Melanoma Detection System based on a Game Theory Model

Djamila Dahmani, Slimane Larabi, Sihame Djelouah, Nafissa Benhebbadj and Mehdi Cheref
Computer Science Department, USTHB University, BP 32 EL ALIA, Algiers, Algeria

Keywords: Melanoma, Skin, ABCD, Zero-sum Game Theory.

Abstract: We propose in this paper a new method for Melanoma detection (the most dangerous form of skin cancer) based on ABCD medical procedure. The ABCD features play a crucial role in the accuracy of diagnosis rates. However, the search for such distinctive data remains difficult, because of the small variability in the appearance of benign and cancerous skin lesions. To cope with this problem, each feature is calculated using different formulas. Then if all the used formulas agree about the lesion classification, it will be classified according to the full agreement. Otherwise, for *doubtful pigmented* skin lesions, the game theory model is applied for final decision. The game model proposed in our work, estimates that the conflict is between two agents (melanoma and non-melanoma). The different formulas applied in the computation of the features A, B, C, and D are the pure strategies. The value sign in the mixed extension of the game allows classifying correctly the skin lesion. The method was tested on two publically available databases PH2 and ISIC, the obtained results are promising.

1 INTRODUCTION

Melanoma is one of the most aggressive human tumors. Moreover, Melanoma has a cure rate of more than 95% if detected in early stage (Roma et al., 2007). Skin cancer recognition on computer Aided Diagnostic (CAD) has been an important research area. The objective of CAD systems is to provide a computer output as second opinion in order to assist the radiologists on interpretation to improve the accuracy and reduce the image reading time (Doi, 2005). New approaches are developed to help earlier diagnostics. Dermoscopy is one of the most used tools in the precocious detection of Melanoma. Dermoscopy (also known as dermatoscopy or epiluminescence microscopy) is a method of acquiring a magnified and illuminated image of a region of skin for increased clarity of the spots on the skin (Binder et al., 1995). The use of dermoscopy gives a magnification of the images of the nevus lesions and it permits the analysis of particular characteristics of the lesion, including symmetry, size, borders, presence and distribution of color features. The typical computer-aided diagnosis (CAD) pipeline for auto-mated skin lesion diagnosis (ASLD) from digital dermoscopic images can be divided into the following steps (Wighton et al., 2011): Image acquisition, Noise and artefact filtering, Lesion segmentation; Feature extraction, and Classification.

The medical diagnostic of skin lesions based on dermoscopy used ABCD rule (Stolz et al., 1994), 7 point-checklist (Argenziano et al., 1998) and Menzies' method (Menzies et al., 1998). These cues are sometimes called the letters of the dermoscopic alphabet since there are features used for the final diagnostic decision. The ABCD rule is proved that it can be easily learned and rapidly calculated and has been proven to be a reliable method providing a more objective and reproducible diagnosis of melanoma (Stolz et al., 1994).

In this paper each feature (Asymmetry, irregularity of Border, presence of specific Colors, and lesion shape and size) is calculated using different formulas, thus reflecting diverse aspects of the feature and not giving necessarily the same result. At first step, if the methods used all the characteristics are unified on the same classification of the lesion, it will be classified according to this agreement; otherwise a game theory model is employed to take decision about the lesion type. The idea behind the proposed model is to consider the disagreement of the formulas in the lesion classification as a zero-sum game where the melanoma and non-melanoma are considered players and the different formulas applied in the computation of the characteristics A, B, C and D

Dahmani, D., Larabi, S., Djelouah, S., Benhebbadj, N. and Cheref, M.
Melanoma Detection System based on a Game Theory Model.
DOI: 10.5220/0008879807030711
In *Proceedings of the 15th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2020) - Volume 5: VISAPP*, pages 703-711
ISBN: 978-989-758-402-2; ISSN: 2184-4321

provide strategies. Then an efficient utility function is proposed for modeling the discord and attributes the lesion to the most persuasive player namely the melanoma or non-melanoma class.

One important difference of our approach compared to previous works is that the ABCD features are taken separately, and each feature is computed with various manners to cope with the problems of the imprecise segmentation of skin lesions, and the narrow variability in the appearance of benign and cancerous skin lesions. The zero-sum game theory architecture with an appropriate utility function is then used to model this variability and to take decision about the lesion classification.

The paper is organized as follows, the section 2 is devoted to the related works, the section 3 to the explanation of the proposed method and finally the experiment results and discussion will be presented in section4.

2 RELATED WORKS

Recently there is a big interesting in development of computer-aided skin diagnostic systems (Moradi et al., 2019; Sadri et al., 2017; Gu et al., 2017; Bi et al., 2016; Kruk et al., 2015; Pennisi et al., 2016). These approaches can be classified into two categories: (i) Dermoscopic based approaches and, (ii) Pattern recognition based approaches. (Pennisi et al., 2016) proposed an automatic skin lesion segmentation algorithm based on Delaunay triangulation. The segmentation approach produced better results in case of benign lesions. The authors in (Gu et al., 2017) proposed a melanoma detection system based on Mahalanobis distance learning and constrained graph regularized non-negative matrix factorization. The method achieved 94,43% in sensitivity and 81,01% in specificity. The authors in (Sadri et al., 2017) proposed a technique based on fixed wavelet grid network (FWGN). The construction of FWGN is performed using D-optimality orthogonal matching pursuit (DOOMP). (Bi et al., 2016) used an automatic melanoma detection technique for dermoscopic images via multi-scale lesion-biased representation (MLR) and joint reverse classification (JRC). Skin lesions are represented using closely related histograms. JRC model provides distinctive additional information for melanoma detection. The method proposed in (Kruk et al., 2015) used extended set of diagnostic features describing the image of skin lesions combined with different solutions of the classifiers. The authors resigned from the ABCD features trying to find more powerful descriptors. The results of the proposed system are: accuracy of 89.5%, sensitivity of 95% and specificity of 88.125%. Moradi and Mahdavi-Amiri (Moradi et al., 2019) proposed a system of skin lesion segmentation and classification based on novel formulation for discriminative kernel sparse coding jointly learns a kernel-based dictionary and a linear classifier. The method is insensitive to noise and image conditions and can be used effectively for challenging skin lesions.

3 METHODS

The proposed method consists from some steps. At first the dermoscopic image is pre-processed to be segmented. The salient features are then extracted from segmented image. Finally the classification phase is performed using a zero-sum game theory modelling.

3.1 The Pre-processing Step

In this step, a method of removing hair and artefacts was applied to facilitate future treatments and to not alter the results. At first, a median filter was applied to the image, and then a morphological transformation was used to close the hair pixels with the pixels of its surrounding area and keep the shape of the lesion. The closing operation was performed separately on the three RGB color channels of the image (see Figure 1).

3.2 Segmentation Step

After pre-treatment, three algorithms were applied namely: the color thresholding segmentation to identify the pixels belonging to the skin around the lesion, along with SLIC (Simple Linear Iterative Clustering) Superpixels algorithm (Achanta et al., 2012) and Otsu segmentation algorithm (Otsu, 1979) to segment the lesion region.

3.2.1 Color Thresholding Segmentation

Several methods of segmentation of the skin into color images are available in the literature. The simplest methods define limits in the color space chosen to identify skin clusters. The main advantage of these methods is that they do not require a training phase. However, it is difficult to define the limits that work well by considering a single color space. For this reason, in our algorithm, we converted the image to HSV and then we set 140

distinct thresholds that include multitude of skin colors.

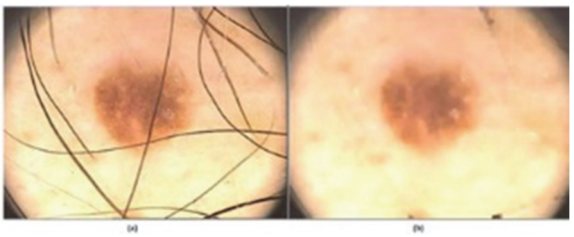

Figure 1: (a) Original image, (b) The image after the processing step.

3.2.2 SLIC Segmentation Algorithm

Each region is represented by a Superpixel created by the SLIC algorithm (Achanta et al., 2012). The advantage of this algorithm is that it generates compact and homogeneous regions of uniform size, regular shape, and almost respecting the limits of the lesion. However, the choice of the appropriate segmentation scale is not obvious because the lesion as well as some details in the image may appear at different sizes. For this reason we applied a third method of segmentation, on the image result obtained by SLIC algorithm.

3.2.3 Otsu Segmentation Algorithm

The Otsu method (Otsu, 1979) is a quick and simple threshold method that automatically calculates a threshold value from the image histogram. The threshold value is then used to classify the pixels in the image based on their intensity.We used Otsu segmentation on the SLIC result, and then applied a morphological closure to remove the outliers. The figure 2 presents an example from PH2 database (Mendonc *et al.*, 2013) of the segmentation step.

3.3 Features Extraction

The ABCD is clinical guideline used by the dermatologists for the skin lesions diagnostic. The measures A, B, and C reflect the geometric proprieties of skin region and C is linked to the chromatic and lightness characteristics. The ABCD requires subjective evaluation of the different aspects of a skin lesion (Ma et al., 2017). In order to cope with the subjective evaluation, and classification decision we integrate in this paper zero-sum game theory modeling. At beginning, each composite feature (A, B, C, and D) is computed with different mathematical formulas and so translate various aspects of each characteristic. In the flowing the computation details will be given.

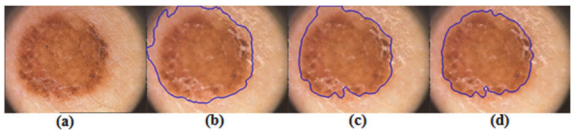

Figure 2: (a) Initial image, (b) color thresholding segmentation, (c) SLIC segmentation algorithm, (d) Otsu segmentation algorithm.

3.3.1 Asymmetry

According to dermatologists, melanomas develop anarchically (they are asymmetrical), while benign tumors are symmetrical.

In order to obtain good result we used the following methods to calculate the asymmetry of the lesion:

- **Best Fit Ellipse:** based on the method proposed in (She et *al.*, 2007), one way to measure asymmetry is to fold the contour of the lesion around the chord of the best-fitting ellipse and looking for the difference (the non-overlapping region). That is calculated as following:

$$A_1 = \frac{\Delta S}{S} \times 100 \quad (1)$$

Where ΔS is the difference area surface and S is the lesion surface.

- **Principal Axis:** this asymmetry index is calculated using the algorithm presented in (Andreassi et *al.*, 1999). It is based on the computation of the smallest difference between the image area of the lesion and the image of lesion reflected from the principal axis.

$$A_1 = \frac{S'}{S} \times 100 \quad (2)$$

Where *S'* is the difference area.

- **Main Axes:** at first the shape is translated so that the lesion will be placed in the center of the image. Then the image is rotated to align with the main axes. The lesion will be divided into four sub regions. The asymmetry value is obtained by subtracting the reflected area on one side of the axis of the reflected form, giving two area differences. It is given by the formula:

$$A_3 = \frac{\Delta S_{\min}}{S} \times 100 \quad (3)$$

where ΔS_{min} is the smallest difference of areas.

- **Centered Sub Regions:** this is the same method as the previous one, except that this time the lesion was translated so that the center of the image coincides with the center of mass of the lesion as proposed in (Stoecker et al., 1992).

3.3.2 Border

Benign lesions are generally defined by clear limits, while melanomas are defined by very contrasting irregular boundaries. We use four features to characterize the border irregularities.

- **Compact Index:** the compact index (CI) of a skin lesion is an important aspect to consider, when looking for melanoma. The factor (CI) indicates how much the skin lesion looks like a circle. It is defined as:

$$CI = \frac{P^2}{4\,\pi\,S} \tag{4}$$

P is the lesion perimeter and S the total area.

- **Fractal Dimension:** the fractal dimension measures how the details change with scale, it indicates the complexity of fractal patterns. It is obtained by the box counting algorithm. The lesion boundary is determined then covered with a grid, and finally the number of occupied boxes in the grid is counted. It is defined by the formula:

$$d_{frac} = \frac{\log(b)}{\log(r)} \tag{5}$$

Where b is the number of smallest boxes that covered the edge line and r is the inverse of the smallest box side length.

- **Length Contour:** If the outline is wide enough then: either the lesion is large, or it is small and its borders are irregular, or it is large with irregular edges, and in all three cases it is a sign of abnormality.
- **Regularity Index:** The regularity index allows the calculation of the uniformity of the form. It is computed by the equation (6).

$$r = \frac{P}{S} \tag{6}$$

Where P is the lesion perimeter and S the total area.

3.3.3 Color

- **Colors Number:** the pigmentation of a lesion can be characterized by several colors. Five to six colors may be present in a malignant lesion. Potential colors of melanoma are: White, Red, Black, Light Brown, Dark Brown and Grey Blue. For each color space we have defined 6 intervals to threshold its 3 components. The idea is to convert the image to HSV (YCbCr, or HLS) and then scan all the pixels of the lesion by calculating the percentage of belonging of each of the 6 colors, if that percentage is above a certain threshold then it is said that this color exists.
- **Kurtosis:** the kurtosis value measures whether the distribution of pixels is maximum or flat compared to a normal color distribution. It is the fourth standardized moment, it is calculated by the formula:

$$\sigma_4 = \frac{1}{N}\sum_{i=0}^{N-1}(p_i - \bar{x})^4 \tag{7}$$

p_i is the i[th] pixel intensity, $\bar{x}$ is the mean intensity and N is the total amount of pixels within the skin lesion.

3.3.4 Diameter

Melanomas usually start with a diameter of more than 6-7 millimetres. For the calculation of diameter we used 4 different methods.

- **Minimal Enclosing Circle:** the radius of the minimal circle enclosing the lesion will be considered as the diameter of this lesion.
- **Lengthening Index:** this measure is used to describe the lengthening and degree of anisotropy of the lesion. The ratio between moment of inertia δ' around the principal axis, and the moment of inertia δ" around the secondary axis quantifies the rate of elongation L given by the formula:

$$L = \frac{\delta'}{\delta''} \tag{8}$$

$$\delta' = \frac{m_{20} + m_{02} - \sqrt{((m_{20} - m_{02})^2 + 4\,(m_{11})^2)}}{2} \tag{9}$$

$$\delta'' = \frac{m_{20} + m_{02} + \sqrt{((m_{20} - m_{02})^2 + 4\,(m_{11})^2)}}{2} \tag{10}$$

Where m_pqdenote the (p + q)th order geometric and central moments of the lesion.

- **Contour Diameter:** The main idea is to find the circle whose perimeter is equal to the perimeter of the lesion, so the diameter of the lesion will be equal to the length of the radius of that circle.
- **Distance between Extreme Points:** To calculate the diameter in this method we first looked

for the 4 end points (top, bottom, left and right), then we calculated the distance between the high and low points and the distance between the left and right points and kept the maximum of the two which is considered as the diameter.

3.4 Classification and Zero-sum Game Theory Modeling

The features explained in the section 3.3 are used with appropriate thresholds to classify a given lesion. The main idea is that if all the characteristics agree about the nature of the lesion, it will be classified according to this agreement. Otherwise, we propose a game theory modeling to classify correctly the doubtful pigments. A lesion will be considered doubtful if at least one formula related to a given characteristic A, B, C, or D classifies it differently from others. The game proposed will be established between two gamers melanoma and non-melanoma players, where the doubtful pigment is considered a disputed territory. Each player would like to conquer all the identical territories to its nature and will face its own defeat if he penetrates the opposite territory. This game would perfectly fit into a zero-sum game (one player's loss is equal to the other player's gain). The pure strategies of each player are defined from the different formulas used in the computation of the features A, B, C and D.

For each class of formulas related to a given feature: Asymmetry, Border, Color or Diameter, the concatenation of the formulas which classified the doubtful lesion as melanoma is considered as strategy of melanoma player related to this feature. The concatenation of the rest of formulas in this class is considered strategy of the non-Melanoma player. So we obtain strategies from type "Asymmetry-Melanoma", "Asymmetry-non-Melanoma", "Border-Melanoma", "Border -non-Melanoma", "Color-Melanoma", "Color-non-Melanoma", "Diameter-Melanoma", "Diameter-non-Melanoma".

In particular case, where all the computation formulas of a given feature A, B, C or D classify the doubtful lesion Melanoma (non-Melanoma respectively) the strategy of this feature will be omitted from the set of strategies of the non-melanoma player(Melanoma player respectively).
The saddle point in the mixed extension of this game will represent a compromise agreement of the two players (Melanoma and non-Melanoma), where the territory will be granted to the most persuasive player, according to the mixed value of the game.

The mathematical formulation of the problem can be presented as follows:
We define the proposed zero-sum game $\emptyset$ by the given elements $\emptyset = (J, S_i, u)$ where:
$J = \{\text{Melanoma palyer}, \text{non} - \text{Melanoma player}\}$: the set of players.
S_i for $i = 1,2$ are the sets of pure of strategies for each player in a doubtful lesion **D.**
u is the utility function explained in the following.

3.4.1 Utility Function

The payoff function is the main subject of this research effort, how could we define an appropriate payoff function providing a meaningful result?

The computation of the utility function is based on the similarity between the characteristics of the lesion and those of melanoma sample images. This similarity was quantified using a correlation distance. In order to define the correlation distance, we determine for each strategy s_i the melanoma data matrix M_{s_i}. The lines of M_{s_i} are consisting of the characteristic vector, associate to the strategy s_i, computed from sample of images classified as melanoma by all formulas presented in the section (3.3).

We notate $\overline{X_j}$ and σ_j the average and the standard deviation of the j^{th} variable in the melanoma data matrix data M_{s_i} given by the equations:

$$\overline{X_j} = \frac{1}{m}\sum_{i=1}^{n} X_{ij} \; ;$$

$$\sigma_j = \left(\frac{1}{m}\sum_{j=1}^{n}(X_{ij} - \overline{X_j})^2\right)^{1/2} \ldots. \qquad (11)$$

Where m is the number of melanoma lesions in the set of sample melanoma images, and n the dimension of the features vector used in the strategy s_i.

The center of gravity of the matrix M_{s_i} is given by the equation:

$$G_{s_i} = (\overline{X_1}, \overline{X_2}, \ldots, \overline{X_n}) \qquad (12)$$

The standard deviation of the matrix $M_{s_i}$is given by

$$\sigma_{s_i} = (\sigma_1, \ldots, \sigma_n) \qquad (13)$$

-Then the centered and standardized matrix obtained from the matrix M_{s_i} is computed by the formula:

$$Z_{s_i} = \begin{bmatrix} \frac{X_{11} - \overline{X_1}}{\sigma_1} & \cdots & \frac{X_{1n} - \overline{X_n}}{\sigma_n} \\ \vdots & \ddots & \vdots \\ \frac{X_{1m} - \overline{X_1}}{\sigma_1} & \cdots & \frac{X_{mn} - \overline{X_n}}{\sigma_n} \end{bmatrix} \qquad (14)$$

-The correlation matrix is computed from the formula:

$$R_{s_i} = \frac{1}{m} {Z_{s_i}}^t Z_{s_i} \quad (15)$$

We note T_{s_i} the features vector of $\boldsymbol{D}$ in the s_i description:

$$T_{s_i} = \begin{pmatrix} T_{s_i}^1 \\ \vdots \\ T_{s_i}^n \end{pmatrix} \quad (16)$$

The $\widetilde{T_{s_i}}$ the centered and standardized vector according to the data the matrix M_{s_i}, is given by

$$\widetilde{T_{s_i}} = \begin{pmatrix} \frac{T_{s_i}^1 - \overline{X_1}}{\sigma_1} \\ \vdots \\ \frac{T_{s_i}^n - \overline{X_n}}{\sigma_n} \end{pmatrix} \quad (17)$$

-Let be the vector ${Y_{s_i}}^*$ a vector belonging to the matrix Z_{s_i} such that:

${Y_{s_i}}^* \in arg \min_{Y_{s_i} \in Z_{s_i}} \left\| \widetilde{T_{s_i}} - Y_{s_i} \right\|$, where $\| \quad \|$ is the Euclidian distance.

-Finally, we define the vector V_{s_i} such that $V_{s_i} = \widetilde{T_{s_i}} - {Y_{s_i}}^*$.

The correlation distance d_{s_i} which characterizes the similarity between the features vector of the doubtful lesion $\boldsymbol{D}$ and the data matrix M_{s_i} of melanoma individuals is then determined by the relation:

$$d_{s_{i,D}} = {V_{s_i}}^t R_{s_i} V_{s_i} \quad (18)$$

The value of $\boldsymbol{d_{s_{i,D}}}$ will be close to zero as long as the T_{s_i} is similar or close to the characteristic vectors of the data matrix M_{s_i}, this means that $\boldsymbol{D}$ is similar or approaching the melanoma lesion characteristics. Otherwise the value of $\boldsymbol{d_{s_{i,D}}}$ will be strongly greater than zero, this means that $\boldsymbol{D}$ is not similar and very different from the characteristic vectors of the data matrix M_{s_i} , and this involves that the entity $1/d_{S_{i,D}}$ roll a way the melanoma's characteristics when it approaches the zero.

Since the melanoma similarity aspect had been modeled, the utility function in a doubtful lesion D can be formulated by the formula.

$$u(s_1, s_2) = \frac{1}{d_{s_{2,D}}} - d_{s_{1,D}} \quad (19)$$

So, the sign of the real $u(s_1, s_2)$ is positive if the doubtful lesion is closer to the melanoma and negative otherwise. This fact translates the zero-sum game interaction between the melanoma and non-melanoma players.

3.4.2 Saddle Point or Nash Equilibrium in the Zero-sum Game

After the elaboration of the game matrix A in a doubtful lesion, the computing of the saddle point or the Nash Equilibrium, will allow us to settle the doubt and take decision about the lesion's nature. The value in a zero-sum game is the payoff value of the optimal strategies for each player. Therefore, the fairest manner to assign the doubtful lesion to melanoma or non-melanoma class is to focus only on the sign value of the game. If this value is equal to zero the game is fair, if it is positive, the game favors the melanoma player, while if it is negative; we say the game favors the no-melanoma player.

The value doesn't always exist in pure games, so we use the mixed (randomized) extension of the game $\emptyset$ that we note $\breve{\emptyset}$. $\breve{\emptyset}$ can be described by the given elements $\breve{\emptyset} = (J, \Delta(S_i), \mu)$ where $\Delta(S_i)$ is the set of all probability distributions over S_i .

$$\Delta(S_i) = \left\{ x \in \mathbb{R}^{|S_i|} : x_i \geq 0 \; et \sum_{1}^{|S_i|} x_i = 1 \right\} \quad for\ i = 1,2 \quad (20)$$

$\mu = E(u(x,y))$ is obtained from the payoff function u of the equation (18) in the zero-sum pure game and the mathematical expectation of the profile (x, y) such us $(x, y) \in \Delta(S_1) \times \Delta(S_2)$

According to the notations above:

$$\mu = E\big(u(x,y)\big) = x^t A y \quad (21)$$

where A is the payoff matrix of the game determined in previous subsection 3.4.1.

In his fundamental Minimax Theorem (the Main Theorem of the theory of Games) (Neumann, 1928) established the existence of a unique value v in mixed finite games such that:

$$\max_{x \in \Delta(S_1)} \min_{y \in \Delta(S_2)} x^t A y = \min_{y \in \Delta(S_2)} \max_{x \in \Delta(S_1)} x^t A y = v^* \quad (22)$$

and some optimal mixed strategies x^*, y^* (Nash equilibrium profile (x^*, y^*)) such that the expected payoff $v^*$is calculated by equation (22).

$$(x^*)^t A y^* = v^* \quad (23)$$

Thus $v^*$is the maximum "floor" of the Player 1 and minimum "ceiling" of player 2.

A solution (x^*, y^*, v^*) of the matrix game A can be obtained by the resolution of linear optimization problem. It was proven that there is a polynomial time algorithm for finding a mixed Nash equilibrium in a two-player zero-sum game, for more details see (Nisan et *al.*, 2007). In this paper, we use the sign of value v^* (the expected payoff) in a doubtful lesion to classify the patch in melanoma (first player) or non-melanoma (second player) class. If the value $v^* = 0$ the lesion is attributed to melanoma class for security measure.

4 EXPERIMENTAL RESULTS

The evaluation of the model performance is very important and the most commonly used performance measure is the classification score. However, for datasets with large class imbalances, a classification score does not make much sense. Instead (Receiver Operating Characteristic) ROC curves offer a better alternative.

For the evaluation of our system and the implemented methods, we followed the approach developed by the researchers, namely the calculation of the accuracy, the recall, the specificity, and the estimation of the ROC curves.

4.1 Used Datasets

In order to test the proposed method, we used the PH^2 dataset (Mendonc *et al.*, 2013) released by the University of Porto, in collaboration with the Hospital Pedro Hispano in Matosinhos, Portugal. This dataset contains 200 RGB dermoscopic images of melanocytic lesions, including 80 common nevi, 80 atypical nevi, and 40 melanomas. The method is also tested on the ISIC 2017 dataset (Codella et *al.*, 2017) which contains 2000 dermoscopic images.

4.2 Comparison of the Game Theory Modeling with the Features ABCD

In this section, we first compare the proposed zero-sum game theory model to the features ABCD. We note that for each characteristic A, B, C, and D we take the best result obtained using the formulas presented in the section (3.4). The comparison was performed using the ROC (Receiver Operating Characteristic) curve; the quality of classification is assessed using the metric AUC (Area Under the receiver operating characteristics). The results for PH2 (Mendonc et al., 2013) and ISIC (Codella et al., 2017) datasets are presented in Figure 3.

From the ROC curve presented in Figure 3, we show that the game theory holds the best result with the value of AUC = 0.94 followed by the color descriptor with the value of AUC = 0.90, then the border with AUC = 0.83, asymmetry and diameter with 0.75 and 0.74 respectively. These rates prove the effectiveness of the proposed game theory modeling as a combination scheme.

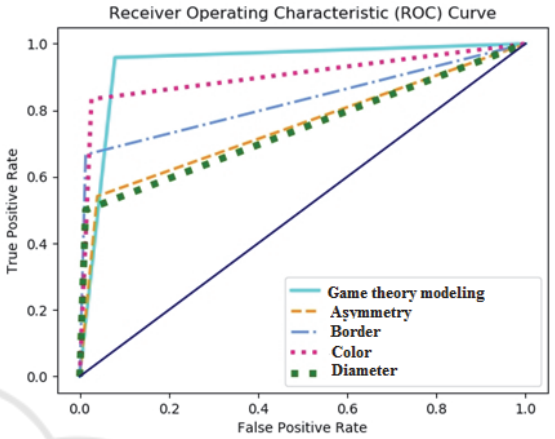

Figure 3: ROC Curves of ABCD features and the proposed game theory modeling using PH2 dataset.

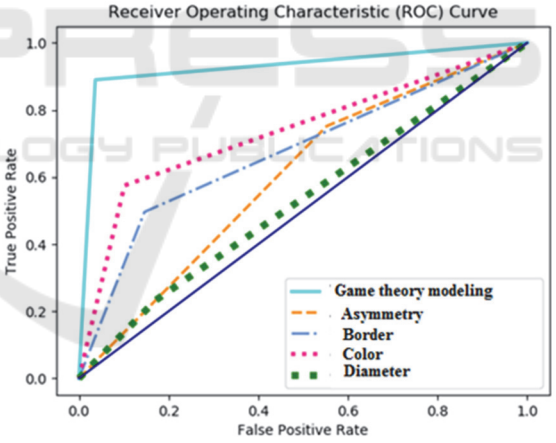

Figure 4: ROC Curves of ABCD features and the proposed game theory modeling using ISIC dataset.

The graph of the Figure 4 represents the result obtained from the evaluation of our approach on the ISIC dataset (Codella et al., 2017); these curves were developed from 1000 images from the ISIC dataset (Codella et al., 2017). Our model of game theory has the highest score with AUC = 0.93, the color descriptor holds the second-best score with the AUC value = 0.74, the asymmetry and the border parameter come next with the area under the curve 0.67 and 0.60 respectively, the diameter descriptor is last with AUC = 0.53. We find that the proposed approach has given

an excellent rating despite the fact that other descriptors have not performed well, which proves the performance of the proposed approach.

4.3 Comparison of the Game Theory Modeling with Some Classifiers

In this section, the proposed classification scheme based on zero-sum game theory modeling has been confronted with four different classification systems using the ABCD rule namely: Adaboost, KNN, Bayes, and Random trees, testing on PH2 database (Mendonc et al., 2013). The results of the classifiers are provided from the works in (Pennisi et al., 2016) adopting the implementation provided by Weka (Witten et al., 2005). The ROC curves along with the index AUC are used to illustrate this comparison. The results are presented in figure 5.We remark that the false-positive rate of our approach is minimal compared to the other classifiers, so our game model holds the maximum score with AUC = 0.94.

We can conclude that our method has proven effective when compared with some interesting classifiers. The proposed utility function allows to our system to reduce significantly the false positive rate (the benign skin lesion detected melanoma).

4.4 Comparison of the Proposed Approach with State of Art Methods

Finally, we present comparative results of the proposed approach with recent state of art methods tested on PH2 database. The comparison is performed using three most used metrics: accuracy, sensitivity, specificity. Table 1 summarizes the obtained results.

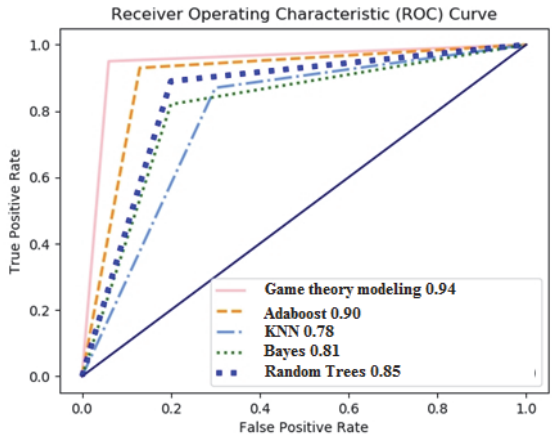

Figure 5: Comparison of the proposed method to some classifiers in PH2 dataset.

We can see that the results of our approach are better than benchmarking results in terms of two metrics among the three selected of the PH2 dataset. Furthermore our algorithm is second ranked in sensitivity rate. The benchmarking results are provided on the official website (Mendonc et al., 2013) of the PH2 dataset. This confirms that the performance of the proposed zero-sum game is undeniable.

Table 1: Comparative results.

Methods	Accuracy	sensitivity	specificity
Moradi and Amiri 2019	93.50	**100**	91.81
Sadri et al. 2017	91.82	92.61	91
Gu et al.,2017	-	94,43	81.01
Bi et al 2016	92	87.5	93.13
Kruk et al.2015	89.5	95	88.125
Our approach	**94.5**	95	**94.375**

5 CONCLUSION

We present in this paper a melanoma detection system based on zero-sum game theory modeling. The proposed system has ability to cope with subjective evaluation of the different aspects of a skin lesion and to select the appropriate characteristics for each suspect lesion. This selection is performed using an interaction between melanoma and non-melanoma agents where the set of formulas involved in the computation of the features: Asymmetry, Border, Color and diameter (ABCD) provide the pure strategies of the game.

The utility function developed in our approach is able to reduce significantly the false positive rate and to maintain a good accuracy performance.

When tested on PH2 database (Mendonc et al., 2013), the proposed algorithm was best ranked in terms of two metrics among the three selected compared with five recent states-of- art works

REFERENCES

Achanta, R. Shaji, A. Smith, K. Lucchi, A. Fua, P. Süsstrunk, S., 2012. SLIC superpixels compared to state-of-the-art superpixel methods. *IEEE transactions on pattern analysis and machine intelligence. 34 (11) pp-2274-2282.*

Andreassi L., Perotti R., Rubegni P., Burroni M., Cevenini G., Biagioli M., Taddeucci P., Dell'Eva G., Barbini P., 1999. Digital dermoscopy analysis for the differentiation of atypical nevi and early melanoma. *Archives of Dermatology.135, 1459-1465.*

Argenziano, G., Fabbrocini, G., Carli, P., De Giorgi, V., Sammarco, E., Delfino, M., 1998. Epiluminescence

microscopy for the diagnosis of doubtful melanocytic skin lesions. comparison of the ABCD rule of dermatoscopy and a new 7-point checklist based on pattern analysis. *Arch.Dermatol. 134, 1563–1570*.

Bi L., Kim J., Ahn E., Feng D., Fulham M, 2016. Automatic melanoma detection via multiscale lesion-based representation and joint reverse classification. *13th International Symposium on Biomedical Imaging (ISBI).*

Binder, M., Schwarz, M., Winkler, A., Steiner, A., Kaider, A., Wolff, K., and Pehamberger, H., 1995. Epiluminescence Microscopy. A Useful Tool for the Diagnosis of Pigmented Skin Lesionfor Formally Trained Dermatologists. *Archives of Dermatology, vol. 131, no. 3, pp. 286-291.*

Codella, N.C.F., Gutman, D., Celebi, M.E., Helba, B., Marchetti, M.A., Dusza, S.W., Kalloo,A., Liopyris, K., Mishra, N., Kittler, H., Halpern, A., 2017. Skin Lesion Analysis Toward Melanoma Detection: A Challenge. *The 2017 International Symposium on Biomedical imaging (ISBI), Hosted by the International Skin Imaging Collaboration (ISIC). 1-5.*

Doi, K., 2005. Current status and future potential of computer-aided diagnosis in medical imaging. *The British journal of radiology, 78 Spec No 1:S3-S19.*

Gu, Y., Jun Z., Bin Q., 2017. Melanoma Detection Based on Mahalanobis Distance Learning and Con-strained Graph Regularized Nonnegative Matrix Factorization. *IEEE Winter Conference on Applications of Computer Vision (WACV), 797-805. Santa Rosa, CA, USA.*

Kruk, M., Świderski, B., Osowski, S., Kurek, J., Słowińska, M., Walecka, I., 2015. Melanoma Recognition Using Extended Set of Descriptors and Classifiers. *EURASIP Journal on Image and Video Processing (43) 2-10.*

Ma. Z., Tavares, J. M., 2017. Effective features to classify skin lesions in dermoscopic images. *Expert Syst. Appl. 84: 92-101.*

Mendonc, T., Ferreira, P.M., Marques, J. S., 2013. PH2, A dermoscopic image database for research and benchmarking. *In Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 5437–5440.*

Menzies, S., Ingvar, C., Crotty, K., McCarthy, W. H., 1996. Frequency and morphologic characteristics of invasive melanomas lacking specific surface microscopic features. *Arch. Dermatol. 132,1178–1182*.

Moradi, N., Mahdavi-Amiri, N., 2019. Kernel sparse representation based model for skin lesions segmentation and classification. *Computer Methods and Programs in Biomedicine (182).*

Nisan, N., Roughgarden., T., Tardos, E. Vazirani, V. V., 2007. Algorithmic game theory in Cambridge press.

Otsu, N., 1979. A Threshold Selection Method from Gray-Level Histograms. *IEEE Transactions on Systems, Man, and Cybernetics 9(1) 62-66*.

Pennisi, A., Bloisi, D., Nardi, D., et al., 2016. Skin Lesion Image Segmentation Using Delaunay Triangulation for Melanoma Detection. *Computerized Medical Imaging and Graphics 52: 89-103.*

Sadri A. R, et al., 2017. WN-based approach to melanoma diagnosis from dermoscopy images. *IET Image Process; 11(7): 475–82.*

She, Z., Liu, Y., Damatoa, A., 2007. Combination of features from skin pattern and ABCD analysis for lesion classification. *Skin Research & Technology, 13(1), 25–33.*

Stoecker, W., Weiling, V., Li, W. and Moss, R., 1992. Automatic detection of asymmetry in skin tumors. *Computerized Medical Imaging and Graphics, 16, 191–197.*

Stolz, W., Riemann, A., Cognetta, A. B., 1994. ABCD rule of dermatoscopy: a new practical method for early recognition of malignant melanoma. *Eur. J. Dermatol. 4, 521–527.*

Roma, P., Savarese, I., Martino, A., Martino, D., Annese, P., Capoluongo, P., 2007. Slow-growing melanoma: report of five cases. *Journal of Dermatological Case Reports 1(1): 1-3.*

Von Neumann, J., 1928. Zur Theories der Gesellschaftsspiele. *Math. Ann., 100, 295–320.*

Wighton, P., Lee, T.K., Lui, H., McLean, D.I., Atkins, M.S., 2011. Generalizing common tasks in automated skin lesion diagnosis. *IEEE Trans Inf Technol Biomed 15 (4), 622–629.*

Witten, I.H., Frank, E., 2005. *Data mining: practical machine learning tools and techniques*, 2nd ed. Morgan Kaufmann.