International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Automated Keratoconus Diagnosis Using Corneal Topography and Tomography: A Literature Review

Shalini R. Bakal[1], Satish R. Sankaye[2]

[1]Research Scholar, MGM University, Chhatrapati Sambhajinagar, India
[2]Professor, MGM University, Chhatrapati Sambhajinagar, India

Abstract

Keratoconus is a progressive eye condition in which the cornea becomes thin and irregular, leading to distorted vision. Detecting the disease at an early stage is reaally important to prevent further visual deterioration, but traditional clinical diagnosis often depends on subjective interpretation of corneal maps. With the availability of corneal topography and tomography, it has become possible to assess corneal struc- ture in a more objective and quantitative manner. This literature review explores the existing research on automated keratoconus diagnosis using topographic and tomographic corneal map data. there are Various approaches which are based on clinical indices, machine learning, as well as k deep learning, and hybrid models are also discussed and compared. The review also highlights the practical challenges such as there is limited datasets available , variability across imaging devices, and the need for interpretable models. Recent trends, including multimodal analysis and explainable artificial intelligence, are briefly discussed.

Keywords: Keratoconus, Corneal Topography, Corneal Tomography, Machine Learning, Deep Learning

Introduction

Localized corneal thinning, protrusion, and irregular astigmatism are the hallmarks of keratoconus (KC), a progressive, non-inflammatory corneal ectatic disease that eventually results in visual distortion and diminished visual acuity. It typically manifests during adolescence or early adulthood and progresses over time, significantly affecting quality of life if not detected and managed at an early stage. Epidemiological studies report a global prevalence ranging from 1 in 375 to 1 in 2000 individuals, with higher incidence observed in Asian and Middle Eastern populations, highlighting keratoconus as a growing public health concern worldwide [1–4].

Traditional diagnosis of keratoconus relies on slit-lamp examination, retinoscopy, and manual interpreta- tion of corneal curvature patterns. However, these methods are often subjective and may fail to detect early or subclinical keratoconus, also referred to as forme fruste keratoconus [5]. The introduction of corneal imaging technologies, particularly corneal topography and tomography, has significantly improved diag- nostic capabilities by enabling objective and quantitative assessment of corneal morphology [6].

Corneal topography primarily evaluates the anterior corneal surface using Placido-disk–based systems, generating curvature maps such as axial and tangential maps that visualize corneal steepening and asym- metry. While effective for detecting moderate to advanced keratoconus, its reliance on anterior surface data limits sensitivity for early disease stages [7]. Corneal tomography extends this capability by provid- ing three-dimensional assessment of the cornea, including anterior and posterior elevation, pachymetric

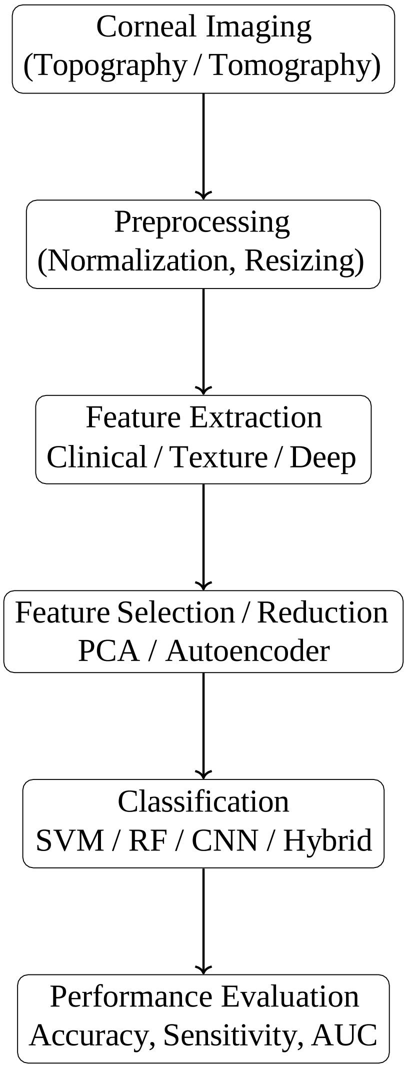

Figure 1: General workflow of automated keratoconus diagnosis systems

distribution, and thickness progression profiles. Scheimpflug-based imaging systems have demonstrated superior performance in detecting early keratoconus by capturing posterior corneal changes that often precede anterior surface deformation [8,9].

With the increasing availability of high-resolution corneal imaging data, automated diagnostic systems based on machine learning and deep learning techniques have gained significant attention. Early auto- mated approaches relied on handcrafted clinical indices combined with traditional classifiers, while recent studies demonstrate that convolutional neural networks can learn discriminative representations directly from corneal maps [10–13]. Despite these advancements, challenges related to dataset diversity, inter- device variability, and lack of interpretability remain unresolved [14,15].

Corneal Topography and Tomography: Overview

Corneal Topography

Corneal topography focuses basicaally on the measurement of the anterior corneal surface using Placido- disk–based imaging systems. Axial and tangential maps are widely used to visualize curvature distri- bution, steepening, and asymmetry. Topographic indices including such as maximum keratometry, infe- rior–superior asymmetry, and surface variance have been extensively utilized d in the automated diagnosis systems. Although topography demonstrates high sensitivity for moderate to advanced keratoconus, its dependence on anterior surface measurements limits its effectiveness for early disease detection [5–7].

Corneal Tomography

Corneal tomography provides three-dimensional structural information by capturing both anterior and pos- terior corneal surfaces along with pachymetric distribution. Scheimpflug-based imaging systems generates the elevation and thickness maps that enables the detection of posterior corneal abnormalities and local- ized thinning patterns. These changes often precede anterior surface deformation, making tomography particularly valuable for early and subclinical keratoconus detection [8–10].

General Workflow of Automated Diagnosis

There are sop many automated keratoconus diagnosis systems that follows a structured workflow con- sisting of basic image processing workflown data acquisition, Imagw preprocessing, feature extraction, feature selection or dimensionality reduction, classification, and performance evaluation. The Preprocess- ing steps such as image normalization and image resizing are applied to reduce the inter- device variability. The Extracted features are then supplied to classification algorithms, and algorithms performance is eval- uated using metrics such as Accuracy, Sensitivity, Specificity, and (AUC)area under the receiver operating characteristic curve(ROC) [11–13].

Comparative Methodological Overview

Topography-based approaches primarily basically relies on the corneal parameters such as anterior curva- ture indices and show limited sensitivity for early detection. Tomography-based methods using corneal maps outperform topography-only systems by incorporating posterior and pachymetric parameters. Hy- brid and deep learning–based methodologies combines this complementary information or data from mul- tiple corneal maps such as Elevation Maps to tract the steepening of the cornea, Thickness Maps such a sPachymetry Maps, and Sagittal Maps, and consistently demonstrates the superior diagnostic performance [12,14].

Datasets, Explainability, and Computational Considerations

There are studies which relies on proprietary single-center datasets, they limits the reproducibility and generalization [15]. Advanced techniques such as Explainable artificial intelligence techniques such as saliency maps and Grad-CAM are increasingly employed to improve the interpretability and explainabil- ity of

deep learning models [13]. The Hybrid frameworks which combines the deep feature extraction with lightweight traditional and advanced classifiers offers a balance between diagnostic performance and computational efficiency [14].

Corneal Topography	**Corneal Tomography**
• Anterior surface only	• Anterior + Posterior surfaces
• Curvature maps	• Elevation and pachymetry maps
• Placido-based	• Scheimpflug-based
• Limited early detection	• Effective early detection

Figure 2: Comparison between corneal topography and corneal tomography

Related Work and Comparative Study

Early automated corneal disease keratoconus diagnosis systems depend on rule-based analysis and hand- crafted clinical indices which are derived from corneal topography [7]. These advanced approaches elab- orated reasonable performance for moderate and advanced keratoconus but given limited sensitivity for early disease stages.

Tomography-based modern approaches significantly improved the diagnostic accuracy by incorporating posterior elevation and pachymetric parameters. Literature Studies have shown that tomographic corneal map features outperform topographic biomechanical indices, particularly to detect forme fruste kerato- conus [8–10].

Advanced Machine learning approaches using handcrafted features and classifiers such as traditional sup- port vector machines and random forests algorithms has achieved high accuracy but also requires careful feature engineering [10,11]. More recently, Deep learning approaches, such as Convolutional Neural Networks, have been employed either as end-to-end classifiers or as feature extractors. These methods demonstrate excellent performance, which includes early-stage keratoconus detection [12,13].

Table 1: Comparative Analysis of Automated Keratoconus Diagnosis Methods

Study	**Imaging Modality**	**Feature Type**	**Classifier**	**Strengths**	**Limitations**
Rabinowitz et al. [7]	Topography	Clinical in- dices	Rule-based	Interpretability	Poor early de- tection
Saad and Gatinel [5]	Tomography	Elevation, pachymetry	Statistical	Early sensi- tivity	Device de- pendency

Lavric and Valentin [10]	Topography	Texture and deep	CNN	High accuracy	Data requirement
Kuo et al. [12]	Tomography	Deep features	CNN	Early detection	Interpretability
Yoo et al. [13]	Multi-map	Deep features	Explainable CNN	Clinical insight	Computational cost

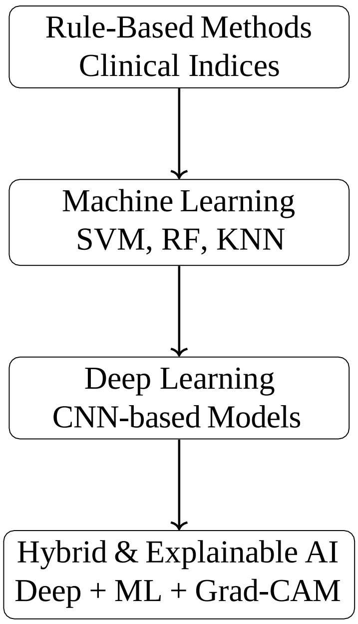

Figure 3: Evolution of automated keratoconus diagnosis methods in literature

Challenges and Research Gaps

Despite significant progress, several challenges remain unresolved. The lack of publicly available datasets limits reproducibility and fair comparison across studies. Inter-device variability further affects model

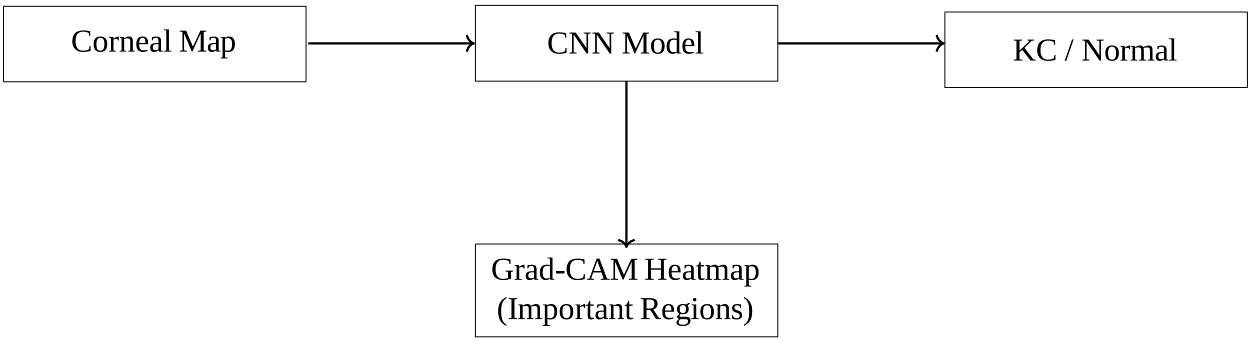

Figure 4: Explainable artificial intelligence framework for keratoconus diagnosis

generalization. Additionally, most studies focus on binary classification, with limited work addressing disease severity grading or progression analysis. The lack of interpretability in deep learning models remains a major barrier to clinical adoption [13–16].

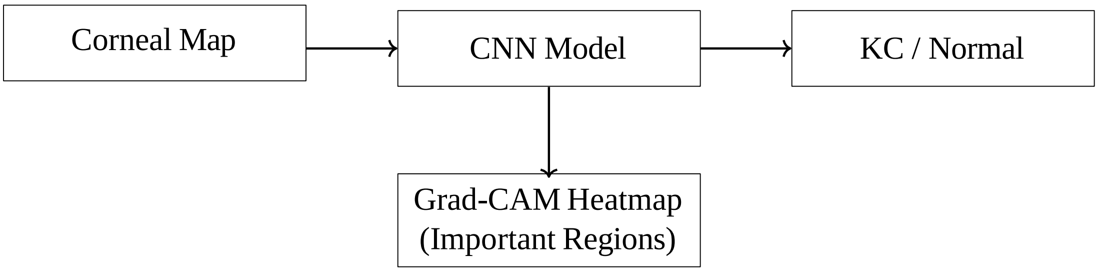

Figure 5: Explainable artificial intelligence framework for keratoconus diagnosis

Future Directions

Future research should focus on multimodal data fusion combining corneal topography, tomography, and biomechanical parameters. The development of large-scale, multicenter datasets is essential to improve robustness and generalization. Explainable artificial intelligence frameworks will play a critical role in en- hancing clinical trust. Hybrid computational pipelines that balance performance and efficiency are promis- ing for large-scale screening and real-world deployment.

Conclusion

Automated keratoconus diagnosis using corneal topography and tomography has evolved from simple index-based analysis to advanced artificial intelligence–driven systems. While deep learning and hybrid approaches have significantly improved early detection accuracy, challenges related to data diversity, in- terpretability, and clinical deployment persist. Addressing these challenges through multimodal imaging, explainable models, and collaborative dataset development will be essential for translating automated ker- atoconus diagnosis systems into routine clinical practice.

References

1. Rabinowitz Y.S., Keratoconus, Survey of Ophthalmology, 1998.
2. Krachmer J.H., Feder R.S., Belin M.W., Keratoconus and related disorders, Survey of Ophthalmology, 1984.
3. Godefrooij D.A., et al., Epidemiology of keratoconus, American Journal of Ophthalmology, 2017.
4. Hashemi H., et al., Global prevalence of keratoconus, Ophthalmic and Physiological Optics, 2020.
5. Saad A., Gatinel D., Forme fruste keratoconus, Investigative Ophthalmology and Visual Science, 2016.
6. Belin M.W., Duncan J.K., Keratoconus: The ABCD grading system, International Ophthalmology Clinics, 2016.
7. Rabinowitz Y.S., Rasheed K., Keratoconus detection using corneal topography, Ophthalmology, 1999.
8. Ambrósio R., et al., Enhanced ectasia detection using corneal tomography, Journal of Refractive Surgery, 2017.
9. Vinciguerra R., et al., Detection of keratoconus with Scheimpflug imaging, British Journal of Ophthalmology, 2016.
10. Lavric A., Valentin P., KeratoDetect: Keratoconus detection using convolutional neural networks, Computers in Biology and Medicine, 2019.
11. Ruiz Hidalgo I., et al., Machine learning techniques for keratoconus classification, IEEE Access, 2020.
12. Kuo B.I., et al., Keratoconus screening using deep learning, Scientific Reports, 2020.
13. Yoo T.K., et al., Explainable deep learning for keratoconus screening, NPJ Digital Medicine, 2021.
14. Toprak I., et al., Hybrid AI models for corneal disease diagnosis, Artificial Intelligence in Medicine, 2022.
15. Kamiya K., et al., Clinical challenges in AI-based keratoconus detection, Progress in Retinal and Eye Research, 2021. 16. Selvaraju R.R., et al., Grad-CAM: Visual explanations from deep networks, International Journal of Computer Vision, 2020.