Skin lesion segmentation and classification based on an improved multi-scale approach

Y. Filali, A. Ennouni, M. A. Sabri, and A. Aarab

***Abstract*—**Skin cancer is one of the most common types of cancer; its incidences have reached epidemic proportions and causes many deaths. Skin cancer can be categorized into three main types; Actinic Keratoses, Basal Cell Carcinoma, and Melanoma. The Melanoma skin cancer is the most aggressive and the deadliest form of skin cancer compared to the others. Early Melanoma detection and diagnosis often allows for more treatment options and can decrease the number of deaths significantly. Many researchers proposed to use image processing for skin lesion detection. The process can be divided into three main stages: lesion identification based on image segmentation, features extraction, and lesion classification. Segmentation and features extraction are the key-steps and significantly influence the outcome of the classification results. In this paper, a new approach for automatic segmentation and classification for skin lesion will be proposed. The proposed approach consists of a preprocess based on a Multi-scale decomposition that is separating the input image into two components. The geometrical component will be used in the segmentation stage and the texture component in the features extraction, also the asymmetry and color of the lesion are extracted to improve the accuracy of our approach. The classification will be performed using the Support Vector Machine (SVM) classifier. The efficiency and the performance of the proposed approach has been evaluated in comparison with recent and robust dermoscopic approaches from literature.

***Keywords*—**Skin cancer, PDE Multi-scale decomposition, Texture analysis, Features extraction, SVM.

I. Introduction

Computational analysis of skin lesion images are considered a wide area of study due to its great role in skin cancer prevention, specifically in terms of getting an effective early diagnosis. Such lesions, which can be classified mainly as benign or malignant, begin by an irregular production of melanocyte cells resulting from factors such as extravagant sun exposure. Melanocyte cells are responsible for the production of the melanin, which supplies the skin pigmentation. In the situation of malignant cells, i.e. melanoma, such cells separates easily and may invade other parts of the body. A growing number of deaths due to melanoma have been noticed globally, this type of malignant Fig.1 is deemed to be the most aggressive compared to other lesion types due to its high level of metastasis. Benign lesions show a more organized structure than malignant lesions. However, these skin lesions have been of global concern, since some types of nevi may become melanoma; in addition a melanoma may look like a seborrheic keratosis or a nevus in its initial state.

Due to the visual aspect of the skin lesions, various non-invasive imaging approaches have been used to help dermatologist in detecting and classifying skin lesions. Macroscopic images, commonly known as clinical images, are used in computational analysis of skin lesions. These images may be attained by a regular camera. However, their image conditions are frequently irregular; for instance, images vary based on the differences in illumination conditions or distances. Moreover, the images may have weak resolution, which is challenging when the images under study are so small. Another problem with clinical images is associated with the presence of artifacts, such as reflections like hair and skin lines that might distort adequate analysis of the imaged skin lesions.

Fig. 1. Examples of skin lesions

Many researchers proposed to use image processing for skin lesion detection. The process can be divided into three main stages: lesion identification based on image segmentation, features extraction, and lesion classification. Segmentation and features extraction are the key-steps to significantly influence the outcome of the classification results. Segmentation will help in extracting the region of interest (ROI) from the macroscopic image of the lesion under analysis. Skin images contain many types of artifacts therefore segmentation is a very hard task and needs some preprocessing. Efficient approaches for preprocessing are based on color space transformation, contrast enhancement, and artifact removal. This has been suggested for preprocessing to enhance the reliability of the next segmentation step. Features extraction is usually based on the way that dermatologists use in their clinical routine diagnosis. Dermatologists use the ABCD rules as a classification criteria based on the Asymmetry, Border, Color, and Diameter

Characteristics of the lesion under research [1], [2]. The Asymmetry criterion may be tested by separating the region of the lesion into two sub-regions by an axis of symmetry. In order to analyze the correspondence of the area by the two sub-regions should be overlapped along the axis. An Asymmetric lesion is associated with malignant lesions. The second criterion looks at Borders with a regular form being linked to benign lesions and Borders with an irregular form are linked to malignant lesions. The next criterion, Color, consists of analyzing the tonal variation of the pigmented skin lesion. Malignant lesions normally present non-uniform colors. The last criterion, the Diameter criterion is correlated with the size of the lesion. It is defined by the greatest distance between any two points of the lesion's border. A Diameter that is equal to or greater than 6 (six) millimeters may indicate it's malignancy. In features extraction, texture analysis may also be used for image-based examination of skin lesion, since it helps discriminate benign from malignant lesions by valuing the harshness of their structure. The last step is the lesion classification, which consists of recognizing and interpreting the information about the pigmented skin lesion based on their features.

The aim of this work is to promote a new computational approach based on the texture, the asymmetry and the color analysis for the identification and classification of pigmented skin lesions images and to supply dermatologists the help to make their diagnosis. In this approach, texture structure decomposition is applied to reduce the noise present in the image under study. Then the k-means is used in the segmentation of the lesion in the preprocessed image. After the features of the lesion are extracted from the segmented image firstly using different texture features extraction: (Gray Level Co-Occurrence Matrix, the Gabor filter, Histogram Of Oriented Gradient and the Local Binary Pattern), then the Asymmetry, and the color of the lesion are extracted. Finally, the features are employed as an input into a Support Vector Machine (SVM) classifier to classify the skin lesion.

The rest of the paper is organized as follows; Section I presents a review of the related studies used to classify the skin lesion. Section II gives a description of the proposed approach for the detection and classification of the skin lesion. The given results will be discussed in Section III. Section IV will explain the metric evaluations used, followed by the conclusion.

II. Related studies

To help dermatologist, Computer Aided Diagnosis (CAD) systems have been used for an early evaluation for skin cancer. It generally consists on three major steps: segmentation, features extraction, and classification. A filtering preprocessing step is always performed to increase the accuracy of the segmentation step. A Median filter is applied to smooth and remove artifacts. Also, it preserves the border and keeps pertinent information of the lesion [3][4]. Anisotropic Diffusion filter is better used to smooth the skin lesion and remove artifacts to get better results. A Morphological filter helps remove noise and may also be applied to improve segmentation and to encompass an area with a more regular border [5].

In image segmentation, many techniques are used to help in extracting the skin lesion. Thresholding algorithms have been used on a large scale [6],[7] due to their simplicity. For example, the Otsu algorithm, which easily separates the regions of interests (ROIs) of an image. Indeed, these techniques might unveil some real problems; as the segmented lesion is normally smaller than its regular size and this process is only effective on regular borders. Algorithms based on active contour models have been continuously suggested for segmentation of skin lesion in images where the initial curves are being moved to the object of interest through convenient deformation [7][8][9]. Region based algorithms have also been widely used to segment skin lesion images. For example, regions growing, splitting, and merging. This consists on organizing the similar pixels, or sub-regions, into larger identical regions, according to an increasing criterion. These methods have confirmed successful performance even under complex conditions such as variations in illumination and color, but remains insufficient when dealing with regions that have low contrast of the skin background. There are many algorithms based on artificial intelligence [10], which are justified by the advantages that they offer. One advantage that they offer is the possibility to learn from the sample case provided by the artificial neural networks[11]or the deep neuronal network[12]. Other segmentation algorithms arise from the search and optimization, such as the genetic algorithms. In addition, Fuzzy logic [13] joined with clustering techniques have been applied in image segmentation of skin lesion such as the Fuzzy C-Means(FCM) and K-means algorithms[14]. Yet, some disadvantages might occur by algorithms based on Artificial Intelligence concerning the complexity of the implementation and the presence of many steps, which demands high computational efforts.

In the features extraction step, based on the identification of the regions of interest (ROIs) in the image, scholars[1] have proposed the use of the approaches that are similarly used by dermatologists. ABCD (Asymmetry, Border, Color and Diameter) characteristics and the Gray Level Co-Occurrence Matrix (GLCM) approaches are the most commonly used[15]. For the process of classification, more than one method has been evaluated to attain the best outcome[16]. The performance depends on several issues like the quality of the segmentation images, the extracted features, and the classification algorithms. Therefore, the output may either be binary class or multi-class [17].

III. The proposed approach

In this part, a multi-scale approach is presented to classify the pigmented skin lesions and provide a method that should help dermatologists in their diagnosis. Fig. 2 explains this given approach, which involves the following steps:

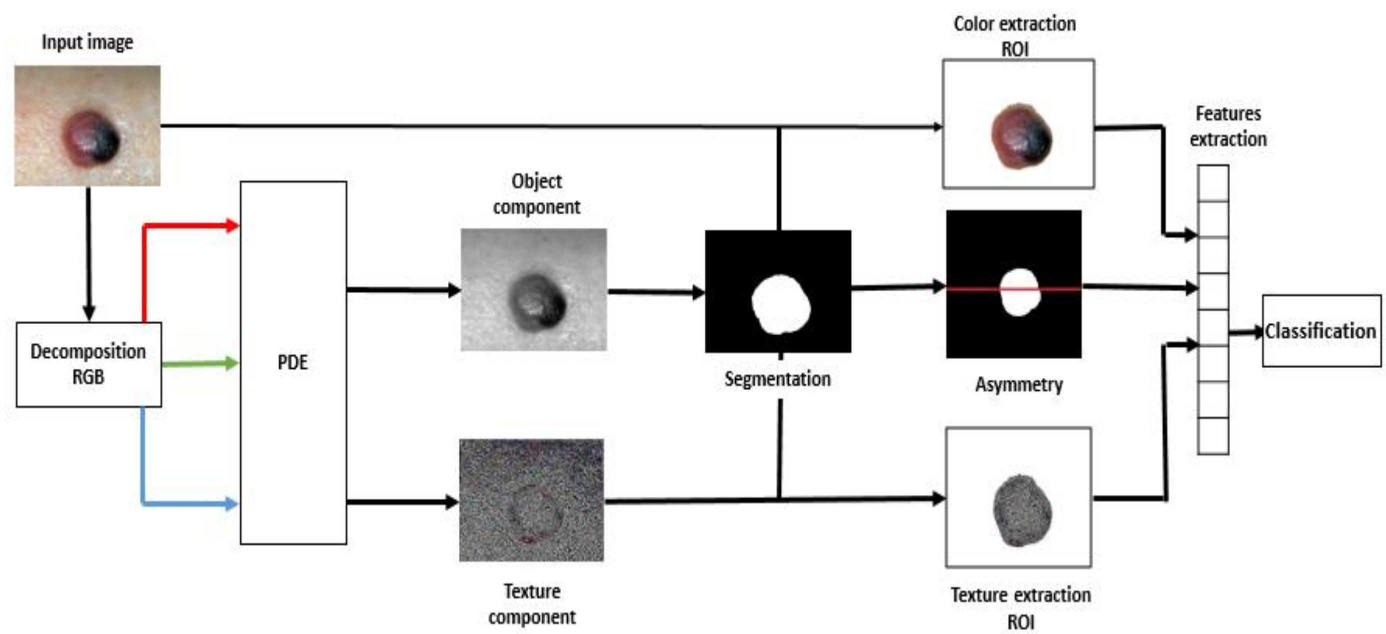

Fig. 2. The proposed approach for the detection of pigmented skin lesion

1) Image preprocessing: Each RGB canal of the input image will be decomposed separately into texture and object components using the adopted multi-scale decomposition.
2) Image segmentation: The segmentation is performed only on the object components. The extracted ROI will be used to identify its paired region from the texture component.
3) Features extraction: The features are extracted from the texture, the color, and asymmetry of the skin lesion region.
4) Classification.

A. Multi-scale decomposition models

The presence of the texture in skin cancer images is the major problem encountered for segmentation and consequently for lesion classification. A poor segmentation involves incorrect identification of the lesion and will negatively influence its classification results. The idea proposed is to use a multi-scale decomposition model to separately extract the texture and the object into components and then to process each of them individually. The segmentation is performed only on the object component and not the texture component. Instead, the textural features will be extracted from the texture component. The preprocessing based on the multi-scale decomposition is able to remove the artifacts (contrast, hairs, blood vessels, skin lines) and facilitate the border detection.

In order to make perplexed image and vision problems resolved, Partial Differential Equations (PDE) can be used. The most common PDE is the ROF model. The objective is to separate the image into two components u and v where the first component, u, is well structured and has the whole geometric information of the image and the second component, v, contains oscillating information such as textures and possible noise[18].

Several decomposition models have been proposed to solve the problem of Meyer [19]. In our work, we are only

concerned with the Aujol model.

$$F_{\lambda,\mu}(\mu, v, w) = J(\mu) + J*\left(\frac{v}{\mu_1}\right) + J*\left(\frac{w}{\mu_2}\right) + \frac{1}{2\lambda}\|f - \mu - v_1 v - v_2 w\|_{L_2}^2 \quad (1)$$

This decomposition is given by minimizing a functional f

where ν1 and ν2 are two functions in R2→] 0; 1] generalizing the idea of adaptive regularization coefficient according to the image area in which there is. The functions v and u can be seen both as oscillators, taken respectively in Gμ1 and Gμ2. The function u will be taken in the BV space.

B. Segmentation

Several segmentation approaches can used in this part. However, and since the segmentation is performed on the object component which not contains any texture, a simplest segmentation algorithm can gives a good results. The K-means algorithm is adopted here based on our previous works [14][20].

K-means is an unsupervised clustering algorithm introduces by Mac Queen first. This algorithm is based on the classification of input data into k groups or clusters where the value of k is fixed a priori to affect a randomly initialized centroid for each cluster. The algorithm is divided into two steps; the centroids are initialized in the first one and placed far away from each other and the second step where each point of the data set is associated to the nearest center. The centers move each time and the second step is repeated until convergence. Finally, this algorithm aims to minimize a squared error function defined as follows:

$$J(U, C) = \sum i \sum k \| x_i - c_k \|^2 \quad (2)$$

Where ‖x_i-c_k‖^2 is the distance of the n data points from their respective cluster center.

The K-means algorithm is as follows:

1) Initialization of centroid groups: Place K points into the space represented by the objects that are being clustered.
2) Calculate the distance between the object and the center for each cluster and assign the object to the closet (minimum distance) group.
3) Iterate for all the object and recalculate the positions of the K centroids.
4) Repeat Steps 2 and 3 until the minimized can be calculated.

K-Means is appropriate for skin image segmentation, especially for lesion detection, as the number of clusters k is usually known [14].

C. Features extraction

Features extraction are the key of a successful classification system. It consists in extracting pertinent information able to describe effectively the lesion that can be used to classify correctly it, as melanoma or not. The features used in literature are especially based on the ABCD (Asymmetry, Border, Color and Diameter) rules. In this paper, we will focus on texture features, color features and the Asymmetry criteria to classify the lesion.

C.1. Textural features

The most known texture descriptors are the Gray Level Co-Occurrence Matrix (GLCM), Gabor filter, Local Binary Pattern (LBP) and Histogram of Oriented Gradient (HOG). In this approach, we will compare the result of these different algorithms:

C.1.1. Gray Level Co-Occurrence Matrix

This Gray Level Co-Occurrence Matrix (GLCM) is used in our work in order to offer better extraction of textural features from the images. The co-occurrence matrices characterize the spatial distribution and the need of the grey levels within a limited surface. Under a predetermined angle and distance, the (I,j) entries of every matrix offer the possibility for it to be accepted from one pixel with a grey level of "i" to another level "j". Feature vectors, which are the result of these settings, are now considered and the matrix is created from both the orientation and the distance between the pixels of the image.

From [21], we note that Haralick offers fourteen different textural features, which were the result of calculating the probability matrix that extracts the characteristics of texture statistics from the remote sensing images. However, each essential statistic is bound to a different texture type. These texture types are: Energy, Contrast, Correlation, Homogeneity, and Entropy:

<u>Energy</u>: measures the texture disorder

$$E = \sum x, y \; p(x, y) \quad (3)$$

P (x, y) the normalized and symmetrical GLCM

<u>Contrast</u>: the key diagonal close the moment of inactivity, which amount the importance of the matrix is dispersed and images of limited variations in number, reflecting the image clearness and texture of shadow depth.

$$I = \sum\sum (x-y)2 \; p(x, y) \quad (4)$$

<u>Entropy</u>: produces a measure of randomness, having its highest value when the all elements equal.

$$S = -\sum x, y p(x, y) \log p(x, y) \quad (5)$$

<u>Correlation Coefficient</u>: Procedures the joint probability incidence of the identified pixel pairs.

$$C = \sum \left(\sum \left((x- \mu x)\,(y-\mu y)\; p\,(x, y) / \sigma x \sigma y \right) \right) \quad (6)$$

<u>Homogeneity</u>: Methods the nearness of the scattering of elements in the GLCM to the GLCM diagonal.

$$H = \sum \left(\sum \left(p\,(x, y) \,/\, (1 + [x-y]) \right) \right) \quad (7)$$

C.1.2. Gabor filter

Gabor filter have been applied in different and many areas of image processing such as edge detection, texture classification, fingerprint identification [22]. Gabor wavelets are used to extract texture features from images[23]; the idea is based on detecting linear directional elements.

Gabor filters can decompose the image into components corresponding to different scales and orientations. Gabor filters achieve optimal joint localization in spatial and spatial frequency domain. In the spatial domain, the Gabor function is a complex exponential, modulated by a Gaussian function. Its impulse response in the two-dimensional(2D) plane has the following general form dimensional(2D) plane has the following general form:

$$h(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left\{-0.5\left[\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right]\right\} \exp\{j2\pi Fx\} \quad (8)$$

Where F denotes the radial frequency of the Gabor function. The space constants σ_x and σ_y define the Gaussian envelope along the x- and y- axes. The Gabor filter with frequency F and orientation θ by coordinate rotation given by:

$$h'(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left\{-0.5\left[\frac{x'^2}{\sigma_x^2} + \frac{y'^2}{\sigma_y^2}\right]\right\} \exp\{j2\pi Fx'\} \quad (9)$$

C.1.3. Histogram of Oriented Gradient

The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection and features extraction. This technique counts occurrences of gradient orientation in localized portions of an image.

The idea of the histogram of oriented gradients descriptor is that local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions. The image is divided into small connected regions called cells, and for the pixels within each cell, a histogram of gradient directions is compiled. The descriptor is the concatenation of these histograms. For improved accuracy, the local histograms can be contrast-normalized by calculating a measure of the intensity across a larger region of the image, called a block, and then using this value to normalize all cells within the block. This normalization results in better invariance to changes in illumination and shadowing.

The HOG descriptor has a few key advantages over other descriptors. Since it operates on local cells, it is invariant to geometric and photometric transformations, except for object orientation. Such changes would only appear in larger spatial regions.

C.1.4. Local binary patterns

Local binary patterns (LBP) is a type of visual descriptor used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990. LBP was first described in 1994. It has since been found to be a powerful feature for texture classification.

The LBP feature vector is created in the following manner:

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors.
- Where the center pixel's value is greater than the neighbor's value, we put "0". Otherwise, we put "1".
- Compute the histogram over this cell then normalize the histogram.

C.2. Color features

In order to calculate the color that the lesion contains, according the literature the melanoma are described by the presence of six different colors that are, white, red, light brown, dark brown, blue-gray and black.

$$\text{Black} = \sum (R<0.2 \ \& \ G<0.2 \ \& \ B<0.2)>0) *100/NB \tag{10}$$

$$\text{Red} = \sum (R>.8 \ \& \ G<.2 \ \& \ B<.2)>0) *100/NB \tag{11}$$

$$\text{Blue gray} = \sum (R<.2 \ \& \ G>0.32 \ \& \ G<0.72 \ \& \ B>.34 \ \& \ B<.74)>0) *100/NB \tag{12}$$

$$\text{White} = \sum (R>0.8 \ \& \ G>0.8 \ \& \ B>0.8)>0) *100/NB \tag{13}$$

$$\text{Light brown} = \sum (R>0.6 \ \& \ R<1 \ \& \ G>0.32 \ \& \ G<0.72 \ \& \ B>0.05 \ \& B<0.45)>0) *100/NB \tag{14}$$

$$\text{Dark brown} = \sum (R>.2 \ \&R<.6 \ \&G>0.06 \ \&G<0.46 \ \& \ B>0 \ \& \ B<.33)>0) *100/NB \tag{15}$$

With NB is the number of pixel, R is the red, G is green and B is blue component in the RGB representation. We add all the color to have the number of color that contain the image.

C.3. Asymmetry features

The asymmetry criterion can be tested by separating the regions of the lesion into two sub-regions by an axis of symmetry. In order to analyze the correspondence of the area, the two sub-regions must be folded over each other along the axis. If there is any part of either sub-region not overlapped, then the lesion is considered asymmetrical. Asymmetry in a lesion is the most important indicator of malignancy.

The axis of symmetry, otherwise known as the major axis, is found by identifying the center of the lesion, the two foci, and the longest diameter. The line must cross the center and the two foci and it must end at the widest points of the perimeter in order to be identified as the major axis. Finally, we rotate the major axis to be parallel to the horizontal axis.

D.Classification

After building the set of features, the next step is to classify the lesion based on the extracted features. The classification process occurs by randomly dividing the available image samples into training and test sets. The training set consists of developing a classification model based on the training samples, which are the input data to the classifier for the learning process and the test set is to evaluate the classification accuracy.

Several algorithms can be used for classification and accuracy is essentially based on the features relevance. In this work, the choice of the classification tool in not a big deal and will not influence significantly on the classification results. The Support Vector Machine (SVM) [23] is the most used classifier in literature for lesion skin classification.

Classification with SVM is an example of Supervised Learning, he look for finding the optimal separating hyper plane between classes, by opting the hyper plane with the maximal margin. To verify whether the system is performing in a right way or not is shown the help of the known labels. This information points to a desired response, validating the accuracy of the system, or be used to help the system learn to act correctly.

IV. Experimentation

In this part, the given results of segmentation and classification were depicted and discussed. The images-set used to evaluate the proposed approach is "Atlas Dermoscopy" [27]. It contains 80 images of pigmented skin lesion manually segmented into Ground of Truth (GT) and classified into melanoma and not melanoma by dermatologists. In Fig. 3 and Fig. 4, an example of images form database is presented:

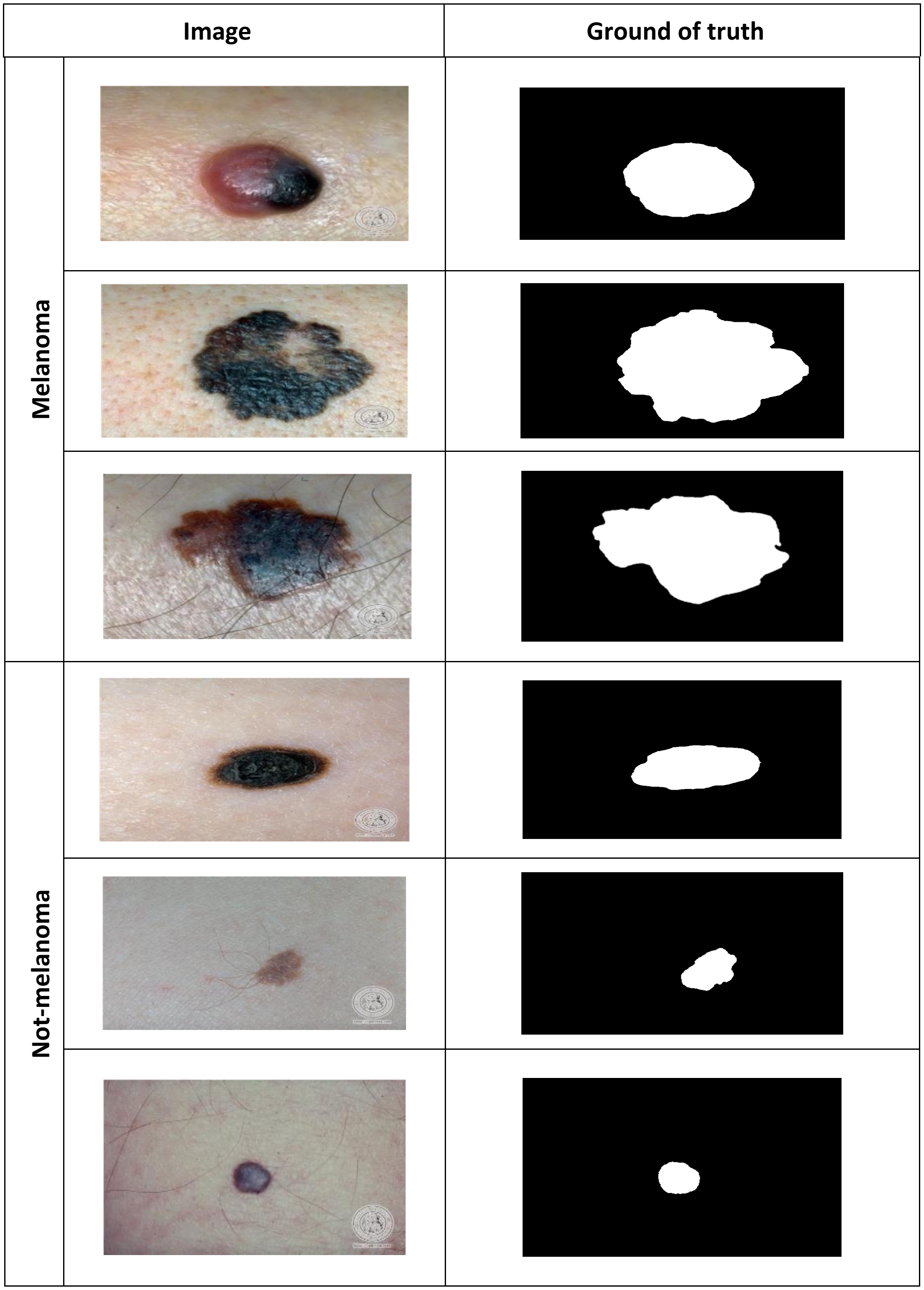

Fig. 3. Example of images from Atlas Dermoscopy dataset

The experimentation will be conducted in three steps:

1) Segmentation evaluation using our proposed preprocessing decomposition in comparison with the segmented GT.
2) Features extraction comparison between Gray Level Co-Occurrence Matrix (GLCM) and Gabor filter Local Binary Pattern (LBP) and Histogram of Oriented Gradient (HOG), and then concatenated with features of color and the Asymmetry that contain the lesion.
3) Lesion classification accuracy of the proposed approach in comparison with known approaches form literature.

A. Preprocessing

In order to remove noise and artifact form the lesions, the decomposition using Aujol Model is conducted on each of the RGB canals. Therefore, every canal is decomposed separately into two components; texture and object Fig.4. The texture and object components of the input image is the concatenation of the three components for each canal.

The segmentation is performed on only the object component that contains only object shape without any texture or noise. Sensitivity (TP rate) and Specificity (TN rate) measures are used to evaluate the decomposition results in regards on the GT.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{16}$$

$$\text{Specificity} = \frac{TN}{FP + TN} \tag{17}$$

Where: TP is the number of true positives,
TN is the number of true negatives,
FP is the number of false positives
FN is the number of false negatives

In Fig.4 presents respectively the segmentation results of an image selected randomly from the database without and with preprocessing by the Aujol model.

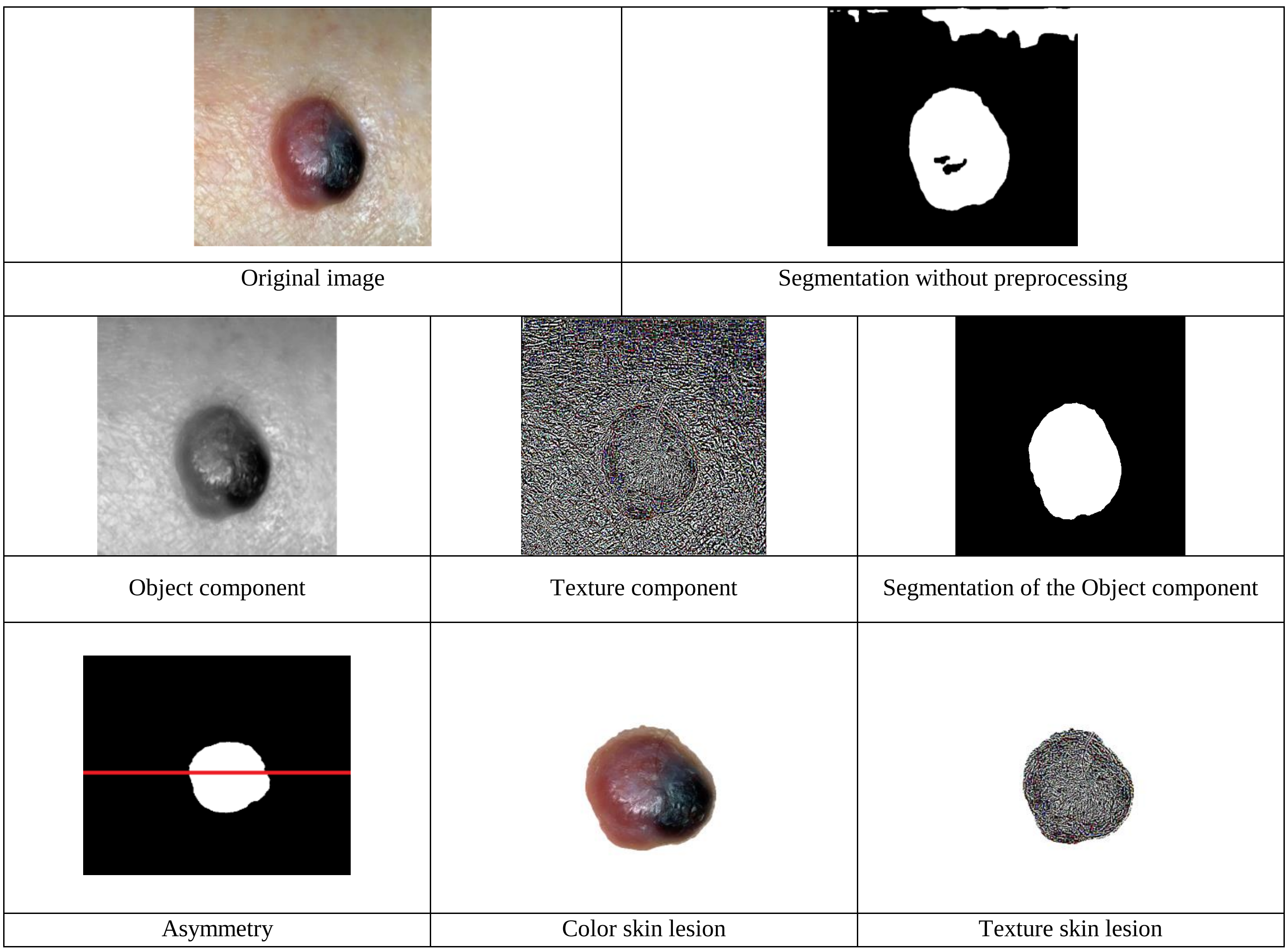

Fig. 4. Segmentation result using with and without preprocessing via the Aujol decomposition

For the segmentation evaluation, Table 1 presents the result of the Sensitivity and Specificity of the proposed approach. The ground truth (GT) for each case-study is used to estimate the TP, TN, FP and FN used to calculate the Sensitivity and Specificity.

Table.1 Evaluation of the segmentation result in term of sensitivity and specificity

	Without Aujol decomposition	**With Aujol decomposition**
Sensitivity	83.33	93.00
Specificity	80.00	95.00

Another comparison is conducted to evaluate the best segmentation approach to use. In TABLE 2 we present the sensitivity and the specificity of the segmentation using K-Means, Otsu, Fuzzy C-Means, Region merge and Expectation-Maximization [3][7] [10][13][24][25].

From results in Fig. 4, TABLE 1 and TABLE 2 we can conclude that the use of the Aujol decomposition as a preprocessing step improve significantly the segmentation result and the choice of k-Means is justified.

B. Classification

Features extraction is the key of the success of a classification method. The issue with lesion image classification is that the segmentation does not identify correctly the lesion region and the features extracted are not very pertinent. The decomposition of the original image by Aujol gives us the opportunity to segment only the objects without textures. That is why the performance of the segmentation presented in the last section was very convincing.

Once we have the segmented region, we will project it on the texture component to create powerful features. The features used will be based on textural, asymmetry and color information extracted from the lesion. The Gray Level Co-Occurrence Matrix (GLCM), Gabor filter, Histograme of Oritented Gradient (HOG) and Local Binary Patern (LBP) was presented as most used for textural features extraction. As we say before, the most important task is the extraction of features and the SVM will be used to evaluate the classification rate. The classification measure used in this paper is the Accuracy

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}$$

A first study was conducted to the best features obtained for different scale and orientation for Gabor filter. In Fig.5 we present the classification accuracy using Gabor features for different number of scales and directions and we can conclude that the best features can be obtained for a scale and orientation values equals to 3 and 8 respectively.

The best accuracy is got by the gabor filter, so just textural features are not very satisfactory. In the next step, we will use. the color features that contain the lesion and the asymmetry of the lesion, then we compare the result with literature.

In order to identify asymmetry in a lesion, we take the major axis and we rotate the image so this axis is parallel to the horizontal axis as we see indicated by the red line in fig.4.

Then, we separate the two sub-regions and we fold them along this axis. If the two sub-regions are aligned perfectly then they considered are symmetric, whereas if there is some or a lot of overlap then the lesion is considered asymmetric. In our approach, we have a feature that determines the excess number of pixels that are not overlapped in asymmetrical lesions.

As for the colors, we have a feature that contains values of the six possible colors and another feature that states which of the six are present. We combine the color feature with the asymmetry feature with the texture feature.

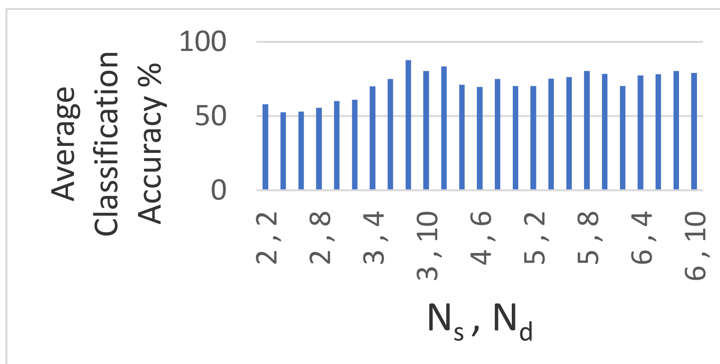

Fig. 5. SVM Classification accuracy, using Gabor features , for different number of scales and directions

Table. 2 Average results using different segmentation algorithms in term of sensitivity and specificity

	Expectation-Maximization	*Otsu*	*Fuzzy C-means*	*Region merge*	*K-Means*
Sensitivity	*90.00*	*93.33*	*90.00*	*93.33*	*96.67*
Specificity	*85.00*	*95.00*	*90.00*	*90.00*	*95.00*

Table. 3 SVM Classification accuracy using different features extraction

	Gray Level Co-Occurrence Matrix	*Gabor filter*	*Histogram of Oriented Gradient*	*Local Binary Pattern*
Accuracy	*80.00*	*83.00*	*80.23*	*81.23*

The best accurancy is got by the gabor filter, so just textural features are not very satisfactory. In the next step, we will use. the color features that contain the lesion and the asymmetry of the lesion, then we compare the result with literature.

In order to identify asymmetry in a lesion, we take the major axis and we rotate the image so this axis is parallel to the horizontal axis as we see indicated by the red line in fig.4. Then, we separate the two sub-regions and we fold them along this axis. If the two sub-regions are aligned perfectly then they considered are symmetric, whereas if there is some or a lot of overlap then the lesion is considered asymmetric. In our approach, we have a feature that determines the excess number of pixels that are not overlapped in asymmetrical lesions.

As for the colors, we have a feature that contains values of the six possible colors and another feature that states which of the six are present. We combine the color feature with the asymmetry feature with the texture feature.

Table.4 SVM Classification accuracy using Gabor filter asymmetry and color features

	R.Amelard [26]	***Alin M. Solomon*** [27]	***Ebtihal Almansour*** [28]	***B.Gohila vani [23]***	***Proposed approach***
Accuracy	*81.17*	*90.00*	*90.32*	*98.70*	*98.80*

From Table 4, R.Amelard [26] proposed the High-Level Intuitive Features that were designed to model the ABCD criteria. In his model each HLIF represents a human-observable characteristic. Alin M. Solomon [27] used Gray Level Co-Occurrence Matrix (GLCM) and color as a features extraction. Almansour[28] similarly used color and texture. The difference in his method to extract texture features was that he used Local Binary Patern (LBP) in addition to Gray Level Co-Occurrence Matrix (GLCM). In contrast, B. Gohila[23] used only Gray Level Co-Occurrence Matrix (GLCM) as a features extraction and instead used PNN as classifiers. From Table 4, we can clearly see the importance of using the Partiel Differential Equation in the preprocess. Also, we can see the necessity of using the Gabor filter, color, and asymmetry in the features extraction. In comparison to the other approaches, our approach has the highest accuracy percent with 98.80%. This shows the effectiveness of our proposed approach.

V. Conclusion

Many solutions in image processing and analysis have been proposed for skin lesion, to help dermatologists in their diagnosis. Our main contribution is to improve the segmentation processing and to increase the accuracy of pigmented skin lesion classification. This approach is based on the model decomposition for structure and texture identification, k-means for segmentation, Gabor filter, asymmetry and color for features extraction and SVM as a classifier. The proposed approach was implemented and tested on medical images and achieved good segmentation results as well as good classification accuracy.

As future work, concerning the segmentation and classification of skin lesion, we intend to use new algorithms and methods to develop more our systems of a higher quality diagnosis on dermatology images.

References

[1] D. N. L. Correa, L. R. B. Paniagua, J. L. V. Noguera, D. P. Pinto-Roa and L. A. S. Toledo, "Computerized Diagnosis of Melanocytic Lesions Based on the ABCD Method," 2015 Latin American Computing Conference (CLEI), Arequipa, 2015, pp. 1-12.

[2] S. Jain, V. Jagtap, and N. Pise, “Computer aided melanoma skin cancer detection using image processing,” Procedia Comput. Sci., International Conference on Computer, Communication and Convergence (ICCC 2015), vol. 48, no. C, pp. 736–741, 2015.

[3] K. Norton, H. Iyatomi, M. E. Celebi, G. Schaefer, M. Tanaka, and K. Ogawa, “Development of a Novel Border Detection Method for Melanocytic and Non-Melanocytic Dermoscopy Images,”. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society pp. 5403–5406, 2010.

[4] Abbas, Qaisar et al. “A perceptually oriented method for contrast enhancement and segmentation of dermoscopy images.” Skin research and technology : official journal of International Society for Bioengineering and the Skin (ISBS) [and] International Society for Digital Imaging of Skin (ISDIS) [and] International Society for Skin Imaging 19 1 (2013): e490-7.

[5] Celebi ME, Aslandogan YA, Stoecker WV, Iyatomi H, Oka H, Chen X. Unsupervised border detection in dermoscopy images. Skin research and technology : official journal of International Society for Bioengineering and the Skin (ISBS) [and] International Society for Digital Imaging of Skin (ISDIS) [and] International Society for Skin Imaging (ISSI). 2007;13(4):454-462. doi:10.1111/j.1600-0846.2007.00251.x.

[6] R. Garnavi, M. Aldeen, M. E. Celebi, A. Bhuiyan, C. Dolianitis, and G. Varigos, “Automatic Segmentation of Dermoscopy Images Using Histogram Thresholding on Optimal Color Channels,” Int. J. Med. Med. Sci., pp. 126–134, 2010.

[7] R. Garnavi, M. Aldeen, M. E. Celebi, G. Varigos, S. Finch, A. Bhuiyan, and C. Dolianitis, "Automatic segmentation of dermoscopy images using histogram thresholding on optimal color channels," Conputerized Med. Imaging Graph., vol. 35, no. January, pp. 105–115, 2011.
[8] A. Chopra and B. R. Dandu, "Image Segmentation Using Active Contour Model," Int. J. Comput. Eng. Res., vol. 2, no. 3, pp. 819–822, 2012.
[9] H. Zhou, G. Schaefer, M. Celebi, H. Iyatomi, K.-A. Norton, T. Liu, and F. Lin, "Skin lesion segmentation using an improved snake model.," Conf. Proc. IEEE Eng. Med. Biol. Soc., vol. 2010, no. 1, pp. 1974–7, 2010.
[10] S. N. Deepa and B. Aruna Devi, "A survey on artificial intelligence approaches for medical image classification," Indian J. Sci. Technol., vol. 4, no. 11, pp. 1583–1595, 2011.
[11] S. Mathew and D. Sathyakala, "Segmentation of skin lesions and classification by neural network," International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE) Volume 4, Issue 2, February 2015.
[12] J. Ko, S. M. Swetter, H. M. Blau, A. Esteva, B. Kuprel, R. A. Novoa, and S. Thrun, "with deep neural networks," Nature, pp. 1–11, 2017.
[13] A. A. I. Mohamed, M. M. Ali, K. Nusrat, J. Rahebi, and A. Sayiner, "Melanoma Skin Cancer Segmentation with Image Region Growing Based on Fuzzy Clustering Mean," International Journal of Engineering Innovations and Research , vol. 6, no. 2, pp. 91–95, 2017.
[14] M. A. Sabri, A. Ennouni, and A. Aarab, "Automatic estimation of clusters number for K-means," 2016 4th IEEE International Colloquium on Information Science and Technology (CiSt). Pages: 450 - 454, DOI: 10.1109/CIST.2016.7805089. Electronic ISSN: 2327-1884. 24-26 Oct. 2016
[15] P. Mohanaiah, P. Sathyanarayana, and L. Gurukumar, "Image Texture Feature Extraction Using GLCM Approach, International Journal of Scientific and Research Publications, Volume 3, Issue 5, May 2013 1 ISSN 2250-3153".
[16] Z. Waheed, "An Efficient Machine Learning Approach for the Detection of Melanoma using Dermoscopic Images," pp. 316–319, 2017.
[17] M. E. Celebi, H. A. Kingravi, B. Uddin, H. Iyatomi, Y. A. Aslandogan, W. V. Stoecker, and R. H. Moss, "A methodological approach to the classification of dermoscopy images," Comput. Med. Imaging Graph., vol. 31, no. 6, pp. 362–373, 2007.
[18] L. I. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," Phys. D Nonlinear Phenom., vol. 60, no. 1–4, pp. 259–268, 1992.
[19] J. F. Aujol, G. Aubert, L. Blanc-Féraud, and A. Chambolle, "Image decomposition into a bounded variation component and an oscillating component," J. Math. Imaging Vis., vol. 22, no. 1, pp. 71–88, 2005.
[20] Y. Filali, A. Ennouni, and M. A. Sabri, "Multiscale approach for skin lesion analysis and classification," International Conference on Advanced Technologies for Signal and Image Processing (ATSIP). ISBN: 978-1-5386-0551-6. DOI: 10.1109/ATSIP.2017.8075545. 22-24 May 2017. Fez, Morocco.
[21] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural Features for Image Classification," 1973.
[22] [22] U. T. a. Rahman, "Gabor filters and gray level co occurrence matrices in texture classification," Citeseer, 2007.
[23] L. Ruiz, a Fdez-Sarría, and J. Recio, "Texture feature extraction for classification of remote sensing data using wavelet decomposition: a comparative study," Int. Arch. Photogramm. Remote Sens., vol. XXXV, no. 1, pp. 1682–1750, 2004.
[24] A. Marghoob, R. Braun, and A. Kopf, "Interactive CD-ROM of Dermoscopy". London, U.K.: Informa Healthcare; 2007.
[25] K. Sirinukunwattana, S. Raza, Y. Tsang, D. Snead, I. Cree, and N. Rajpoot, "Locality Sensitive Deep Learning for Detection and Classification of Nuclei in Routine Colon Cancer Histology Images," IEEE Trans. Med. Imaging, vol. 62, no. February, pp. 1–1, 2016.
[26] D. A. L and M. I. M, "k -Means Clustering and Ensemble of Regressions : An Algorithm for the ISIC 2017 Skin Lesion Segmentation Challenge," pp. 1–5, 2017.
[27] R. Amelard, S. Member, J. Glaister, S. Member, A. Wong, D. A. Clausi, and S. Member, "High-Level Intuitive Features (HLIFs) for Intuitive Skin Lesion Description," vol. 62, no. 3, pp. 820–831, 2015.
[28] A. M. Solomon, A. Murali, R. B. Sruthi, M. K. Sreekavya, S. Sasidharan, and L. Thomas, "Identification of Skin Cancer based on Colour , Subregion and Texture," vol. 6, no. 7, pp. 8331–8334, 2016.
[29] E. Almansour and M. A. Jaffar, "Classification of Dermoscopic Skin Cancer Images Using Color and Hybrid Texture Features," vol. 16, no. 4, pp. 135–139, 2016.

Yousef FILALI 13 March 1992 in fez, received his Master's degree from faculty of Sciences Ben M'Sik Casablanca Morocco in 2015. He is pursuing his PhD. degree in Faculty of Sciences Dhar-Mahraz, Sidi Mohamed Ben Abdellah University in LIIAN Laboratory. His doctoral study focused on machine learning and deep learning for medical image analysis.