Transfer Learning-Based Keratoconus Detection from Scheimpflug Images

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Abstract

Preclinical detection of keratoconus is crucial to avoid irreversible corneal damage associated to refractive surgery for laser myopia correction. This work proposes, for the first time, a deep learning-based approach for preclinical keratoconus diagnosis using corneal images. Our model, trained in 22,750 images, achieved an overall accuracy of 90.70%, specificity of 94.29% and an AUC of 0.96, outperforming state of the art clinical standards.

Introduction

Keratoconus is a bilateral disorder characterized by thinning and conical protrusion of the cornea, leading to visual impairment. As keratoconus typically develops at different rates in each eye, when one eye exhibits clinical keratoconus and the fellow eye appears clinically normal, the latter is often referred to as forme fruste (FF) keratoconus and can be used as a surrogate for the preclinical stage.

Accurate detection of FF keratoconus is essential to prevent complications associated to refractive surgery. Hence, numerous mathematical models, traditional machine learning, and recent deep learning techniques have been proposed [1]. However, the limitation of these approaches in detecting preclinical cases lies in the input data itself—since FF keratoconus does not produce noticeable changes in corneal shape.

A more recent and promising area of research explores corneal densitometry, which quantifies light backscatter to objectively analyze corneal tissue as a reliable marker for detecting FF cases [2]. Building on this premise, this work introduces, for the first time, a deep learning model using raw corneal images as input data. Thus, leveraging both corneal shape (Figure 1, yellow)—traditionally the primary focus in keratoconus detection—and corneal tissue characteristics (Figure 1, green), a novel yet promising approach. This dual-focus strategy allows the model to extract and integrate information from both structural and tissue-based features, potentially enhancing its ability to identify subtle changes associated with preclinical keratoconus.

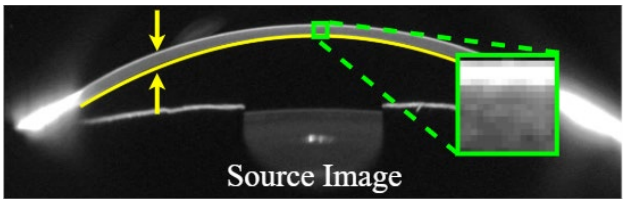

Figure 1. Representative raw corneal image. For illustrative purposes, the corneal contour is highlighted in yellow to indicate shape-related characteristics, while a zoomed-in region in green shows the pixel intensity distribution, which may contain information related to tissue characteristics.

Methodology

Dataset

We use a retrospective dataset comprising 22,750 grayscale corneal images from 910 eyes, captured with a Pentacam HR. Participants were divided into three groups according to labels provided by clinical experts: controls (492 eyes), clinical keratoconus (339 eyes), and FF keratoconus (79 eyes).

For each explored eye, the Pentacam HR captures images for 25 corneal meridians, which results in a total of 22,750 labeled images. These grayscale images have an original spatial resolution of 2400 × 1782 pixels. Nevertheless, after preprocessing—including corneal segmentation, cropping a 7 mm region centered on the corneal apex, and downsampling to optimize memory usage—the images are resized to 600 × 150 pixels.

Model Architecture

The architecture of our model is shown in Figure 2. Given five input images from equidistant meridians, we use a VGG16-based convolutional neural network (CNN) pre-trained on ImageNet and fine-tuned on our own dataset, in a transfer learning

approach. The features extracted from each of the images undergo global average pooling and then are concatenated and passed through two dense layers, each followed by dropout and batch normalization. Finally, a softmax activation is applied to the output layer to obtain, for each of the three classes, the probability that the input sample belongs to that class.

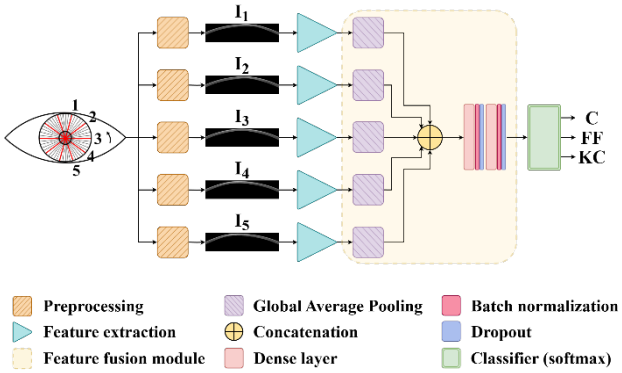

Figure 2. Workflow of our proposed deep learning-based model fed by corneal images (I_i). The output labels are C: control, FF: forme fruste, and KC: clinical keratoconus.

Class Imbalance Strategy

The number of FF samples is significantly lower than that of the other two classes. To mitigate this class imbalance, we implement a combination of random oversampling (ROS) and data augmentation (DA) techniques to our dataset. Our DA procedure is conducted using three different transformations—small image rotations (between -5 and +5 degrees), image horizontal flips, and image sharpening—and it is illustrated in Figure 3.

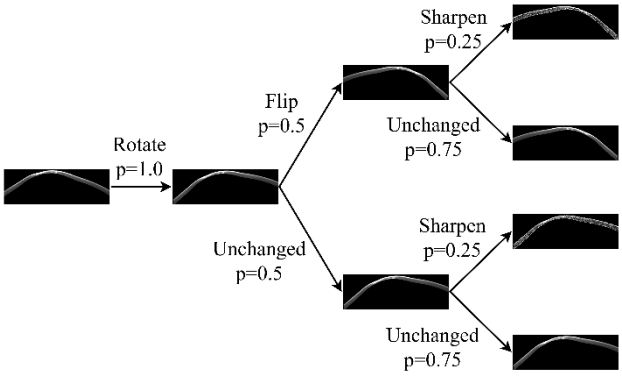

Figure 3. Diagram of the data augmentation (DA) process with its stacked probabilistic transformations.

Results

The proposed model achieved an overall accuracy of 90.70%, with a specificity of 94.29%, sensitivity of 79.96%, and an AUC of 0.96. The class-wise AUCs were 0.98 for clinical keratoconus, 0.95 for FF keratoconus, and 0.94 for the control group. To enhance the model's ability to detect FF cases, a probability-based threshold adjustment for FF classification was implemented, resulting in a sensitivity of 80.57% and a specificity of 80.56%.

GradCAM heatmaps were also utilized (Figure 4), in order to enhance model interpretability.

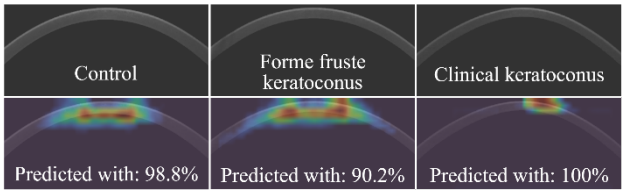

Figure 4. GradCAM visualizations for the three classes. Top row: Input images. Bottom row: Corresponding GradCAM heatmaps showing areas of high predictive influence, together with prediction accuracies.

Conclusions

This study presents the, to our knowledge, first application of deep learning to raw corneal images for preclinical keratoconus detection, a significant departure from previous approaches. The complexity of the problem is heightened by our focus on FF keratoconus, a condition that lacks distinct topographic alterations when compared to control eyes, making its detection inherently challenging.

Despite this, the model achieves strong performance in classifying both clinical and preclinical cases, demonstrating the feasibility of using raw corneal images to detect subtle corneal changes.

Acknowledgments

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