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Keratoconus Detection Using Convolutional Neural Networks

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Abstract

Keratoconus is a progressive, non-inflammatory eye disorder characterized by thinning and outward bulging of the cornea, resulting in visual distortion and impaired vision. Early and accurate detection of the disease is crucial, as surgical treatment options are expensive and not effective for all patients. This paper presents KeratoDetect, a deep learning–based automated system for the detection and severity assessment of keratoconus using corneal topography images. The proposed approach employs a Convolutional Neural Network (CNN) to automatically extract discriminative features related to corneal curvature and surface irregularities without manual feature engineering. Based on these learned features, the system classifies the disease into four stages: mild, moderate, advanced, and severe, enabling improved understanding of disease progression. The CNN model was trained and evaluated on a labeled dataset of corneal topography images and achieved an accuracy of 99.33% on the test dataset. The experimental results demonstrate that AI-based diagnostic systems can assist ophthalmologists in faster patient screening, reduce diagnostic errors, and support informed and cost-effective clinical decision-making while complementing existing medical expertise.

Keywords – Keratoconus Detection, Convolutional Neural Networks, Deep Learning, Corneal Topography, Medical Image Analysis.

I. Introduction

Keratoconus is a progressive, non-inflammatory corneal disorder characterized by thinning and outward bulging of the cornea, resulting in irregular astigmatism and visual distortion [1]. The disease typically manifests during adolescence or early adulthood and may progressively worsen if not diagnosed at an early stage. Advanced cases can lead to severe visual impairment and may require invasive surgical procedures such as corneal transplantation [2].

Conventional diagnostic methods for keratoconus include slit-lamp examination, corneal topography, and clinical evaluation by experienced ophthalmologists

Although these techniques are widely used in clinical practice, they are often time-consuming and rely heavily on expert interpretation. This dependency can lead to inter-observer variability, particularly in the early or subclinical stages of the disease where corneal abnormalities are subtle [3]. Moreover, surgical treatment for keratoconus is costly and does not always result in favorable outcomes for all patients, highlighting the importance of accurate severity assessment prior to intervention.

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) techniques have shown significant promise in medical image analysis and automated disease diagnosis [4]. Among these techniques, Deep Learning models—particularly Convolutional Neural Networks (CNNs)—have demonstrated superior performance in image-based classification tasks due to their ability to automatically learn hierarchical and spatial features from raw image data [5]. CNNs are especially effective for analyzing corneal topography images, as they can capture complex patterns related to corneal curvature, thinning, and deformation.

This paper proposes KeratoDetect, a CNN-based automated system for the detection and severity classification of keratoconus using corneal topography images. The proposed approach classifies the disease into four stages—mild, moderate, advanced, and severe—thereby supporting early screening and aiding ophthalmologists in surgical suitability assessment. Experimental results demonstrate that the proposed system achieves high classification accuracy.

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II. Literature Survey

Several studies have been conducted to address the problem of keratoconus detection using computational and machine-learning based approaches. Early research in this domain primarily relied on handcrafted features extracted from corneal topography or tomography data, followed by traditional classifiers such as Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN). While these methods demonstrated reasonable performance, their effectiveness was highly dependent on manual feature selection and domain expertise, limiting their generalization capability across diverse datasets [6], [7].

With the advancement of Machine Learning techniques, researchers began exploring automated approaches for keratoconus classification. Statistical learning models using corneal parameters such as curvature, thickness, and refractive indices were proposed to distinguish between normal and keratoconus-affected eyes. Although these approaches improved diagnostic accuracy compared to manual methods, they often struggled to capture complex nonlinear patterns present in high-dimensional medical imaging data, especially in early or subclinical stages of the disease [8].

Recent developments in Deep Learning have significantly improved performance in medical image analysis tasks. Convolutional Neural Networks (CNNs), in particular, have shown superior results in ophthalmology-related applications such as retinal disease detection, corneal abnormality classification, and refractive error prediction [9]. CNN-based approaches eliminate the need for handcrafted feature extraction by automatically learning hierarchical and spatial features directly from image data. Several studies have reported improved accuracy in keratoconus detection using CNNs applied to corneal topography and tomography images, highlighting their robustness and scalability [10], [11].

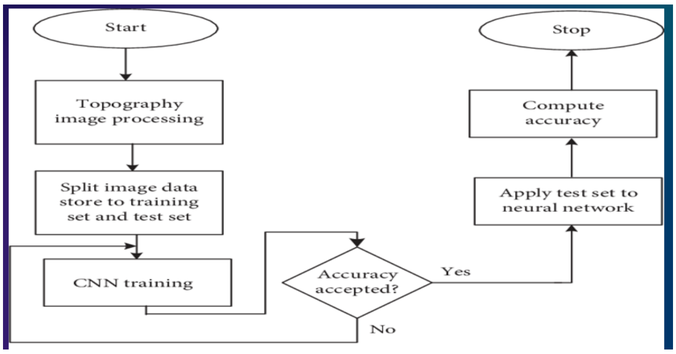
Despite these advancements, existing studies often face challenges related to limited dataset size, class imbalance, and lack of stage-wise severity classification. Many approaches focus only on binary classification (normal vs. keratoconus), which is insufficient for clinical decision-making. Motivated by these limitations, the proposed work aims to develop a CNN-based system capable of accurately detecting keratoconus and classifying it into multiple severity stages, thereby providing enhanced support for early screening and treatment planning.

While several deep learning-based approaches have demonstrated promising results in keratoconus detection, many existing studies primarily focus on binary classification, distinguishing only between normal and keratoconus-affected eyes. Such approaches provide limited clinical insight, as they do not capture the progressive nature of the disease.

Accurate stage-wise severity classification is crucial for effective treatment planning and surgical decision-making. Additionally, some studies rely on relatively small or homogeneous datasets, which may limit model generalization in real-world clinical settings. These limitations highlight the need for automated systems that not only achieve high detection accuracy but also provide reliable multi-stage classification to support early diagnosis and personalized patient management. The proposed approach addresses these challenges by focusing on severity-based classification using corneal topography images and deep learning techniques.

III. Proposed Methodology

The proposed system aims to automatically detect keratoconus and classify its severity using corneal topography images through a deep learning–based approach. The overall methodology consists of data acquisition, image preprocessing, CNN-based feature extraction, disease classification, and performance evaluation. The complete workflow is designed to function as a clinical decision-support system to assist ophthalmologists in early screening and diagnosis.



The overall workflow of the proposed system is illustrated in Fig.1.

A. Data Acquisition

The input to the proposed system consists of corneal topography images, which represents the curvature and surface characteristics of the cornea. These images are widely used in ophthalmology to analyze corneal abnormalities associated with keratoconus. Each image in the dataset is labeled according to the disease condition and severity stage, enabling supervised learning.

B. Image Preprocessing

Prior to model training, the corneal topography images undergo preprocessing to ensure consistency and improve learning efficiency.

This includes image resizing, normalization, and noise reduction where necessary.

Preprocessing helps standardize the input data and reduces variations caused by differences in image resolution or acquisition conditions. The processed dataset is then divided into training and testing subsets to enable unbiased performance evaluation.

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C. CNN-Based Feature Extraction

A Convolutional Neural Network (CNN) is employed as the core feature extraction and classification model. The CNN automatically learns discriminative features from the corneal topography images, such as curvature irregularities and deformation patterns, without requiring manual feature engineering. Convolutional layers are used to capture spatial features, while pooling layers reduce dimensionality and computational complexity.

D. Keratoconus Classification

Following feature extraction, fully connected layers perform classification of the input images into four keratoconus severity stages: mild, moderate, advanced, and severe. The network output represents the predicted disease stage, which can be used by clinicians to assess disease progression and surgical suitability.

E. Model Training and Evaluation

The CNN model is trained using labelled data through an iterative optimization process. During training, the model parameters are updated to minimize classification error. After training, the model is evaluated on unseen test data, and performance is measured using accuracy metrics. This evaluation ensures the generalization capability and reliability of the proposed system.

IV. Experimental Setup and Dataset

The proposed KeratoDetect system was implemented using Python-based deep learning frameworks. The experimental evaluation was conducted on a labeled dataset of corneal topography images, which represent the curvature and surface characteristics of the cornea. These images were categorized according to the presence of keratoconus and corresponding severity stages, enabling supervised learning.

Prior to training, the dataset was preprocessed and divided into training and testing subsets to ensure unbiased performance evaluation. The training dataset was used to learn the model parameters, while the testing dataset consisted of previously unseen images used to evaluate the generalization capability of the proposed CNN model. This separation helps prevent overfitting and ensures reliable assessment of model performance.

The CNN model was trained iteratively using the training dataset, during which the network parameters were optimized to minimize classification error. The performance of the trained model was evaluated using classification accuracy as the primary evaluation metric. Accuracy was selected as it provides a clear measure of the model's ability to correctly classify keratoconus severity stages from corneal topography images.

All experiments were conducted in a controlled software environment, and the obtained results demonstrate the effectiveness of the proposed deep learning–based approach for keratoconus detection and severity classification.

IV. Results and Discussion

The performance of the proposed KeratoDetect system was evaluated using the test dataset of corneal topography images. The trained Convolutional Neural Network (CNN) achieved a classification accuracy of 99.33%, indicating a high level of reliability in detecting keratoconus and classifying its severity stages. The obtained results demonstrate the effectiveness of deep learning techniques in capturing complex corneal patterns associated with keratoconus.

The qualitative classification results obtained from corneal topography images are illustrated in Fig.2

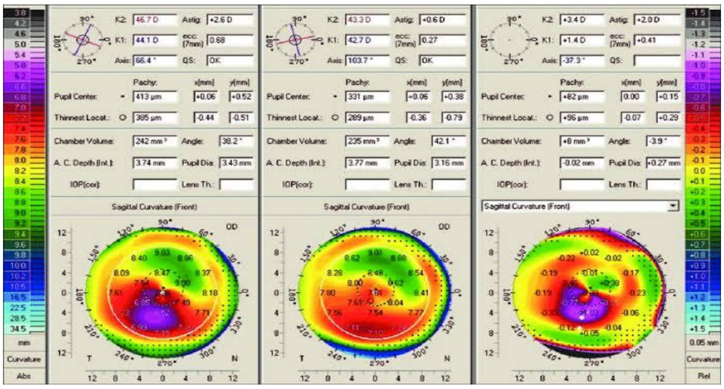

Fig.2 Sample corneal topography images showing different stages of keratoconus detected by the proposed CNN-based system.

The high accuracy achieved by the proposed model can be attributed to the CNN's ability to automatically learn discriminative features from corneal topography images, such as curvature irregularities and deformation patterns. Unlike traditional machine learning approaches that rely on handcrafted features, the CNN-based model extracts relevant features directly from raw image data, improving classification performance and robustness.

The stage-wise classification into mild, moderate, advanced,

and severe categories provides valuable clinical insight beyond simple disease detection. This enables ophthalmologists to better assess disease progression and make informed decisions regarding treatment and surgical suitability. Additionally, the automated nature of the proposed system reduces dependence on manual interpretation, thereby minimizing diagnostic errors and inter-observer variability.

Overall, the experimental results confirm that the proposed KeratoDetect system can serve as an effective clinical decision-support tool, enabling faster patient screening and supporting cost-effective diagnostic processes.

However, further evaluation using larger and more diverse datasets is required to validate the system's performance in real-world clinical environments.

V. Conclusion

This paper presented KeratoDetect, a deep learning–based system for automated detection and severity classification of keratoconus using corneal topography images. The proposed approach employed a Convolutional Neural Network (CNN) to automatically learn discriminative corneal features and classify the disease into four stages: mild, moderate, advanced, and severe. Experimental evaluation demonstrated that the proposed system achieved a high classification accuracy of **99.33%**, indicating its effectiveness and reliability in identifying keratoconus and assessing disease severity.

The results highlight the potential of CNN-based diagnostic systems to support ophthalmologists in early screening and clinical decision-making. By reducing reliance on manual interpretation and minimizing diagnostic variability, the proposed system can contribute to faster patient assessment and more cost-effective treatment planning. Overall, the study demonstrates that deep learning techniques can play a significant role in improving automated medical image–based diagnosis, particularly in ophthalmology.

VI. Future Scope

Although the proposed KeratoDetect system demonstrates high accuracy and reliable performance in detecting and classifying keratoconus, several opportunities exist for future enhancement. One important direction is the evaluation of the model on larger and more diverse datasets obtained from multiple clinical sources. This would help improve the robustness of the system and ensure its generalizability across different populations and imaging conditions.

Future work may also involve integrating additional clinical parameters such as corneal thickness maps, topography data

patient demographic information to further improve diagnostic accuracy. The use of advanced deep learning architectures, including transfer learning and transformer-based models, could be explored to enhance feature extraction and classification performance. Additionally, optimizing the model for real-time inference would support its deployment in clinical environments.

Another potential extension is the development of a user-friendly clinical interface that allows ophthalmologists to upload corneal images and receive automated severity assessments. Such integration would facilitate real-world adoption and enable the system to function as a comprehensive decision-support tool. Overall, these enhancements can contribute to improving early diagnosis, treatment planning, and patient outcomes in keratoconus management.

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