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Using A Machine Learning Approach, Keratoconus Severity Can Be Detected From Raw Data Such As Elevation, Topography, And Pachymetry.

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ABSTRACT— The major goal of this study is to see how accurate machine learning algorithms are at detecting keratoconus from corneal characteristics like elevation, topography, and pachymetry. Using a Pentacam Scheimpflug device, we constructed multiple machine learning models to detect keratoconus from corneal elevation, topography, and pachymetry characteristics gathered. The created method can differentiate early KCN eyes from healthy eyes with great accuracy, achieving an AUC of 0.98.

Keywords— Elevation, topography and pachymetry raw data, machine learning, keratoconus, support vector machine.

I. INTRODUCTION

Keratoconus is a non-inflammatory corneal condition that affects both eyes often. Keratoconus affects about 45 people out of every 100,000. Keratoconus is a condition in which the cornea, the transparent, dome-shaped front surface of your eye, thins and bulges outward into a cone shape. Blurred vision and sensitivity to light and glare are common symptoms of a cone-shaped cornea.

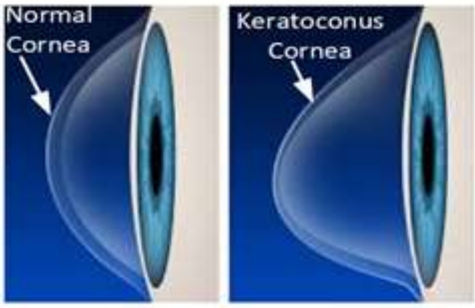

FIGURE 1. Normal cornea versus a cornea affected by keratoconus

Keratoconus severity was determined using keratometry readings in the worse afflicted eye and the patients' age at diagnosis. Elevation- To direct the eye upward or downward, two muscles work together while the opposing muscles relax. The superior rectus, for example, is used to raise the eye while looking straight ahead. Corneal topography is a computer-aided diagnostic tool that produces a three-dimensional map of the cornea's surface curvature. A pachymetry test measures the thickness of your cornea in a straightforward, rapid, and painless manner. Your doctor can better comprehend your IOP reading and establish a treatment plan that is appropriate for your situation using this measurement. Medical data is used to test the detection algorithm. This technique can assist the ophthalmologist by allowing the observation and study of specific corneal elevation and pachymetry (thickness), both of which are vital in properly defining corneal problems.

The goal of this research is to create, test, and validate a machine-learning (ML) algorithm for detecting KCN more accurately. A new machine learning model will also be created to detect the severity of the disease. Three important corneal parameters are also examined in order to determine which ones are more sensitive to KCN detection. After the approximate some research, different kinds of algorithm based on different theory concepts were introduced. The following is how the paper is organized: Section 1 begins with a brief explanation of the study's motivations. The related work on KCN detection is described in Section 2. Section 3 discusses the study's materials and methodology, as well as the performance evaluation and validation. The results are shown in Section 4, while the comments and conclusions are presented in Section 5. This research builds on our prior work, which includes building algorithms to improve KCN identification and severity levels.

II. RELATED WORK

A number of studies in the scientific literature advocate the use of machine learning techniques in ophthalmology. We live in an era where computer vision and artificial intelligence (AI) are assisting in the development of new screening approaches that provide an accurate diagnosis process. As a result, a KCN detection algorithm must be developed, implemented, and tested to assist ophthalmologists in correctly detecting the condition. Quick and accurate diagnosis saves lives while also minimising the eventual expenditures that the health-care system must cover by preventing subsequent complications. The main purpose and contribution of this work is to create and implement an algorithm that will aid in the early detection of KCN, hence improving patient quality of life. A recent paper gave a brief assessment of many machine learning algorithms for diagnosing keratoconus.

Furthermore, the relevance and importance of artificial intelligence (AI) algorithms in keratoconus prevention and monitoring has lately been highlighted. AI models have shown promise so far, but more work is needed to stimulate and support the development of more precise algorithms for detecting keratoconus, particularly in the early stages of the illness.

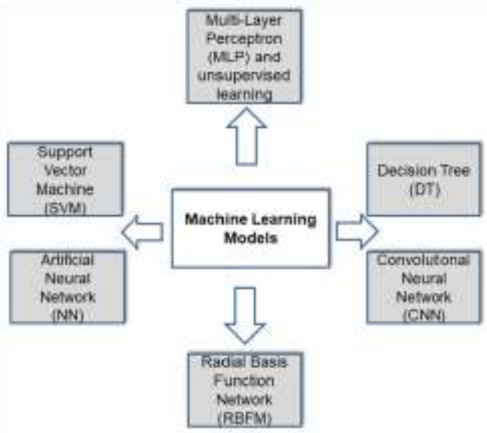

FIGURE 2. Machine learning algorithms that can be used in keratoconus detection.

To identify KCN disease, the performance of three methods (support vector machine, multi-layer perceptron, and radial basis function neural network) was studied in [34]. Despite the strong performance, the results were equal to an AUC of 0.99 due to the tiny dataset employed. Arbelaez et al. employed SVM to study corneal characteristics collected from a Sirius CSO coupled Placido and Schiembflug topographic device, while the eyes were categorised according to the severity level of the KCN.

When it comes to KCN severity detection levels, there is a gap in the scientific literature. In this research, we look at machine learning techniques that can be used to detect KCN severity levels while also establishing the most discriminative corneal characteristics. The algorithm is being evaluated on a huge set of medical data obtained in Brazil, which includes a variety of factors monitored by a Pentacam system [41]. Another novelty of this study is the use of machine learning methods to detect keratoconus from raw corneal characteristics like as elevation, topography, and pachymetry without the use of machine-generated.

All instrument–processed measurements and indices were removed from the original Pentacam dataset utilised in this investigation. As a result, we solely used corneal characteristics obtained from direct corneal measurements, rather than those processed and created by instrument algorithms. For example, the KPI (Keratoconus Progression Index) parameter, which is linked to KCN severity, was left out.

The extraction algorithm process is the inverse of the embedding process. It is assumed that the watermark as well as the see value is available at the receiver end to the authorized users.

The operation of channel separation is applied on the watermarked color image to generate its sub images, and then 2-level discrete wavelet transform is applied on the sub images to generate the approximate coefficients and detail coefficients.

III. MATERIALS AND METHODS

The KCN detection algorithm is based on Pentacam data from patients in Brazil who were examined for keratoconus disease. Using a Pentacam device, elevation, topography, and pachymetry values were acquired from 5881 eyes of 2800 patients in Brazil (Oculus, Germany).

The Institutional Review Board of the Federal University of So Paulo - UNIFESP/EPM accepted the study protocol (0094/2020). The research was carried out in compliance with the Declaration of Helsinki and its subsequent modifications' ethical standards. Cleaning the initial dataset by removing measurements that did not have the right calibration status noted or scans that were incomplete was part of the pre-processing phase. All computed corneal parameters that were not the result of a cornea measurement were also removed. The initial dataset was then divided into three datasets, each of which contained corneal characteristics for elevation, topography, and pachymetry. These datasets contain

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real-world data that we utilised to train, test, and validate models independently.
The environment enables complex computational problems to be solved. Using CPUs and GPUs to solve machine learning challenges. Parallel loops for performing algorithms with multiple cores, as well as multi-core clusters and high-level processing architectures, such as various hardware platforms in concurrent tasks. Only three cornea parameters were used in a bespoke technique are thought to have the most discriminatory power in determining the level of KCN severity.

A. ANALYSIS OF MACHINE LEARNING

Figure 2 depicts the workflow for detecting KCN severity from raw data in elevation, topography, and pachymetry using a machine learning approach, which includes splitting the initial dataset into elevation, topography, and pachymetry datasets, data cleaning and elimination, feature selection, machine learning validation, and performance evaluation.

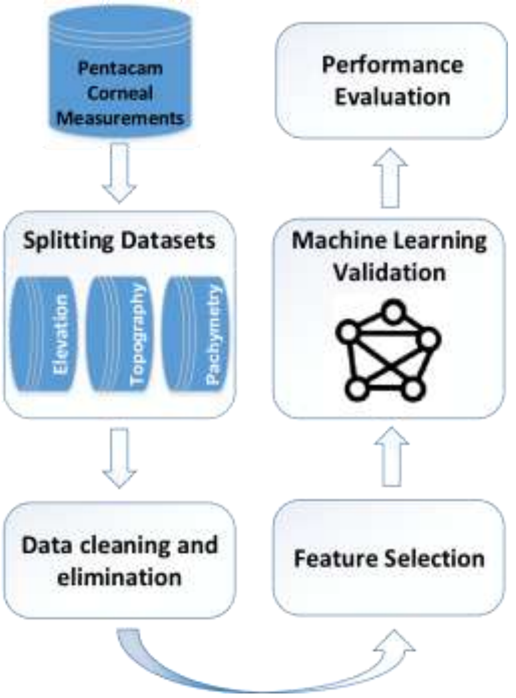

FIGURE 3. Proposed machine learning approach.

The measurements taken using a Pentacam system are used in this investigation. The division of this large dataset into three sections according to corneal form (topography), thickness (pachymetry), and elevation parameters was the initial step in the pre-processing operations. Three distinct subsets of elevation (18 corneal parameters), topography (10 corneal parameters), and pachymetry (10 corneal parameters) parameters were built and tested for KCN identification and severity levels. The initial step was to clean all of the datasets and remove any records with missing information. After cleaning the data, the datasets had 5881 samples from 2800 patients. The dataset distribution for KCN diagnosis is shown below.

We are interested in evaluating these three cornea measurement methods in a separate manner and determine which are the corneal parameters with the most discriminative power in determining the KCN severity level. The accuracy of each model was computed using each set of parameters separately.

TABLE 1. Class Distribution.

Diagnosis	Number of Eyes
Healthy eyes	1726
Fruste keratoconus stage I (KCN I)	345
Keratoconus stage II (KCN II)	1380
Keratoconus stage III (KCN III)	1800
Keratoconus stage IV (KCN IV)	630

To identify healthy eyes from KCN eyes, several machine learning methods were used (2-classclassification). The classification problem was then expanded to a 3-class system, which included healthy eyes, keratoconus fruste, and KCN, and then to a 5-class system (healthy eyes, fruste KCN, KCN stage II, KCN stage III and KCN stage IV).

TABLE 2. Machine Learning Algorithms implemented and tested in this study.

Machine Learning Category	Machine Learning Algorithm
Decision Tree	Fine Tree Medium Tree Coarse Tree
Discriminant	Linear Discriminant
Naïve Bayes	Gaussian Naive Bayes Kernel Naive Bayes
Support Vector Machine (SVM)	Linear SVM Quadratic SVM Cubic SVM Fine Gaussian SVM Medium Gaussian SVM Coarse Gaussian SVM
k-Nearest Neighbor (KNN)	Fine KNN Medium KNN Coarse KNN Cosine KNN Cubic KNN Weighted KNN
Ensemble	Ensemble Boosted Trees Ensemble Bagged Trees Ensemble Subspace Discriminant Ensemble Subspace KNN Ensemble RUSBoosted Trees

Table 2 summarizes the implemented and tested algorithms in this study. The machine learning algorithms belong to the following categories: decision tree, discriminant type machine learning, support vector machine, k-Nearest Neighbor and Ensemble type machine learning algorithms.

B. SUBSET SELECTION OF CORNEAL PARAMETERS FOR KCN SEVERITY PREDICTION.

The features rating and selection procedure are presented in this section. Our goal is to examine which cornea characteristics are the most discriminating among those included in the dataset. The installation of a feature ranking mechanism enables the proposed algorithm to evaluate the performance level of each applied feature as input. As a result, any redundant information is removed, and the algorithm's accuracy may improve significantly. A large number of parameters can typically lead to a decline in machine learning algorithm performance.

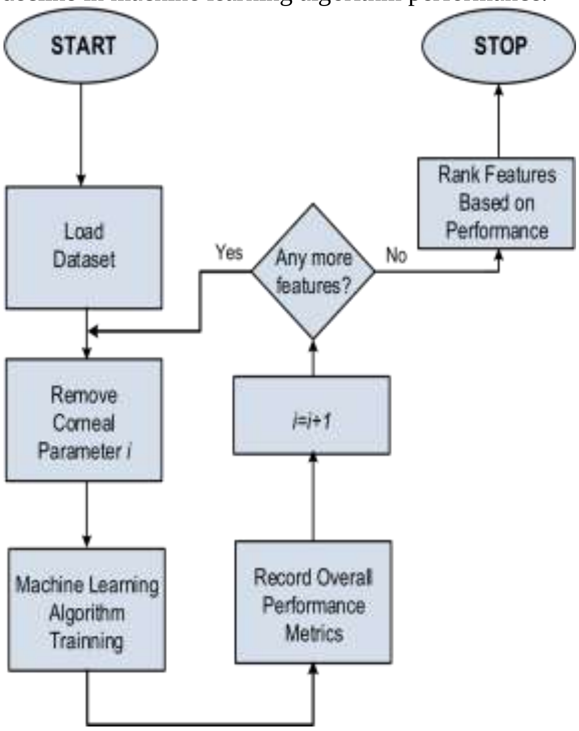

FIGURE 4. Features ranking using a machine learning approach.

As an attribute evaluator, the implemented feature-ranking algorithm uses a correlation-based features subset selection type and a best first search method that uses a greedy mechanism enhanced with a backtracking facility to explore the space of attribute subsets.

The second feature ranking technique was created by applying a procedure of removing features one by one and evaluating their impact on performance metrics like AUC and global accuracy. This job was completed for all of the previously discussed machine learning methods in this research. The logical diagram of the completed features ranking method is shown in Figure 3. This method is significant since it is linked to the detection of KCN severity levels. This assessment could influence how keratoconus severity levels are assigned and different corneal characteristics are monitored by medical personnel.

IV. RESULTS

The ROC (Receiver Operating Characteristic) curve of the SVM machine learning method with an AUC of 0.99 is shown in Figure 5 (left). The ROC curve depicts how well the developed machine learning algorithm performs. The acquired data indicates that the level of performance is really high.

The cubic SVM outperformed all other machine learning classifiers (Table 2) with an AUC of 0.99 for detecting KCN using elevation parameters only. The highest accuracy of classifiers for detecting keratoconus using pachymetry only and topography only parameters were 96.6% and 95.2%, respectively. The elevation parameters provided the highest level of performance when detecting KCN. To reduce the size of elevation corneal parameters, a ranking mechanism is deployed using a machine learning approach. A total of 23 machine learning algorithms were implemented and tested for keratoconus severity level detection. After the 2-class classification, the classification task was extended to 3-class (healthy eyes, keratoconus fruste and keratoconus) and then to a 5-class (healthy eyes, fruste keratoconus/ early KCN, keratoconus stage II, keratoconus stage III and keratoconus stage IV based on topographical KCN classification).

For each built ML algorithm, two performance measures were recorded: total accuracy and AUC. Figure 6 shows the findings for the three classes, demonstrating that the elevation dataset provides the best performance.

With an AUC of 0.96 for the elevation dataset, the quadric SVM was able to virtually correctly differentiate healthy eyes from those with keratoconus, including keratoconus fruste.

The second scenario that was introduced was for the early detection of questionable KCN eyes. When the elevation dataset is utilised, the tested method can discriminate early KCN eyes from healthy eyes with good accuracy, achieving an AUC of 0.97 for an SVM ML algorithm. The diagnosis of suspect KCN is critical from a clinical standpoint since these individuals are frequently misdiagnosed

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due to early symptoms. This contribution is one of the work's unique features.

The majority of approaches for diagnosing eyes with keratoconus rely on subjective topographical map evaluation, which might lead to human observer bias. Several machine learning algorithms for objectively diagnosing keratoconus from noninvasive corneal imaging data were used to solve this limitation. To find the best performing model for keratoconus identification, we analysed the accuracy of the machine learning models and picked a subset of corneal characteristics.

Feature selection is a crucial phase in machine learning since it may have a big influence on model accuracy. This is also a crucial duty in clinical medicine. Medicine has been interested in determining which factors increase the likelihood of acquiring a certain disease.

Figure 9 displays the scatter plot for two of the selected corneal features for the 5-class problem using a machine learning technique. The 5 classes are clearly distinguished, indicating a link between the specified corneal characteristics and KCN severity levels. The machine learning techniques that have been evaluated can be incorporated into the Pentacam measuring system to help ophthalmologists diagnose.

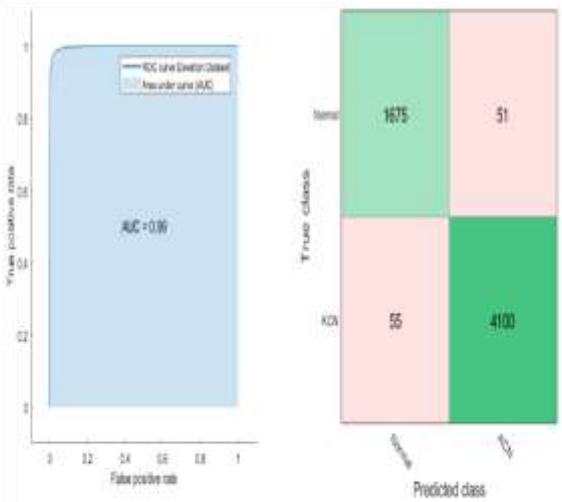

FIGURE 6. ROC curve (Left) and the confusion matrix (Right) of the SVM machine learning applied on elevation parameters only.

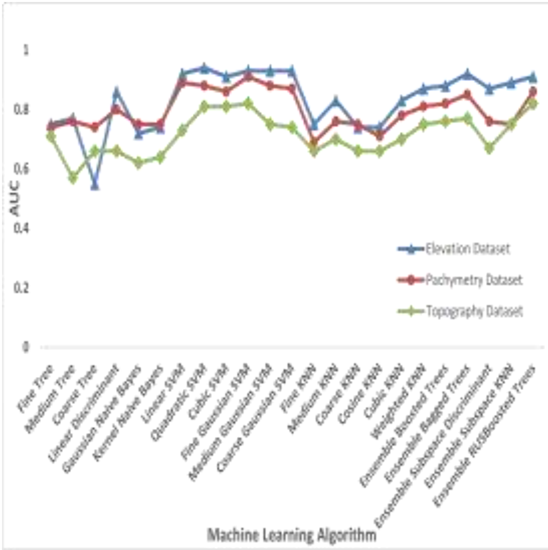

FIGURE 8. AUC curves for 5 classes (Healthy Eyes, fruste keratoconus stage I, keratoconus stage II, keratoconus stage III and keratoconus stage IV) including keratoconus severity level detection evaluated for elevation, pachymetry and topography datasets.

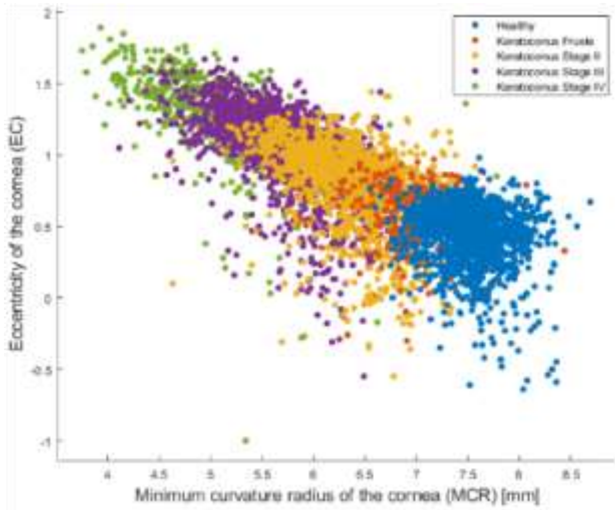

FIGURE 9. Scatter plot for two of the selected corneal parameters (Minimum curvature radius of the cornea versus the eccentricity parameter of the cornea).

V.CONCLUSION

The creation and testing of an algorithm that aids the identification of advanced as well as early keratoconus is the paper's key contribution. This tool is designed to assist ophthalmologists in the identification of keratoconus by distinguishing particular corneal patterns that are not visible to the untrained eye. As a result, appropriate medication may be given at the right moment, assisting in the

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long-term management of the disease by slowing or even preventing the advancement of keratoconus, considerably increasing the patient's quality of life.

We generated machine learning models with high levels of accuracy in detecting KCN and severity levels in this work, which might have an influence on how keratoconus is managed.

One of the disadvantages of using Placido images to measure anterior curvature is that only about 60% of the surface of the cornea is analysed [32]. Many ocular peripheral diseases might be missed if these assessments are insufficient. The anterior and posterior surfaces of the cornea may be measured using Scheimpflug tomography, which is employed by tools like Pentacam to provide an in-depth study of the eye.

According to recent research, up to 10% of suspicious KCN cases can go unnoticed using standard diagnostic methods particular to Scheimpflug imaging systems. Our machine learning method can assist in the diagnosis of these individuals. When it comes to identifying keratoconus severity levels using our ML technique, the corneal characteristics collected are deemed the most discriminative.

The suggested machine learning was compared to other implementations provided in the scientific literature in order to confirm our findings. Medical data is used to test the detection algorithm. The ML algorithm must assist the ophthalmologist by allowing the observation and analysis of specific corneal patterns that are otherwise difficult to perceive with the naked eye.

Finally, utilizing machine learning models, a limited number of corneal elevation parameters such as the cornea's minimum curvature radius, eccentricity of the corneal parameter, and asphericity [5] of the corneal parameter may convey enough information to detect KCN and its severity levels. Machine learning models may help clinicians monitor patients with KCN and supplement clinical practice. The algorithm has enormous promise due to its potential contribution to expediting the keratoconus diagnosis procedure and early detection of this ailment, perhaps saving lives.

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