FAST PREDICTION OF KERATACONUS DETECTION USING SVM AND CORNEAL FEATURES

Abhin Prakash MP[1], Adhil Naseem[2], Akhil PS[3], Ashique Soloman Paul[4], Athulya MS[5], Harish Venu[6], Ajith PJ[7], Bindu Anto[8]

[1] Abhin Prakash MP Student, Computer Engineering, KKMMPTC Mala, Kerala, India
[2] Adhil Naseem Student, Computer Engineering, KKMMPTC Mala, Kerala, India
[3] Akhil PS Student, Computer Engineering, KKMMPTC Mala, Kerala, India
[4] Ashique Soloman Paul Student, Computer Engineering, KKMMPTC Mala, Kerala, India
[5] Athulya MS Student, Computer Engineering, KKMMPTC Mala, Kerala, India
[6] Harish Venu Student, Computer Engineering, KKMMPTC Mala, Kerala, India
[7]Ajith PJ Head of Department, Robotics Process Automation, KKMMPTC Mala, Kerala, India
[8]Bindu Anto Head of Department, Computer Engineering, KKMMPTC Mala, Kerala, India

ABSTRACT

Keratoconus affects approximately one in 2,000 individuals worldwide. It is typically associated with the decrease in visual acuity. Given its wide prevalence, there is an unmet need for the development of new tools that can diagnose the disease at an early stage in order to prevent disease progression and vision loss. The aim of this study is to develop and test a machine learning algorithm that can detect keratoconus at early stages. Several machine learning algorithms were applied to detect keratoconus and then tested the algorithms using real world medical data. Implemented 25 different machine learning models in Matlab and achieved a range of 62% to 94.0% accuracy. The highest accuracy level of 94% was obtained by a support vector machine (SVM) algorithm using a subset of eight corneal parameters with the highest discriminating power. The proposed model may aid physicians in assessing corneal status and detecting keratoconus, which is otherwise challenging through subjective evaluations, particularly at the preclinical and early stages of the disease. The algorithm can be integrated into corneal imaging devices or used as a stand-alone-software for cornea assessment and detecting early-stage keratoconus.

Keyword: - *SVM (Support Vector Machine), Keratoconus, prevalence, machine learning algorithms, unmet, corneal, subset, discrimination, preclinical, stand-alone-software*

---

1. INTRODUCTION

Keratoconus is a disease that affects the cornea, and it can be detected using various machine learning algorithms. One such algorithm is SVM, which is used in a paper titled "Detecting Keratoconus by Using SVM and Decision Tree Classifiers with the Aid of Image Processing". Another paper titled "Detecting Keratoconus from Corneal Imaging Data using Machine Learning" uses multiple machine learning algorithms to detect keratoconus at early stages. A hybrid deep learning construct is used in a paper titled "A Hybrid Deep Learning Construct for Detecting Keratoconus from Corneal Maps". The accuracy of the algorithm is tested to detect keratoconus based on corneal topographic maps. In another paper titled "Diagnosis of Subclinical Keratoconus Based on Machine Learning Techniques", machine learning techniques are used to diagnose subclinical keratoconus. Finally, a paper titled "Preventing Keratoconus through Eye Rubbing Activity Detection: A Machine Learning Approach" uses machine learning to analyze corneal topography and extract keratoconus eye features. The accuracy of the algorithm is tested to detect keratoconus.

2. MILESTONES

The article titled “Corneal blindness: A global perspective. Bull. World Health Organ” authored by Whitcher, J.P.; Srinivasan, M.; Upadhyay MP was published in 2001 [1]. The second most common cause of blindness worldwide, behind cataracts, is diseases of the cornea. The epidemiology of corneal blindness is complex and includes a wide range of inflammatory and viral eye diseases that result in corneal scarring, which eventually causes functional blindness. Furthermore, the prevalence of corneal illness varies from population to population and even from country to country. Nearly 20 million of the 45 million blind people worldwide are due to cataracts, but 4.9 million people are blinded by trachoma, primarily due to corneal scarring and vascularization. Ocular trauma and corneal ulceration are substantial, underreported causes of corneal blindness that may account for 1.5–2.0 million new cases each year.

The article title “Pathogenesis of Keratoconus: The intriguing therapeutic potential of Prolactin-inducible protein. Prog. Retin. Eye Res” authored by Sharif, R.; Bak-Nielsen, S.; Hjortdal, J.; Karamichos, D was published in 2018 [2]. The most prevalent ectatic corneal condition is keratoconus (KC), with symptoms such as pain, visual impairment, and, in severe cases, blindness. Approximately 1:400 to 1:2000 people globally, including males and females, are affected by KC. It is difficult to treat or reverse the condition because the aetiology and onset of KC are still a mystery. The structure and integrity of the human cornea are known to be maintained by sex hormones. During various phases of the menstrual cycle, hormone levels have been shown to change corneal thickness, curvature, and sensitivity. Surprisingly, the significance of sex hormones in KC and corneal disorders has received less attention. A novel KC is the prolactin-induced protein, which is known to be controlled by sex hormones.

The article titled “Keratoconus in Children: A Literature Review. Cornea” published on 2020 by Buzzonetti, L.; Bohringer, D.; Liskova, P.; Lang, S.; Valente, P [3]. Based on the most recent research, this review examines the key features of pediatric keratoconus (KC) and offers recommendations for early diagnosis and improved treatment effectiveness. The databases from Elsevier, Ovid, and PubMed were used to conduct this review of the literature. The key term input for the database search was "pediatric keratoconus," which was linked to terms like "keratoconus," "screening," "corneal cross-linking" (CXL), and "keratoplasty." Original scientific articles and review articles were among the scholarly, peer-reviewed resources that were included. KC incidence varies between populations. Middle-Eastern people have the highest incidence, with an estimated incidence of 50,000 individuals annually. Early diagnosis is frequently found using slit-scan tomography, optical coherence tomography, and scheimpflug imaging. The therapy that should be explored is epithelium-off CXL.

This article titled “Trends in corneal transplantation at the University Eye Hospital in Tübingen, Germany over the last 12 years: 2004–2015” published by Röck, T.; Bartz-Schmidt, K.U.; Röck, D on 2018 [4]. In this study, we looked at the most common indications for corneal transplants performed over the previous 12 years as well as developments in surgical techniques. Retrospective analysis was done on the information from the University Eye Hospital in Tübingen's corneal graft waiting list and all keratoplasties performed between 2004 and 2015. In the period from 2004 to 2015, this hospital handled 1,185 keratoplasties. The two most frequent surgical indications for corneal transplantation were keratoconus (18.9%) and Fuchs' endothelial corneal dystrophy (35.2%), with keratoconus being the primary cause in the early years (from 2004 to 2009) and Fuch's dystrophy being the dominating cause from 2010 to 2015. Overall, the number of keratoplasties performed grew from 385 corneal transplantations in the first six years to a total of 1,045 in the second six years.

The article titled “Australian Corneal Graft Registry. Corneal transplantation for keratoconus: A registrystudy. Arch. Ophthalmol” authored by Kelly, T.L.; Williams, K.A.; Coster, D.J was published on 2011 [5]. In 4834 eyes of 4060 patients who had their first penetrating corneal graft for keratoconus, it was determined what parameters affected long-term graft survival and visual acuity. Data were collected prospectively and processed retroactively as part of a large cohort research from a nationwide registry of corneal grafts. Snellen vision acuity and graft survival were the primary outcome indicators. The period of follow-up reached 23 years. At 10, 20, and 23 years, the first graft survival rates for keratoconus were 89%, 49%, and 17%, respectively. The graft survival rate after 15 years was equal to or worse than all other penetrating grafts (P =.36). Time to suture removal, uveitis or microbial keratitis following the first graft, and corneal vascularization before the graft were among the multivariate risk factors that affected the failure of the first grafts for keratoconus.

The article titled “Big data for health. IEEE J. Biomed. Health Inform” authored by Andreu-Perez, J.; Poon, C.C.; Merrifield, R.D.; Wong, S.T.; Yang, G.Z was published on 2015 [6]. An overview of recent big data innovations in the context of biomedical and health informatics is given in this paper. It outlines the salient features of big data and demonstrates how medical and health informatics, translational bioinformatics, sensor informatics, and imaging informatics will profit from an integrated approach of assembling various aspects of personalized data from a wide range of data sources, both structured and unstructured, covering imaging, clinical diagnosis, and long-term continuous physiological sensing of Recent developments in big data are anticipated to increase our knowledge for testing novel theories about the management of diseases, from diagnosis to prevention to tailored treatment.

The article titled “Big Data in Medicine is Driving Big Changes Yearb. Med. Inform” authored by Verspoor, K.; Martin-Sanchez, F published on 2014 [7]. To provide an overview of recent studies using "Big Data" in applications for biomedical and health informatics. Examination of the literature describing the use of large-scale structured and unstructured data sources to support applications ranging from systems biology and genetics to clinical decision making and health policy, as well as drug development and pharmacovigilance. The survey shows the continued development of strong new techniques for transforming these vast, frequently complex data sets into knowledge that offers fresh perspectives on human health across a variety of domains. When this body of work is taken into account, numerous significant paradigm shifts are revealed, including the transition from hypothesis-driven to data-driven research in clinical and translational research and the transition from evidence-based practice to evidence-based medicine. To evidence based in practice In order to address the growing demand for enormous amounts of health data, solutions for data management, data linkage, and data integration that go beyond the capabilities of many already used information systems are being actively pursued. The value of the data will keep rising as our capacity for understanding it expands. All facets of biomedicine, including health systems, genetics and genomics, population health, and public health, can gain from the use of big data and related technologies.

The article titled “Introduction to artificial intelligence in medicine. Minim. Invasive Ther. Allied Technol” authored by Mintz, Y.; Brodie, R was published on 2019 [8]. AI is now present in many aspects of our daily life, including personal assistants (Siri, Alexa, Google Assistant, and others), automated public transportation, aircraft, and video games. AI has more recently started to be used in medicine to enhance patient care by accelerating procedures and obtaining higher accuracy, paving the way for improved healthcare overall. Machine learning is evaluating radiological pictures, pathology slides, and patient electronic medical records (EMR), assisting in the process of patient diagnosis and treatment, and enhancing clinicians' abilities. Here, we discuss the current state of AI in medicine, how it is applied across specialties, and anticipated developments.

The article titled “Bowman’s topography for improved detection of early ectasia. J. Biophotonics” was authored by Chandapura, R.; Salomao, M.Q.; Ambrosio, R.; Swarup, R.; Shetty, R.; Roy, A.S was published on 2019 [9]. The purpose of this study was to determine whether clinical keratoconus (KC) and forme fruste (FFKC) could be diagnosed more accurately using artificial intelligence (AI) and OCT topography of the Bowman's layer. The number of corneas included was normal (n = 221), FFKC (n = 72), and KC (n = 116). The fellow eye (VAE-NT) of some of the FFKC and KC patients (n = 30) exhibited normal topography. The corneal Scheimpflug and OCT scans were examined. The air-epithelium (A-E) interface on the anterior corneal surface and the epithelium-Bowman's layer (E-B) interface (in OCT only) surface aberrations were calculated. Scheimpflug alone, OCT A-E alone, OCT E-B alone, and OCT A-E and E-B combined were the four models that were built standard eyes. These eyes could be distinguished using both Scheimpflug and OCT (A-E and E-B combined) equally well (P =.23). However, OCT A-E and E-B demonstrated that the majority of VAE-NT eyes shared topographic characteristics with normal eyes and did not require a distinct classification based only on topography.

The article titled “Topography and tomography in the diagnosis of corneal ectasia. Expert Rev. Ophthalmol” was published on 2015 [10]. Tomography is now a crucial tool for the selection of patients for refractive surgery, as well as for the diagnosis and treatment planning of ectatic disorders of the cornea, for today's refractive surgeons. The comparison of the Scheimpflug and Placido disc systems is attempted in this review article, which also emphasizes the utility of elevation-based topography and the significance of posterior float. The most popular tomography systems—the Orbscan IIz, anterior segment optical coherence tomography, Pentacam, and Galilei Scheimpflug systems—are reviewed in depth in this article's concluding section. Regarding corneal elevation, corneal curvature (power), pachymetry, and calculation of intraocular lens power following refractive surgery, comparisons of the aforementioned tomographers published in the literature have also been reviewed.

The article titled “Corneal Tomography for Screening of Refractive Surgery Candidates: A Review of the Literature, Part I. Med. Hypothesis DiscInnov. Ophthalmol” authored by Motlagh, M.N.; Moshirfar, M.; Murri, M.S.; Skanchy, D.F.; Momeni-Moghaddam, H.; Ronquillo, Y.C.; Hoopes, P.C. Pentacam was published on 2019 [11]. The corneal surface. Is regularly examined using corneal tomography and Scheimpflug imaging, particularly in the context of cataract and refractive surgery. One of the most often utilized commercially available systems for this purpose is the Pentacam system. The technology can produce a three-dimensional map of the cornea using a revolving Scheimpflug camera. These developments in tomography have improved clinicians’ capacity to assess surgical candidates and identify minute changes in the cornea associated with conditions like keratoconus. To better identify mild and early types of corneal ectasia, improved diagnosis is still required. It is crucial to properly evaluate patients before surgery since iatrogenic ectasia and keratoconus are feared consequences of refractive surgery.

The article titled “Comparison of Methods for Detecting Keratoconus Using Videokeratography. Arch.Ophthalmol” authored by Maeda, N.; Klyce, S.D.; Smolek, M.K was published on 1995 [12]. Researching the genetics of keratoconus and selecting candidates for refractive surgery require the identification of keratoconus patterns using videokeratography. In order to compare the strengths and weaknesses of each test and assess their applicability for usage in clinical settings, we investigated three quantitative methods for determining keratoconus from videokeratographic data. Videokeratographs representative of 44 cases of clinically diagnosed keratoconus and 132 cases of non-keratoconus conditions, including pellucid marginal degeneration, normal, with-the-rule astigmatism, contact lens-induced corneal warpage, and photorefractive keratectomy and keratoplasty, were chosen. Keratometry (average Simulated Keratometry [SimK] readings > 45.7 diopters [D]), the modified Rabinowitz-McDonnell test (central corneal power > 47.2 D and/or Inferosuperior Asymmetry [I-S] value > 1.4 D), and an expert system were employed as the three ways to identify keratoconus.

The article titled “Bivariate analysis of sensitivity and Specificity produces informative summary measures in diagnostic reviews. J. Clin. Epidemiol” authored by Reitsma, J.B.; Glas, A.S.; Rutjes, A.W.S.; Scholten, R.J.; Bossuyt, P.M.; Zwinderman, A.H was published on 2005 [13]. Studies on the accuracy of diagnostic tests often present pairs of sensitivity and specificity. We illustrate the benefit of analyzing such data with bivariate meta-regression models. By reanalyzing the data from a published meta-analysis, we describe the technique of both the summary Receiver Operating Characteristic (sROC) and the bivariate approach. For meta-analyzing diagnostic investigations that report pairings of sensitivity and specificity, the sROC technique is the industry standard. This strategy eliminates the impact of a potential threshold but also loses important clinical information regarding test performance by using the diagnostic odds ratio as the primary outcome measure. The original data’s two-dimensional structure is preserved by the bivariate method. Sensitivity and specificity pair analyses are combined with any correlation.

The article titled “Investigation of publication bias in meta-analyses of Diagnostic test accuracy: A meta-epidemiological study. BMC Med. Res. Methodol” authored by Van Enst, W.A.; Ochodo, E.; Scholten, R.J.; Hooft, L.; Leeflang, M.M was published on 2014 [14]. In light of the potential consequences of publication bias, the validity of a meta-analysis can be better understood. Diagnostic test accuracy (DTA) systematic review authors have little direction because the bulk of methodologies to examine publication bias in terms of small study-effects are created for meta-analyses of intervention trials. The purpose of this study was to compare the outcomes of various statistical techniques used to measure publication bias and to determine whether and how publication bias was assessed in meta-analyses of DTA. To locate DTA reviews that included a meta-analysis and were published between September 2011 and January 2012, a methodical search was started. The reviews and two-by-two tables provided us with all the data we needed to determine publication bias. Presently available statistical techniques for detecting.

The article titled “The performance of tests of publication bias and other sample size effects in systematic reviews Of diagnostic test accuracy was assessed. J. Clin. Epidemiol” authored by Deeks, J.J.; Macaskill, P.; Irwig, L was published on 2005 [15]. Just like randomized trials, meta-analyses of test accuracy include problems with publication bias and other sample size effects. We examine the drawbacks of conventional funnel plots and tests when used in meta-analyses of test accuracy and search for more effective techniques. In simulated meta-analyses of test accuracy, type I and type II error rates for current and alternative tests of sample size effects were computed and compared. For normal diagnostic odds ratios (DOR), when illness prevalence is less than 50%, and when thresholds favor sensitivity over specificity or vice versa, type I error rates for the Begg, Egger, and Macaskill tests are inflated.

Valid, if occasionally cautious, methods for sample size include regression and correlation tests based on functions of effective sample size.

The article titled “Automated topographic screening for keratoconus in refractive surgery candidates” authored by N S Kalin et al. CLAO J was published on July 1996 [16]. We evaluated an automated corneal topography relegation system developed as an adjuvant for screening patients prior to keratorefractive surgery. We screened for patterns suspicious for keratoconus by applying the system to the analysis of a series of patients who presented for evaluation for surgical rectification of myopia.Both ocular perceivers of 53 consecutive patients who were included in an aforetime reported prospective study were evaluated utilizing the Expert System relegation algorithm. This quantitative relegation system incorporating eight indices was applied to the videokeratoscopic data from each patient to divide the topographic patterns into keratoconus and non-keratoconus groups. The group assignment of the Expert System classifier was compared with the clinical diagnosis of keratoconus versus non-keratoconus predicated on the topographic pattern and objective biomicroscopy signs. The Expert System relegated eight of the videokeratographs as keratoconus. All five corneas that had clinical evidence of keratoconus were relegated as such by the Expert System (sensitivity 100%). The other three corneas that were relegated as keratoconus were of patients who wore rigid contact lenses and had pseudo-keratoconus topographic patterns, without other clinical designations of keratoconus. The specificity with which the Expert System detected mundane corneas was 97% (98/101).Evaluation of the videokeratographic data with computerized algorithms designed to detect keratoconus may avail preoperative evaluation and facilitate distinction between keratoconus and some keratoconus-like topographic patterns.

The article titled “Accuracy of ultrasonic pachymetry and videokeratography in detecting keratoconus” authored by Yaron S Rabinowitz, Karim Rasheed, Huiying Yang, Janet Elashoff Journal of Cataract & Refractive Surgery was published on 1998 [17]. To compare the precision of ultrasonic pachymetry quantifications- and videokeratography-derived indices in distinguishing keratoconus patients from those with mundane ocular perceivers. A subspecialty cornea practice (Los Angeles, California, USA) and the Keratoconus Genetics Research Project. Corneal thickness was quantified by ultrasonic pachymetry at the center and inferior margins of the pupil of 142 mundane and 99 keratoconus patients. The corneal surface topography of patients was studied with the Topographic Modeling System (TMS-1). The videokeratographs obtained were analyzed with a computer program that automatically calculates two indices derived from data points in the central and paracentral cornea: central K and I-S values. Linear discriminant analysis was habituated to determine the correct relegation percentages utilizing pachymetry quantifications and indices derived from videokeratography as the independent variables. The range of corneal thickness in mundane and keratoconic ocular perceivers overlapped considerably. In the discriminant analysis, videokeratography indices provided a 97.5% correct relegation rate and pachymetry data, an 86.0% rate ($P < .01$, McNemar's test). Keratoconus is more accurately distinguished from the mundane population by videokeratography-derived indices than by ultrasonic pachymetry quantifications. This may be due to the astronomically immense variation in corneal thickness in the mundane population or the inability of ultrasonic pachymetry to accurately detect the location of corneal thinning in keratoconus by quantifying standard points on the cornea. pachymetry should not be relied on to omit or diagnose keratoconus because the erroneous-negative and erroneous-positive rates are unacceptably higher than those obtained by videokeratography.

The article titled “Automated decision tree relegation of corneal shape Optometry and vision science: official publication of the American Academy of Optometry” authored by Michael D Twa, Srinivasan Parthasarathy, Cynthia Roberts, Ashraf M Mahmoud, Thomas W Raasch, Mark A Bullimore was published on 2005 [18]. The volume and involution of data engendered during video keratography examinations present a challenge of interpretation. As a consequence, results are often analyzed qualitatively by subjective pattern apperception or abbreviated to comparisons of summary indices. We describe the application of decision tree induction, an automated machine learning relegation method, to discriminate between mundane and keratoconic corneal shapes in an objective and quantitative way. We then compared this method with other kenned relegation methods. The corneal surface was modeled with a seventh-order Zernike polynomial for 132 mundane ocular perceivers of 92 subjects and 112 ocular perceivers of 71 subjects diagnosed with keratoconus. A decision tree classifier was induced utilizing the C4. 5 algorithm, and its relegation performance was compared with the modified Rabinowitz–McDonnell index, Schwiegerling’s Z3 index (Z3), Keratoconus Prognostication Index (KPI), KISA%, and Cone Location and Magnitude Index utilizing recommended relegation thresholds for each method. We withal evaluated the area under the receiver operator characteristic (ROC) curve for each relegation method. Our decision tree classifier performed equipollent to or better than the other classifiers tested: precision was 92% and the area under the ROC curve was 0.97. Our decision tree classifier minimized the information needed to distinguish between mundane and keratoconus ocular perceivers utilizing four of 36 Zernike polynomial coefficients. The four surface features culled as relegation attributes by the decision tree method were inferior ascension, more preponderant sagittal depth, oblique toricity, and trefoil. Automated decision tree relegation of corneal shape through Zernike polynomials is a precise quantitative method of relegation that is interpretable and can be engendered from any instrument platform capable of raw ascension data output. This method of pattern relegation is extendable to other relegation quandaries.

The article titled "Automated keratoconus detection utilizing height data of anterior and posterior corneal surfaces Japanese journal of ophthalmology" published by Kenichiro Bessho, Naoyuki Maeda, Teruhito Kuroda, Takashi Fujikado, Yasuo Tano, Tetsuro Oshika on 2006 [19]. To develop a keratoconus detection algorithm utilizing the corneal topographic data of the anterior and posterior corneal surfaces. Topographic quantifications of the cornea were made with a slit-scanning corneal topographer. We examined 120 subjects (165 ocular perceivers); keratoconus patients and keratoconus suspect patients comprised the keratoconus group, and post-photorefractive keratectomy patients, with-the-rule astigmatism patients, and controls without disease comprised the nonkeratoconus group. Two variables of the anterior corneal surface, two variables of the posterior corneal surface, and one corneal thickness variable were obtained by applying the Fourier harmonic decomposition formula. By performing a logistic regression analysis with a training set to differentiate the keratoconus group from the nonkeratoconus group, the Fourier-incorporated keratoconus detection Index (FKI) was engendered. The validity of the FKI was tenacious by utilizing independent validation sets. The FKI distinguished the keratoconus group from the nonkeratoconus group with 96.9% sensitivity and 95.4% specificity in the validation set. An incipiently developed automated keratoconus classifier can be habituated to screen keratoconic patients. The index is predicated on information obtained by Fourier analysis from not only the anterior corneal surface but additionally from the posterior corneal surface and corneal thickness.

The article titled "Topographic and tomographic properties of forme fruste keratoconus corneas Invest Ophthalmol Vis Sci" authored by Alain Saad et al was published on November 2010 [20]. To investigate the efficacy of topography and tomography indices cumulated in discriminant functions to detect mild ectatic corneas. The authors retrospectively reviewed the data of 143 ocular perceivers disunited into three groups by the Corneal Navigator OPD scanning system (Nidek, Gamagori, Japan): mundane (N; LASIK surgery with a 2-year follow-up; n = 72), forme fruste keratoconus (N topography with contralateral KC; FFKC; n = 40), and KC (n = 31). Topography and tomography indices, corneal thickness spatial profile (CTSP), and anterior and posterior curvature spatial profiles were obtained with the Orbscan IIz (Bausch & Lomb Surgical, Rochester, NY). The percentage of thickness increase (PTI) from the thinnest point to the periphery, the percentage of variation of anterior (PVAK), and posterior curvature were calculated and compared by Kruskal-Wallis test. The usefulness of these data to discriminate among the three groups was assessed by receiver operating characteristic (ROC) curve analysis. Posterior ascension of the thinnest point (TP), all positions of CTSP, PTI for all distances from the TP, and PVAK from a 5- to 7-mm distance from the TP were significantly different in the FFKC compared with the N group. The discriminant functions between the FFKC and the N groups and between the KC and the N groups reached an area under the ROC curve of 0.98 and 0.99, respectively. PTI indices and maximum posterior central ascension were the most paramount contributors to the discriminant function. Indices engendered from corneal thickness and curvature quantifications over the entire cornea centered on the TP can identify very mild forms of ectasia undetected by a Placido-predicated neural network program.

The article titled "Detection of Subclinical Keratoconus Using an Automated Decision Tree Classification. Am. J. Ophthalmol" authored by .Smadja, D.; Touboul, D.; Cohen, A.; Doveh, E.; Santhiago, M.R.; Mello, G.R.; Krueger, R.R.; Colin, J was published on 2013 [21]. In a retrospective case-control study conducted at the University Hospital of Bordeaux, involving 372 eyes of 197 patients, a novel method was developed for automating the detection of subclinical keratoconus using a tree classification approach. Utilizing data from dual Scheimpflug analyzer imaging and analyzing 55 parameters from corneal measurements, a machine learning algorithm, the classification and regression tree, exhibited remarkable performance. It achieved 100% sensitivity and 99.5% specificity in distinguishing normal eyes from keratoconus and 93.6% sensitivity and 97.2% specificity in identifying forme fruste keratoconus. Notably, the algorithm highlighted posterior surface asymmetry and thickness spatial distribution as critical parameters for discrimination. This innovative approach holds promise as a valuable tool for aiding surgical decisions related to refractive surgery by effectively detecting ectasia-susceptible corneas with high sensitivity, thus advancing the prospects of automated medical reasoning in this field.

The article titled “Expanding the Cone Location and Magnitude Index to Include Corneal Thickness and Posterior Surface Information for the detection of Keratoconus. Am. J. Ophthalmol” authored by Mahmoud, A.M.; Nuñez, M.X.; Blanco, C.; Koch, D.D.; Wang, L.; Weikert, M.; Frueh, B.E.; Tappeiner, C.; Twa, M.; Roberts, C.J was published on 2013 [22]. In a retrospective case-control study aiming to enhance the accuracy of keratoconus detection, a new index, ConeLocationMagnitudeIndex_X, was developed by combining topographic data from both the anterior and posterior corneal surfaces along with corneal thickness measurements. This innovative approach was assessed using three independent datasets: one for development and two for validation. The AnteriorCornealPower index was employed to stratify keratoconus severity, and ConeLocationMagnitudeIndex_X was applied to tomography data obtained from a dual Scheimpflug-Placido-based tomographer. The logistic regression model generated by ConeLocationMagnitudeIndex_X exhibited complete separation in the development set, and when applied to the validation sets, it demonstrated remarkable sensitivity and specificity of 99.4% and 99.6%, respectively, surpassing the performance of the original ConeLocationMagnitudeIndex, which achieved 89.2% sensitivity and 98.8% specificity. In conclusion, ConeLocationMagnitudeIndex_X presents a robust and improved approach for identifying keratoconus patterns in corneal tomography maps by incorporating both anterior and posterior surface data, thus enhancing sensitivity and specificity compared to the anterior surface-only approach.

The article titled “Corneal Enantiomorphism in Normal and Keratoconic Eyes. J. Refract. Surg” authored by Saad, A.; Guilbert, E.; Gatinel, D was published on 2014 [23]. In a prospective, non-randomized study, the objective was to assess the capability to distinguish between normal and keratoconic corneas by analyzing intereye corneal asymmetry parameters and defining a similarity score to outline the normal range of asymmetry between right and left eyes. This investigation included 102 normal corneas from 51 patients and 64 keratoconic corneas from 32 patients, where topographic and tomographic parameters were extracted from corneal topography data. Significant intereye asymmetry differences were observed for most variables, except specific corneal thickness measurements and posterior keratometry values. A discriminant function incorporating three variables achieved remarkable discrimination power, with an area under the receiver operator characteristic curve of 0.992, a sensitivity of 94%, and a specificity of 100%. This suggests that utilizing intereye differences in corneal indices, especially in topography-based assessments, could offer an accurate method for detecting advanced keratoconus. Furthermore, the potential integration of such data into automated artificial intelligence software may enhance the early detection of keratoconus in the future.

The article titled “Epithelial Remodeling as Basis for Machine-Based Identification of Keratoconus. Investig. Opthalmol. Vis. Sci” authored by Silverman, R.H.; Urs, R.; RoyChoudhury, A.; Archer, T.J.; Gobbe, M.; Reinstein, D.Z was published on 2014 [24]. This study set out to develop and assess automated computerized algorithms aimed at discerning between normal and keratoconus-affected corneas exclusively based on epithelial and stromal thickness data. By utilizing corneal thickness maps generated from high-frequency ultrasound scans of 130 normal and 74 keratoconic subjects, the severity of keratoconus was graded using various metrics. The computational analysis extracted 161 features from randomly selected eyes per subject. Employing both stepwise linear discriminant analysis (LDA) and neural network (NN) methods, multivariate models were constructed using selected features to accurately classify cases. The results were highly promising, with the LDA model achieving complete separation of keratoconic from normal corneas, displaying an impressive AUC of 100%. Neural network analysis, utilizing the same six variables, maintained this exceptional performance during training and on test sets, showcasing remarkable specificity and sensitivity. These findings underscore the potential of epithelial and stromal thickness data as a robust and independent means of distinguishing normal from advanced keratoconus corneas, offering significant implications for future diagnostic applications in this field.

The article titled “Quantitative assessment of corneal vibrations during intraocular pressure measurement with the air-puff method in patients with keratocdnus. Comput. Biol. Med” was published on 2015 [25]. The study presents a novel approach for intraocular pressure measurement using the Corvis tonometer and ultrahigh-speed Scheimpflug camera, allowing for the observation of corneal deformation during the process. By employing advanced image analysis and processing techniques, the research included data from 493 healthy subjects and 279 patients with keratoconus. Their unique algorithm enabled the separation of eyeball reaction, low frequency, and high-frequency corneal deformations from the air puff’s effect. Additionally, a decision tree-based classification method was introduced to distinguish between healthy individuals and those with keratoconus, achieving impressive specificity (98%), sensitivity (85%), and accuracy (92%). These findings highlight the potential of this innovative approach in utilizing corneal vibrations during intraocular pressure measurement, offering valuable insights for improved diagnostic capabilities and inter-individual variability assessment in patients.

The article titled “A Novel Zernike Application to Differentiate between Three-dimensional Corneal Thickness of Normal Corneas and Corneas with Keratoconus. Am. J. Ophthalmol” authored by Shetty, R.; Matalia, H.; Srivatsa, P.; Ghosh, A.; Dupps, W.; Roy, A.S was published on 2015 [26]. The Scheimpflug imaging technique was used to accomplish corneal tomography in normal (43 eyes) and KC (85 eyes) corneas. The anterior and posterior surfaces' axial and tangential cone location magnitude indexes (axial CLMI and tangential CLMI, respectively) were determined. Zernike polynomials were used to investigate the anterior corneal surface aberrations. It was possible to map the cornea's 3-D thickness distribution using pachymetric Zernike analyses (PZA). With the aid of CLMI, PZA, and aberrations, a diagnosis method for KC was created using logistic regression. For each regression model, a receiver operating characteristic curve was built. Additionally, the volume of the normal and KC corneas' corneas was compared. For all analyses, just the center 5 mm zone was used. The greatest predictors of KC corneas among the PZA coefficients were the second- and third-order root mean squares of PZA coefficients (P .0001). The greatest predictors of KC among the CLMI variables were axial CLMI of anterior and tangential CLMI of posterior surface (P .0001). The best Zernike corneal aberration coefficient predictors of KC were second- and third-order root mean squares of coefficients (P .0001). The Zernike corneal aberrations, CLMI, and PZA logistic regression models all have comparable sensitivity and specificity (P >.05.)

The article titled “Accuracy of machine learning classifiers using bilateral data from a Scheimpflug camera for identifying eyes with preclinical signs of keratoconus. J. Cataract. Refract. Surg” authored by Kovács, I.; Miháltz, K.; Kránitz, K.; Juhász, É.; Takács, Á.; Dienes, L.; Gergely, R.; Nagy, Z.Z was published on 2016 [27]. Eyes of refractive surgery candidates (control group), normal fellow eyes of patients with unilateral keratoconus, patients with bilateral keratoconus (keratoconus group), clinically and in accordance with the keratoconus indices of the Pentacam HR Scheimpflug camera. Using the Scheimpflug camera, keratoconus indices, topographic data, and tomographic data were measured in both eyes. The efficacy of automated classifiers based on bilateral data as well as individual factors was evaluated using receiver operating characteristic (ROC) analysis to distinguish fellow keratoconus patient eyes from control eyes. Pachymetry values were significantly lower and keratometry, elevation, and keratoconus indices values were significantly greater in unilateral keratoconus instances in keratoconus eyes compared to fellow eyes (P .001). In comparison to control eyes, these colleague eyes had significantly lower pachymetry values and significantly increased keratometry, elevation, and keratoconus index values (P .001). When separating the buddy eyes of patients with keratoconus from control eyes, automated classifiers trained on bilateral data of the index of height decentration performed better than the unilateral single parameter (area under ROC 0.96 versus 0.88).

The article titled “Evaluation of a MachineLearning Classifier for Keratoconus Detection Based on Scheimpflug Tomography. Cornea” authored by Hidalgo, I.R.; Rodriguez, P.; Rozema, J.J.; Dhubhghaill, S.N.; Zakaria, N.; Tassignon, M.J.; Koppen, C was published by 2016 [28]. 860 eyes with pentacam data from 5 groups of 454 KC, 67 forme fruste (FF), 28 astigmatic, 117 following refractive surgery (PR), and 194 normal eyes (N) were used in the study. Using a support vector machine algorithm created in the machine-learning program Weka, 22 parameters were employed for categorization. Calculated and evaluated against other well-known classification techniques were the cross-validation accuracy for three different classification tasks (KC vs. N, FF vs. N, and all five groups). The KC versus N discrimination task was completed with 98.9% accuracy, 99.1% sensitivity, and 98.5% specificity for KC detection. In the FF versus N task, accuracy was 93.1%, with sensitivity and specificity for the FF discrimination being 79.1% and 97.9%, respectively. The accuracy for the 5-group classification was 88.8%, with 95.2% specificity and 89.0% weighted average sensitivity.

The article titled “Integration of Scheimpflug-Based Corneal Tomography and Biomechanical Assessments for Enhancing Ectasia Detection. J. Refract. Surg” authored by Ambrósio, R.; Lopes, B.T.; Faria-Correia, F.; Salomão, M.Q.; Bühren, J.; Roberts, C.J.; Elsheikh, A.; Vinciguerra, R.; Vinciguerra, P was published on 2017 [29]. Retrospective research was done on patients from different continents. One eye from 480 patients with normal corneas was randomly chosen for the normal group, and one eye from 204 patients with keratoconus was randomly chosen for the keratoconus group. The 94 individuals with highly asymmetric ectasia were divided into two groups: the fellow eyes of these patients with normal topography and the 72 ectatic eyes from these patients without surgery (VAE-E group). We used various artificial intelligence techniques to assess and merge the Pentacam HR and Corvis ST (Oculus Optikgeräte GmbH, Wetzlar, Germany) parameters. Areas under receiver operating characteristic curves (AUROCs) were used to evaluate the ectasia detection accuracies of the Belin/Ambrósio Deviation (BAD-D) and Corvis Biomechanical Index (CBI) to those of the TBI. The top artificial intelligence model was produced by the random forest method with leave-one-out cross-validation (RF/LOOCV). The TBI's AUROC for detecting ectasia (in the keratoconus, VAE-E, and VAE-NT groups) was 0.996, which was statistically superior than the BAD-D's (0.956), and the CBI's (0.936) (DeLong et al., P .001). For the detection of clinical ectasia (in the keratoconus and VAE-E groups), the TBI cut-off value of 0.79 had 100% sensitivity and 100% specificity. The VAE-NT group's AUROCs for the TBI, BAD-D, and CBI were respectively 0.985, 0.839, and 0.822 (DeLong et al., P .001). In the VAE-NT group, an optimized TBI cut-off value of 0.29 yielded 90.4% sensitivity and 96% specificity.

The article titled "Combined tomography and epithelial thickness mapping for diagnosis of keratoconus. Eur. J. Ophthalmol" authored by Silverman, R.H.; Urs, R.; Roychoudhury, A.; Archer, T.J.; Gobbe, M.; Reinstein, D.Z was published on 2017 [30]. Scanning Scheimpflug offers data on corneal thickness and two-surface topography, and arc-scanned high-frequency ultrasound enables visualization of the distributions of epithelial and stromal thickness. Both methods are effective at finding keratoconus. Our goal was to create and evaluate a keratoconus classifier that utilized data from both approaches. We used Artemis-1 and Pentacam data to scan 111 healthy individuals and 30 people who had clinical keratoconus. After choosing one random eye per subject, we used stepwise linear discriminant analysis on a dataset to combine the characteristics produced by each method and create classification models for both the individual and combined use of each methodology. Based solely on Artemis data, discriminant analysis produced a 4-variable model (R2 = 0.740), and solely on Pentacam data, it produced a 4-variable model (R2 = 0.734). Three Artemis- and four Pentacam-derived variables made up the combined model (R2 = 0.828). In comparison to each model separately, the combined model's R value was significantly higher (p = 0.031, one-tailed). Cross-validation results showed that the combined model had 97.3% sensitivity and 100% specificity, while Pentacam had 100% sensitivity and 99.2% specificity.

The article titled "Support Vector Machine Algorithm in Machine Learning" authored by Qiyu Wang was published on June 2022 [31]. The Support Vector methods was proposed by V.Vapnik in 1965, when he was trying to solve problems in pattern recognition. In 1971, Kimeldorf proposed a method of constructing kernel space based on support vectors. In 1990s, V.Vapnik formally introduced the Support Vector Machine (SVM) methods in Statistical Learning. Since then, SVM has been widely applied in pattern recognition, natural language process and so on. Informally, SVM is a binary classifier. The model is based on the linear classifier with the optimal margin in the feature space and thus the learning strategy is to maximize the margin, which can be transformed into a convex quadratic programming problem. It uses the principle of structural risk minimization instead of empirical risk minimization to fit small data samples. Kernel trick is used to transform non-linear sample space into linear space, decreasing the complexity of algorithm. Even though, it still has broader prospects for development.

The article titled "A Study on Support Vector Machine based Linear and Non-Linear Pattern Classification" authored by Sourish Ghosh; Anasuya Dasgupta; Aleena Swetapadma was published on February 2019 [32]. The best way to acquire knowledge about an algorithm is feeding it data and checking the result. In a layman's language machine learning can be called as an ideological child or evolution of the idea of understanding algorithm through data. Machine learning can be subdivided into two paradigms, supervised learning and unsupervised learning. Supervised learning is implemented to classify data using algorithms like support vector machines (SVM), linear regression, logistic regression, neural networks, nearest neighbor etc. Supervised learning algorithm uses the concepts of classification and regression. Linear classification was earlier used to form the decision plane but was bidimensional. But a particular dataset might have required a non-linear decision plane. This gave the idea of the support vector machine algorithm which can be used to generate a non-linear decision boundary using the kernel function. SVM is a vast concept and can be implemented on various real world problems like face detection, handwriting detection and many more. This paper surveys the various concepts of support vector machines, some of its real life applications and future aspects of SVM.

The article titled "Support vector machines" authored by M.A. Hearst; S.T. Dumais; E. Osuna; J. Platt; B. Scholkopf was published on 1998 [33]. My first exposure to Support Vector Machines came this spring when heard Sue Dumais present impressive results on text categorization using this analysis technique. This issue's collection of essays should help familiarize our readers with this interesting new racehorse in the Machine Learning stable. Bernhard Scholkopf, in an introductory overview, points out that a particular advantage of SVMs over other learning algorithms is that it can be analyzed theoretically using concepts from computational learning theory, and at the same time can achieve good performance when applied to real problems. Examples of these real-world applications are provided by Sue Dumais, who describes the aforementioned text-categorization problem, yielding the best results to date on the Reuters collection, and Edgar Osuna, who presents strong results on application to face detection. Our fourth author, John Platt, gives us a practical guide and a new technique for implementing the algorithm efficiently.

The article titled “The research of the fast SVM classifier method” authored by Yujun Yang; Jianping Li; Yimei Yang was published on December 2016 [34]. Support vector machine (SVM) is a machine learning method developed in the mid-1990s based on statistical learning theory. SVM classifier is currently more popular classifier. This paper presents a boundary detection technique for retaining the potential support vector. Through seeking to structural risk minimization of the SVM, it improves the learning generalization ability and achieves the minimization of empirical risk and confidence range in the case of small statistical sample size and it can also obtain the desired good statistical law.

The article topic “Introduction of SVM Related Theory and Its Application Research” authored by Ting-ting Dai; Yan-shou Dong was published on April 2020 [35]. This paper introduces the principle of SVM, kernel function selection and multi-class classification problem. At the same time, which expounds and summarizes the SVM algorithm. Secondly, it summarizes the application research of support vector machine from the aspects of handwritten digit recognition, text classification and image recognition. Finally, we discuss the advantages and disadvantages of SVM, and prospect the prospects of its application research.

The article titled “Support Vector Machine Classification Algorithm Based on Relief-F Feature Weighting” authored by Jing Huang; Jinzhi Zhou; Linwen Zheng was published on March 2020 [36]. Aiming at the problem that the existing support vector machines only consider the importance of samples and ignore the importance of features on the classification results, this paper proposes a support vector machine method based on Relief-F feature weighting. This method first uses the Relief-F feature weighting algorithm to calculate the weight value of each feature, and then uses the feature weight value to weight the inner product in the support vector machine kernel function. This method effectively avoids the influence of weakly correlated features or uncorrelated features on the support vector machine classification results. Training and verification are performed on the data provided by the UCI public data set; experimental results show that the method can improve the classification accuracy of the classifier, reduce the number of support vectors, and have better robustness and classification ability than traditional SVM.

The article titled “A View of Support Vector Machines Algorithm on Classification Problems” authored by Ranzhe Jing; Yong Zhang was published on August 2010 [37]. Support vector machine (SVM) algorithm has shown a good learning ability and generalization ability in classification, regression and forecasting. This paper mainly analyzes the the performance of support vector machine algorithm in the classification problem, including the algorithm in the kernel function selection, parameter optimization, and integration of other algorithms and to deal with multi-classification issues improvements. Concludes with a discussion of the SVM algorithm is the direction of further improvement.

The article titled “Image classification via support vector machine” authored by Xiaowu Sun; Lizhen Liu; Hanshi Wang; Wei Song; Jingli Lu was published by December 2015 [38]. With the rapid growth of images information, how to classify the images has been a main problem, and most of researchers are concerning on the neural networks to realize the images classification. However, the neural networks cannot escape from its own limitations including the local optimum or the dependence on the input sample data. In this paper, another new algorithm named support vector machine, whose main idea is to build a hyperplane as the decision surface, is introduced to solve the problems. In the theory part, in order to solve the optimal hyperplane for the separable patterns problem, the method of Lagrange multiplier is transformed into its dual problem. In the application section, where it proves that the support vector machine can solve the problem of classification perfectly, with regard to the input data, the eigenvalues of the images' gray information which are treated by the method of Principal Component Analysis are abstracted as input sample. It is found that the precision of the classification could arrive at 89.66%, which is far higher than the neural networks' 41.38%.

1. CONCLUSIONS

Keratoconus current, thorough analysis of the application of machine learning in KC detection and point out the significant obstacles that must be removed to improve the effectiveness of the early keratoconus diagnostic procedure. We feel that both enhanced machine learning model performance in early KC detection and increased quality machine learning research in KC are desperately needed in light of our findings on pooling detection performance and low adherence to the TRIPOD criteria. With the development of cutting-edge imaging modalities, the future of incorporating machine learning technologies into clinical practice appears bright, despite a number of obstacles. Further research on machine learning's potential for widespread application to the entire procedure of KC detection and management is possible. In specifically, several unexplored areas of study include Early KC detection, assessment of risk factors, prognosis of progression, and advice on clinical therapy. Global cooperation is necessary to produce larger data sets and more reliable models, though.

2. REFERENCES

[1]. Whitcher, J.P.; Srinivasan, M.; Upadhyay, M.P. Corneal blindness: A global perspective. Bull. World Health Organ. 2001, 79, 214–221. [PubMed]
[2]. Sharif, R.; Bak-Nielsen, S.; Hjortdal, J.; Karamichos, D. Pathogenesis of Keratoconus: The intriguing therapeutic potential of Prolactin-inducible protein. Prog. Retin. Eye Res. 2018, 67, 150–167. [CrossRef] [PubMed]
[3]. Buzzonetti, L.; Bohringer, D.; Liskova, P.; Lang, S.; Valente, P. Keratoconus in Children: A Literature Review. Cornea 2020, 39, 1592–1598. [CrossRef] [PubMed]
[4]. Röck, T.; Bartz-Schmidt, K.U.; Röck, D. Trends in corneal transplantation at the University Eye Hospital in Tübingen, Germany over the last 12 years: 2004–2015. PLoS ONE 2018, 13, e0198793. [CrossRef]
[5]. Kelly, T.L.; Williams, K.A.; Coster, D.J.; Australian Corneal Graft Registry. Corneal transplantation for keratoconus: A registry study. Arch. Ophthalmol. 2011, 129, 691–697. [CrossRef]
[6]. Andreu-Perez, J.; Poon, C.C.; Merrifield, R.D.; Wong, S.T.; Yang, G.Z. Big data for health. IEEE J. Biomed. Health Inform. 2015, 19, 1193–1208.
[7]. Verspoor, K.; Martin-Sanchez, F. Big Data in Medicine is Driving Big Changes. Yearb. Med. Inform. 2014, 23, 14–20
[8]. Mintz, Y.; Brodie, R. Introduction to artificial intelligence in medicine. Minim. Invasive Ther. Allied Technol. 2019, 28, 73–81.
[9]. Chandapura, R.; Salomao, M.Q.; Ambrosio, R.; Swarup, R.; Shetty, R.; Roy, A.S. Bowman's topography for improved detection of early ectasia. J. Biophotonics 2019, 12, e201900126.
[10]. Ramamurthy, S.; Reddy, J.; Jhanji, V. Topography and tomography in the diagnosis of corneal ectasia. Expert Rev. Ophthalmol. 2015, 10, 215–228.
[11]. Motlagh, M.N.; Moshirfar, M.; Murri, M.S.; Skanchy, D.F.; Momeni-Moghaddam, H.; Ronquillo, Y.C.; Hoopes, P.C. Pentacam® Corneal Tomography for Screening of Refractive Surgery Candidates: A Review of the Literature, Part I. Med. Hypothesis DiscInnov. Ophthalmol. 2019
[12]. Maeda, N.; Klyce, S.D.; Smolek, M.K. Comparison of Methods for Detecting Keratoconus Using Videokeratography. Arch.Ophthalmol. 1995
[13]. Reitsma, J.B.; Glas, A.S.; Rutjes, A.W.S.; Scholten, R.J.; Bossuyt, P.M.; Zwinderman, A.H. Bivariate analysis of sensitivity and specificity produces informative summary measures in diagnostic reviews. J. Clin. Epidemiol. 2005, 58, 982–990. [CrossRef]
[14]. Van Enst, W.A.; Ochodo, E.; Scholten, R.J.; Hooft, L.; Leeflang, M.M. Investigation of publication bias in meta-analyses of diagnostic test accuracy: A meta-epidemiological study. BMC Med. Res. Methodol. 2014, 14, 70. [CrossRef]
[15]. Deeks, J.J.; Macaskill, P.; Irwig, L. The performance of tests of publication bias and other sample size effects in systematic reviews of diagnostic test accuracy was assessed. J. Clin. Epidemiol. 2005, 58, 882–893. [CrossRef] [PubMed]
[16]. Kalin, N.S.; Maeda, N.; Klyce, S.D.; Hargrave, S.; Wilson, S.E. Automated topographic screening for keratoconus in refractive surgery candidates. CLAO J. Off. Publ. Contact Lens Assoc. Ophthalmol. Inc. 1996, 22, 164–167.
[17]. Rabinowitz, Y.S.; Rasheed, K.; Yang, H.; Elashoff, J. Accuracy of ultrasonic pachymetry and videokeratography in detecting keratoconus. J. Cataract. Refract. Surg. 1998, 24, 196–201. [CrossRef]
[18]. Twa, M.D.; Parthasarathy, S.; Roberts, C.; Mahmoud, A.M.; Raasch, T.W.; Bullimore, M.A. Automated decision tree classification of corneal shape. Optom. Vis. Sci. Off. Publ. Am. Acad. Optom. 2005, 82, 1038–1046. [CrossRef]
[19]. Bessho, K.; Maeda, N.; Kuroda, T.; Fujikado, T.; Tano, Y.; Oshika, T. Automated keratoconus defection using height data of anterior and posterior corneal surfaces. Jpn. J. Ophthalmol. 2006, 50, 409–416. [CrossRef] [PubMed]
[20]. Saad, A.; Gatinel, D. Topographic and Tomographic Properties of Forme Fruste Keratoconus Corneas. Investig. Opthalmol. Vis. Sci. 2010, 51, 5546–5555. [CrossRef]

Smadja, D.; Touboul, D.; Cohen, A.; Doveh, E.; Santhiago, M.R.; Mello, G.R.; Krueger, R.R.; Colin, J. Detection of [21]. Subclinical Keratoconus Using an Automated Decision Tree Classification. Am. J. Ophthalmol. 2013, 156, 237– 246.e1. [CrossRef]

[22]. Mahmoud, A.M.; Nuñez, M.X.; Blanco, C.; Koch, D.D.; Wang, L.; Weikert, M.; Frueh, B.E.; Tappeiner, C.; Twa, M.; Roberts, C.J. Expanding the Cone Location and Magnitude Index to Include Corneal Thickness and Posterior Surface Information for the Detection of Keratoconus. Am. J. Ophthalmol. 2013, 156, 1102–1111. [CrossRef]

[23]. Saad, A.; Guilbert, E.; Gatinel, D. Corneal Enantiomorphism in Normal and Keratoconic Eyes. J. Refract. Surg. 2014, 30, 542–547. [CrossRef]

[24]. Silverman, R.H.; Urs, R.; RoyChoudhury, A.; Archer, T.J.; Gobbe, M.; Reinstein, D.Z. Epithelial Remodeling as Basis for MachineBased Identification of Keratoconus. Investig. Opthalmol. Vis. Sci. 2014, 55, 1580–1587. [CrossRef] [PubMed]

[25]. Koprowski, R.; Ambrosio, R. Quantitative assessment of corneal vibrations during intraocular pressure measurement with the air-puff method in patients with keratocdnus. Comput. Biol. Med. 2015, 66, 170–178. [CrossRef]

[26]. Shetty, R.; Matalia, H.; Srivatsa, P.; Ghosh, A.; Dupps, W.; Roy, A.S. A Novel Zernike Application to Differentiate between Three-dimensional Corneal Thickness of Normal Corneas and Corneas with Keratoconus. Am. J. Ophthalmol. 2015, 160, 453–462.e2. [CrossRef]

[27]. Kovács, I.; Miháltz, K.; Kránitz, K.; Juhász, É.; Takács, Á.; Dienes, L.; Gergely, R.; Nagy, Z.Z. Accuracy of machine learning classifiers using bilateral data from a Scheimpflug camera for identifying eyes with preclinical signs of keratoconus. J. Cataract. Refract. Surg. 2016, 42, 275–283. [CrossRef]

[28]. Hidalgo, I.R.; Rodriguez, P.; Rozema, J.J.; Dhubhghaill, S.N.; Zakaria, N.; Tassignon, M.J.; Koppen, C. Evaluation of a MachineLearning Classifier for Keratoconus Detection Based on Scheimpflug Tomography. Cornea 2016, 35, 827–832. [CrossRef]

[29]. Ambrósio, R.; Lopes, B.T.; Faria-Correia, F.; Salomão, M.Q.; Bühren, J.; Roberts, C.J.; Elsheikh, A.; Vinciguerra, R.; Vinciguerra, P. Integration of Scheimpflug-Based Corneal Tomography and Biomechanical Assessments for Enhancing Ectasia Detection. J. Refract. Surg. 2017, 33, 434–443. [CrossRef]

[30]. Silverman, R.H.; Urs, R.; Roychoudhury, A.; Archer, T.J.; Gobbe, M.; Reinstein, D.Z. Combined tomography and epithelial thickness mapping for diagnosis of keratoconus. Eur. J. Ophthalmol. 2017, 27, 129–134. [CrossRef] [PubMed]

[31]. Support Vector Machine Algorithm in Machine Learning Qiyu Wang June 2022

[32]. A Study on Support Vector Machine based Linear and Non-Linear Pattern Classification Sourish Ghosh; Anasuya Dasgupta; Aleena Swetapadma February 2019

[33]. Support vector machines M.A. Hearst; S.T. Dumais; E. Osuna; J. Platt; B. Scholkopf 1998

[34]. The research of the fast SVM classifier method Yujun Yang; Jianping Li; Yimei Yang December 2016

[35]. Introduction of SVM Related Theory and Its Application Research Ting-ting Dai; Yan-shou Dong April 2020

[36]. Support Vector Machine Classification Algorithm Based on Relief-F Feature Weighting Jing Huang; Jinzhi Zhou; Linwen Zheng March 2020

[37]. A View of Support Vector Machines Algorithm on Classification Problems Ranzhe Jing; Yong Zhang August 2010

[38]. Image classification via support vector machine Xiaowu Sun; Lizhen Liu; Hanshi Wang; Wei Song; Jingli Lu December 2015.