

Detection of Subclinical Keratoconus using Machine Learning Algorithms

¹T.Sravan Kumar, ²P.Hemanth, ³Sk.Nawaz Shareef, ⁴S.Preethi, ⁵B.Siva Prasad.

^{1,2,3,4}U. G Scholars, Department of ECE, N S Raju Institute of Technology, Sontyam, Visakhapatnam, A.P. India

⁵Associate Professor, Department of ECE, N S Raju Institute of Technology, Sontyam, Visakhapatnam, A.P. India

Abstract: A non-inflammatory corneal condition called keratoconus frequently affects both eyes. Due to corneal deformation and scarring, the bilateral ectatic illness known as keratoconus can impair vision. The prevalence of keratoconus varies from 1 in 375 people in Northern Europe to as high as 1 in 48 in various ethnic groups. Studies indicate a higher incidence and faster advancement in Middle-Eastern, West Indian, and Asian populations. The disease normally starts after puberty and progresses over the following two to three decades at a varied rate. As the condition worsens, corneal distortion may become so severe that patients will no longer be able to see well enough to function without the use of soft or hard contact lenses. Contact lenses are not always well-tolerated, and vision loss can significantly lower quality of life. About 20% of patients are given the option of a corneal transplant during the course of the disease to help them see better, but doing so carries the risk of postoperative complications including microbial keratitis and inflammation, probable allograft rejection, and transplant failure. The majority of people with keratoconus are found to have visual disturbances or an increase in refractive astigmatism.

Keywords: Microbial keratitis and inflammation, Probable allograft rejection, Transplant failure, Contact lenses, astigmatism.

I. INTRODUCTION

Keratoconus is a non-inflammatory corneal disorder which often affects both eyes. Keratoconus is a bilateral ectatic disease of the cornea that can cause visual loss through corneal distortion and scarring. The prevalence of keratoconus varies from 1 in 375 people in Northern Europe to as high as 1 in 48 in some ethnic groups, with studies suggesting a higher incidence in Middle-Eastern, West Indian, and Asian populations with faster progression. The onset of the disease typically occurs after puberty, with subsequent progression at a variable rate over 2 to 3 decades.

As the disease advances, corneal distortion can reach a stage where spectacle-corrected vision is inadequate, and patients must rely on soft or rigid contact lenses to achieve good functional vision. However, contact lenses are not always tolerated, and visual impairment can severely affect quality of life. In the natural course of the disease, approximately 20% of the patients are offered a corneal transplant to improve their vision but at the risk of postoperative complications (eg, microbial keratitis and inflammation), potential allograft rejection, and transplant failure. Most individuals with keratoconus are identified because of the symptoms of visual disturbance or an increase in astigmatism at refraction. Therefore, it is inevitable that most individuals with keratoconus are detected at a stage when visual deterioration

has already occurred.

The detection of keratoconus at an earlier stage has become increasingly relevant since the introduction of corneal collagen cross-linking (CXL). This is a photochemical treatment of the cornea with UV-A light following the application of riboflavin (vitamin B2), which can arrest the progression of keratoconus in 98.3% of the eyes even in relatively advanced cases

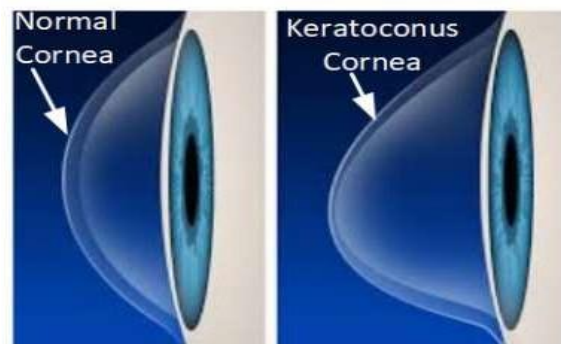


Figure 1: Normal Cornea Versus a Cornea Affected by Keratoconus

II. LITERATURE REVIEW

Hallett et al. proposed a deep learning-based unsupervised and semi-supervised classification model to identify keratoconus at an early stage with the aim of providing clinicians ample time to select an appropriate treatment [1]. They achieved an accuracy level of 80.3% using 124 keratoconus eyes. However, their small sample size may limit generalization of their findings. In [2], a logistic regression statistical model was used to detect early-stage keratoconus cases. However, the only corneal parameter used in this study was auto-keratometer. In [3], the authors have proposed a classification technique using cornea shape data obtained from OCT-based instruments and obtained an accuracy level of 92% using 244 eyes. However, there is no information on the severity level of the keratoconus eyes and whether the eyes at the early stages of keratoconus were included. Moreover, this study used a relatively small sample. Machine learning has also been applied in keratoconus management with regard to guiding intra-corneal ring segment implantation [4]. This is promising and shows that AI models can be applied to different aspects of keratoconus management to enhance care delivery.

A short review of several machine learning techniques for detecting keratoconus has recently been published [5]. In addition, the role and importance of the development of artificial intelligence (AI) algorithms in prevention and monitoring keratoconus was recently highlighted [6]. As of

now, AI models have generated promising results, but more efforts are required to stimulate and encourage development of more accurate algorithms for detecting keratoconus particularly at early stages of the disease. Included in our results below, we provide a comprehensive summary of previous work on major machine learning models including multi-layer perceptron, support vector machine (SVM), unsupervised machine learning algorithms, artificial neural networks, radial basis networks, convolutional neural networks and decision tree techniques that have been developed to detect keratoconus. The algorithm was built on these previous findings in order to target the development and validation of machine learning algorithms that identify early-stage keratoconus at high accuracy levels using large scale multi-center datasets collected from multiple corneal clinics.

III. METHODOLOGY

MACHINE LEARNING: Machine learning is a branch of artificial intelligence centred on writing a software capable of learning from data in an autonomous fashion by minimizing a loss function or maximizing the likelihood. It can be broadly classified as either supervised or unsupervised learning. In supervised learning, the algorithm is trained with input data labelled with a desired output so that it can predict an output from unlabelled input data. In comparison, in unsupervised learning, the algorithm is not trained using labelled data

(A) MACHINE LEARNING ALGORITHMS

In most cases, researchers have used combinations of parameters and indices within machine learning algorithms to diagnose subclinical keratoconus. This section is subdivided according to the machine learning techniques that were applied. Figure 2 presents an organizational diagram of the relevant machine learning algorithms.

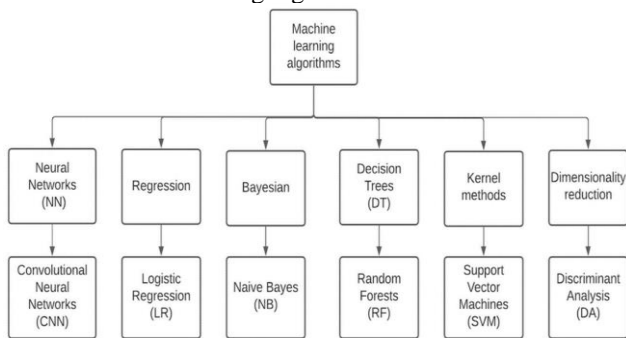


Figure 2: Diagram of Relevant Machine Learning Algorithms

(B) PROPOSED METHODOLOGY

There are a number of limitations to the existing study which could be addressed in follow-up studies. Compared the clustering outcome with Casia ESI index and showed that there is a good agreement between our finding and ESI index spectrum. However, to assess the generalizability of this unsupervised clustering approach method, it needs to be validated by other keratoconus indices such as Bellin-Ambrosio (BA) index. Therefore, it is required to conduct another study to confirm how this approach is generalizable to corneal parameters generated by the Pentacam instrument by accessing such datasets. Also, the accuracy of this approach can be validated if the clinical diagnosis labels of all eyes were available. However, accessing clinical diagnosis

labels for all eyes in such big datasets is a challenging and tedious task. Nevertheless, it is beneficial to assess the proposed approach in a follow-up study with a dataset that includes clinical diagnosis labels

In this study a large dataset containing 423 features has been used to train the machine learning algorithms. Out of these features, features with highest discriminating power are found out by performing a univariate selection, which is one of the feature extraction techniques.

(C) FEATURE SELECTION

When we encounter a dataset that has a lot of features it can be difficult to identify the relevant ones that are highly related to the label/target column and can improve the model's accuracy and the irrelevant ones that can impact negatively the model's performance. Thus, we need to apply Feature Selection to help us remove, manually or automatically, the irrelevant features in order to improve the model's performance and reduce training time as well as overfitting.

Overfitting: is when a model learns from the training data too well, meaning that it learns the noise and the details to the point that it can no longer generalize and predict new data. There are two important techniques to limit overfitting:

1. Resampling (example: k-fold cross validation)
2. Evaluate the model using a validation dataset.
3. In simpler words, overfitting is basically: good performance score on the training data and poor performance score on a new data.

Model performance: It is the ability of the model to perform a certain task (example: classification) accurately not only with the training data but also when the model is deployed through a website or an app, to perform on a real-time data. Feature scores obtained using Univariate feature selection method to find out the best features.

IV RESULTS AND DISCUSSION

Algorithm	Accuracy	Recall	Precision
Optimized kNN	0.952	0.852	0.922
Decision Tree	0.933	0.861	0.847
Random Forest	0.958	0.917	0.914
Linear SVM	0.946	0.913	0.941
Kernel SVM	0.946	0.837	0.913
Logistic Regression	0.946	0.859	0.923

CONCLUSION






Keratoconus status and severity can now be well identified using automated unsupervised machine learning algorithms using topographic, tomographic, and thickness profiles of cornea. This approach can be used in corneal clinics and research settings to better diagnose, monitor changes and progression and improve our understanding of corneal changes in keratoconus

FUTURE WORK

Follow up studies can explore the efficiency of deep learning models using corneal images. The other aspect that can be examined in the future is KCN progression detection, which is critical in clinical practice to adjust treatment plan based on progression of the disease

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	Dr. B. SIVA PRASAD , M. Tech, Ph.D, MBA, FIETE, MIAENG, Associate Professor in ECE department of N S Raju Institute of Technology. having 18 years of Teaching experience with knowledge of Radar & Microwave Engineering, Antenna and Embedded System.
	T. Sravan Kumar , Studying B. Tech in Electronics and Communication Engineering at N S Raju Institute of Technology Visakhapatnam.
	P. Hemanth , Studying B. Tech in Electronics and Communication Engineering at N S Raju Institute of Technology Visakhapatnam.
	SK. Nawaz Shareef , Studying B. Tech in Electronics and Communication Engineering at N S Raju Institute of Technology Visakhapatnam.
	S. Preethi , Studying B. Tech in Electronics and Communication Engineering at N S Raju Institute of Technology Visakhapatnam.