Keratoconus Eye Disease Detection Using CNN with VGG-19

Abstract:

The eyes are among the most important organs in the human body. We rely on our sense of sight to see the world and comprehend what is going on around us. It can be challenging to detect and identify some eye conditions. Keratoconus is one of the rarest and most challenging to diagnose eye conditions. A progressive corneal condition called Keratoconus causes corneal scarring and thinning [1]. As the etiology of Keratoconus is yet unclear, early detection is highly challenging. However, doctors do believe that aggressive eye rubbing and a mix of hereditary and hormonal factors may contribute to the condition. Early Keratoconus detection makes it easier for ophthalmologists to identify the eye, and the patient is better equipped to adjust to the changes. As a result, early Keratoconus detection is necessary, and we created a model for that aim. Even though there are previously many Machine Learning and Deep Learning techniques existed, which were used in the detection of Keratoconus but the model we used is more efficient and reliable than the existing algorithms. The model which is used is a Deep Learning algorithm known as VGG-19. The VGG-19, often referred to as the Visual Geometry Group, is used to identify Keratoconus. With 19 convolution layers, the deep convolution neural network architecture VGG-19 is ideal for accurate object identification and picture categorization. As opposed to VGG-16, which has 16 Convolution layers, it is an upgraded version. Due to its higher accuracy and quicker training pace, VGG-19 outperforms the currently used techniques.

Keywords

Keratoconus, Health Care, Deep Learning, Convolution Neural Networks (CNN), Visual Geometry Group (VGG-19)

1. Introduction

The resolution of human eye is 576 Mega Pixels, nothing can capture a moment or vision like a human eye does. Eye plays a vital role in capturing and providing vision for humans which makes it one of the most significant part of everyone's lives and human body. The Human Eye has three layers; the Retina is found in the innermost layer, and the main blood supply for the eye is located in the middle layer [2]. The Cornea and Sclera make up the Human Eye's outermost layer. An important component of the human eye is the cornea, which is the transparent clear area that covers the iris and pupil. The clear part of the eye which covers the front of the eye is called the cornea, which is a very important part of the human eye. It tops the anterior chamber, which is filled with fluid inside the eye, the iris, which is the coloured portion of the eye, and the pupil, which is the aperture in the center of the eye. The important role of the cornea is to refract the light or to bend the light. The light that enters into the eye is always concentrated by the cornea most of the times. Cells and proteins may be found in the cornea. Cornea has no blood arteries, in contrast to most of the tissues in the human body [3]. The cornea can get clouded by blood vessels, impairing eyesight by preventing appropriate light refraction.

Keratoconus is one of the rarest disease. Keratoconus is a very slowly progressive corneal disorder that results in thinning and scarring of the cornea, because of this the patients can have distorted vision and face difficulties in viewing the world[4]. Keratoconus is slowly progressive in nature which worsens over time and which weakens the cornea and the cornea protrudes outward taking the form of a cone[5]. The cornea's irregular shape results in visual distortions and can seriously cause impaired eyesight. Keratoconus is believed to be the result of vigorous eye rubbing, and a combination of genetic and hormonal causes, while its exact cause is still unclear. [6]. According to many researches, some genetic mutations may put people at risk for Keratoconus which is assumed and not proved as a fact. The illness may develop or worsen as a result of other variables such as hormone imbalances, allergies, persistent eye irritation, and eye rubbing.

Numerous eye examinations, including Keratometry, Slit-lamp Examination, Corneal mapping and Visual Acuity Test, these tests have been used to identify and diagnose Keratoconus till date [7]. Trained Ophthalmologists with high and specialized skills are required to efficiently interpret medical pictures of Keratoconus to identify the Keratoconus disease. Even specialized ophthalmologists may not recognize Keratoconus disease in its early stage and may confuse it with other vision problems like myopia. Also, there may be a delay in the detection and diagnosis of Keratoconus if there's a lack of specialists who can recognize Keratoconus disease, which is extremely dangerous for the patient.

Keratoconus may impact both of your eyes. The degree of severity may change depending on the situation. There are times when one eye may become Keratoconus while the other eye is healthy [8]. Keratoconus can also sometimes affect both eyes. And on occasion, one eye with extremely severe Keratoconus may need laser treatment or surgery, whilst the other eye with very mild Keratoconus may be managed with soft lenses and eyeglasses.

Keratoconus is difficult to identify and diagnose due to the sluggish rate of development and few structural changes to the cornea [9]. People might not initially notice any major visual problems since Keratoconus progresses slowly. One of the early indicators of Keratoconus is blurry or distorted vision, which can be mistaken for myopia or astigmatism as well as other eye conditions. Astigmatism results in light rays converging on many distinct spots on the retina rather than just one because of an uneven shape or curvature [10]. This has the effect of making distant objects look distorted or hazy. Myopia, a similar word, refers to near-sightedness. In those with myopia, a common visual impairment, objects further away seem fuzzy while those that are closer to the eye do so clearly. Early treatment will help the patient in the future as there will be some changes in the lifestyle. This invention will be very helpful to all, as the detection of Keratoconus becomes easy and the diagnosis can be started at an early stage. This reduces the risk of worsening the eye condition.

The remaining sections will be ordered as follows; Section 2 includes the related task which is the literature review for our proposed plan. Section 3 describes the existing and the proposed methodology, which includes a description of the dataset, pre-processing, and model description. Section 4 describes the experiment, analysis of results, and comparison of results. Section 5 outlines the conclusion and prospective scope of the study.

2. Related Work

For early diagnosis and lowering patient risk, using different machine learning and deep learning algorithms to identify Keratoconus is highly helpful, and its application is growing daily. The premise for diagnosing Keratoconus in eyes is a set of computer vision-based algorithms, and up till now, a number of studies have been conducted in this area.

[11] For the purpose of identifying Keratoconus, CNN was used for topographical photos. The input will be divided into two categories: a healthy eye with normal topography and an eye impacted by Keratoconus. The KeratoDetect algorithm

performs well, earning a 99.33% accuracy rate on the test set of data. To evaluate the topography of the cornea, a CNN (Convolution Neural Networks) algorithm is used.

[12] Implemented a variety of machine learning algorithms to focus on and evaluate the identification of Keratoconus using actual medical data. The Support Vector Machine (SVM) technique was accustomed to attain the greatest accuracy level of 94%. The research emphasizes the significance of feature selection in machine learning and how it might enhance patient care and clinical procedures.

[13] Researchers have developed an Ensemble of Deep Transfer Learning (EDTL) using 4 pre-trained networks, SqueezeNet, AlexNet, ShuffleNet, and MobileNet-v2, and a PI classifier. The Ensemble of Deep Transfer Leraning approach reaches to a judgement based on the combination of output probabilities on probability fusion. The Accuracy were ranged from 86% to 89.9% for the deep networks with the highest accuracy of 98.3% using ensemble-specific combinations of classifiers and PI. This study shows the importance for the prospect of building ensembles of deep classifiers that are updated using a transfer learning technique, which leads to even more better accuracy.

[14] In this study in order to detect the different stages of Keratoconus disease which are mild, moderate, and advanced , they used two different types of Deep Learning models which are ResNet50 and EfficientNet. The dataset contains four distinct classes that shows the Keratoconus disease's phases, with each folder consisting of around 550 photos. The dataset collection includes both pentacam pictures and corneal topographic maps, and the Deep Learning model's respective levels of accuracy were 97% and 94%. The study's primary motives include improving patient treatment and customer relationship management by classifying Keratoconus in different severity levels.

[15] This study used the Deep Learning from AS-OCT to detect and diagnose Keratoconus with a resulted accuracy of 0.874%. A popular classification for detecting Keratoconus is used here which is the Amsler-Krumeich classification. More research is required to state the accuracy and apply deep learning concept to other corneal diseases.

[16] This study showcases the identification and detection of early clinical Keratoconus(KCN) with the help of a Deep Learning algorithm using three different corneal maps. The proposed model of the study was examined using the Xception and InceptionResNetV2 DL architectures on 1371 eyes which resulted in the accuracy of 97-100% and an AUC of 0.99.

[17] This study showcased the research with use of Deep Learning of color-coded map with the usage of Placido disk-based corneal topography to examine the detection and diagnosability of Keratoconus. This study examined 179 Keratoconic eyes and 170 healthy normal eyes with the use of high quality pictures from the corneal topography. The results showed that the color-coded maps deep learning resulted an accuracy of 0.966 in seperating Keratoconus from normal eyes and 0.785 in detecting the Keratoconus disease severity stage. According to the Grade 0 (normal) through Grade 4 grading scales, the area under the curve values were 0.997, 0.955, 0.899, 0.888, and 0.943, respectively.

[18] Technologies like convolutional neural networks (CNN) have improved the early diagnosis and categorization of Keratoconus. This study trains pre-trained CNN models and segments topographical pictures using particle swarm optimization. The system outperforms other algorithms for a 3-class classification, with an accuracy rate of 95.9%.

[19] The Logistic Index for Keratoconus (Logik) is a machine learning method that accurately classifies the disease based on the stages of severity, objectively separates suspected diseased eye from normal healthy eyes, and provides a trustworthy, grading method to evaluate Keratoconus progression. The combination of algorithms of Feed-forward Neural Network (FNN) and a Moving Average Filter (MAF), it results the stages of Keratoconus with an accuracy of 99.9%. Logik can be assumed to be a reliable indicator for the identification of the disease and also categorizing the stages of the severity. Its main problem can be that it may overlap a healthy eye with the one of a suspected Keratoconus case. It needs more efficient development in order for people to rely on it.

[20] This study is about a deep learning technique known as Kernet is used for the identification of Keratoconus disease using the raw data from Pentacam HR system. With the use of a multi-level fusion architecture Kernet detects the disease. The study found the proposed model outperforms other networks in performance. Grad-CAM, is used to link model performance to clinical practice.

3. Methodology

3.1 Dataset description

The dataset includes the training data needed to build a Deep Learning model. The caliber and variety of the dataset have a direct bearing on a model's effectiveness and generalizability. A robust dataset is necessary for a model to comprehend complicated patterns and make precise predictions.

The dataset considered for this model is a public dataset [21], which consists of more than 4000 images which were separated into training and testing datasets respectively. The images used here are Corneal Topography images which is a test used for the detection of Keratoconus. The images were classified into three classes: Keratoconus, Suspect, and Normal. For the training dataset, there were 150 Keratoconus cases that contains 7 images per case, 150 for Normal cases, and 123 for Suspected Keratoconus cases. While the testing dataset there were 50 cases each of Keratoconus, Normal, and Suspected Keratoconus cases. The values of the parameters used to categorize Keratoconus, Normal, and Suspected eyes are shown in the accompanying figure. Fig. 1 displays the original image.

The curated dataset is highly efficient and simple to comprehend, which is a significant advantage for anyone who is interested to work in this field.

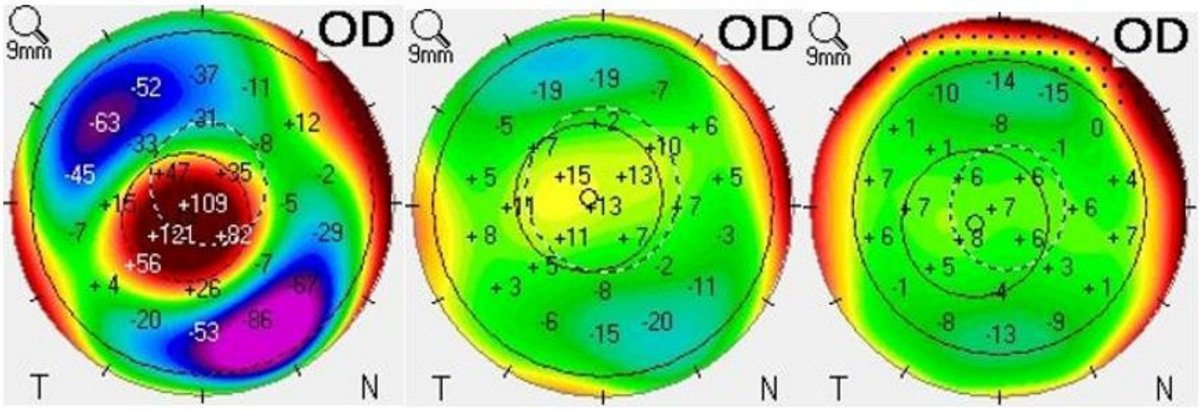

Fig1. Corneal images of Keratoconus Eye VS Normal Eye VS Suspected Eye

3.2 Pre-processing

Pre-processing of the obtained data is essential since the vast majority of real-life data is noisy, inconsistent, and incomplete. Data preparation is the procedure of putting the available data in a manner that is appropriate for machine learning tasks. The dataset that was utilised is a hybrid dataset, and the publicly accessible dataset contains several redundant and ambiguous photos. All of this noise in the image dataset was manually removed, and images from other datasets were combined to form a single effective dataset. Each and every picture in the collection has been individually tagged in accordance with the different classifications.

3.3 Existing Methodologies

3.3.1 CNN

Convolutional neural network (CNN), which is a deep learning model [11] analyzes visual input like images and videos. It is modeled like the human visual cortex and is made up of interconnected layers of neurons. CNNs are mostly used for tasks which involve analyzing visual images and may perform tasks like object detection, feature extraction, classification tasks. CNN contains several layers which help with the feature extraction and object detection tasks. The first layer of the CNN is the input layer where the input images will be taken by the input layer. The second layer is the hidden layer where the task of fetaure extraction is done and with the extracted features a feature map is generated for the task of classification. Then any activation function is applied like ReLu and SoftMax. The next layer is the pooling layer and its important role is to decrease the volume that makes for the fast computation, reduction in the memory and also preserves overfitting. The next is dense layer which connects all the preceeding layers of the network. The output will be displayed in the flatten layer. CNNs can work well with large datasets and gives efficient result. CNNs are one of the most used powerful deep learning model which can be used for feature extraction and can be trained independently and also deliver a excellent performance.[11]

3.3.2 ResNet 50

ResNet-50’s architecture contains 50 layers of residual networks which is a convolutional neural network. The residual connections are assumed to be a shortcut or skip connections [14]. The data will be passed from one layer to another layer with the help of links that are made by the network. This method assists in the performance to train the multi-layer neural networks and addresses the issue of disappearing gradients. There are idle blocks in ResNet-50. Multiple convolutional layers, batch normalization, and activation function layer are all included in the residual block. Skip connections are produced by adding elements one at a time between the residual block's input and output. This phenomenon leads to a condensed information channel and allows gradients to propagate efficiently during training. In ResNet-50, a max-pooling layer that comes after a convolutional layer samples the input picture. Over the course of the four phases, there are varying numbers of blocks left. There are three phases with increasingly higher spatial resolutions after the initial residual block. The network gradually reduces the spatial dimensions while increasing the number of filters in order to capture significant levels of features. In the higher layer of the network, global average pooling combines spatial information into a fixed-dimensional feature vector. After that, probabilities for photo categorization classes are created using a fully connected layer and a SoftMax layer.

3.3.3 SqueezeNet

SqueezeNet [13] is a deep learning architecture which is made to achieve high accuracy while also minimizing parameters and computation complexity in comparison to Convolution Neural Network (CNN). SqueezeNet is quite pupular for its small size and effective operation performance. SqueezeNet is developed by deep-scale researchers.SqueezeNet uses 1x1 filters, which are referred to as “squeeze” layers, which are used to minimize the number of input channels with also preserving expressiveness which is very important. SquuezeNet has expand layers, which is the combination of 1x1 filter and 3x3 filter to add more channels which is to ensure a balance line between model compactness and expressive power. SqueezeNet uses “down-sampling via max-pooling” to minimize the size of the model and also spatial dimension of the model. The squeeze layer and expand layer are made of fire modules that are the backbone of the squeeze network. This kind of arrangement showcases a depper desihn still sustaining compactness. Due to its lower model size, SqueezeNet support real-time inference and its brilliant performance take part on datasets like ImageNet. This kind of arrangement allows for a deeper design still sustaining compactness, due to its lower model size.

3.3.4 AlexNet

AlexNet [13] is a Convolution Neural Network which provides the efficiency in changing the area of deep learning with its accomplishments in image classification tasks. AlexNet achieves an amazing result with the help of learning hierarchical features from raw data using different kinds of layers which are convolutional layers, max pooling layers, fully connected layers. To improve the model’s generalization the architecture used the ReLu, max-pooling layers, and data augmentation approaches. Also, Alexnet is the first method to prove a thought of speeding deep learning training and efficiently processing enormous amount of data by adapting GPUs for deep learning calculations. The last layer is the fully-connected layer that reduces overfitting. AlexNet performs several tasks including object identification, segmentation, and transfer learning.

3.3.5 ShuffleNet

ShuffleNet's [13] architecture is used by CNN for more effective computation and parameter reduction. ShuffleNet was introduced in 2018 by Zhang et al. In order to reduce computation complexity without compromising accuracy. The ShuffleNet's design is unique channel operation, where the information flows from channel to channel and also enables reuse of features. ShuffleNet is made up of two main fundamental processes which are channel shuffle and point-wise group convolution. The computation cost is lowered by the channel shuffle operation with the use of communication between several channels, which also increases the network expressiveness. The channel split in ShuffleNet is is used for feature map down sampling, which lowers features maps spatial resolution. Because of its small size it allows for implementation even on the devices with a limited source which enables real-time inference and decreasing the usage of power. The success of ShuffleNet has allowed more studies into better effective model construction and also the creation of succeeding topologies that showcase the computational and memory effectiveness is also encourages.

3.3.6 MobileNetV2

MobileNetV2 [13] is a deep learning archictecture with brilliant performance on devices with very limited resources and also the computation is done efficiently. The new features of the MobileNetV2 increases the precision and effectiveness by optimization. The main new features were the width multiplier, linear bottlenecks with shortcut connections, depth-wise seperable convolutions, and inverted residual blocks. MobileNetV2 can be used in a situation where computation sources and memory are forced since these lower computational cost and memory. The MobileNetV2 architecture's is designed in a way to make it possible for it to use for real-time inference on mobile devices.

3.4 Proposed Methodologies

3.4.1 CNN with VGG-19

CNN has changed the segment of computer vision with its task performance which include feature extraction, object detection, image classifictation and many more. CNN is the Convolutional Neural Network which is known for its ability in the performance of computer vision tasks. Visual Geometry Group(VGG)-19 is a type of CNN that contains 19 layers in its architecture and it is a pre-trained model. VGG-19 architecture is designed of having 16 convolutional layers, 3 fully connected layers, 5 maxpool layers, 1 softmax layer and a ReLu activation function layer. The VGG-19 performs an excellent task of object detection, image classification and many more compute vision tasks. VGG-19 may not have the best architecture when compared with others in terms of computation cost and memory utilization. VGG-19 utilizes transfer learning , which is a method that allows pre-trained models to be made of improvements on new tasks, which will be made useful for a variety of computer vision issues. The VGG-19 architecture has an input layer where the output from the CNNs flatten layer is taken as an input here. The convolution layers are used for feature extraction and some learnable filters known as kernel will be applied to the given input dataset. The fully connected layers id given the input from the previous layer and gives us the final classification of the given input datset. The max pool layers would give us a output feature map which contains the most outstanding when compared with other features will be taken and , efficient features of the previous feature map. The activation function ReLu is applied. Soft max is used as an activation function. The output of the software gives us the likelihood of a particular image belonging to a certain class. Due to its popularity and influence even more, complex and potent designs have been created, advancing the field of image recognition technology.

3.4.2 VGG-16

VGG-16 is a Convolutional Neural Network Architecture. There are sixteen layers total in the VGG-16 architecture, including three fully connected layers, pooling, and convolutional layers. The architectural design is characterized by the use of small 3x3 filters in each convolutional layer, which improves feature representation acquisition. In order to execute feature map-down sampling and decrease the spatial dimensionality of the input data, the network comprises max-pooling layers. The VGG19 architecture may be formally expressed as a series of nonlinear transformations that enable the mapping of an input picture to a probability distribution across a present range of classes. The network's layers may be described as a mathematical function that receives an input feature map and performs a convolution operation with a set of adaptive filters. A non-linear activation function, like ReLU, and maybe a pooling mechanism come next. The subsequent layer subsequently receives its input from the output of the previous layer. Back propagation and stochastic gradient descent are used to compute the weights of the convolutional layer filters during the training phase.

3.4.3 Inception V3

Strong CNN architecture InceptionV3 strikes a balance between precision and processing speed, making it suitable for a variety of image recognition applications. It was created to deal with deep learning issues on massive picture datasets for image recognition and classification. The network may learn regional and global trends in the input photographs. The network can analyze wider receptive fields while spending less money on computing thanks to this factorization. With the use of batch normalization, which normalizes mini-batch activations, the Inception V3 may be trained more quickly. This network was trained using the millions of categorized images in ImageNet, which span hundreds of categories. Pre-training equips the model with a wide range of traits that may be adjusted or applied to different picture recognition tasks. The design is extensively used in research and practice because it performs better than other image classification architectures on image classification benchmarks. ReLu activation is used in Inception V3 after the majority of the convolutional layers and fully linked layers. Negative values are set to zero and the positive values are left unaltered when ReLu converts each neuron's output.

Results

Our result shows that the CNN model with a pre-trained architecture VGG-19 delivers a 98% accuracy and is simple to execute the epochs with less time requisition after assessing the results of numerous models for the Detection of Keratoconus eye disease based on various parameters.

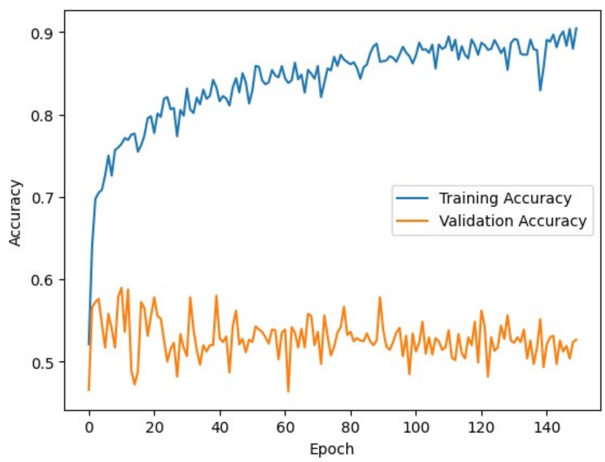

Fig 2. Graph for the Training and Validation Accuracy

The above figure shows the training and validation accuracies for CNN with VGG-19 for the Detection of Keratoconus eye disease, trained for 150 epochs.

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Epoch 150/150
47/47 [==============================] - 23s 496ms/step - loss: 0.2183 - accuracy: 0.9804 - val_loss: 3.2030 - val_accuracy: 0.8267
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Fig 3. Accuracy of the proposed model (CNN with VGG-19) after 150 Epochs

TABLE1. COMPARISON TABLE BETWEEN DIFFERENT DEEP LEARNING MODELS

S.No	Algorithm	Published	Accuracy
1	**CNN with VGG-19**	**2023**	**98%**
2	VGG-16	2023	96%
3	InceptionV3	2023	95%
4	CNN	2019	95.9%
5	ShuffleNet	2021	86%
6	AlexNet	2021	89.9%
7	ResNet 50	2022	96.7%
8	MobileNet-v2	2021	86.4%
9	SqueezeNet	2021	89.2%
10	EfficientNet	2022	94%

The above table is the comparison between the existing algorithms and proposed algorithms for the identification of Keratoconus. The performance of the VGG-19, VGG-16, InceptionV3, ResNet 50, EfficientNet, CNN, SVM, ShuffleNet, AlexNet, MobileNet-v2, SqueezeNet, models were compared based on their model's obtained accuracy.

Limitations

- The VGG-19 has a highly deep architecture with many filters and parameters since it consists of 19 convolution layers. With both training and inference, this demands a lot of processing and memory.

- It might be difficult to externally validate models trained on public datasets, especially if the models are tested on different patient populations or clinical settings.
- The dataset contains limited number of corneal topographic images as, medical images are hard to acquire for privacy concerns. This has an impact on how the model performs, as the given or input dataset is limited.

Conclusion

The primary goal of this research is the early identification of Keratoconus which will help for the diagnosis of Keratoconus and also the classification of that eye condition into three groups, namely:

- Normal Eyes
- Keratoconus Eyes
- Suspected Eyes

With the help of CNN with VGG-19 we successfully classified them according to their respective classes. We also achieved this with an efficient accuracy of 98%, where the goal of this project is reached. This project will be helpful to everyone as the detection of Keratoconus is done at an early stage where even if there's a suspected case we can identify it and the diagnosis can be done, which makes it very helpful for everyone.

We used CNN with VGG-19 algorithm, to detect the Keratoconus and also classify them. The CNN with VGG-19 algorithm offers real-time image classification and object detection capabilities, making it the most suitable application that requires fast and efficient Keratoconus detection.

As the study is expanded, the emphasis can be placed on increasing the amount of data that can be enhanced for training the model. Since access to medical images is very limited, future advancements rely on the increased number of corneal topographic images that can be included when training the model for even more effective classification and detection purposes. How a model can perform may be improved by using a high-quality, varied dataset. Additionally, training on a big, diverse dataset enables us to develop deeper learning models.

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