vote of the seven individual classifiers and leads to a diagnosis with an accuracy of 85%. The experimental results show that the proposed approach is comparable as performance to the results obtained by other scientists studying the same research field.

ACKNOWLEDGMENT

The work has been funded by UPB, Program GEX2017, project SET 22/2017 and project CAMIA 25/2017.

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