Machine learning approach for detection of keratoconus

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Abstract. Keratoconus is a progressive eye disease and it should be detected in early stage, to avert probable refractive surgery that could develop ecstasies. In this the authors proposes a new computer aided diagnosis model based on Support Vector Machine (SVM) learning to detect the early stage of keratoconus using the available topographic, pachymetric and aberrometry parameters of patients with keratoconus, subclinical keratoconus and normal corneas. The proposed SVM produces 91.8% accuracy with 94.2% sensitivity, 97.5% specificity for classification of early keratoconus from normal; 100% accuracy with 100%, 100% of sensitivity and specificity respectively for classification of early keratoconus from subclinical keratoconus.

Keywords: Ophthalmology, Support Vector Machine, Normalization, Feature Selection, Corneal Ectasia.

1 Introduction

Keratoconus is a bilateral and non-inflammatory corneal condition that can cause refractive myopia, irregular astigmatism, corneal thinning, and poor visual acuity due to the hallmark conical shape of the cornea and in progressive states, corneal scarring[1]. The recorded prevalence of keratoconus differs generally based upon the geographic region, diagnostic criteria adopted, and the cohort of patients chosen. The popularity of keratoconus in surveys can range from 0.3 per 100,000 in Russia to 2300 per 100,000 in Central India (0.0003%-2.3%) [2]. The scrupulous measurement of corneal topography is crucial for early diagnosis and monitoring of disease. Corneal topographers prepare distinct maps to represent the measurements that describe the surface of a keratoconic eye. The ophthalmologist has to conclude what range could be considered in each incident in order to arrive at the best decision from a clinical point of view. Different modern instruments have emerged for interpretation of the cornea such as Orbscan which is based on Placido Disk Based Slit-scanning, Pentacam utilized combination of slit illumination system and rotating scheimpflug camera, and Galilei which combines corneal Placido disk topography with a dual Scheimpflug camera[3]. Also, many studies have aimed to assess the accuracy of the corneal imaging devices in keratoconus eyes. There are several grading systems that have been used in the literature for classifications of clinical keratoconus namely Amsler-Krumeich, KISA%, Chastang method, Belin/Ambrosio Enhanced Ectasia Display III (BAD III), Keratoconus Severity Index, keratoconus index, keratoconus prediction index, Rabinowitz and McDonell Index. The topographers provide axial map, anterior elevation map,
All these new technologies have provided a big volume of data, and should be analyzed by the ophthalmologists to differentiate the keratoconus with normal eyes and interpretation from large volume of data is overhead to the ophthalmologist. So, there is a need for computer aided diagnosis to assist the ophthalmologist in interpreting and arriving at a diagnosis result as early as possible. Recently, artificial neural networks, decision trees, support vector machine, and other machine learning and deep learning techniques have been adopted in different medical applications including ophthalmology to help doctors to arrive at accurate diagnosis results\[4\][5–7][8].

2 Related Works

Castro-Luna and Perez-rudea developed a system to differentiate the early stage keratoconus (ESKC) from normal eyes and also detect the keratoconus eye from normal eye. The topographic, pachymetric, and aberrometry variables are obtained using the Pentacam device and achieved 98.18% of accuracy using binary logistic method[9]. Larvic used CASIA OCT devices to obtain corneal topography, elevation and pachymetry maps. Four hundred and forty three attributes are derived from corneal topography, elevation and pachymetry maps and used decision tree, SVM, neural network, multi layer perceptron classifiers to detect the suspected eye is keratoconus, or forme fruste keratoconus or normal eye[10]. Random forest, SVM, k-neural network classifiers are used to differentiate Subclinical KC and Control eyes by using eleven attributes obtained using Pentacam and clinical examination[11]. Issarti used feed forward neural networks for classification of normal, Suspect keratoconus, mild keratoconus, moderate keratoconus. The corneal maps are obtained using Pentacam and the maps are directly reduced and then fourteen anterior and posterior features are derived from the reduced matrix[12]. Chandapura et al. used optical coherence tomography (OCT) and Pentacam devices to capture the anterior and posterior segments of the cornea. Different combinations of features derived from the corneal maps captured using both devices [13]. Each method uses different features and different imaging devices to obtain the corneal details.

3 Materials and Methods

3.1 Date Set

The dataset used in this study has taken from [14]. The dataset consists of 205 samples with 82, 43, 80 samples and normal, early stage keratoconus, clinical keratoconus respectively[14] . Table 1 describes the attributes, the range of values for each attribute.

3.2 Proposed Methods

The sequence of steps implemented to develop and test the model is depicted in Figure 1.

![Figure 1 Logical Step in the Proposed Machine Learning Model](image-url)
### Table 1 Description about dataset with minimum and maximum values of each attributes

| Parameters                                                                 | Minimum | Maximum |
|---------------------------------------------------------------------------|---------|---------|
| **Corneal topography of the anterior face**                               |         |         |
| Minor curvature (K1)                                                      | 39.1    | 62      |
| Major curvature (K2)                                                      | 41.1    | 66      |
| Mean curvature (Km)                                                       | 40.4    | 63.9    |
| Maximum curvature (KMAX)                                                  | 42.2    | 87.6    |
| Asphericity (Q)                                                           | -2.34   | 0.27    |
| Vertical asymmetry index (VAI)                                            | -1.44   | 2.4     |
| **Corneal topography of the posterior face**                              |         |         |
| Minor curvature (K1)                                                      | -9.8    | -4.8    |
| Major curvature (K2)                                                      | -10.9   | -5.7    |
| Mean curvature (Km)                                                       | -10.3   | -5.3    |
| Asphericity (Q)                                                            | -2.44   | 0.57    |
| Central corneal thickness (CCT)                                           | 256     | 654     |
| Minimum corneal thickness (MCT) with its coordinates                      | 354     | 649     |
| Mean square root of total abrreations (Total RMS)                         | 0.673   | 33.428  |
| Mean square root of high order aberrations(HOA RMS)                      | 0.182   | 8.496   |
| Secondary corneal astigmatism to 0° (Z2^2)                               | -7.734  | 5.412   |
| 45° (Z2^-2)                                                               | -9.237  | 4.064   |
| Anterior horizontal coma to 0°                                             | -3.227  | 3.925   |
| Posterior horizontal coma to 0°                                           | -0.885  | 0.724   |
| Total horizontal corneal coma to 0° (Z3^1)                                | -2.966  | 3.674   |
| Anterior vertical coma to 90°                                             | -7.977  | 0.536   |
| Posterior vertical coma to 90°                                            | -0.106  | 2.241   |
| Total vertical corneal coma to 90° (Z3^-1)                               | -7.265  | 0.721   |
| Trefoil to 0° (Z3^-3)                                                     | -1.432  | 0.979   |
| Trefoil to 30° (Z3^3)                                                     | -1.764  | 1.767   |
| Tetrafoil to 0° (Z4^3)                                                    | -1.18   | 1.031   |
| Tetrafoil to 22.5° (Z4^-3)                                                | -0.96   | 9.077   |
| Spherical aberration (Z4^0)                                               | -3.408  | 0.927   |
| Age                                                                       | 18      | 77      |
| Sphere                                                                    | -20     | 6       |
| Cylinder                                                                  | -6      | 3.75    |
| Gender                                                                    | Male:106 Female:99 |
| Grade                                                                     | Normal: 82; Clinical KC (QC 1) : 83 Early Stage Keratoconus (QCS/QCFF): 40 |
3.2.1 Pre-processing
The objective of the normalization is to transform the numeric dataset to a common range, without misinterpreting the differences in the ranges of values. In machine learning, normalization is demanded particularly when the data points have distinct ranges, since SVM optimization reveals by reducing the decision vector, the optimal hyperplane is prompted by the scale of the input points. Different number of normalization techniques namely Min-Max, Z-score, utilized in the literature. Table 1 it is observed that the attributes are of different scale, Min-Max normalization is used to normalize these features.

Feature subset selection stipulates the selection of the feature subset which maximizes the classification efficiency by eliminating the redundant and inappropriate features. Feature selection practices have augmented an apparent need in many machine learning techniques. In the last few decades, various feature-selection techniques have been designed and many comprehensive comparative investigations have been attempted to evaluate the performance of the techniques. Figure 2 shows the correlation among the attributes. The value of correlation coefficient ranges from 0 to 1 represents no correlation to strong positive correlation, whereas 0 to -1 no correlation to strong negative correlation. The strongly correlated features provide similar knowledge while learning, hence the redundant and similar features need to be eliminated to get better learning.

![Figure 2 Correlation between the attributes](image)

Recursive Feature elimination (RFE) is a wrapper type feature selection method in which a machine learning algorithm is utilized as an estimator to determine weights to features in the core. Further, it adopts a filter based technique internally. The objective of RFE is reckoned from the name, selects the features by recursively analyzing smaller and smaller sets of features. First, the estimator is
trained on the entire set of features and the influence of each feature is attained through principles such as correlation and feature importance. Then the least important features are pruned from the current set of features. This strategy is recursively reiterated on the pruned set until the convergence value is reached. RFE selects only five features out of 31 features. The selected features are anterior vertical coma 90°, posterior vertical coma 90°, vertical asymmetry index, and trefoil to 0°.

3.2.2 Support Vector Machine (SVM) Classifier
SVM is a kernel based machine learning model for classification and regression problems. Due to its outstanding generalization efficiency, its optimal result and its differentiation capability, SVM has overwhelmed the recognition among data mining, pattern recognition and machine learning researchers in recent years. The prime motive of SVM is to split diverse classes in the training set with a surface which maximizes the margin between the classes. Each training sample is illustrated by a data point in a two-dimensional area, and a line can be drawn to divide the data point with the objective of reducing mis-classifications. More accurately, there are an enormous number of lines that can contribute to a reasonably acceptable partition between the data points. The aim of SVM classification is to select the most acceptable line, the one maximizing the margin between the two classes. New data points are later mapped into the same space and automatically attached to any of the class labels depending on the support of which side of the gap they fall in. This design can be now stretched to any higher-dimensional space with a line inclining a plane in three dimensional cases and a hyperplane for more than three dimensions.

4 Results and Discussion
Figure 4 reveals that the variables, COMA POST 90°, COMA CORNEA 90, COMA ANT 90, vertical asymmetry index, RMS Total, RMS HOA have similar range of values for normal and early stage keratoconus samples (QCS/QCFF). But subclinical keratoconus (QC1) samples have different ranges of values in all the attributes. The challenge is to classify the early keratoconus samples from normal samples. After the pre-processing step, the dataset with 205 samples is grouped into two data sets; one with normal and early keratoconus samples and another group with norma and subclinical keratoconus samples. The binary classifier model is constructed with 10-fold validation for both groups of data. Table 2 demonstrates the performance of this proposed model for both groups of dataset in terms of accuracy, sensitivity and specificity. In the classification of normal vs early-stage keratoconus, 82 normal, and 43 early-stage keratoconus were used. Since there is an imbalance among
the dataset, the accurate classification of minority samples is a challenging task. Whereas, in normal
vs keratoconus, a balanced data set has used with 82 normal and 82 keratoconus samples. Also, Figure
4 shows that there is a better discriminating capability among the attributes to classify keratoconus
from normal samples. Hence this produces 100% accuracy, specificity, and sensitivity.

| Normal vs ESKC                  | Accuracy | Sensitivity | Specificity |
|---------------------------------|----------|-------------|-------------|
| Without Pre-processing          | 90.2     | 93.8        | 97.6        |
| With Pre-processing             | 91.8     | 94.2        | 97.5        |
| Normal vs KC                    | 100      | 100         | 100         |
| Without Pre-processing          | 100      | 100         | 100         |
| With Pre-processing             | 100      | 100         | 100         |

Figure 4 Correlation between the Class label and other attributes
The performance of the various state-of-the-art machine learning models in detection and classification is exhibited in Table 3.

| Techniques                    | Performance                        | Reference |
|-------------------------------|------------------------------------|-----------|
| Binary Logistic Regression    | Normal vs ESKC: Accuracy: 89.32    | [9]       |
|                               | Normal vs KC: Accuracy: 98.18      |           |
| Feed Forward Neural Network   | Accuracy: 96.4                      | [12]      |
| SVM                           | Normal vs KC: Accuracy: 94         | [10]      |
|                               | Normal vs KC vs FKC: Accuracy: 91  |           |
| Random Forest                 | AUC for KC: 0.99                    | [13]      |
| Random Forest                 | AUC: 0.97                           | [11]      |
| SVM                           | Sensitivity: 0.94                   |           |
| k-NN                          | Specificity: 0.90                   |           |
| SVM                           | Normal vs ESKC: Accuracy: 91.8     | Proposed  |
|                               | Normal vs SKC: Accuracy: 100       | Method    |

The proposed SVM gives 91.8% of accuracy for detection of early stage keratoconus and 100% accuracy for classification of normal and subclinical keratoconus, which shows this produces better classification performance than [9]. From Table 3 it is observed that random forest [13] gives better performance than other models. It is very difficult to compare the performance of the state-of-art research, since it uses different devices for data acquisition, variations in grading the category and levels of severity of the patients.

5 Conclusions

Keratoconus is the most prevalent corneal ectasia. The visual symptoms and signs of keratoconus differ based on disease severity. Keratoconus medication and administration has advanced considerably in recent days. A machine learning model is hindered by the nature of the dataset utilized to train and validate it. Machine learning can be challenging to predict the amount of training data required in a dataset to build the model. Nonetheless, the demand for an enormous volume of data endures the most indispensable problem.

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