Support Vector Machine for Keratoconus Detection by Using Topographic Maps with the Help of Image Processing Techniques

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Abstract: In recent years many researchers tried to find an accurate method to diagnose eye disease. Researchers used different methods and devices for that. In this paper a method is present which depends on the details extracted from the topographic maps to detect Keratoconus (KC) that affects the cornea in diseased eye; with the help of image processing techniques. Twelve features (12) have been extracted from topographic maps collected from the Pentacam which is a device that acquired maps of the cornea and provide an information of the health of the eye, and applying these features to the support vector machine SVM (which is a supervised classification) to detect whether the cornea is healthy or diseased. Results showed that there is accuracy of about 90% for the tested data. Each normal indication will be written as Ok; and a red flag will be written for the abnormal indications.

Key Words: Image processing, Keratoconus (KC), SVM, Topographic Maps.

I. Introduction

The eye cornea is the outermost layer of the eye, it is the dome shaped clear surface that covers the front of the eye and plays an important role of focusing the vision. Although the cornea may seem clear and lacking of substance, but on the contrary, it is a highly organized tissue, unlike most tissues in the body, it contains no blood vessels to nourish and protect it from infections. Instead the cornea receive it nourishment from tears and from the aqueous humans (a fluid in the front part of the eye that lies behind the cornea) [1]. The cornea can be affected by many diseases such as Fuchs’ endothelial dystrophy, Bulbous keratopathy Glaucoma etc[2]. One of these diseases is Keratoconus; which is a non-inflammatory corneal disease that can be identified by locating a protrusion along with conical thinning in the cornea[3], as a result it will cause a distortion in vision. It is important to diagnose the affected cornea to give the right treatment for it; therefore researchers put their efforts to improve the software as well as hardware to present devices that gives accurate readings. There are different ways to detect KC[4]; the most used one is by using the Pentacam; which is a device that provide maps of the cornea as well as readings that gives information about the health of the cornea[5]. The Four Refractive maps are the maps that help to detect Keratoconus (KC), these maps contains from four maps (Sagittal, Pachymetric, Elevation front and Elevation back maps), each map gives an indication about the eye; and after revising all of the features from the four maps; decision will be made. There are some difficulties of diagnosing KC corneas; for the clinicians have to observe the maps that acquired from the device along with the reading and also, the results of examinations from other instruments to give the final decision; therefore, it is a very long complicating process. In the past years; researchers combine features that extracted from the maps with machine learning, such as Tout unchain et al.[6] employed 82 corneal maps and classified them into two groups normal and Keratoconus corneas; 12 features of each map were extracted and used as an input for the classifiers, the classifiers that were used are NN, RBFNN, SVM and Decision Tree. Cheboli and Ravindran[7] proposed to use semi-supervised learner to label the un label data (clinically undiagnosed corneas). Souza et al. [8] proposed a way to estimate the performance of multi-layer perception, SVM and radial basis function neural network as contributory tools to recognise Keratoconus from maps that were taken from Orbscan II.

This paper presented a method of diagnosing by using image processing and geometrical techniques to extract features from the four refractive maps provided by the Pentacam, and then entering these features to the SVM classifier to give an accurate diagnosing that support clinician opinion. In this work each normal indication will be written as ok; and a red flag will be written for the abnormal indications.

II. Methodology

Data Collection: Data are acquired from Al-Amal Eye Private Clinic in Baghdad by using the Pentacam, where the cases are already examined and checked by the specialist doctors. The four refractive maps are used for this work; for they are the maps that are used to diagnose Keratoconus.
Subjects: 40 cases are used from both gender (22 females and 18 males), divided into two groups normal and abnormal. For each case the right corneal map (OD) is used. The range ages of the patents are between 54 to 20 years. Ten cases are used in this search.

III. Application of Image Processing Techniques on The Maps:
This search focused on the four refractive maps because these are the maps that are used to detect KC. These maps are Sagittal map, Pachymetric map, Elevation map front and Elevation map back, each map can be acquired individually and also, all of them together as in figures (1, 2, 3, 4, and 5)

Fig. (1) The Four Refractive Maps.

Fig. (2) Individual Sagittal Map.
Support Vector Machine for Keratoconus Detection by Using Topographic Maps with the Help of...

Fig. (3) Individual Pchymetric Map.

Fig. (4) Individual Elevation Map Front.

Fig. (5) Individual Elevation Map Back.
The work is divided into five steps depending on each map and the applying techniques that are done on them. The features that are extracted from the four refractive maps are restricted in a circle with a diameter of 6mm; as it is the focal zone of the cornea and all changes will be happening inside this 6mm circle. Also, all maps are converted from RGB into gray level before extracting the features from them.

**SagittalMap:** The features for the first three columns in table (1) represents the area of the bowtie shape, the area for the top half and the area for the bottom half respectively in the Sagittal map. A threshold has been applied to separate the shape from the background and calculating the area and knowing the value of the pixel for that area, then by dividing the bowtie shape from the centre of the map to count the area of each part as in figure (6) by using equation(1) [9]. The area is counted in pixels. If there are big difference between the areas for both top and bottom halves then a red flag will be written as an indication of an abnormality.

\[ G(x, y) = \begin{cases} 1 & \text{if } \geq \text{threshold} \\ 0 & \text{if } < \text{threshold} \end{cases} \]

\[
\text{Slope} = \frac{(x_2 - x_1)}{(y_2 - y_1)} \quad (2)
\]

\[
\text{The angle} = \tan^{-1} \text{slope} \quad (3)
\]
Support Vector Machine for Keratoconus Detection by Using Topographic Maps with the Help of...

**Pachymetric Map:** There are two features that are extracted from the Pachymetric map. First is the shape. As the Ophthalmologist familiar with; if the shape is circle like then there is red flag; and if the shape is more ellipse like then it is ok, after applying contour on the Pachymetric map to separate the concentric shapes from each other and then to be able to calculate the vertical and horizontal radius of the shape inside the 6mm circle as in equation (4,5) [10]. If both horizontal and vertical diameters for the shape are equal then it is a circle like and there is more indication of having Keratoconus, if not then the cornea is ok, as shown in figure (8).

![Pachymetric Map Diagram](image)

**Fig. (8) The contour ,the 6mm circle and the axis on the Pachymetric Map.**

\[
\begin{align*}
    r_1 &= \frac{|(X_2 - X_1)|}{2} \quad (4) \\
    r_2 &= \frac{|(Y_2 - Y_1)|}{2} \quad (5)
\end{align*}
\]

Where: \( r_1 \) is the vertical radius.
\( r_2 \) is the horizontal radius.

The other features for this map is the location of two points which are the thinnest location and the centre of the map. These points acquired by clicking on the two points on the map and then calculate the distance (d) from equation (6) [11]. If d is less or equal than both radius then the two points are inside the shape, then the cornea is ok; if d is larger than both radius that means one of the points or both of them are not inside the shape then the cornea has a red flag for this map as explained in figure(9).

\[
d = \sqrt{(x_1-x_2)^2 + (y_1-y_2)^2} \quad (6)
\]

![Thinnest Point Diagram](image)

**Fig. (9) The thinnest point and the centre of the map in Pachymetric map.**

**Elevation Maps Front and Back:** For the elevation maps back and front the concept of bag of features are applied, this concept is a program of extracting and classifying features[12]. It is an algorithm of text retrieval its strategy is by dividing the image into small regions then representing each region by feature vector, the last stage of bag of feature is training process, it will form a histogram of how frequent each feature appears in the image[13]. Because there will be thousands of features that will be extracted from the image it need to do clustering; k-mean clustering is used for the bag of features [14] which gather all of the similar features around one centre and then give a classification for the map. The decision is given as ok for normal cases and red flag for abnormal cases.
The Four Refractive Maps: Using the four refractive maps as in figure (10) to compare the thinnest points value between the Pachymetric map and Elevation map front, and between Pachymetric map and Elevation map back, and the value of the thinnest point and Elevation maps front and back. All of the cases are diagnosed from a professional ophthalmologist and the decision was used as a reference.

**Classification**

SVM: The SVM attempt to find the best separating hyper plane between the classes depending on training cases that are consider on class descriptors so, the support vectors is representing by training cases. the less training cases are in such a manner as to achieve a desired result, the high classification accuracy is obtained in choosing less training classes.

Let us consider a supervised binary classification problem. The training data can be representing as [X₁, Yᵢ], where the value of i = 1, 2, ..., N, Yᵢ has the value in the rang (1, -1) and N is the number of training cases, the (+1) is for W₁ and the (-1) for class W₂, linear separation are consider for the two classes, the hyper plane which separated the classes is [15].

\[ F(\mathbf{x}) = \mathbf{w} \cdot \mathbf{x} + w_0 = 0 \] (7)

the value of w and w₀ is obtained in a manner that Yᵢ(\mathbf{w} \cdot \mathbf{x} + w_0) ≥ +1, class W₁ for which Yᵢ is +1 and Yᵢ(\mathbf{w} \cdot \mathbf{x} + w_0) ≤ -1 class W₂ in which Yᵢ is -1 these can be combine together to obtained the following equation [15].

\[ Yᵢ(\mathbf{w} \cdot \mathbf{x} + w_0) - 1 ≥ 0 \] (8)

The super vector mechanism aims to find the suitable hyper plane that have the best merge between the classes, the super vector machine are on the hyper plane which are parallel it gives by [15].

\[ \mathbf{w} \cdot \mathbf{x} + w_0 = -1, +1 \] (9)

the hyper plane can be represented by solving the following equation [14].

\[ \text{Minimize} \frac{1}{2} \| \mathbf{w} \|² \] (10)

subject to

\[ Yᵢ(\mathbf{w} \cdot \mathbf{x} + w_0) - 1 ≥ 0 \] (11)

where i = 0, 1, ..., N.

the Lagrange can be used to transform the above equation to Maximize

\[ \sum_{i=1}^{N} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{N} \lambda_i \lambda_j Yᵢ Yⱼ (\mathbf{x}_i \cdot \mathbf{x}_j) \] (12)

subject to \[ \sum_{i=1}^{N} \lambda_i Yᵢ = 0 \quad \text{and} \quad \lambda_i ≥ 0 \] (13)

in which i = 0, 1, 2, ..., N

where \( \lambda_i \) is the Lagrange multipliers, the optimal hyper plane is [14].

\[ f(\mathbf{x}) = \sum_{i \in s} \lambda_i Yᵢ (\mathbf{x} \cdot \mathbf{x}_i) + w_0 \] (14)

The support vector mechanism is represented by the subset of training samples (s) which has non zero Lagrange multiplier.

After extracting all of the features from the 40 cases; the SVM classifier applied to give the final result. Total of 12 features are extracted from the four refractive maps, 30 cases are entered as training and 10 cases are entered.
as testing. To evaluate the performance of the SVM classifier [8], the one leave out is utilized. Accuracy is calculated as given (TP) true positive, (TN) true negative, (FP) false positive, (FN) false negative as the following equation (15) [16]. The SVM classifier for the training data is with accuracy of 80% and the tested data accuracy is 90%.

\[
\text{Accuracy} = \frac{TP + TN}{\text{total cases}} \times 100\% \quad (15)
\]

IV. Results and Discussion

This paper employs one classifier in recognition phase; which is the SVM classifier. Table (1) shows the result features of the ten tested cases after using image processing techniques and geometrical methods. The red flag is when the values of features are more than the abnormal values where ok is when the values are with the normal values depending on the ophthalmologists values for the normal and abnormal cases. Table (2) is the doctor decision and SVM classifier the (12) features which has been calculated must checked to say what case is normal or not, in table(2) case No.1 doesn’t satisfy all the (12) features so, there is a difference between the doctor and SVM decision. Table(3) shows the confusion matrix between the normal corneas and the KC corneas for the ten cases; it shows that the SVM classifier has predicted the KC cornea with an excellent accuracy of 100%, whereas there is an accuracy of 83.3% for the normal cornea but the SVM classifier has wrongly predicted the normal cornea as KC cornea with an accuracy of 16.7%. Mean and standard deviation are counted from equations (16 and 17) [17,18] for the 10 tested cases as in tables (4)and (5).

Table (1). The features for the tested ten cases.

<table>
<thead>
<tr>
<th>Case</th>
<th>Feature 1</th>
<th>Feature 2</th>
<th>Feature 3</th>
<th>Feature 4</th>
<th>Feature 5</th>
<th>Feature 6</th>
<th>Feature 7</th>
<th>Feature 8</th>
<th>Feature 9</th>
<th>Feature 10</th>
<th>Feature 11</th>
<th>Feature 12</th>
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</table>

\[
M = \frac{\sum(x)}{N} \quad (16)
\]

\[
S^2 = \frac{\sum(x-M)^2}{N-1} \quad (17)
\]

Where M = The mean value of the data.

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Support Vector Machine for Keratoconus Detection by Using Topographic Maps with the Help of...

\[ \Sigma = \text{Sum of data.} \]
\[ X = \text{Individual data points.} \]
\[ N = \text{Sample size (number of data points).} \]
\[ S = \text{Standard deviation of data.} \]

<table>
<thead>
<tr>
<th>Case No.</th>
<th>Doctor Decision</th>
<th>SVM Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>KCN</td>
<td>NORMAL</td>
</tr>
<tr>
<td>2</td>
<td>NORMAL</td>
<td>NORMAL</td>
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<td>3</td>
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<td>4</td>
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<td>5</td>
<td>NORMAL</td>
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<tr>
<td>6</td>
<td>KCN</td>
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<td>7</td>
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<td>KCN</td>
<td>KCN</td>
</tr>
<tr>
<td>10</td>
<td>NORMAL</td>
<td>NORMAL</td>
</tr>
</tbody>
</table>

Table (3). The confusion matrix predicted

<table>
<thead>
<tr>
<th></th>
<th>KCN</th>
<th>NORMAL</th>
<th>( \Sigma \text{sum} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>KCN</td>
<td>100.0%</td>
<td>16.7%</td>
<td>5</td>
</tr>
<tr>
<td>NORMAL</td>
<td>0.0%</td>
<td>83.3%</td>
<td>5</td>
</tr>
<tr>
<td>( \Sigma \text{sum} )</td>
<td>4</td>
<td>6</td>
<td>10</td>
</tr>
</tbody>
</table>

Table (4). Standard deviation and mean for the normal cases.

<table>
<thead>
<tr>
<th>Normal cases</th>
<th>Area of the top half</th>
<th>Area of the bottom half</th>
<th>The angle of skewing</th>
<th>Subjective axis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>8196</td>
<td>12666.6</td>
<td>23.12</td>
<td>7</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>13980.17747</td>
<td>10792.43417</td>
<td>35.8852616</td>
<td>6.708203932</td>
</tr>
</tbody>
</table>

Table (5). Standard deviation and mean for the KC cases.

<table>
<thead>
<tr>
<th>KC cases</th>
<th>Area of the top half</th>
<th>Area of the bottom half</th>
<th>The angle of skewing</th>
<th>Subjective axis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>8873.8</td>
<td>40937.6</td>
<td>64.82</td>
<td>73</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>11722.19</td>
<td>27938.21</td>
<td>51.1497</td>
<td>63.89444</td>
</tr>
</tbody>
</table>

Fig. (11) Standard deviation and mean for the KC and Normal cases.

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From table( 4,5) and figure(11).There are small differences in the mean for the top and bottom halves for the normal and KC cases, but there is big difference for the mean between the angle of skewing for the normal and the KC cases, also there is big difference between the mean for the subjective axis between the normal cases and the KC cases. The angle of skewing for the KC is greater than that for the normal one, the standard deviation is higher for the KC so is the subjective axis. The mean value for the top half area for the KC is higher than that for the normal case, while the standard deviation for the top half for KC is smaller than that for the normal case, the area of the bottom half for the normal case is higher than that for the KC, while the standard deviation is higher than that for the normal case.

V. Conclusion
1. The area of the top half for the circle with diameter of 6mm for the eye in the Keratoconus case is higher than that for the normal case for the mean value, while for the standard deviation value is smaller than that for the normal case.
2. The Keratoconus case has lower area of the bottom half value than that for the normal case for the mean value, while for the standard deviation value area of the bottom half in the Keratoconus case is higher than that for the normal case.
3. The confusion matrix shows that the SVM classifier has predicted the KC cornea with an excellent accuracy of 100%, whereas there is an accuracy of 83.3% for the normal cornea but the SVM classifier has wrongly predicted the normal cornea as KC cornea with an accuracy of 16.7%.
4. To say that the case is normal or has a Keratoconus the (12) features which are calculated in table(1) must be obtained and satisfy for all (10) cases to judge that the case is normal or it is in risk case.

Reference