Early Keratoconus Disease Detection By Orbscan II Corneal Topography

Abstract :

Keratoconus is a disease of the eye, which results in progressive thinning of the cornea. The diagnosis of keratoconus disease may be difficult to make, especially in the early stages (fruste keratoconus), since the symptoms associated tothis disease can also be associated toother eye disorders.
This led us to propose a new image processingpipeline allowing to automatically calculate the principal descriptors used by Ophthalmic Doctors (ODs) for the detection of the keratoconus disease, and classify these data in order to propose an intelligent system able to help OD for the early recognition of this pathology. To do that, we have elaborated a new benchmark database from a corneal topographicOrbscan II device.

For this, in this paper we tested five differentmachines learning algorithmson thenew locally collected database which are:two Neural Networks classifiers (Multi Layer Perceptron (MLP) and radial basis function (RBF)), Support Vector Machines (SVM), K-Nearest Neighbors (K-NN) and Decision Trees (DT).The obtained results are satisfying, promising, and prove the efficiency and the coherence of our new database. They also were confirmed and validated by different doctors in ophthalmology.

Keywords: Keratoconus, Image processing, Classification, SVM, MLP, RBF, K-NN, DT.

1. Introduction :

The medical field has been able to integrate diagnostic assistance tools and health has been a very motivating issue for scientist research in recent years.Several studies have been developed concerning several high-risk areas such as the loss of vision due to keratoconus disease (KC) which is the subject of our study.

Keratoconus (KC) is an eye disease characterized by progressive thinning and changes in the shape of the cornea. This change causes different vision problems. The cornea is the transparent front part of the eye that covers the iris, pupil, and anterior chamber. She presents arounded form or dome-shaped in healthy patients. In those with keratoconus, slowly progressive thinning of the cornea causes a cone-shaped bulge to develop towards the center of the cornea in the areas of greatest thinning.

KC is a non-inflammatory disease. It can reach both eyes, but not with the same severity. It usually becomes clinically evident at puberty, and its etiology remains unknown[1].Although it has well-described clinical signs, however, early forms of the disease may be undetected [2]. The Ophthalmologist Doctor (OD) detects this disease using a corneal topographic machine.For early detection, it is necessary to use a corneal topographic machine able to give information of the anterior and posterior cornea at the same time. Knowing that keratoconus disease can be located in the anterior and/or posterior cornea side, associated to a stromal thinning.For this reason, in this work we have collected a new database using Orbscan II corneal topographic machine, which give information about both anterior and posterior cornea it the same time.

Individuals with a family history of keratoconus are at a greater risk of developing the condition than general population.Its incidence has been reported to be 1 in 2000 in the general population. Nevertheless some studies suggest the prevalence of keratoconus to be higher.[3]

Currently, there are no formal clinical criteriafor the early recognition of the keratoconus disease. That is why; several studies have been developed in the literature. Machine learning models have already been used in the detection of this disease [4, 5, 6, 7]. Previous works have focused on the assessment of several techniques: neural networks, support vector machine and radial basis function neural network (RBFNN) in keratoconus diagnosis. For example,we can cite the work presented in [5],where the authors have developed an intelligent system based on three different machines learning algorithm which are: SVM, MLP and RBFNN. These techniques have been appliedin order to detect keratoconus apart from all other corneal patterns, using Orbscan II data. A total of 318 maps were selected and classified into four categories: normal, astigmatism, keratoconus and photorefractive keratectomy. For each map, 11 descriptors were obtained orcalculated from the data provided by the Orbscan II corneal topographic machine which are: Anterior best-fit sphere, Posterior best-fit sphere, Simulated astigmatism, 5mm irregularity, Maximum simulated keratometry, Minimum simulated keratometry, Maximum anterior elevation, Maximum posterior elevation, Thinnest point, I-S and Central corneal power. Ten-fold cross-validation was used and overall, the obtained results suggest that SVM, MLP and RBFNN classifiers, trained on Orbscan II data, could represent useful techniques for keratoconus detection.

Ruiz Hidalgo et al. proposed in [7] an automatic system able to detect keratoconus disease. 860 eyes data from Pentacam corneal topographic machine were included in the study and divided into 5 groups: keratoconus, fruste keratoconus, astigmatic, after refractive surgery and 194 normal eyes. Twenty-two descriptors were used for classification using a support vector machine algorithm. The accuracy rate achieved was of 98.9%, and sensitivity and specificity were of 99.1% and 98.5%, respectively.

In [8], the authors have developed a new Keratoconus Assistant (KA) for automatic and objective keratoconus detection based on machine learning technique. 131 patient have been used in this study from pentacam corneal topographic machines and divided into 4 groups: normal eyes, keratoconus suspect, keratoconus,and postrefractive surgery. Two different centers : Rothschild Foundation and University Hospital Antwerp have separately diagnosed the data in order to validate this KA score.The obtained results wereas follow: for keratoconus, KA score agreed in 92.6% of cases with the clinical diagnosis by Antwerp University Hospital and in 98.0% of cases with the diagnosis by Rothschild. In keratoconus suspect and formefruste detection, KA score agreed in 65.2% Antwerp University Hospital and 100% (Rothschild) of cases with the clinical assessments.

Between 2009 and 2011, Damien Gatinel and Alain Saad have developed the SCORE Analyzer software based on the use of machine learning algorithmes. This score was designed to provide an aid to clinical decision-making in refractive surgery for the early detection and follow-up of keratoconus. In this work, 183 images from Orbscan II corneal topographic machine have been used. The detection by SCORE software included 6 false positives and 2 false negatives, a sensitivity of 92% and a specificity of 96% [9].

In March 2012Fatemeh et al. have developed an intelligent system based on the classification of infra-clinical Keratoconus by using different machines learning algorithms which are: two artificial neural network (multi-layer perceptron, radial basis function), support vector machine, and Decision Tree. This study employed82 topography maps of eye from dataset and classifies them into two categories: normal and Keratoconus. For each map, 12 descriptors have been used. The obtained accuracy rate wasabout 91% accuracy [10].

In the same field, Damien GATINEL have proposed a novel keratoconus study based on the use of the SCORE Analyze which title is .[11]

In [12], Alyaa H et al. have proposed an algorithm based on image processing able the help OD to detect the keratoconus disease. Twelve descriptors have been extracted from topographic maps collected from the Pentacam topographer. Data of 40 patients wereused in this study. The SVM classifier wasapplied on the obtained descriptors. The obtained accuracy rate was of90% in this work.

To the best of our knowledge, there is no works in the literature that propose an automatic detection of keratoconus disease by combining the numerical descriptors given by the corneal topographe and extracted descriptors from corneal topographe after image processing.

The goalof our work is to develop an intelligent system based on the topographic image (anterior, posterior and axial power keratometric) on one side, and the numerical parameters given by the Orbscan II on the other side. Because ophthalmic doctors achieve the detection of keratoconus disease by analyzing the numerical parameters and the images given by the corneal topographer at the same time.

An image processing and different machines learning methods will be applied on a new collected database in order to help OD foran early detection of keratoconus disease.

In this work, we target three distinct objectives: the first one is the collection of a the numerical values given by the ORBSCAN II. The second one, making an image processingpipeline applied to three different images from the same corneal topographer (anterior, posterior, and axial power keratometric) in order to detect others descriptors. The third one is the data classification by using several classifiers on all the descriptors (the numerical values given by the ORBSCAN II and the calculated descriptors obtained after image processing).

This paper is organizedas follow: in section two, we present our collected database and the different parameters that characterize it. In section three, we present the automatic extraction of the Number of colors in 3, 5 and 7 mm in anterior and posterior image, the centering of the thinnest point and the symmetry of the blue and red axes in the axial power-metric image. After that, in the results and interpretation section, we present our performed experiments. Finally, we conclude the paper by presenting the different advantages of our suggested system.

2. The collected database :

Our work focuses on the collection of a new database, the selection and the validation of descriptors with ophthalmic doctors in order to propose an intelligent system for early keratoconus detection.

Our initiative to gather this database is due to the unavailability of a standard and universal database containing the different descriptors used for the detection of the keratoconus disease, which are used by all Ophthalmic Doctors (ODs). Thatis why; we had to collect our own database in collaboration with them. The collected database was obtained using Orbscan II corneal topography.

Currently, our database contains the data related to780 patients on which we exploited the left eye and the right eye (1560 studied eye). Each of whom having 14 different numericaldescriptors,presented in table1, and three images for the corneal topographer (posterior image, anterior image, and Axial power keratometric).

These patients are from different regions of Algeria: west (47.17%), east (4.87%), center (29.87%), and south (18.09%). We can note however that the number of patients collected in the eastern part of the country is not significant (4.87%) compared tothe totality of our database. The good distribution of the data proves the robustness and the coherence of our database because we can find diseases in a region that does not exist in others.

Our database is made up of 780 patients: 384 women, 348 men and 48 children whose age varies between 11 and 61 years. 466patients have keratoconus diseaseand 314 presenthealthy cases.

The number of children in our database is very low compared to adults because the realization of the corneal topography examination of this category is difficult. Also, symptoms usually become apparent during adolescence or young adulthood (i.e. late teens through early 20s).

Each patient studied in our database is represented by 23 descriptors (15numerical descriptors are given directly by the machine and 8 descriptors which are obtained after detection using the image processing techniques proposed in this work).Knowing that the ODs use the numerical values as well as the image obtained to decide if the patient is healthy or has a keratoconus disease.

For this, our database is divided into two Under Bases (UB1 and UB2). The first concerns the numerical values calculated by the corneal topographer, and the second concerns the values calculated by our image processing process (anterior and posterior corneal topographic images and axial power keratometric image). These calculated values are then added to UB1 to perform an analysis similar to that performed by the ODs as shown in the following figure 1.

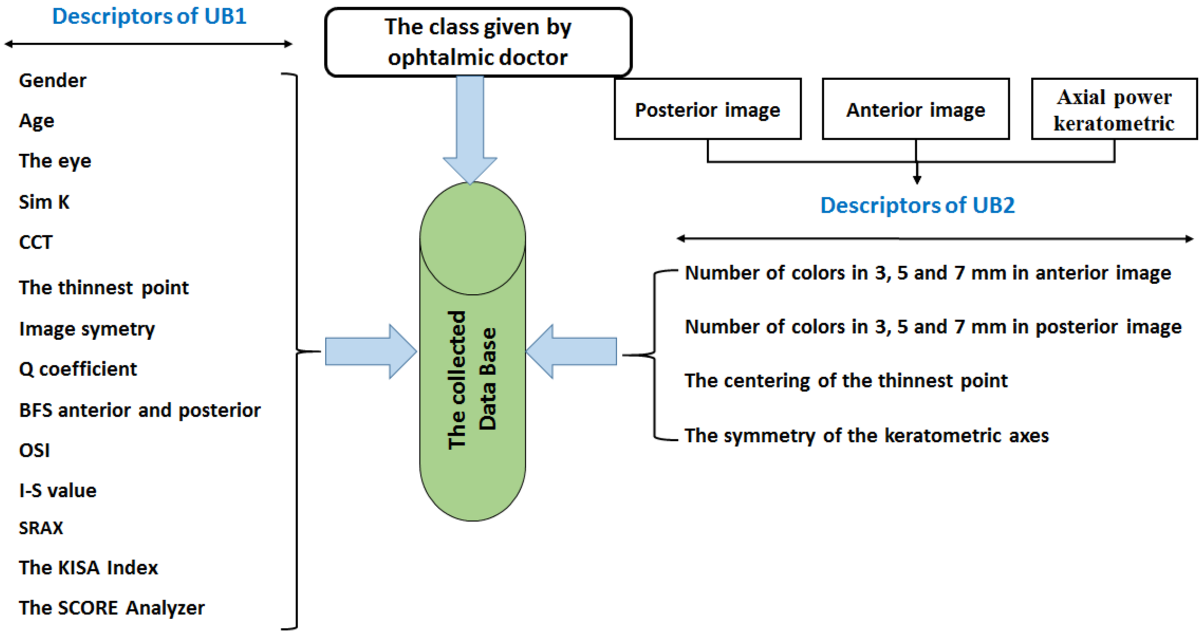


Figure 1: The different descriptors of our database

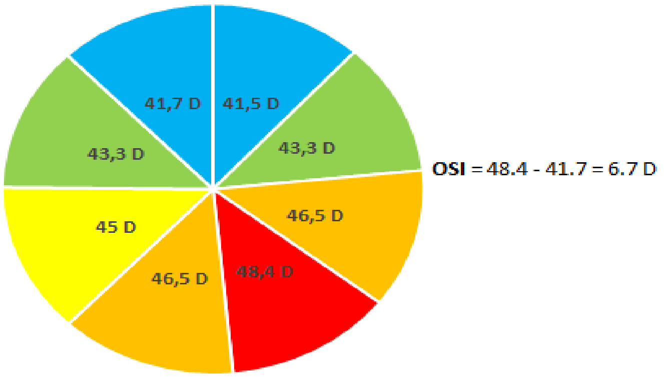
In the following section, we will present the different descriptors of our two under bases UB1 and UB2.

2.1.The descriptors of UB1 :

The following table summarizes the different numerical descriptors given by the Orbscan II corneal topographer on one hand and the class given by the OD on the other hand: Patient with keratoconus, healthy patient. The different descriptors are presented in Table 1 below:

Descripteurs	Signification
Gender	Man or woman
Age	Between11and 61 years.
The eye	OS : left eye, OD : right eye
Simulatedkeratometry (Sim K)	This index provides information on the diopter power of the flattest and most curved meridians. This index is expressed as K1 and K2, and the difference between theese two values provides a quantitative value of corneal astigmatism.

	Below 47.2D : normal, between 47.2 and 48.7D : suspect keratoconus, higher than 48.7D: clinical keratoconus.
The Central Corneal Thickness (CCT)	Measurement of the thickness of the cornea, it is measured in microns. When the Pachymetry is less than 470 microns keratoconus is suspected. Since Orbscan II is an antero-posterior corneal topographic machine, it can measure the distance between these two surfaces to make a complete mapping of corneal thickness.
The ThinnestPoint (TP)	It corresponds to the minimum thickness of the corneal wall. This point is essential for maintaining the corneal structure and determining the progressive thinning of the cornea when the severity of keratoconus progresses [13,14, 15].
Image Symetry (Isym)	Knowing that the shape of the cornea is aspherical and regular this involves that the image is almost mirror. In the case of keratoconus there is no symmetry because the cornea loses its irregularity.
Asphericity coefficient (Q)	This parameter is the most common used in literature. This parameter describes how the corneal curvature changes from the central region to the peripheral region. A normal cornea in the shape of a prolate ellipse. • Q<-1 : the curve is a hyperbola. • Q= -1 : the curve is a parabola. • -1<Q<0 : the curve is a prolate ellipse. • Q=0 : the curve is a circle. • Q>0 : the curve is an oblate ellipse.[16]
The Best Fit Sphere Anterior and Posterior (BFSA, BFSP)	It corresponds to the measurement of the ratio between the radius of the anterior and posterior spheres. When this ratio is < 1.25 normal, between 1.25 and 1.27 suspect cases (frustkeratoconus), > 1.27 keratoconus cases. **There are two values**of this parameter: the first value for the anterior image and the second value for the posterior image.
The Opposite Sector Index (OSI)	For the calculation of this parameter, the corneal surface is divided into eight equal sectors, whose internal angle is 45°. OSI is equal to the maximum difference measured between two opposite sectors.

	 **Figure 2: Example of OSI calculation** Its value increases in case of irregular astigmatism characterized by the presence of a large degree of asymmetry.
Inferior - Superior Value (I-S)	This index is defined as the power difference between five points of the inferior hemisphere and five points of the superior hemisphere of the corneal region located at 3 mm from the corneal apex at spatial intervals of 30°. When the values of this index are : Below 1.4 D (normal), between 1.4 and 1.8 D (suspected keratoconus), when are higher than 1.8 D (clinical keratoconus) [15].
Skewed Radial Axes (SRAX).	This parameter is calculated as follow : 180° - the angle between two steep axis above and below the horizontal meridian (smaller of the two angles). A value greater than 20 ° is considered indicative of keratoconus, but due to the high dispersion of values in some astigmatic corneas, this value is only valuable if corneal astigmatism is greater than 1.5 D [17].
The KISA Index (%)	This index was developed by Rabinowitz and Rasheed [18]. It is based on three values : SRAX, I-S, and keratometry. The formula allowing the calculation of the KISA% index is: $\text{KISA\%} = \text{K} \times (\text{I} - \text{S}) \times \text{SRAX} \times 0.3$ According to Rabinowitz and Rasheed study: • KISA% <60: normal cornea • 60 <KISA% <100: fruste keratoconus • KISA%>100:keratoconus.
The SCORE Analyzer (SCA)	It is based on the results of a clinical research study using Orbscan topography data (Bausch & Lomb, Technolas PV). A negative value (score <0) corresponds to a healthy cornea A positive value (score> 0) corresponds to a cornea judged to have a rough form of keratoconus. [9]

Class	Patient with keratoconus, healthy patient The ODs determine whether the patient presents keratoconus disease or not. Among the 780 collected patients, 314 are non-attained which represents 40.25% of the whole and 466are attained with 59.74%.

Table1 : The different descriptors of the first underbase

2.2.The descriptors of UB2 :

For each patient collected in our database we took three different images as shown in the following figure 3: anterior and posterior image of corneal topography and the axial keratometry image.

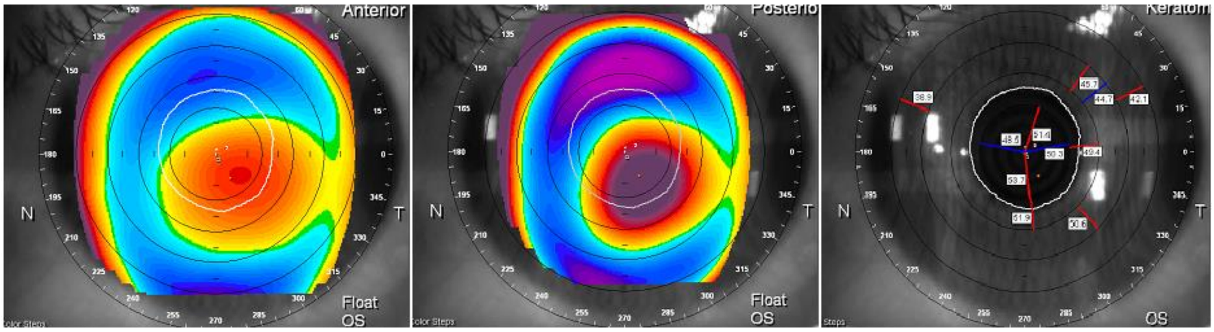


Figure 3: Topographic images

(a) :Anterior image; (b) : Posterior image; (c) Axial keratometry image

This second under base UB2 contains (780 anterior images, 780 posterior images and 780 axial keratometrie images).

After applyingsomeimage processing techniques toall these images, we have automatically calculated the following descriptors:

- Number of colors in 3, 5 and 7 mm in anterior and posterior image in three different areas (3, 5 and 7 mm).
- The centering of the thinnest point in anterior and posterior image.
- The symmetry of the keratometric axes in axial keratometry image.

The following table 2 summarizes a description of the different descriptors calculated automatically from the anterior, posterior and axial keratometry images.

Number of colors in 3, 5 and 7 mm in anterior and posterior image	We have automatically identified the different colors in the 3, 5 and 7 mm area by an algorithm in order to make it easier for ophthalmic doctors. The calculation algorithm is illustrated in the following section. When there are many colors in a small area of a topographic image (3 to 7 mm) mean there are corneal irregularities.
The centering of the thinnest point	This descriptor corresponds to the measurement of the distance between the thinnest point and the geometric center of the cornea. The calculation process will be presented in the following section. When the thinnest point is off-center a keratoconus disease may be suspected because this point is essential for maintaining the corneal structure.
Axial power keratometric	In this part we are interested in studying the symmetry of the blue and red axes. The blue axis corresponds to the most convex hemi-meridian, the red axis corresponds to the thinnest hemi-meridian. In healthy case, the axes are aligned i.e. symmetrical, however in keratoconus case the axes are not aligned. This process was carried out automatically using the image process algoriyhm. This process will be presented in the following section.

Tableau 2 : Les différents descripteurs de la deuxième sous base de données collectée

3. Automatic calculation of the descriptors of the second under-base :

3.1.*Automatic calculation of the colors number for the posterior and anterior image :*

In order to extract the information which is usually drawn by ophthalmic doctors in a visual way, we have applied an algorithm on anterior and posterior images in order to obtain the same information's but in a numerical and automatic way.In this paper, we applied the same algorithm on the posterior and anterior of corneal topography images for the colors number calculation. The steps of our algorithm are illustrated in the following figure 4.

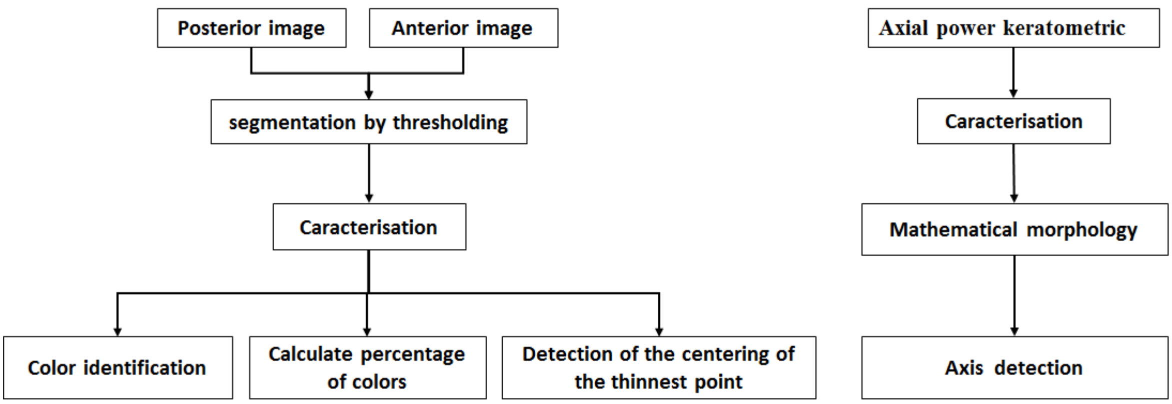


Figure 4 : The different steps of image processing for extracting descriptors of UB2

3.1.1 Segmentation :

We have performed an automatic thresholding segmentation process applied tothe original image (Figure 5 (a)) followed by a surface opening (removing bright details smaller than a surface λ) (Figure 5 (b)), after transforming the color image into a grayscale image to extract the circles presented in black in the original image (3, 5, 7, 9 and 11 mm).

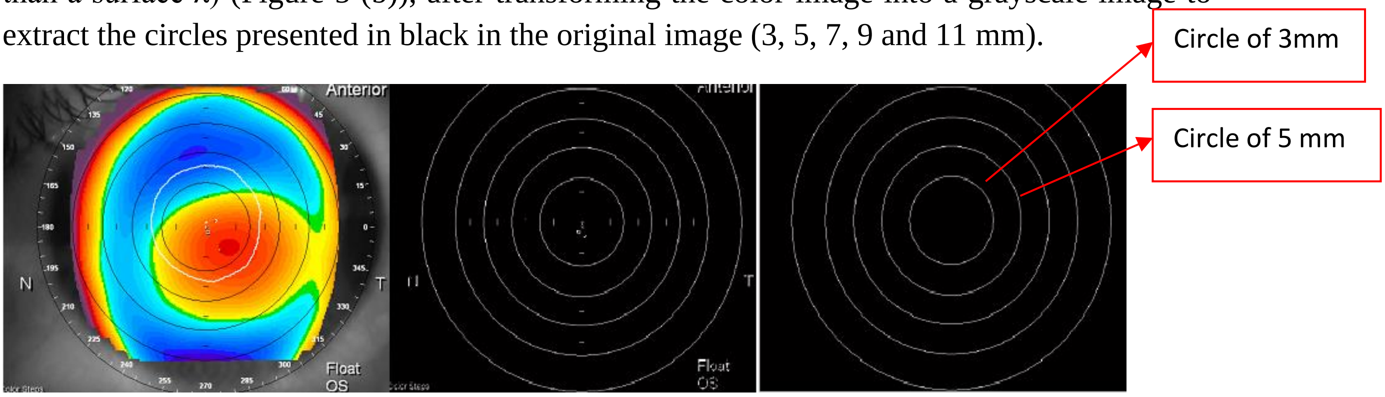


Figure 5: ;(a) Original image, (b) automatic segmentation by thresholding , (c) : surface opening

3.1.2 Characterization:

To calculate the color numbers, we started with a step of the regions extraction (3, 5 and 7 mm), where the doctors relies on these regions to interpret the topographic image and to classify the results according to the gravity degree.

After extracting of each region (3, 5 and 7 mm), we have combined the method of segmentation by thresholding with the closing operator [19] in order to obtain a smooth edge. The small holes are eliminated and the holes in the edge are filled. The closing operator is a dilation followed by erosion operator with the same structuring element.

The closure of the set A (regions of 3, 5 and 7 mm) by the structuring element B, is given by the following equation [19] :

$$A \cdot B = (A \oplus B) \ominus B$$

We obtained a good segmentation results for the three different region.

Figure 6 shows the results obtained after regions detection 3, 5 and 7 mm in order to automatically calculate of the colors number in each region.

Figure 6: binary images for each region 3, 5 and 7 mm:
(a) : region of 3mm, (b) : region of 5mm, (c) : region of 7mm

Finally, the multiplication of the original image(anterior and posterior images) with the images obtained after segmentation operation (3mm, 5 mm and 7 mm) is necessary to obtain each region in colors image (Figure 7). After the extraction of these images (the interest areas), the colors identification becomes simpler.

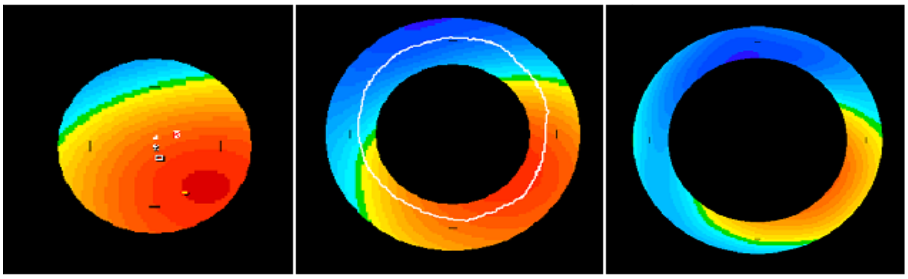


Figure 7: Colors image for each region 3, 5 and 7 mm:

(a) : region of 3mm, (b) : region of 5mm, (c) : region of 7mm

After acquiring only the areas of interest, the identification of colors becomes simpler.

- **Colors Identification :**

A color scale is provided by the Orbscan II topographer. As shown in the following figure 8, this scale consists of 35 colors varying between cool colors and warm colors. Knowing that warm colors translate the cornea deformation forward and cold colors reflect flat corneas.

Then, the calculation of the colors number in each plane (Red, Green and Blue) is necessary in order to separate the healthy cases of pathological cases.

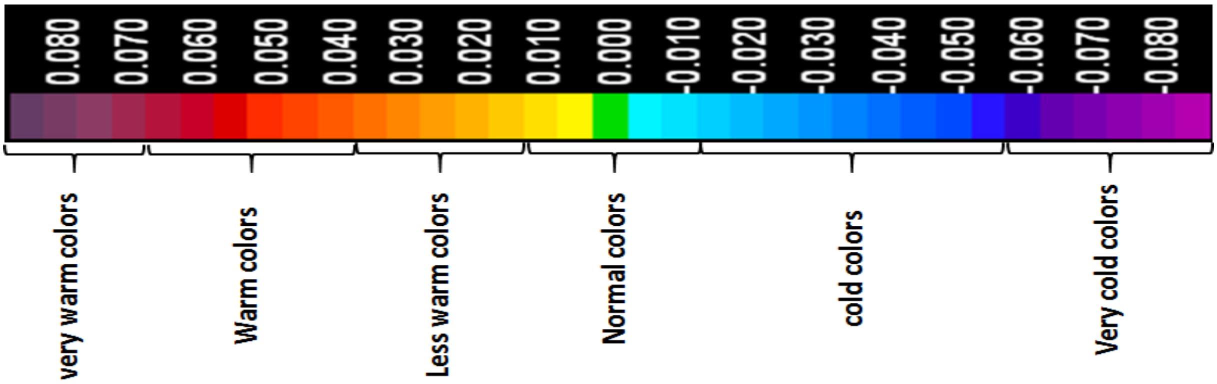


Figure 8:Scale of colors

- **The colors percentage :**

The colors percentage is obtained after calculating the area of each region and separating the pixels of similar colors.

Then, with the collaboration with ophthalmologist's doctors, we divided the scale into six (06) intervals as shown in (Figure 8).

- The intervals 1, 2, and 3: correspond the corneal forms "mounted"
  - ✓ Interval 1: Very hot colors.
  - ✓ Interval 2: Hot.

- ✓ Interval 3: Less hot
- ➢ The interval 4: corresponds to normal cornea "level 0".
- ➢ The intervals 5 and 6: correspond to flat corneas
  - ✓ Interval 5: Cold colors.
  - ✓ Interval 6: Very cold

The detection of the colors number is very important but it is necessary to determine the membership percentage of these colors from the colors scale in order to be able to classify the severity degree of the keratoconus. The colors percentage is calculated by comparing the pixels number belonging to each interval with the total area of the regions (3mm, 5mm and 7mm).

- **<u>Detection of the thinnest point :</u>**

The thinnest point of the cornea is an important element in the keratoconus prediction. To locate this point, we have located of the thinnest point in the topographic image (Figure9) which has different intensity values compared to other pixel values. After that, we calculated the distance between the gravity center and the finest point in order to indicate whether the finest point is centered or not.

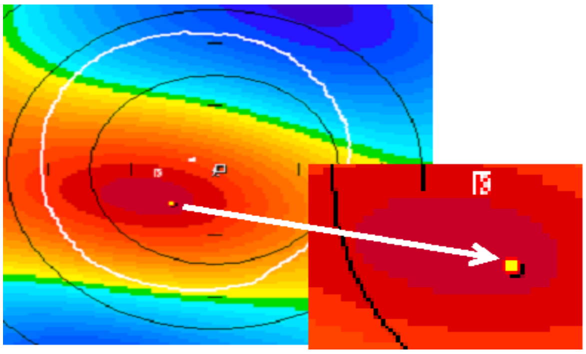


Figure 9:Detection of the thinnest point.

3.2.Axial keratometry images

The images of axial keratometry are obtained from the corneal topographic machine;these images (figure 10) offer another tool for the diagnosis of keratoconus,so that the blue axis represents the domed part of the cornea and the red axis represents the flat part of the cornea.

In order to extract the 2 axes present in the axial keratometry images (figure 10), we used the technical of mathematical morphology. [19]

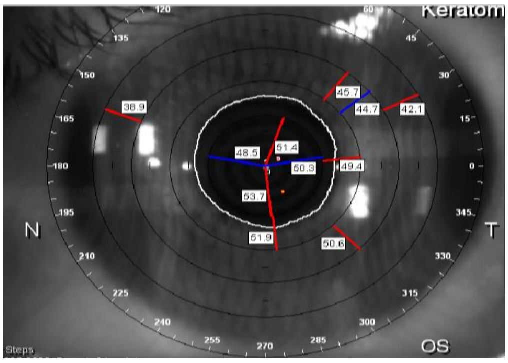


Figure10 :Axial keratometry images

3.2.1. <u>Characterization :</u>

In this section, we detect the 3mm region by multiplying the axial keratometry image by the 3mm binary image. The treatment is done only on this region (region of 3mm) (figure 11), because this region gives the majority of information.

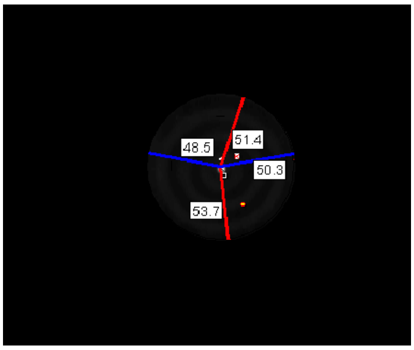


Figure 11:The 3mm region of axial keratometry

We used the colors identification and a surface opening [19] to keep only the two red and blue axes (Figure 12).

Figure 12 : axes detection : (a) red axe , (b) : blue axe

After the axes detection and calculation of the gravity center of the image, we divided the image into four quadrants of same size in order to locate the axes. After, we performed a quadrant overlay that contains axes and we used the skeletonization technique [20] and a dilation followed by erosion to obtain a correct axis.

The distance between the selected axis and the inverted axis is calculated to evaluate the symmetry of the image.

3.2.2. <u>**Mathematical morphology:**</u>

After the axes detection and calculation of the gravity center of the image, we divided the image into four quadrants (same sizes) in order to locate the axes. After, we performed a quadrant overlay that contains axes and we used askeletonization technique [21] and a dilation followed by erosion to obtain a correct axis.

The distance between the selected axis and the inverted axis is calculated to evaluate the symmetry of the image as shown in figure 13.

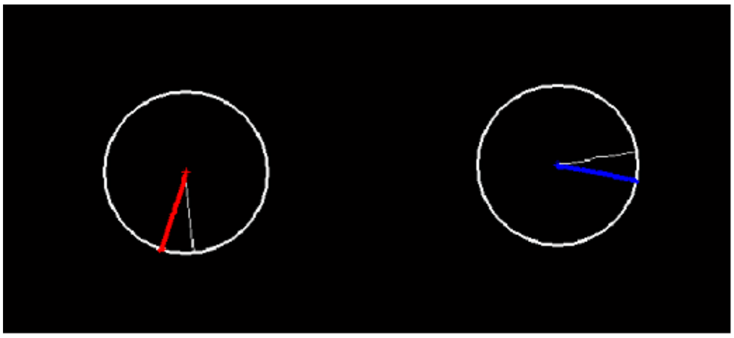


Figure 13: Result of axis symmetry: a)red overlay   b) blue overlay

4. Results and interpretation:

The aim of this research is to the collect of a new keratoconus database and the classification of this database using five different supervised learning classifiers which are the SVM, the MLP, the RBF, the CART and the K-NN. These machines learning classifiers have been successfully applied in the literature for the detection of the keratoconus disease.
The principle operating of our prototype is illustrated by the diagram of Figure 14:

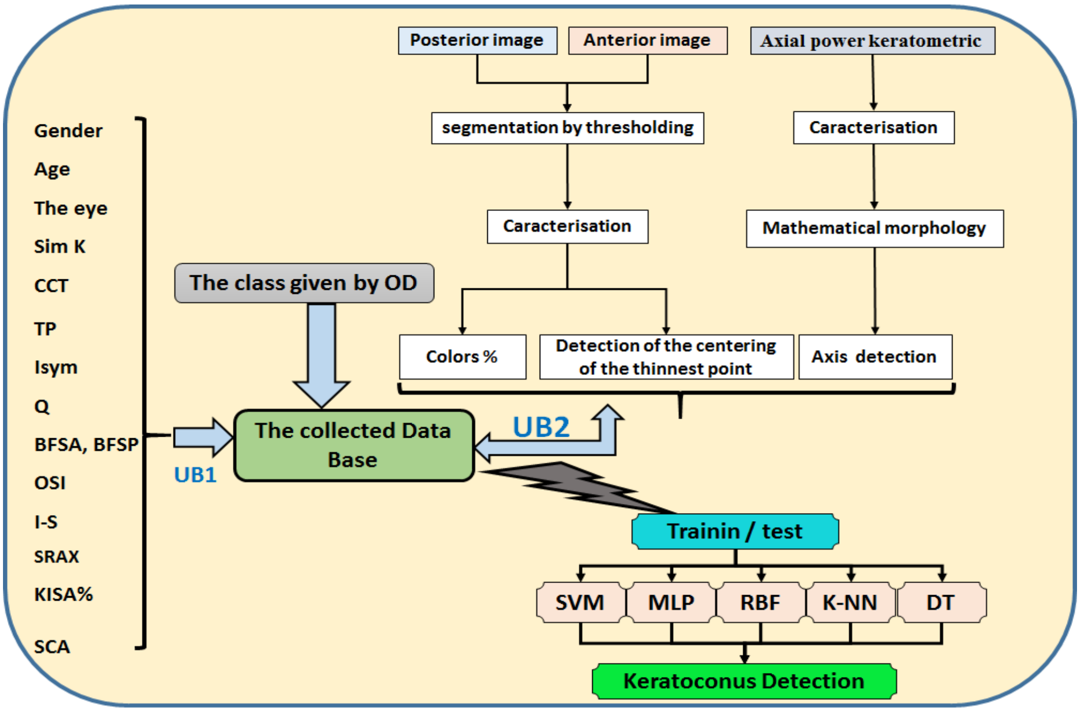


Figure 14. The operating principle of our prototype

In this study, we used five different machines learning algorithms. These algorithms are:the two neuronal network classifiers (MLP and RBF), Classification And Regression Trees (CART), Support Vector Machine and the K-Nearest Neighbor classifier. We have chosen to use five different machines learning approaches because in this work we have used a new database.

Our results were obtained by using the k-Cross-validation technique. This method is used for the evaluation of the reliability of the results obtained by a given classifier. This method is based on a sampling mechanism. For example, in computer aided-diagnosis system, this technique measures the error rate of a classification model using all available data (entire database), both in learning and test, [22]. The K-cross validation technique is useful when the number of data is not really important (small datasets). Its operating principle is summarized in the following points:

- The available data are divided into K disjoint blocks (see Figure 15)
- The classification model is trained using data of K -1 blocks.
- The test is done by using the remaining block of data.
- Training and testing are repeated K times (K experiments) since all blocks can serve as a training and test samples.
- The final error rate of the system is an average of errors committed in all experiments.

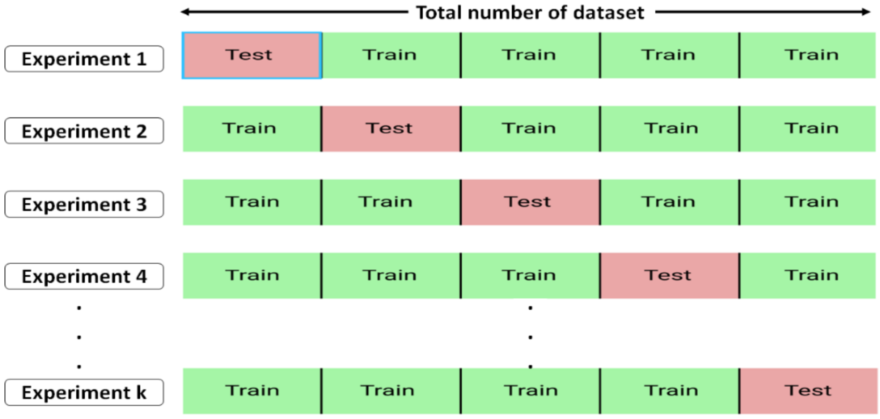


Figure 15 Example of a k-cross validation

The following table (table 3) summarizes the obtained results into three experiments: using only UB1 descriptors, using only UB2 descriptors, using all descriptors of database (UB1 and UB2). After 10 cross validations, the classification performances with the five different implemented classifiers were evaluated by calculating the percentage of Accuracy Rate (AR) and the Area Under the Curve (AUC). The classification results are summarized in the following table:

Experiment 1	**The Obtained Results Using UB1 descriptors**				
	SVM	***MLP***	***RBF***	***K-NN***	***DT***
Classification Rate	86,21	83,04	82,1	73,27	85,34
AUC	0,766	0,72	0,603	0,567	0,758
Experiment 2	**The Obtained Results Using UB2 descriptors**				
	SVM	***MLP***	***RBF***	***K-NN***	***DT***
Classification Rate	89,28	83,54	82,86	85,32	90,39
AUC	0,818	0,722	0,653	0,752	0,858
Experiment 3	**The Obtained Results Using all database (UB1 and UB2)**				
	SVM	***MLP***	***RBF***	***K-NN***	***DT***
Classification Rate	95,04	90,92	84,33	81,16	91,13
AUC	0,945	0,863	0,747	0,711	0,871

Table 3. The performances of our prototype in the two experiments

We notice that a good recognition was generally achieved by the five different machines learning classifiers for the three experiments. The results of the third experiment (using UB1 and UB2 in the same time) are better than those of the first and the second experiment, and this proves that for the detection of keratoconus disease it is necessary to use the different numerical descriptors given by the Orbscan II and the obtained descriptors obtained after image processing. This result confirm the medical approach proposed because for the keratoconus disease detection, ophthalmic doctor used the numerical parameter and the obtained image given by the topographer.

As shown in table 3, the best classification for keratoconus disease detection in the third experiment was obtained by the support vector machinesalgorithm (95.04%).

Among the five classifiers used in the experiment, the Multi-Layer Perceptron algorithm and the C4.5 decision tree algorithm provide more or less the same prediction accuracy 90.92% and 91.13% respectively.

The accuracy rate of the RBFand the KNN algorithms are the lowest among the others machines learning techniques: 84.33% and 81.16% respectively.

As often reported in the scientific literature, MLP, SVM, CART, RBF and K-NN machines learning classifiers represent reliable techniques for the recognition of diseases in the field of computer aided diagnosis [5], and that is why we applied them in our database.

Our database is new and has been tested for the first time, for this reason. Our initiative was to apply several classification techniques together for testing this keratoconus database.

Our prototype provides us whether the patient has keratoconus or not. Indeed, this step is very important in clinical routine ophthalmic, because this pathology is a redundant disease and a major cause of blindness. The results obtained in this paper are very interesting for a first test on a new database collected locally and used for the first time.The obtained results have been validated by ophthalmic doctors.

5 Conclusion

In this paper we have proposed asystem allowing to automatically detect the presence or the absence of keratoconus disease in order to help the ophthalmic doctors to support the patient quickly and effectively in routine clinical. The absence of a standard database in this area led us to collect locally a new database composed of 780 patients.

Themain objective ofthis data collection is to be able to collaborate with several ophthalmic doctors, in order to expand our database onone hand and to validate our obtained results on theother hand.

Ophthalmic doctors make the detection of keratoconus disease by analyzing the numerical parameters and the images given by the corneal topographer at the same time. That is why; in this paper, we have developed an image-processing algorithm able to process posterior image, anterior image, and axial power keratometric at the same time in order to find the parameters of the corneal topographer images. These parameters will be used with the numerical parameters given by the corneal topographer to have a good recognition of keratoconus disease.

To assess our database, we first designed different machines learning classifiers, which are: the multi-layer perceptron, the support vector machines, the K- nearest neighbors and the C4.5 decision trees. The obtained results with the different classification techniques are satisfactory since the best accuracy rate obtained with the support vector machine was of 95.04%.

This model can be improved in ourfuture works by using a larger number of machines learning methods with a larger size database, especially patients who have undergone refractive and crosslinking surgery. Also, we want to add more details about the proposed diagnosis for the patient specifying the most suitable namely contact lenses and surgery.

Finally, we want to develop a new keratoconus score in order to provide an accurate help to ophthalmic doctors allowing them to quantify this pathology.

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