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CoforDes - An invariant feature extractor for the drug pill identification

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***Abstract*—Around 6 to 8 thousand people die annually in the world due to the fact of having taken a pill erroneously. Some works have already proposed pill recognition systems commonly using attributes related to shape, color, and others. In this work, we propose a pill feature extractor to classify them based on shape and color (CoforDes). The proposed method was compared with the descriptors GLCM, SCM, LBP, Tamura, Fourier and the Zernick, Central, Statistical and Hu Moments. Three classifiers (KNN, SVM, and Bayes) were used to evaluate the feature extractors. The attributes were extracted in 0.01006 seconds in the PILL BR dataset and 0.00810 seconds in the NIH NLM PIR dataset using CorforDes, obtaining an accuracy of 99.85% in the PILL BR dataset and 99.82% in the NIH NLM PIR dataset. The specificity was 99.82% in the PILL BR dataset and 99.91% in the NIH NLM PIR base. The results show that CoforDes is an excellent feature extractor for the extraction of drug pill images and they can be embedded in real-time applications due to their rapid processing.**

***Keywords*-Pills Identification, Feature Extractor, CoforDes.**

I. Introduction

Identification of pills using digital image processing techniques has a great importance, according to Ushizima *et al.* [1], around 6 to 8 thousand people die annually in the world due to the fact of having taken a pill erroneously. This issue has already been addressed by Yu *et al.* [2], which created a pill recognition system based on three attributes: imprint, color, and shape. In the imprint extraction process, they proposed the Modified Stroke Width Transform (MSWT) to detect traces of the impression. For Lee *et al.* [3], developing a successful automatic pill detection tool is critical to compensate for the variation in the pills appearance due to change of perspective, lighting or occlusion. Due to these reasons, they used the gradient magnitude information. In the imprint descriptor construction, Lee *et al.* [3] used two methods for object recognition, the Scale-Invariant Feature Transform (SIFT) [4] and Multi-scale Local binary patterns (MLBP) [5].

Ushizima published a paper on the same subject to meet a demand from NML (National Laboratory of Medicines of the United States of America). This work was intended to foster the growth of studies in the area of image-based pill recognition, promoted a contest entitled *"Pill Image Recognition (PIR)"* in January 2015. This project aimed at the creation of image recovery software based on image content. Chupawa and Kanjanawanishkul [6] proposed an algorithm that seeks to extract features of information printed on the pill (imprint). In the proposed method, the radius of the pill is divided by 5. Then the pixels number of what is printed on the pill which is within the circle with a radius of 0.2 r, 0.4 r, 0.6 r, 0.8 r, are calculated. These data are invariant features of image rotation.

The works of Lee, Yu, Chupawa, and Kanjanawanishkul focus on the recognition of medicines using the imprint features which are characters printed on the pill. However, these characters are not present in all pills produced in Brazil. In an initial sampling performed, only 12% of the medicines produced in Brazil have this feature.

Feature extraction is a key point in pattern recognition. It is responsible for computing relevant features of input images. These features are commonly used as input data for an classifier.

The GLCM or Gray-Level Co-Occurrence Matrix is a feature extractor that analyzes textures, proposed by Haralick in the 1970s. This method analyzes the co-occurrences between pairs of pixels, that is, it does not analyze each pixel individually, but a set of related pixels across a certain distance d in a certain direction (σ).

Moments are widely applied in image analysis, such as pattern recognition, object classification, posture estimation, interior localization, coding, and image reconstruction. Hu [7] proposed seven invariants of scale, rotation, and translation to describe shapes. These Moments are known as Invariant Moments or Hu Moments.

The Zernike Moments are defined as projections of the image intensity function $f(x, y)$ on orthogonal basis functions. In this case, the Zernike polynomials form a complex orthogonal set inside a unit circle, and are therefore bounded by the curve $x^2 + y^2 = 1$.

The Zernike Moments have features that are important to be used as class descriptors, such as invariance of rotation, translation, and scaling, as well as being able to retain the most meaningful information using a reduced

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amount of descriptors.

Local Binary Standards (LBP) are efficient and straightforward texture descriptors, proposed by Ojala [8]. LBP operator assigns a label (a binary number) to each analyzed pixel. For the assignment of this label, each pixel next to the analyzed pixel in a given radius, or not, exceeds a given threshold that is determined by the central pixel value.

Tamura proposed an extractor that has six texture descriptors which are the coarseness, contrast, directionality, regularity, line-likeness, and roughness. These features are related to human visual perception. In their methodology they did a psychological experiment in which several textures photos are presented to a public two by two, thus each participant indicates which of the photos presents the highest value for each feature.

Ramalho *et al.* [9] proposed an analytical-structural method of images based on co-occurrence statistics called the Structural Co-Occurrence Matrix (SCM). This method analyzes necessary structural information considering the gray level of a pixel and its neighbors; SCM is invariant to rotation. The SCM input is two images, one of which is a copy degraded by a low-pass filter (Average and Laplace were used in our work). These authors state that the SCM captures the structural changes of the degraded image.

According to Kuhl [10], Fourier descriptors have been used by many researchers for the near contours characterization. They presented a procedure to obtain the Fourier coefficients of a contour chain coding. The authors named this technique as Elliptic Fourier Features (EFF). Fourier descriptors do not require integration and the use of fast Fourier transform techniques. The results of the Fourier descriptors are invariant to the rotation, translation and dilation of the contour and its initial point, however, it loses information of the shape of the contour.

In this work, we propose an extractor for identification of pill images, invariant to rotation, based on shape and color (CoforDes). The proposed method will be evaluated by comparing it with GLCM, SCM, LBP, Central Moments (CM), Statistical Moments (SM), Hu Moments, Zernick Moments, Tamura and Fourier in pattern recognition experiments in two different datasets.

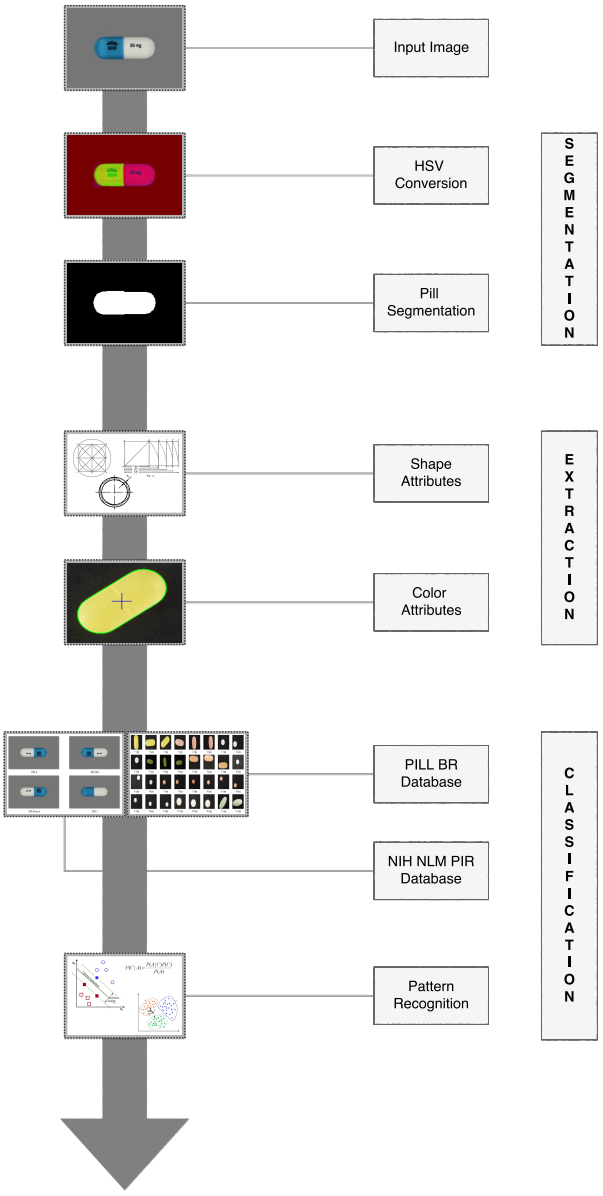

Figure 1. Flowchart of the proposed method.

II. CoforDes

The CoforDes is a feature extractor of digital images that extracts invariant information of shape and color from a pill image. Figure 1 presents the schematic flowchart of the proposed method.

A. Pill images segmentation

The proposed approach begins with the pill segmentation step from the conversion of the input image in the RGB system to the HSV system. Thus, a points collection of image edges is performed, collecting the input image edges. These points are stored in a one-dimensional array, then the average and standard deviation of the color background in the HSV system are calculated. Soon after, we create a threshold that is calculated by a factor multiplied by the standard deviation of the background color. This threshold is adaptive, that is, it adapts according to the image background information.

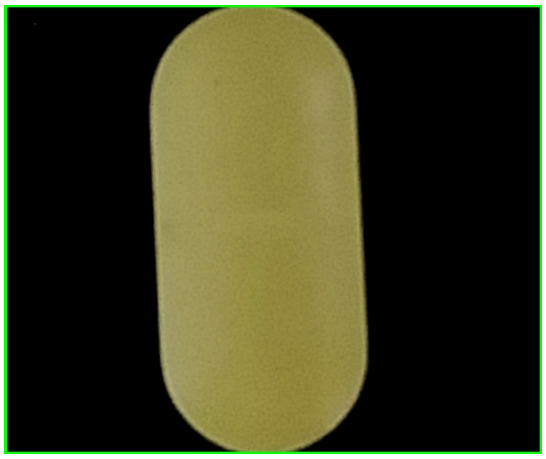

Figure 2. The green points are the points selected for the calculation of the average and standard deviation of the background.

Then the all the image is verified and at each pixel, we calculate the Euclidean distance of the colors H, S, and V in relation to the averages previously calculated. If this distance is higher than the threshold previously calculated the pixel is considered pill. Otherwise, it is regarded as the background. At the end of this process, the resulting image is a binary image, as we can see in Figure 2. Subsequently, the binary image is converted to grayscale, and morphological operations of opening and closing are performed to remove noise and try to detect the pill contour.

The pill contour is defined by the selection of an uniform points collection, when there is an unique contour. If the algorithm is not able to find the unique contour, it restarts. The threshold multiplier factor is decreased, and this process is repeated until the pill contour is detected. We can see examples of segmentation results in Figure 3.

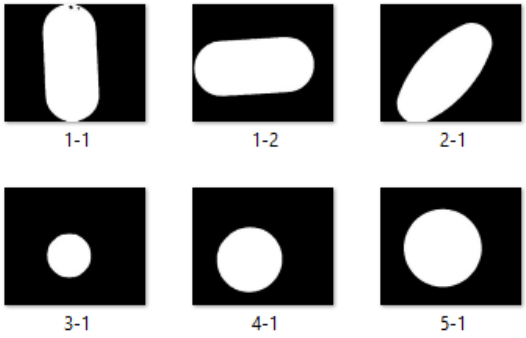

Figure 3. Segmentation result in base PILL BR.

B. Feature Extraction

1) Shape attributes used to compose CoforDes: Shape attributes extraction is performed after pill contour segmentation and detection. We use the following attributes in our model:

Circularity, defined by:

$$C = \frac{4 \times \pi \times area}{perimeter^2}; \tag{1}$$

Rounding, defined by:

$$R = \frac{4 \times area}{xMajorAxis^2}; \tag{2}$$

Proportion, defined by:

$$P = \frac{majorAxis}{minorAxis}; \tag{3}$$

Solidity, defined by:

$$S = \frac{Area}{convexHullArea}; \tag{4}$$

Reason Perimeter/Area, defined by:

$$PA = \frac{perimeter}{area}; \tag{5}$$

Circumcised, defined by:

$$Cir = \frac{perimeter^2}{area}; \tag{6}$$

Rectangularity, defined by:

$$Rect = \frac{area}{surroundingSquareArea}. \tag{7}$$

2) Color attributes used to compose CoforDes: The color attribute calculation uses the contour found in the segmentation process. Then, using invariant moments, we calculate the contour center point of the segmented pill using Hu [7].

We collected forty points above the center point, forty points below the center point, forty points to the right of the center point, and forty points to the left of the center point.

To ensure that the points collected are always within the desired contour, we also use as boundary variables the rightmost, leftmost, topmost, and lowest points of the contour. With these points, we calculate the average and standard deviation of colors in the LAB system. This data is stored in databases as attributes. We can observe this process in Figure 4, where the blue points are selected for these attributes calculation.

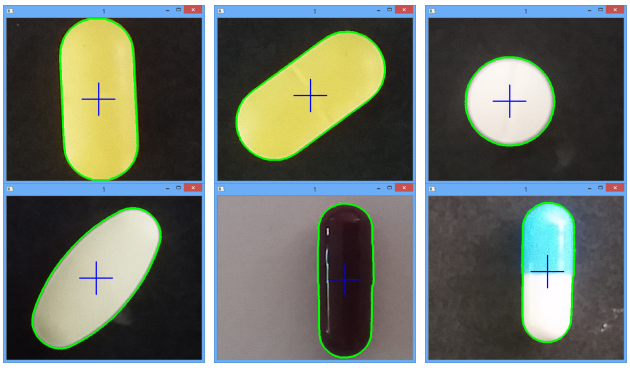

Figure 4. The points selected in blue are an example of collecting points for the calculation of color attributes.

C. Datasets used for CoforDes evaluation

1) PILL BR: The PILL BR dataset is a public dataset comprised of 1000 pill images in 100 different pills labels. Another feature of this dataset is that all 100 pill labels were produced in Brazil. These images were captured using a partially controlled environment. In obtaining the images, there was variation of rotation, translation, background and illumination. In our work, we use all the images from this dataset.

The images have a resolution of 480X400; we can see in Figure 5 some of these images labels.

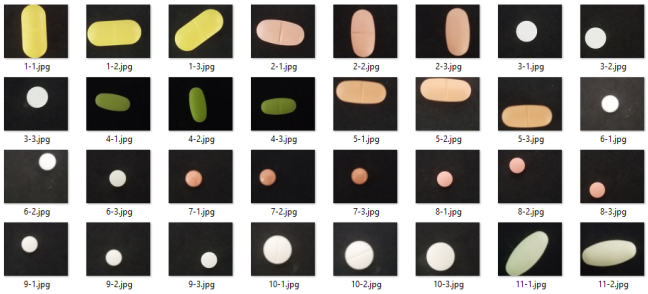

Figure 5. Some samples of the PILL BR dataset.

2) NIH NLM PIR: National Library of Medicine Image Dataset (NIH NLM PIR) is a set of public images, containing JPEG images, with patterns that are promising to enable recognition. This image base consists of two directories: *DC* and *DR*. The DR directory with reference images contain 2000 high-quality images (double-sided 1000 pills) [1].

In our work, we selected 200 images from the DR directory. We decided to use these images by analyzing the variation of shape and colors. These images have 100 different pills labels; each label has two images, one of the front, and the other of the back of the pill.

We create new images, modifying the original images through rotations and flips, resulting in a total of 400 images for evaluation. In Figure 7, we can observe resultant images after rotations and flips from an original image 6.

Figure 6. An original sample of the NIH NLM PIR dataset.

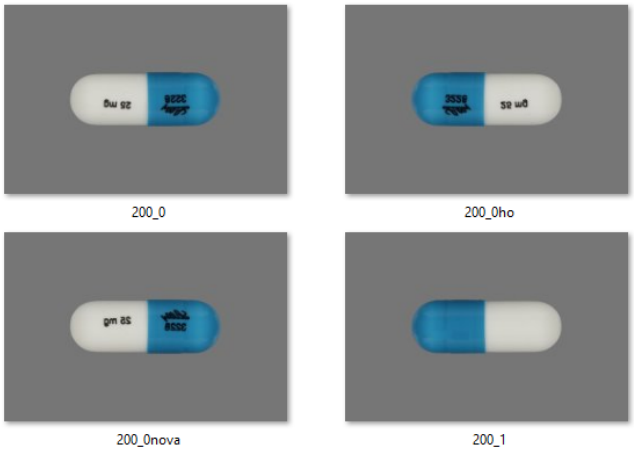

Figure 7. Some samples of the NIH NLM PIR dataset after rotations and flips operations.

III. Results

In this section, we will present and analyze the results obtained by the classifiers KNN, Bayes, and SVM, in the classification process of the pills. This classification used the CoforDes attributes for the extraction process explained in Section II-B. Then, our approach is compared with extractors widely used in the literature, which are: Statistical Moments, Central Moments, Hu Moments, Zernick Moments, LBP, Tamura, SCM-Mean, and SCM-Laplace that were presented in Section I. All extractors were applied to the two datasets, and the same classifiers were used for the validation of the results.

The analysis of the classifiers results was made based on average extraction time, accuracy and sensitivity.

Based on this analysis, we can prove that CoforDes has an efficiency higher than all the analyzed extractors for identification of pill images. TablesI and II contain the average and standard deviation values of 10 interactions for each extractor combined with a classifier on both datasets. The results are divided into accuracy in Table I and specificity in Table II.

Table I
AVERAGE AND STANDARD DEVIATION VALUES (10 ITERATIONS) OF EXTRACTORS ACCURACY: COFORDES, GLCM, STATISTICAL MOMENTS(SM), CENTRAL MOMENTS(CM), HU MOMENTS, ZERNICK MOMENTS, LBP, TAMURA, SCM-AVERAGE, SCM-LAPLACE AND FOURIER IN THE PILL BR AND NIH NML PIR DATABASES.

PILL BR					
Accuracy	Baynes(%)	KNN1(%)	KNN3 (%)	KNN5 (%)	SVM (%)
CoforDes	99.75 ± 0.045315	99.85± 0.013596	99.83± 0.020100	99.74± 0.026170	99.52 ± 0.035053
GLCM	98.74± 0.023811	99.41± 0.049063	99.33± 0.026534	99.66± 0.013396	99.28± 0.020869
SM	98.46± 0.026357	98.41± 0.038164	98.33± 0.023440	98.30± 0.014233	98.28± 0.029106
CM	98.28± 0.025346	98.37± 0.027620	98.27± 0.017241	98.26± 0.030463	98.21± 0.023936
HU Moments	98.44± 0.047402	98.30± 0.024111	98.28± 0.021541	98.28± 0.028762	98.17± 0.014052
Zernick	97.70± 0.027950	97.81± 0.029017	97.84± 0.060754	97.76± 0.027970	97.69± 0.023309
LBP	99.01± 0.041182	98.97± 0.048036	98.80± 0.034280	98.75± 0.038758	99.04± 0.027654
Tamura	98.78± 0.054597	98.79± 0.030692	98.76± 0.037946	98.78± 0.034160	98.56± 0.017583
SCM-Average	98.16± 0.576074	99.20± 0.343373	98.90± 0.381750	98.91± 0.264103	69.36± 22.320944
SCM-Laplace	98.65± 0.024401	98.83± 0.032042	98.71± 0.036537	98.69± 0.035531	98.44± 0.040883
Fourrier	98.80± 0.000000	98.76± 0.000000	98.77± 0.014239	98.72± 0.000000	98.53± 0.000000
NIH NML PIR					
Accuracy	Baynes(%)	KNN1(%)	KNN3 (%)	KNN5 (%)	SVM (%)
CoforDes	99.78± 0.030011	99.82± 0.020403	99.61± 0.035052	99.02± 0.027930	99.76± 0.019617
GLCM	99.67± 0.020508	99.75± 0.024985	99.42± 0.035781	98.94± 0.024580	99.55± 0.036395
SM	98.94± 0.054486	99.18± 0.044053	98.89± 0.026458	98.71± 0.040995	98.93± 0.059026
CM	98.31± 0.036187	98.45± 0.032385	98.29± 0.043773	98.23± 0.028439	98.21± 0.026151
HU Moments	99.31± 0.028572	99.67± 0.037996	99.25± 0.048179	98.80± 0.033529	99.27± 0.039040
Zernick	99.50± 0.074056	99.59± 0.047911	98.89± 0.043313	98.62± 0.030658	98.94± 0.032248
LBP	99.74± 0.040744	99.72± 0.018468	99.48± 0.027852	98.94± 0.035631	99.66± 0.034695
Tamura	99.56± 0.019206	99.66± 0.049034	99.19± 0.033776	98.84± 0.022109	99.21± 0.043684
SCM-Average	77.75± 1.167608	77.71± 1.200355	77.62± 3.090893	77.76± 1.537860	56.90± 8.164029
SCM - Laplace	99.10± 0.040306	99.28± 0.054987	98.72± 0.040300	98.54± 0.029058	98.70± 0.025286
Fourrier	98.85± 0.057659	98.86± 0.022554	98.66± 0.029932	98.51± 0.042237	98.73± 0.052150

Table II
AVERAGE AND STANDARD DEVIATION VALUES (10 ITERATIONS) OF EXTRACTORS SPECIFICITY: COFORDES, GLCM, STATISTICAL MOMENTS(SM), CENTRAL MOMENTS(CM), HU MOMENTS, ZERNICK MOMENTS, LBP, TAMURA, SCM-AVERAGE, SCM-LAPLACE AND FOURIER IN THE PILL BR AND NIH NML PIR DATABASES.

PILL BR					
Specificity	Baynes(%)	KNN1(%)	KNN3 (%)	KNN5 (%)	SVM (%)
CoforDes	99.83± 0.012275	99.92± 0.006869	99.91± 0.010151	99.87± 0.013218	99.76± 0.017701
GLCM	99.36± 0.012027	99.70± 0.024780	99.66± 0.013396	99.64± 0.010541	99.45± 0.017040
SM	99.22± 0.013319	99.20± 0.019273	99.15± 0.011837	99.14± 0.007191	99.13± 0.014695
CM	99.13± 0.012801	99.18± 0.013948	99.13± 0.008708	99.12± 0.015390	99.10± 0.012088
HU Moments	99.21± 0.023943	99.14± 0.012182	99.13± 0.010879	99.13± 0.014526	99.08± 0.007093
Zernick	98.83± 0.014156	98.89± 0.014701	98.91± 0.030764	98.86± 0.014156	98.83± 0.011807
LBP	99.50± 0.020800	99.48± 0.024255	99.40± 0.017312	99.37± 0.019581	99.52± 0.013964
Tamura	99.38± 0.027579	99.39± 0.015506	99.37± 0.019167	99.38± 0.017249	99.27± 0.008885
SCM-Average	99.79± 0.296507	99.94± 0.003010	99.64± 0.364931	98.68± 0.942655	99.32± 0.643490
SCM-Laplace	99.32± 0.012327	99.41± 0.016179	99.35± 0.018456	99.34± 0.017947	99.21± 0.020651
Fourrier	99.39± 0.000000	99.42± 0.000000	99.37± 0.000000	99.35± 0.000000	99.26± 0.000000
NIH NML PIR					
Specificity	Baynes(%)	KNN1(%)	KNN3 (%)	KNN5 (%)	SVM (%)
CoforDes	99.89± 0.015161	99.91± 0.010301	99.80± 0.017706	99.51± 0.014105	99.88± 0.009910
GLCM	99.83± 0.010364	99.88± 0.012616	99.71± 0.018077	99.46± 0.012413	99.77± 0.018379
SM	99.46± 0.027521	99.58± 0.022252	99.44± 0.013362	99.35± 0.020701	99.46± 0.029812
CM	99.15± 0.018271	99.22± 0.016356	99.14± 0.022108	99.11± 0.014367	99.10± 0.013208
HU Moments	99.65± 0.014429	99.83± 0.019193	99.62± 0.024333	99.40± 0.016932	99.63± 0.019716
Zernick	99.74± 0.037405	99.79± 0.024200	99.44± 0.021876	99.30± 0.015483	99.46± 0.016288
LBP	99.87± 0.020578	99.86± 0.009327	99.74± 0.014069	99.47± 0.017990	99.83± 0.017526
Tamura	99.78± 0.009703	99.83± 0.024763	99.59± 0.017059	99.41± 0.011169	99.60± 0.022067
SCM-Average	98.38± 0.378300	88.98± 5.588367	88.44± 7.366587	87.59± 7.938099	92.21± 7.179486
SCM-Laplace	99.55± 0.020354	99.63± 0.027774	99.35± 0.020354	99.26± 0.014675	99.34± 0.012775
Fourrier	99.42± 0.029119	99.42± 0.011394	99.32± 0.015115	99.25± 0.021335	99.36± 0.026341

These tables show us the best results of accuracy and specificity highlighted in blue. The second best results are highlighted in orange and the best result is marked green.

In the PILL BR dataset, as we can see in Tables I and II, CoforDes showed the best results for all classifiers tested. In the Baynes classifier the accuracy was 99.75% and the specificity 99.83%, in the KNN1 classifier the accuracy was 99.85% and the specificity was 99.92%, in the KNN3 classifier, the accuracy was 99.83% and the specificity was 99.91% in the KNN5 classifier accuracy was 99.74% and the specificity was 99.87%, finally, in the SVM classifier the accuracy was 99.52% and the specificity was 99.76%.

In the NIH NLM PIR dataset, the CoforDes also proved superior to all the evaluated extractors, where for the Baynes classifier it presented an accuracy of 99.78% and specificity of 99.89%, in the KNN1 classifier the accuracy was 99.82% and the specificity was 99.91%, in the KNN3 classifier the accuracy was 99.61% and the specificity was 99.80%, in the KNN5 classifier the accuracy was 99.02% and the specificity was 99.51%, finally, in the SVM classifier the accuracy was 99.76% and the specificity was 99.88%. These data can be observed in the Tables I and II.

Table III
AVERAGE AND STANDARD DEVIATION VALUES (10 ITERATIONS) OF EXTRACTION TIME OF THE FOLLOWING EXTRACTORS: COFORDES, GLCM, STATISTICAL MOMENTS(SM), CENTRAL MOMENTS(CM), HU MOMENTS, ZERNICK MOMENTS, LBP, TAMURA, SCM-AVERAGE, SCM-LAPLACE AND FOURIER.

PILL BR(sec)		
	Average	Standard deviation
CoforDes	0.00810	0.001209503
GLCM	9.57529	1.610136269
SM	2.62642	0.563721059
CM	2.60863	0.55109201
HU Moments	2.68166	0.567847482
Zernick	4481.11635	678.7262805
LBP	12.81661	1.664180141
Tamura	1067.08507	147.4518874
SCM-Average	2.12376	0.424818071
SCM-Laplace	2.07500	0.409213951
Fourrier	2.72297	0.964689292

NIH PILL(sec)		
	Average	Standard deviation
CoforDes	0.00810	0.001209503
GLCM	53.33743	8.463361737
SM	2.62642	0.563721059
CM	2.60863	0.55109201
HU Moments	2.68166	0.567847482
Zernick	4481.11635	678.7262805
LBP	233.84617	36.34139737
Tamura	1067.08507	147.4518874
SCM-Average	38.88127	6.661692082
SCM-Laplace	38.71981	7.0220423
Fourrier	35.45031	6.37205723

The Table III presents the average and the standard deviation of the times that each extractor took to perform its task. We can observe that the most efficient extractor in this evaluation was the proposed extractor and the worst extractor in this evaluation was the Zernick Moments.

A. General Analysis of Results

In summary, this Section showed the results obtained by the CoforDes extractor, proposed in Section 2, achieved through the classifiers Bayes, KNN, and SVM in the classification of pill images. Besides, we compared the proposed extractor with some other methods, that we already cite, in two distinct datasets.

In a comparison of CoforDes with the existing methods in the literature, CoforDes obtained the bests results of accuracy, specificity and time of extraction.

Another factor contributing to CoforDes's best results was the combination of color features and shapes. The use of colored images in this specific problem had a positive impact on the results.

Regarding the extraction time analysis, the CoforDes extractor obtained the best results and the Zernike Moments obtained the worst results, in both datasets.

Thus, the use of CoforDes for pill identification is presented as an approach capable to obtain good results.

IV. Conclusion

We present CoforDes an approach to extract relevant information from drug pill images based on shape and color.

We evaluated CoforDes using two datasets in three different classifiers and found that CoforDes showed better results in accuracy, specificity and in extraction time than descriptors GLCM, SCM, LBP, Tamura, Fourier and the Zernick, Central, Statistical and Hu Moments. As a main contribution, we present a new approach to compute the color feature, another important contribution was the creation of a public dataset with pills produced in Brazil.

For future works, we have two important aspects to note, in which we highlight: Growth of the national dataset: the dataset we propose has 100 classes of different pill, however, in Brazil we currently have more than 30,000 classes of drug pill authorized by the national regulatory agency; Adding Texture to CoforDes: the initial proposal although having an excellent accuracy can still be improved, one of the best possibilities would be the addition of texture features.

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