Fusion of structural and textural features for melanoma recognition
Faouzi Adjed, Syed Jamal Safdar Gardezi, Fakhreddine Ababsa, Ibrahima Faye, Sarat Chandra Dass

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Abstract: Melanoma is one of the most increasing cancers since past decades. For accurate detection and classification, discriminative features are required to distinguish between benign and malignant cases. In this paper, we introduce a fusion of structural and textural features from two descriptors. The structural features are extracted from wavelet and curvelet transforms while the textural features are extracted from different variants of local binary pattern operator. The proposed method is implemented on 200 images from PH2 Dermoscopy database including 160 non melanoma and 40 melanoma images where a rigorous statistical analysis for the database is performed. Using SVM classifier with random sampling cross validation method between the three cases of skin lesions given in the database, the validated results showed a very encouraging performance with a sensitivity of 78.93%, a specificity of 93.25% and an accuracy of 86.07%. The proposed approach outperforms the existing methods on the PH2 database.

1 Introduction

Melanoma is amongst one of the most dangerous cancers. An estimated of 2 to 3 millions people suffer from non-melanoma, and around 132,000 of melanoma cases are diagnosed globally every year [1–3]. Skin cancer represents approximately 1.6% of the total number of cancer worldwide [3, 4]. Its treatment needs chemotherapy and radiotherapy like other cancers types, such as breast cancer, blood cancer, brain tumor or lung cancer, when reached in metastasis state [3, 5]. To avoid these painful procedures, and for a successful treatment, early detection is one of the most reliable solutions.

Skin cancer detection has been an attractive topic to researchers since 1984 in computerized analysis of pigment skin lesions (PSL). A survey by Korotkov et al. [6] summarizes the issues in dermoscopic and clinical images of PSL. Their work provides good background information on the nature of skin lesions, imaging modalities and techniques, procedures for clinical diagnosis and automated melanoma diagnosis systems. Over the years, many researchers have proposed various methods/techniques in Computer-aided diagnosis (CAD) systems to improve the performance metrics such as accuracy, sensitivity and specificity. Area Under Curve (AUC) and/or Receiver Operator Curve (ROC) as explained and detailed by Celebi et al. [7]. Like all other CAD systems in medical image analysis, the skin images also undergoes image acquisition, preprocessing, segmentation, feature extraction and finally, classification step.

In the current work, we explore a new approach for discrimination of melanoma lesions using multisresolution analysis, such as wavelet and curvelet coefficients, combined with local binary pattern operator (LBP) applied on dermoscopic images. The developed approach uses the fusion of different features extracted from various operators. The structural features are obtained from multisresolution analysis (wavelet and curvelet coefficients) which are used to discriminate the structures as borders, dots and streaks. On the other side, the textural features computed by LBP operator are used to discriminate the local variation of colors, the pigment network, etc. Later, these features are fused in multiple combinations to investigate the influence of each combination in the performance of melanoma detection.

In this paper, we also investigate a deep statistical representativeness and the inference representation of the database used, which is important for the confidence of the obtained results. We also applied Dullrazor [8] software as a preprocessing step to remove hairs.

The rest of this paper is organized as follows: Section 2 presents a brief literature review of the methods used in skin cancer recognition for each step of CAD system. Section 3 provides the mathematical background of wavelet and curvelet transforms, and the local binary pattern operator. Section 4 presents the proposed method of feature extraction. The used database is presented and statistically analyzed in section 5. Section 6 presents the experimental works and the details of features used followed by the experimental results section (7), where the results of each configuration are presented and the analysis of the results discussed. Finally, the conclusion is depicted in Section 8.

2 Literature Review

In the literature, several researchers have focused on developing CAD systems for skin cancer detection. In hospitals, to detect the melanoma tissues, patients generally undergo a skin examination using the skin surface microscopy techniques commonly known as dermoscopy [9]. To measure the severity of skin deformation, physicians often use scoring methods such as the ABCD rule [10] or the 7-point checklist [11] for diagnosis and detection of melanoma. As Image processing techniques, the contributions of different papers in the literature are in image preprocessing, segmentation, feature extraction and/or classification.

For preprocessing of melanoma images, many methods proposed in the literature focused on hair removing and contrast enhancement. Once of such methods, named Dullrazor, was introduced by Lee et al. [8] to remove hair and image artifacts. It is one of the most widely known software in dermoscopic images [6]. With a similar objective, Abbas et al. [12] proposed a matched filtering with first derivative-of-Gaussian method for hair detection. This method shows accurate results but the multitude of parameters complicates its implementation. Applied on 100 dermoscopic images, the method shows a detection accuracy of 93.3%. Barata et al. [13] used a bank of directional filters and PDE-based interpolation for hair detection and inpainting respectively. Then, the authors applied a bank of directional filters and connected component analysis to detect the
lines of pigment network. Recently, Koehoorn et al. [14] proposed a new approach based on thresholding set decomposition and morphological analysis, which is a detection by the authors applied their method on more than 300 skin images and compared visually their results to the literature. They also compared the execution time of these methods. Mizaarlian et al. [15] proposed an alternative approach to detect hair in dermoscopic images using the measurement of turbulence quaternion [16] and dual matched filters for hair detection and suppression. On a database of 40 dermoscopic images and 94 synthetic images, the results obtained are, for segmentation, 86% and 85% of accuracy for dermoscopic and synthetic images respectively.

Once the preprocessing step is completed, the next challenging task is the segmentation of melanocytic lesions from the processed images. It refers to separate an image into disjoint homogeneous regions respecting some properties, such as luminance, color, and texture. This procedure is detailed in Celebi et al. [17] and completed in [7], where the authors classified several methods of image segmentation explored in the literature into different categories, such as histogram thresholding, clustering, edge-based, etc. They also compared the recent border detection methods (50 methods), and concluded that half (25/50) of them use smoothing filters, and those based on thresholding are inherently robust against noises. The authors noted that two methods, clustering (19/50) and thresholding (18/50), are the most popular segmentation methods. Previously, Celebi et al. [18] used the Otsu thresholding method for lesion localization. In Capdehornat et al. [19], Color-Based Otsu method was adapted, which is biased and signiﬁcant. Safi et al. [20] used a total variation (TV) method developed by [21], which is the generalization of Chan and Vese model [22]. The main idea is to minimize the convex energy of the image. The results of this methods are very encouraging. In a similar kind of study, an extension of Chan and Vese model to differentiate the melanoma and non-melanoma cases in skin cancer images is explored and presented in [23].

The feature extraction step plays a crucial role in CAD systems, because the classification and diagnosis depends on the types of features extracted and their discriminating power. There are several feature extraction methods in skin cancer research as [20], where the authors used the idea of the ABCDE rule for extracting the image’s features from the Regions of Interest (ROIs). In this rule, A is Asymmetry, B is Border, C stands for Color, D is Diameter and E is Elevation or Evolving (less used in clinical treatment). A set of features are extracted by Celebi et al. [18] from multiple operators describing the shape, like asymmetry and compactness of the lesions, and color features computing several statistical measures over channels and color spaces. They also used textural features where gray level co-occurrence (GLCM) was applied. Multiscale roughness descriptors were used by Clawson et al. [24], Capdehornat et al. [19] and Arroyo et al. [4] where the authors computed important statistical features as variance, Hessian matrix and entropy. In [4], they extracted Gaussian features using different values of σ and spectral texture features. To select the best features, a decision tree by means rule was implemented to obtain the 23 most significant features from a total of 80 extracted features. Similarly, Barata et al. [9] compared the global/local texture and color features to classify skin lesion. For smart-phone-based real-time systems, Abuzaghleh et al. [25] proposed fast Fourier transform mixed with discrete cosine transform applied on color and shape for feature extraction.

Classification is the last step in the typical workflow for the computerized analysis pigmentation skin lesion images. The classification performance is often measured in terms of accuracy, sensitivity and specificity. The computation of these metrics is mostly used to compare the results. The most used classification and often explored by radiologist on ABCD Criteria is scoring system by thresholds [6, 19], where the score is computed following the value and the weight attributed to each feature (see table 2). They also used a 7-point checklist, which is another scoring system. The checklist is divided into two parts, i.e. major criteria (Atypical pigment network, Blue-whitish veil and atypical vascular pattern) and minor criteria (Irregular streaks, irregular pigmentation, irregular dots/globules and regression structures). The major criteria received 2 points and those lying under minor criteria were awarded 1 point [6, 19]. The classification is also done by thresholding for 7-point checklist.

For the non-melanoma cases in skin cancer images is explored and presented in [23].

As evident from the literature, the detection of melanoma is a very challenging task in dermoscopic images. Thus, in the current study, we present an approach to distinguish between the benign and malignant lesions. Multiresolution techniques e.g wavelet and curvelet provide shape representation of lesions by finding the borders and streaks in skin cancer image, while LBP operator is proposed to classify melanoma. Thus, there is a need to explore new directions in skin cancer detection. In the current paper, we explore a set of features describing the local characteristics, such as dots and network pigments, using LBP operator and global characteristics, such as border irregularities and asymmetry, exploring multisolution analysis using wavelet and curvelet transforms.
highlighted. Two comparisons are done, intermediary one which is performed between different combinations of textural and structural features. Then we compared the obtained results to the ones achieved in the literature using the same public database.

3 Mathematical tools

Subsections 3.1, 3.2 and 3.3 introduce the mathematical background of wavelet, curvelet transforms and local binary pattern operator respectively, which are implemented in the current study for the extraction of features.

3.1 Wavelet transform

Wavelet transform was introduced by Grosmann and Morlet [29] using translation and dilations on square integrable function $\psi \in L^2(\mathbb{R})$. The wavelet transform is defined by the following formula:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}} \psi \left( \frac{t - b}{a} \right)$$

where $a > 0$ defines the scale and $b$ the shift parameter.

A multiresolution approximation of $L^2(\mathbb{R})$ is a sequence $(V_j)_{j \in \mathbb{Z}}$ of closed subspaces of $L^2(\mathbb{R})$, such that: $0 \subseteq V_1 \subseteq \ldots \subseteq V_j \subseteq V_{j+1} \subseteq \ldots$ where $\{ \phi_j \}$ is the orthonormal basis of $V_j$ [30] with:

$$\phi_{j,k}(x) = \sqrt{2} \phi (2^j x - k), \quad k \in \mathbb{Z}$$

The subspaces $\ldots, V_1, V_0, V_{-1}, \ldots$ design the orthonormal complements of the subspaces $\ldots, V_1, V_0, V_{-1}, \ldots$ defined above, such that: $V_0 \oplus W_0 = V_{-1}$

In multiresolution analysis, the subspaces $V_j$ are generated by the function $(\phi_{j,k})_{k \in \mathbb{Z}}$ and $W_j$ are generated by $(\psi_{j,k})_{k \in \mathbb{Z}}$. Then, the subspace $V_j$ represents the large scale (approximations) and $W_j$ represents the small scale (details).

Let $f(x)$ be a 1 dimension discrete function as sequence of numbers, the discrete wavelet transform coefficients are defined as:

$$W_0(j_0, k) = \frac{1}{\sqrt{M}} \sum_{x=0}^{M-1} f(x) \phi_{j_0,k}(x)$$

$$W_j(j, k) = \frac{1}{\sqrt{M}} \sum_{x=0}^{M-1} f(x) \psi_{j,k}(x)$$

where $j > j_0$, $M$ is power of 2 which ranges from 2 to $j - 1$ and $W_0(j_0, k)$, $W_j(j, k)$ are the approximation coefficient and details coefficients respectively. Using these coefficients, the signal function $f(x)$ can be reconstructed as:

$$f(x) = \frac{1}{\sqrt{M}} \sum_{k} W_0(j_0, k) \phi_{j_0,k}(x)$$

$$+ \frac{1}{\sqrt{M}} \sum_{j=j_0}^{\infty} \sum_{k} W_j(j, k) \psi_{j,k}(x)$$

The implementation of wavelet transform was presented by Mallat [30] introducing a set of filters $(h_l)_{l \in \mathbb{Z}}$ and $(g_l)_{l \in \mathbb{Z}}$ where:

$$\phi_{j,k} = \sum_{l} h_l \phi_{j+1,2k+l}$$

$$\psi_{j,k} = \sum_{l} h_l \psi_{j+1,2k+l}$$

and

$$h_l = (-1)^n g_{l-n}$$

Therefore, the approximation and details coefficients are computed.

In a two dimensions case, we have a scaling function $\phi(x, y)$ and three directional wavelets defined below:

$$\begin{align*}
\phi(x, y) &= \phi(x) \phi(y) \\
\psi^H(x, y) &= \psi(x) \phi(y) \\
\psi^V(x, y) &= \phi(x) \psi(y) \\
\psi^D(x, y) &= \psi(x) \psi(y)
\end{align*}$$

where $\psi^H$, $\psi^V$ and $\psi^D$ measure the horizontal, vertical and diagonal variation respectively.

Finally, the wavelet coefficients of a given image $I (M \times N)$ are computed using the following formulas:

$$W_0(j_0, k) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x, y) \phi_{j_0,k}(x, y)$$

$$W^H(j, k) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x, y) \psi_{j, k}^H(x, y)$$

$$W^V(j, k) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x, y) \psi_{j, k}^V(x, y)$$

$$W^D(j, k) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x, y) \psi_{j, k}^D(x, y)$$

The potential of wavelet representation has had a wide impact in theory and in practice. It is used for non-linear approximation, compression and image denoising on different database.

3.2 Curvelet Transform

Curvelet Transform is an extension of wavelet transform and it was introduced in 2000 by Candès and Donoho [31]. The same authors presented the second generation of curvelet [32], known as the fast digital curvelet transform (DFCT), which is less redundant, and has better performances than its predecessor. Curvelets have the capability of detecting the finest edges, those that can present more details in curvelet coefficients [31]. The application of curvelet can be found in many fields such as face detection [33], mammogram classification [34] and various other medical image classifications [35].

In a two dimensional space $R^2$ with a spatial variable $x$ and frequency-domain variable $\omega$, the polar coordinates of the frequency-domain are $r$ and $\theta$. Curvelet transforms are defined by two windows, $W(r)$ and $V(t)$, called radial window and angular window respectively [32]. These windows will always obey the following admissibility conditions:

$$\sum_{j=-\infty}^{\infty} W^2(2^j r) = 1, \quad r \in (3/4, 3/2)$$

$$\sum_{l=-\infty}^{\infty} V^2(t - l) = 1, \quad t \in (-1/2, 1/2)$$

The frequency window $U_j$, in Fourier domain given by the equation (16), represents a polar wedge supported by $W(t)$ and $V(t)$.

$$U_j(r, \theta) = 2^{-3j/4} (2^{-j} r) V \left( \frac{2^{\lfloor j/2 \rfloor}}{2\pi} \right)$$

At scale $2^{-j}$, orientation $\theta_j$ and position $x_k(j, l)$, the curvelet transform function of $\{ x = (x_1, x_2) \}$ is given by the equation (17).

$$\varphi_{j,l,k}(x) = \varphi_j \left( R_{\theta_j} \left( x - x_k^{(j,l)} \right) \right)$$
where \( R_{N} \) is the rotation in radians and \( \varphi_{j} \) is the waveform and its Fourier transform is \( \hat{\varphi}(w) = U_j(w) \). It is considered as another mother wavelet in the sense that all curvelets are calculated by rotations and translations of \( \varphi_{j} \) [32].

Then, the curvelet coefficient, \( c \) given in the equation (18), is obtained by the inner product between the element \( f \in L^2(\mathbb{R}^2) \) and the curvelet transform \( \varphi_{j,k,l} \).

\[
c(j,k,l) = \int_{\mathbb{R}^2} f(x) \varphi_{j,k,l}(x) dx. \tag{18}
\]

There are two implementations of curvelet transforms namely: unequispaced fast fourier transform (UFFT) and fast digital curvelet transform via wrapping (FDCT via wrapping). In the current study, FDCT via wrapping has been implemented and a brief introduction is presented in 3.2.1

3.2.1 Fast Digital Curvelet Transforms via Wrapping: Fast Digital Curvelet Transform (FDCT) via wrapping was introduced by Candès et al. in their second generation of curvelet [32]. This implementation is based on wrapping of Fourier samples with 2D image as input in Cartesian array form \( f[m,n] \) where \( 0 \leq m \leq M, 0 \leq n \leq N \), and \( M \) and \( N \) are the dimension of the array (image). Then, the discrete coefficients of FDCT are given below:

\[
c^{D}(j,l,k_1,k_2) = \sum_{0 \leq m \leq M, 0 \leq n \leq N} f[m,n] \varphi_{j,l,k_1,k_2}[m,n] \tag{19}
\]

Equation (19) defines the Digital curvelet coefficients, \( c^{D}(j,l,k_1,k_2) \) is indexed by a scale \( j \), an orientation \( l \) and the spatial location parameters \( k_1 \) and \( k_2 \). Where \( \varphi_{j,l,k_1,k_2} \) is the digital waveform.

![Fig. 1: A comparison between wavelet (a) and curvelet (b) [35]](image)

Figure 1 illustrate the advantages of curvelet transform in curve detection compared to wavelet transform [35]. It can be seen that for the same curve, curvelet transform needs less coefficients to fit widely the curve than wavelet transform. However, when the image has more dot singularities, the wavelet transform could give more performances.

3.3 LBP Histogram Features

Local Binary Patterns (LBP) operator is used for texture description. It is one of the best performing texture descriptors and it has been widely used in multiple applications [36, 37]. This operator was developed by Ojala et al. [38, 39]. Many variants of LBP were developed, for example Heikkila et al. [40] proposed center-symmetric local binary pattern, then, Zhang et al. [41] developed a new approach replacing the neighbor pixels by the mean of the neighbors’ blocks, and Wolf et al. [42] proposed novel patches based LBP where they explored the similarities between neighboring patches of pixels. The majority of these developments are applied in face detection and recognition.

The LBP operator attributes for each pixel of the image a new value from 0 to 255 depending on its neighborhood as explained below:

Let the image \( I(x,y) \) and \( g_c \) denotes the gray level of an arbitrary pixel \((x,y), \text{i.e.} g_c = I(x,y) \). And let \( g_p \) denote the gray value of a sampling point in a circular neighborhood space \( P \) and radius \( R \) around the point \((x,y)\):

\[
g_p = I(x_p,y_p), \quad p = 0, \ldots, P - 1
\]

\[
x_p = x + R \cos(2\pi p/P)
\]

\[
y_p = y - R \sin(2\pi p/P)
\]

Assuming that the local texture of the image \( I(x,y) \) is characterized by the joint distribution \( t(.) \) of gray values of \( P+1 \) \((P > 0) \) pixels:

\[
T = t(g_c, g_0, g_1, \ldots, g_{P-1}). \tag{20}
\]

Without loss of information, the center pixel value can be subtracted from the neighborhood pixel values and the equation (20) can be written as the following formula:

\[
T = t(g_c, g_0 - g_c, g_1 - g_c, \ldots, g_{P-1} - g_c). \tag{21}
\]

Assuming that the center pixel is statistically independent to the differences, the equation (21) is approximated by:

\[
T \approx t(g_c) t(g_0 - g_c, g_1 - g_c, \ldots, g_{P-1} - g_c). \tag{22}
\]

The important information is given by the differences distribution part \( t(g_0 - g_c, g_1 - g_c, \ldots, g_{P-1} - g_c) \). However, the estimation of this distribution from image data is difficult. Ojala et al. [38] proposed to apply vector quantization given by the following formula:

\[
t(s(g_0 - g_c), s(g_1 - g_c), \ldots, s(g_{P-1} - g_c)). \tag{23}
\]

where \( s(z) \),

\[
s(z) = \begin{cases} 
1, & z \geq 0 \\
0, & z < 0.
\end{cases} \tag{24}
\]

Then, we can define the generic local binary patterns operator [43]:

\[
LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{25}
\]

According to [44], the choice of \( P = 8 \) and \( R = 1 \) is the best case for melanoma description.

Ojala et al. [39] introduced uniform pattern and invariant rotation local binary pattern. Three variants were added, the first variant called uniform pattern indexed by \( LBP_{u} \) keeps only the pattern containing a maximum of 2 transition 0/1 and/or 1/0, this variant contains 39 combinations. The second variant is the invariant rotation pattern indexed by \( LBP_{r} \), it has the same configuration for all rotations, and it contains 36 combinations. The third variant is the invariant rotation uniform pattern indexed by \( LBP_{u}^{m2} \), it contains only the uniform patterns in the invariant rotation variant, indeed, it keeps only 9 combinations.

4 Proposed method

The multitude of skin cancer lesions, benign and malignant, complicates the recognition of Skin cancer. In addition to that, melanoma is developing randomly in different directions. Finding the best descriptor to discriminate melanoma is one of the challenging tasks in medical image processing. In the current study, we present a set of discriminating features obtained from different descriptors to distinguish between benign and malignant cases as detailed in experimental work section (6). A detailed statistical analysis of the used database is also reported. The flowchart of the proposed feature extraction and fusion method is illustrated in Fig.2. The methodology can be divided into two stages i.e. computation of features (structural and texture) and fusion of features.
5 Database

PH² Database was introduced in 2013 by Mendoca et al. [45] and more detailed in 2015 by the same authors [46]. PH² is a public and free database, built to perform and compare the evaluation of several systems. The database was built up through the joint collaboration between Universidade do Porto, Técnico Lisboa, and the Dermatology service of Hospital Pedro Hispano in Matosinhos, Portugal. The acquisition of images was obtained under the same conditions. They are 8-bit RGB color images with a resolution of 768 × 560 pixels.

The database contains a total of 200 dermoscopic images divided into 100 benign lesions and 100 melanomas. The benign lesions contain 80 common nevi and 20 atypical nevi. The quality, resolution and dermoscopic features of images are highlighted in the current database. Every image was segmented manually and diagnosed by several dermatologists. It contains also the clinical diagnosis and dermoscopic criteria such as asymmetry, color and presence of typical and atypical structures.

Table 1 summarizes all the given characteristics of PH² database. It shows the percentage of the presence / absence of each characteristic. For each percentage, the number of images is noted between brackets. The table is to be read by columns, thus for example, the common nevus is 96.25% fully symmetric, 2.5% is symmetric in one axe and only 1.25% is fully asymmetric and melanoma is 12.5% fully symmetric, 5% symmetric in one axe and 82.5% fully asymmetric. The table shows the dominant characteristics for each feature.

Table 1

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Presence (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asymmetry</td>
<td>96.25</td>
</tr>
<tr>
<td>Symmetry</td>
<td>2.50</td>
</tr>
<tr>
<td>Melanoma</td>
<td>12.5</td>
</tr>
<tr>
<td>Common Nevus</td>
<td>80</td>
</tr>
<tr>
<td>Atypical Nevus</td>
<td>20</td>
</tr>
<tr>
<td>Border</td>
<td>5</td>
</tr>
<tr>
<td>Color</td>
<td>5</td>
</tr>
<tr>
<td>Textural features</td>
<td>5</td>
</tr>
<tr>
<td>Structural features</td>
<td>5</td>
</tr>
</tbody>
</table>

Based on the given features in table 1, intuitively, the most difficult is to recognize the atypical nevus. Thus, for example the asymmetry feature makes a real border between common nevus and melanoma only. The pigment network feature separates more common nevus with a total absent of pigment network to atypical and melanoma. However the dots/globules features are not descriptive between the three cases. We can observe also that streaks and regression area features are more common in common nevus and atypical nevus than melanoma. Blue-whitish veil discriminates better between benign and malignant compared to other features. Finally, the color increases gradually from common nevus to melanoma.

Another way of reading table 1 is horizontally. Indeed, it shows the influence of each sub-feature. For example, the typical Dot/Globules feature is more frequently in common nevus than atypical nevus and almost inexist in melanoma case. However, the atypical Dot/Globules feature shows an opposite behavior with a high presence in melanoma, less in atypical nevus and rarely present in common nevus. A statistical analysis of the database is performed and compared to a based scoring system used in the hospitals in the next sub-section.

5.1 Significance of the database

The informations given by the PH² database used in this study contain all ABCD rules, expect border irregularity scores, developed by Stolz et al. [10] and used for comparison by Capdehourat et al. [19] and Doliánities et al. [47].

The PH² database quantifies each pigment following ABCD rule excepting border irregularities. According to Capdehourat et al. [19]. The evaluation of ABCD rule follows the scores summarized in table 2, where dermoscopic structures contain pigment network, structures are, dots, globules and branched streaks. The authors added to these features Blue-whitish veil which is a major criteria of the 7-point checklist system [19].

Table 2 describes the Stol’s ABCD rule scoring system, it specifies a list of visual features associated with malignant lesions. Thus, the evaluation and the classification is done following the score value $S$ attributed to each image, then it is classified as benign if $(S < 4.75)$, clinical doubt lesion if $4.75 \leq S \leq 5.45$, or malignant if $(S > 5.45)$. The function $S$ is given by the following formula:

$$S = \sum_{i=0}^{4} p_i w_i$$

where $p_i$ and $w_i$ are the point value and the weight factor given in the table 2. This scoring system is applied on the features described in table 1 is same as used by Capdehourat et al. [19] where:

- Asymmetry is evaluated from 0 to 2 , with 0 being fully symmetric, 1 for symmetric in one axis and 2 for fully asymmetric. It has the highest weight factor of 1.3.
- Border is evaluated with score from 0 to 8, drawing eight segments; one point is given for each abrupt pigment cutoff with a weight factor of 0.1.
- Color is evaluated from 1 to 6, attributing one point for each color with a weight factor of 0.5. Colors considered are white, red, black, light brown, dark brown and blue-gray.
- Dermoscopic structures encompass five structures which are: pigment network, structureless area, dots, globules and branched streaks. One point per structure with a weight factor of 0.5.

We notice that there are some differences between extracted features in PH² database and ABCD rule. Therefore, the threshold of the scoring system is adapted removing the contribution of border irregularities. Then, the $S$ score value of the function given in the equation (26) is evaluated as follow: benign if the score is $S < 4.50$, clinical doubt: lesion if the score lies between $4.50 \leq S \leq 5.20$, malignant: if the score is $S > 5.20$. There are other characteristic explored in the database, such as blue-whitish veil, not used in ABCD rule, but used in another scoring system which is 7-points checklist[19]. However, the objective evaluation is difficult to be achieved due the visual features characterized depending only on the decision of absence or presence of each characteristic.

The results reported by Doliánities et al. are presented in table 3. They are compared to the results obtained from PH² database applying ABCD rule. These results show a similar behavior and equivalent results for the three performance metrics which are sensitivity, specificity and accuracy. As mentioned above, the threshold of ABCD rule, given in table 2, applied on PH² database was adapted taking in consideration the missing values of border irregularities. Then, the value of the threshold is reduced to 4.5 and 5.20 instead of 4.75 and 5.45 respectively.

Analysis of Variance (ANOVA) is implemented on the vector obtained by ABCD rule by testing the $H_0$ (same population) against
Table 1: Summary of the characteristics of PH² database

<table>
<thead>
<tr>
<th>Database characteristics</th>
<th>Common Nevus (80)</th>
<th>Atypical Nevus (80)</th>
<th>Melanoma (40)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asymmetry</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fully symmetric</td>
<td>96.25% (77)</td>
<td>43.75% (35)</td>
<td>12.5% (5)</td>
</tr>
<tr>
<td>Symmetric in 1 Axe</td>
<td>2.5% (2)</td>
<td>33.75% (27)</td>
<td>5% (2)</td>
</tr>
<tr>
<td>Fully Asymmetric</td>
<td>1.25% (1)</td>
<td>22.5% (18)</td>
<td>82.5% (33)</td>
</tr>
<tr>
<td>Pigment network</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Typical</td>
<td>100% (80)</td>
<td>3.75% (3)</td>
<td>2.5% (1)</td>
</tr>
<tr>
<td>Atypical</td>
<td>0% (0)</td>
<td>96.25% (77)</td>
<td>97.5% (39)</td>
</tr>
<tr>
<td>Dots / Globules</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absent</td>
<td>36.25% (29)</td>
<td>50% (40)</td>
<td>45% (18)</td>
</tr>
<tr>
<td>Typical</td>
<td>57.5% (46)</td>
<td>10% (8)</td>
<td>0% (0)</td>
</tr>
<tr>
<td>Atypical</td>
<td>6.25% (5)</td>
<td>40% (32)</td>
<td>55% (22)</td>
</tr>
<tr>
<td>Streaks</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absent</td>
<td>98.75% (79)</td>
<td>80% (64)</td>
<td>67.5% (27)</td>
</tr>
<tr>
<td>Present</td>
<td>1.25% (1)</td>
<td>20% (16)</td>
<td>32.5% (13)</td>
</tr>
<tr>
<td>Regression area</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absent</td>
<td>100% (80)</td>
<td>95% (76)</td>
<td>47.5% (19)</td>
</tr>
<tr>
<td>Present</td>
<td>0% (0)</td>
<td>5% (4)</td>
<td>52.5% (21)</td>
</tr>
<tr>
<td>Blue-whitish veil</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absent</td>
<td>100% (80)</td>
<td>92.5% (74)</td>
<td>25% (10)</td>
</tr>
<tr>
<td>Present</td>
<td>0% (0)</td>
<td>7.5% (6)</td>
<td>75% (30)</td>
</tr>
<tr>
<td>Color</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 color</td>
<td>42.5% (34)</td>
<td>25% (20)</td>
<td>0% (0)</td>
</tr>
<tr>
<td>2 colors</td>
<td>53.75% (43)</td>
<td>63.75% (51)</td>
<td>32.5% (13)</td>
</tr>
<tr>
<td>3 colors</td>
<td>3.75% (3)</td>
<td>11.25% (9)</td>
<td>27.5% (11)</td>
</tr>
<tr>
<td>4 colors</td>
<td>0% (0)</td>
<td>0% (0)</td>
<td>32.5% (13)</td>
</tr>
<tr>
<td>5 colors</td>
<td>0% (0)</td>
<td>0% (0)</td>
<td>7.5% (3)</td>
</tr>
</tbody>
</table>

Table 2: Scoring system evaluation of ABCD rule [19].

<table>
<thead>
<tr>
<th>Feature</th>
<th>Points (p)</th>
<th>Weight factor (w)</th>
<th>Sub-scoring range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asymmetry</td>
<td>0 – 2</td>
<td>1.3</td>
<td>0 – 2.6</td>
</tr>
<tr>
<td>Border</td>
<td>0 – 8</td>
<td>0.1</td>
<td>0 – 0.8</td>
</tr>
<tr>
<td>Color</td>
<td>1 – 6</td>
<td>0.5</td>
<td>0.5 – 3</td>
</tr>
<tr>
<td>Dermoscopic Structures</td>
<td>1 – 5</td>
<td>0.5</td>
<td>0.5 – 2.5</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>1 – 8.9</td>
</tr>
</tbody>
</table>

Table 3: Result of ABCD rule obtained from PH² database.

<table>
<thead>
<tr>
<th>Diagnostic Parameter</th>
<th>Doliantilis et al.</th>
<th>PH² Database</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>77.5%</td>
<td>77.5%</td>
</tr>
<tr>
<td>Specificity</td>
<td>80.4%</td>
<td>97.5%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>73.2%</td>
<td>87.5%</td>
</tr>
</tbody>
</table>

$H_1$ (different classes). The P-value obtained is less than 0.01, then, the hypothesis $H_0$ is significantly rejected with risk of 5%. Thus, the database presents significantly heterogeneous population (more than two classes).

The box plot in figure 3 illustrates graphically the variability of each group and deduce three different classes in the population. The figure 4 describes the results of ABCD rule (blue) of the whole database and the mean of each class (red). Descriptively, using ABCD rule results, the graph shows more stability in common nevus lesion than the two other cases (atypical nevus and melanoma).

**Fig. 3:** Variability of the three classes of the PH² database. (1): Common nevus. (2): Atypical nevus. (3): Melanoma.

6 Experimental Work

The proposed method detailed in section 4 is applied on the 200 dermoscopic images from PH² database [46]. This database contains...
60 non melanoma (benign) and 40 melanoma (malignant) images. The classification is performed using SVM classifier with the linear kernel, 70% of the database is used for training and 30% for test. A random sampling cross validation method is applied to validate the obtained results, where a thousand (1000) combinations of training and test sets are chosen randomly from the database. Thus, each image is used in average 700 times for training and 300 times for tests. An unbiased standard deviation (Std) for the thousand combinations is also computed for the three performance metrics (sensitivity, specificity and accuracy) detailed in the next section.

### 6.1 Hair removing

To preprocess and enhance the image quality in the current study, DullRazor Software is used for hair removing, it was applied on all the visible hairs as illustrated in figure 5. The statistical validity of dataset and robustness of the proposed approach is also explored in this study.

### 6.2 Feature extraction

1. First, the structural features are extracted using wavelet and curvelet coefficients. Two level decompositions of Discrete Wavelet Transform (DWT) and Fast Digital Curvelet Transform (FDCT) via warping (see 3.2.1) are applied on the melanoma region of interest (ROIs). For each coefficient matrix seven statistical features were computed namely: Energy, Entropy, Mean, Standard deviation, Maximum, Moment and Homogeneity.

2. Second, a set of textural features using different variants of local binary pattern (LBP) i.e. rotationally invariant, uniform and non-uniform rotationally invariant distinct textures features are extracted.

3. A feature fusion of structural and textural features is done.

4. Lastly, SVM classifier is used for classification and diagnosis. Then, 1000—random sampling cross validation is explored to validate the obtained results.

- For wavelet, we used Daubechies 4 wavefront, then 8 coefficient matrices are computed, 4 from the first level and 4 from the second level (one approximation coefficient matrix and three details coefficient matrices) using the equations (10) to (13). In total, we extracted 64 features from wavelet transforms.

- For two level of curvelet decomposition 9 curvelet coefficient matrices were obtained for each image i.e. 1 matrix from the first level and 8 matrices from the second level. This matrices are built using the equation (19) detailed in the next section. Thus for each level, seven statistical features were computed. Thus a total of 63 features from curvelet two level decomposition were obtained.

For textural features, Local Binary Pattern (LBP) operator is used to extract local textural variations. Thus, depending on the variant of

![Image](http://www.dermweb.com/dull_razor/)

### 7 Experimental results

The evaluation of the proposed method is measured using three performance metrics which are sensitivity ($sen$), specificity ($spe$) and accuracy ($acc$) [7], as given in the equations (27) to (29).

\[
sen = \frac{TP}{TP + FN} \tag{27}
\]

\[
spe = \frac{TN}{TN + FP} \tag{28}
\]

\[
acc = \frac{TP + TN}{TP + FN + TN + FP} \tag{29}
\]

Where $TP$ (True Positives) defines the melanoma classified as melanoma, $TN$ (True Negatives) defines the non melanoma classified as non melanoma, $FP$ (False Positives) and $FN$ (False Negatives) are the melanoma and non melanoma which are not classified on the right set respectively.

The equation (29) depends on the number of benign and malignant lesions. To remove this dependence, we estimate the accuracy

![Image](http://www.dermweb.com/dull_razor/)

---

*Dullrazor software is available on http://www.dermweb.com/dull_razor/*
In the following way:

\[
\hat{\text{acc}} = \frac{\alpha TP + TN}{\alpha TP + \alpha FN + TN + FP} \tag{30}
\]

The parameter \(\alpha\) is added to compensate the difference of images number in the accuracy performance. This parameter is obtained by the following formula:

\[
\alpha = \frac{\#\text{Benign}}{\#\text{Malignant}} \tag{31}
\]

Where \(\#\text{Benign}\) and \(\#\text{Malignant}\) design the number of benign and malignant images respectively. Therefore, \(\alpha = 2\) for the first and second classification (melanoma vs atypical, and melanoma vs common nevus) and \(\alpha = 4\) for the last classification (malignant and benign lesions). The performance results are computed also by accuracy given by the equation (30).

The equation (30) can be also used with different values of the parameter \(\alpha\) to give more weight for false negatives or false positives to tolerate or reject some special situations, such as let cancerous patients without treatment which are false negatives. In our case, the \(\alpha\) chosen is used just to regulate the difference between benign and malignant lesions. This formulation is equivalent to \((\text{sens} + \text{spec})/2\) used in Barata et al. [28]. In the next section, the results show a significant difference between the two metrics.

Figure 6a presents the evolution of the modified accuracy (\(\hat{\text{acc}}\)) depending on different values of \(\alpha\), from 0.1 to 5, fixing others variables (sensitivity, specificity, malignant number and benign number). While, figure 6b illustrates the dependence of the accuracy metric (eq.(29)) on malignant and benign number, presented by the dark curve. By varying the \(\beta\) value from 0.1 to 5 in \(M = \beta B\), where \(M\) is malignant number, \(B\) is benign number, we can see easily that the accuracy (\(\text{acc}\)) is strongly dependent on those quantities. The blue color line present the modified accuracy (\(\hat{\text{acc}}\)), with \(\alpha = 1/\beta\), to compensate the difference between malignant and benign number.

Knowing that the database is presented in three different classes: Common nevus, Atypical nevus and Melanoma. Then, to have a representative training set, 70% of each class (common and atypical) is taken for training and the other 30% for test. This choice guarantees the representativeness of atypical and common nevus in training and test sets.

To detect melanoma lesions, the results are classified in to three cases. Firstly, we explored the classification between melanoma and atypical nevus. Secondly, we explored classification performance between melanoma and common nevus and finally we performed the classification between melanoma and the whole benign lesions. Three performance metrics i.e. sensitivity, specificity and accuracy modificated accuracy given by the equations (30) are computed. For each performance, we compute also 1000 random combinations for the choice of the training and test sets. In the result tables (4, 5 and 6), VP defines the validation performance and Std represents the standard deviation of the thousand combinations used for validation. The results are divided into three categories which are textural features using local binary pattern operator, structural features using wavelet and curvelet coefficients and finally the mixture of textural and structural features.

7.1 Melanoma Vs Atypical Nevus

In this part, the classification is focused on the detection and the recognition of melanoma mixed only with atypical nevus, those presented by the second and the third columns in the table 1. The results obtained are given in the table 4. Therefore, for textural features, the best performances are obtained by LBP\(_u^2\) followed by the LBP\(_u^1\), and the worst result is obtained by the LBP\(_n^2\). For structural features, waveform shows better results than curvelet for all metrics performances used. The fusion of textural and structural features gives better results in wavelet coefficients with LBP operator and it shows a smallest standard deviation for the variability of validation results expressed by the variable Std. Wavelet with LBP\(_u^2\) improves the three metrics used and gives the best results compared to all the methods studied. The fusion of curvelet coefficients with LBP operator improves the specificity metric compared to curvelet and LBP separately.

7.2 Melanoma Vs Common Nevus

As mentioned above, the second classification is done only between melanoma and common nevus lesions. Table 5 shows the performance validation of specificity, sensitivity and accuracies metrics. For textural features, LBP\(_u^1\) and LBP\(_u^2\) show a higher performance than LBP\(_n^1u^2\), and we can see that LBP\(_u^1\) is more sensitive and less specific than LBP\(_u^2\). The textural features performances show that waveform coefficients discriminate melanoma better than curvelet coefficients and the fusion LBP operator contributes in the reduction of the variabilility between different combinations in validation step.

It can be seen that the best results validation are performed using waveform and the fusion of waveform with different variants of LBP. The fusion of waveform and LBP\(_u^2\) is the most stable operator showing the smallest standard deviation value for the three metrics.

7.3 Melanoma Vs Atypical and Common Nevus

In this part, the classification is performed between malignant and benign (atypical and common nevus) lesions. The results are presented in table 5. Thus, for textural features, we can see that LBP\(_u^1\) is more sensitive and more accurate than LBP\(_u^1u^2\) and LBP\(_u^2\). The opposite results are obtained for specificity where LBP\(_u^2\) gives the...
Table 4 Results obtained for Melanoma Vs Atypical nevus giving Performance validation VP and the standard deviation Std for 100 random-cross validation under SVM classifier.

<table>
<thead>
<tr>
<th>Features</th>
<th>Methods</th>
<th>Sensitivity (sen)</th>
<th>Specificity (spe)</th>
<th>Accuracy (acc)</th>
<th>Accuracy (aacc)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>VP</td>
<td>Std</td>
<td>VP</td>
<td>Std</td>
</tr>
<tr>
<td>Textural Features</td>
<td>LBP^0</td>
<td>77.44%</td>
<td>11.88</td>
<td>81.97%</td>
<td>8.04</td>
</tr>
<tr>
<td></td>
<td>LBP^m12</td>
<td>74.17%</td>
<td>12.09</td>
<td>73.19%</td>
<td>9.29</td>
</tr>
<tr>
<td></td>
<td>LBP^m2</td>
<td>76.55%</td>
<td>12.32</td>
<td>85.15%</td>
<td>7.35</td>
</tr>
<tr>
<td>Structural Features</td>
<td>Wavelet</td>
<td>79.47%</td>
<td>12.93</td>
<td>88.99%</td>
<td>7.10</td>
</tr>
<tr>
<td></td>
<td>Curvelet</td>
<td>73.10%</td>
<td>13.56</td>
<td>82.01%</td>
<td>7.56</td>
</tr>
<tr>
<td>Fusion of Structural and Textural Features</td>
<td>Wavelet + LBP^m1</td>
<td>78.13%</td>
<td>12.08</td>
<td>88.63%</td>
<td>6.90</td>
</tr>
<tr>
<td></td>
<td>Wavelet + LBP^m2</td>
<td>77.51%</td>
<td>12.37</td>
<td>88.22%</td>
<td>5.80</td>
</tr>
<tr>
<td></td>
<td>Wavelet + LBP^m3</td>
<td>81.84%</td>
<td>11.29</td>
<td>88.57%</td>
<td>6.80</td>
</tr>
<tr>
<td></td>
<td>Curvelet + LBP^m1</td>
<td>79.08%</td>
<td>12.50</td>
<td>85.65%</td>
<td>7.34</td>
</tr>
<tr>
<td></td>
<td>Curvelet + LBP^m2</td>
<td>76.15%</td>
<td>13.31</td>
<td>82.84%</td>
<td>7.66</td>
</tr>
<tr>
<td></td>
<td>Curvelet + LBP^m3</td>
<td>78.75%</td>
<td>11.89</td>
<td>86.83%</td>
<td>6.89</td>
</tr>
<tr>
<td></td>
<td>Wavelet + Curvelet</td>
<td>78.97%</td>
<td>12.84</td>
<td>85.54%</td>
<td>7.14</td>
</tr>
</tbody>
</table>

Table 5 Results obtained for Melanoma Vs Common nevus giving Performance Validation VP and the standard deviation Std for the 100 random-cross validation under SVM classifier.

<table>
<thead>
<tr>
<th>Features</th>
<th>Methods</th>
<th>Sensitivity (sen)</th>
<th>Specificity (spe)</th>
<th>Accuracy (acc)</th>
<th>Accuracy (aacc)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>VP</td>
<td>Std</td>
<td>VP</td>
<td>Std</td>
</tr>
<tr>
<td>Textural Features</td>
<td>LBP^0</td>
<td>82.28%</td>
<td>11.11</td>
<td>84.29%</td>
<td>7.71</td>
</tr>
<tr>
<td></td>
<td>LBP^m12</td>
<td>78.92%</td>
<td>12.07</td>
<td>77.68%</td>
<td>8.35</td>
</tr>
<tr>
<td></td>
<td>LBP^m2</td>
<td>80.82%</td>
<td>12.56</td>
<td>87.80%</td>
<td>6.78</td>
</tr>
<tr>
<td>Structural Features</td>
<td>Wavelet</td>
<td>88.47%</td>
<td>10.36</td>
<td>91.99%</td>
<td>5.67</td>
</tr>
<tr>
<td></td>
<td>Curvelet</td>
<td>88.80%</td>
<td>12.25</td>
<td>84.53%</td>
<td>7.63</td>
</tr>
<tr>
<td>Fusion of Structural and Textural Features</td>
<td>Wavelet + LBP^m1</td>
<td>88.82%</td>
<td>9.44</td>
<td>90.95%</td>
<td>5.93</td>
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<td>Wavelet + LBP^m2</td>
<td>88.91%</td>
<td>10.06</td>
<td>91.45%</td>
<td>5.85</td>
</tr>
<tr>
<td></td>
<td>Wavelet + LBP^m3</td>
<td>89.25%</td>
<td>9.26</td>
<td>90.80%</td>
<td>5.59</td>
</tr>
<tr>
<td></td>
<td>Curvelet + LBP^m1</td>
<td>81.25%</td>
<td>11.36</td>
<td>85.68%</td>
<td>7.30</td>
</tr>
<tr>
<td></td>
<td>Curvelet + LBP^m2</td>
<td>81.64%</td>
<td>11.93</td>
<td>85.34%</td>
<td>7.40</td>
</tr>
<tr>
<td></td>
<td>Curvelet + LBP^m3</td>
<td>82.86%</td>
<td>11.12</td>
<td>87.17%</td>
<td>6.86</td>
</tr>
<tr>
<td></td>
<td>Wavelet + Curvelet</td>
<td>87.73%</td>
<td>10.57</td>
<td>90.40%</td>
<td>6.99</td>
</tr>
</tbody>
</table>

highest value and the smallest variation compared to the other variants of LBP. The accuracy obtained from the validation results is higher than 81% for both, LBP^m2 and LBP^m3 variants.

For structural features, in our case, the wavelet coefficient shows a better performance compared to curvelet coefficients with an accuracy performance of 85.54% and 79.85% respectively.

The fusion of the wavelet and LBP^m3 increases considerably the specificity and the accuracy performances as shown in the table 6. However, the fusion does not show any significant effect on sensitivity performance.

The best results for all the performances metrics validation is obtained by the fusion of wavelet coefficients and LBP^m3 with 78.93% of sensitivity validation, 93.25% of specificity validation and 86.07% of accuracy validation.

7.4 Results Analysis

From tables 4, 5 and 6, we can deduce by using the two sets of features (textural and structural) that the detection of melanoma mixed with common nevus is easier as compared with melanoma mixed with atypical nevus, which is expected as the class overlap between melanoma and common nevus is less than that between melanoma and atypical nevus. Thus, the stability of common nevus is illustrated in figure 4 and presented by the result obtained in the table 5 with a highest accuracy of 90%. We can conclude that the detection and the recognition performances of melanoma depends on the kind of the benign lesions used for computation.

The fusion of wavelet and LBP^m2 outperforms all the tested methods in the current work, as it can be seen from the results in tables 4.5 and 6.

In general, curvelets have better performances than wavelets. However, in our case, the results obtained show better performances from wavelet coefficients compared to curvelet coefficients in the three tables. These results can be explained by the multitude of singularity points coming from the random development of skin cancer lesions. It could also be expressed by the redundancy of curvelet coefficients which represent the double of the redundancy of wavelet coefficients [48].

As detailed in the section 3.1 and 3.2, the wavelet is efficient for singularity points and curvelet is more efficient for the detection or characterization of curves. Therefore, we also evaluate a fusion between the two sets of coefficients as Li et al. [49] used for image compression. Thus, the results obtained are not showing any significant improvement in the detection.

Table 7 presents a comparison of the proposed method with recent works on classification and recognition of melanoma using the same
database PH². Our proposed method shows the highest performance in terms of specificity and accuracy compared to Barata et al. [28], showing a validated result of 93% and 86% respectively. Although accuracy is higher for Abuzaghleh et al. proposition [25], they did not perform any validation comparing neither the current work validation nor k-fold cross validation used by Barata et al. In addition to this, the authors used 75% of the database for training in place of 80% frequently used in the literature. The authors used the fusion of fast fourier transform with discrete cosine transform, and their results are still less efficient than the proposed method (see table 7), because the authors did not present sensitivity and specificity performances, and no information on training and test sets is presented. Furthermore, knowing that the benign lesions are heterogeneous [3], then, if we choose some special configurations of training and test sets we could present higher results than those presented in tables 4, 5 and 6. Thus, the validation result step is crucial for the adaptability of the proposed method.

The known ABCD rule, often used in hospitals manually, has achieved an accuracy of 87.5% as in table 3. In this work, the proposed automation of the ABCD rule achieved an accuracy of 86.07% as in table 7, which is fairly comparable to the result obtained manually. This achievement shows a great potential of developing CAD system for melanoma detection.

### 8 Conclusion

In this paper, fusion of structural and textural features are explored for melanoma recognition. The structural features are obtained from the first and second level of wavelet and curvelet coefficients, and the textural features are obtained from the different variants of local binary pattern operator. The best results are performed by the fusion of wavelet coefficients and LBP². The obtained results are also validated using random sampling cross-validation under SVM classifier with the linear kernel used for classification on PH² dermoscopy database. The proposed methods show great potential results in terms of sensitivity, specificity and accuracy metrics.

As suggested in the literature [50], it is important to provide the necessary details of the methods presented, for example, the configuration parameters and algorithms. In addition, a random sampling cross validation is performed using 1000 random combinations of training and test sets from the database. The validation step is necessary and important for robustness of the proposed method.
For a systematic comparison between research methods, the use of a free public database is required. Therefore, we used the first, unique and complete public database published by Mendoca et al. [46]. Another huge public database is available (but still underdevelopment) proposed in ISIC Archive [51], the clinical informations and the border segmentation lesions are not yet completely available.

9 References


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