Keratoeye: Deep Learning for Keratoconus Detection and Classification

Prof. Priya D¹, Dr. G S Mamatha²

¹Assistant Professor, Department of ISE, RV College of Engineering, Bengaluru-59, India.
²Professor & Associate Dean, Department of ISE, RV College of Engineering, Bengaluru-59, India.

Abstract

Convolution neural network model to diagnose keratoconus disease with various stages of the disease. This KeratoEye algorithm uses 1000 samples of non-KTC eyes and 1000 samples of KTC eyes, training set includes 750 samples while validation and test set include 150 and 100 samples. Model is developed with the layers in the sequence as Convolution layer, Normalization layer, Rectified layer, pooling layer and finally fully connected layer. Result is presented in confusion matrix with precision, recall, f1-score, support and accuracy. The algorithm implemented is solely proposed for diagnostic purpose and assisting ophthalmologists for Keratoconus detection. The algorithm when incorporated as diagnostic tool, it will surely help in Keratoconus diagnosis and help in reducing corneal transplants.

Keywords: Deep Learning, Data Augmentation, CNN, CNN Architectures, features and parameters, Model Training

1. INTRODUCTION

Keratoconus is a corneal disease where cornea will be progressively thinned and it will not be in round shape anymore and it bulges outward and downward. Decrease in the Antioxidants which are helpful in protecting the collagen fibers from damaging by-products produced by cornea cells is generally the main reason for keratoconus disease. This disease results in blurry vision, astigmatism, light sensitivity and near-sightedness. Spectacles or rigid gas permeable contact lenses can be used in the early stages of the disease but in severe conditions corneal transplantations are generally used.

Convolution neural network is ML algorithm mainly applied on images by using convolution layer as a first layer by applying pre-processing on images to produce optimal input data for the next layer. This network will also handle dependencies available in pixels of the image and then it reduces parameters to the next level. So, it works better for sophisticated images. In our dataset images show the elevation of the cornea through the color codes like red indicates too much bulge from the base. By using a filter value these images are converted to a linear matrix that can be further processed in normalization, RELU, Pooling layers. Normal or Affected eye can be identified as an output of this network.

2. THEORETICAL BACKGROUND AND SYMPTOMS

Keratoconus is generally observed in the ratio of one in two thousand people. Over the past few years significant increases in cases are found in children. Due to the increase in better diagnosing systems more people are diagnosed when screened with eye topography. Thus, recent incidence is higher. Recent data shows that Russia has only 3 per 10,00,000 people and in India it is 3% in Israel 2.34%, and 2.5% in Iran [1]. This disease affects both sex in all ethnicities. Starting with a single eye it affects both the eyes This disease needs to be dealt with carefully as it affects young as well as elderly people. Hence more data needed from all age groups. This paper is the implementation of our algorithm which is used to diagnose keratoconus disease and predict the stage of disease during analysis. Due to presence of better topographical data and good processing power in the recent systems we can produce better results than the previous models with better complexity.

2.1 Keratoconus and Indian Scenario

In North India, In the year 2008, Dr Shroff’s Charity Eye hospital, New Delhi for all the people who are attending keratoconus contact lens clinic. They diagnosed 77 patients on various data like age, contact lens type, gender etc. With 49 male and 28 females. With a median age of 24 for the people [2].

In a territory care ophthalmic center around 120 patients were diagnosed for bilateral and unilateral keratoconus. Various data were collected on symptoms, nature with 76 males and 44 females, family history if found in 5% of the patients, impact of earlier age and eye rubbing was studied for risk of surgery [3].

In western India, Retrospective cohort analysis was performed for data of duration 2 years. From the patients of 274 (male:189, female:85) who visited Clear Vision Eye center, Various studies on allergy and asthma were performed to predict the age group which is usually Diagnosed in western population [4].

In Central India, Prevalence of keratoconus dropped with the increase in corneal refractive power as 2.3% for power Greater than 47 which dropped to 0.6 for power greater than 48 and 0.1 using cut off of 50 [5].
3. LITERATURE SURVEY

Observing previous implementation would definitely help in getting to know the results obtained. Accuracy and many more details on implementation, we can also predict the changes that would result in an increase in the previous prediction and their mistakes that can be corrected through implementation. Those implementations are listed in the next paragraphs.

This system is implemented for classification of keratoconus disease. 4 subgroups are created based on stage of the disease with topographical eye images for training, with PyTorch a neural network model developed for classification. Input data that is topographical photos off dimension 224*224 and output ranges from 0-4. 0.991 accuracy obtained in this model to identify between normal and affected eyes. This system not only helped in diagnosing but also identifying the stage of the disease through grade. Commercializing this system by training with more data will definitely yield good prediction [6].

This system is implemented to identify how disease in Iran’s population is spread across adult age groups. Four indices are developed from two villages in Iran to study the distribution and by excluding abnormal eyes who had keratoconus. With multiple linear regression these four indices are implemented and various studies performed on ophthalmologic and optometric data. Mean with standard deviation are obtained to present the result. Even though study was done on place of living, age and type of refractive error, major observation was obtained when they studied gender [7].

This system used a neural network to study four video keratography approaches for disease classification [8]. 300 examined data were randomly split into test and train sets. Inputs are chosen from 10 indices with 9 different categories. Outputs are divided into 3 class as positive, suspect and other to distinguish the patients. Correctly trained model will definitely yield percent accuracy and very good model for commercialization [8].

4. KERATOEYE ALGORITHM

The algorithm implemented is based on the Convolutional Neural network which is a deep learning algorithm. The corneal topography is used to diagnose keratoconus which can be further interpreted by ophthalmologists. The images obtained are considered as input for KeratoEye algorithm, and are associated with the learning process of convolutional neural network (CNN) [9]. The developed neural network is capable of classification and learning process. The neural networks are used for analysis and identification of patterns, features and other characteristics for classification. The weights of the neurons in the connection are used by the developed networks to process the input while the learning process continuously adjusts these weights to reduce errors in the learning and classification process. CNN is the most used method in neural networks for image classification. Face detection and object recognition is another area where CNNs are used. In this paper, we have used CNN for the diagnosis of keratoconus.

![Figure 1: Colors denoting elevation parameter in cornea.](image)

![Figure 2: Working of a CNN model.](image)
Classification of images by CNN starts with the initial step of image processing. The process is as follows: dataset images are first decomposed at pixel-level and the matrix obtained is fetched as input to our neural network. Images are passed through kernel convolution filters, pooling layer, and fully connected layer. Classification uses SoftMax function and classifies the object between 0 to 1 as a probabilistic value. Figure 2 represents the working of a CNN model which shows all the layers like convolutional layer, pooling layer, FC layer and output layer. Feature extraction is done by convolutional layer which uses certain filters for classification. The colors in the topography (as in Figure 1) represent the elevation parameter of the cornea. Red denoting high elevation (might be presence of cone) and light colors like green and yellow represents uniform distribution of the parameter.

Color scale is used by the topographical maps to identify the curvature of the cornea. Warm colors like red indicate curved steep areas while cool colors like blue and green indicates flat bends areas. The implemented CNN-KeratoEye algorithm processes these topographical maps to classify an eye into a Keratoconus eye or healthy eye.

Fig 4 represents the flow of the KeratoEye algorithm. The images fetched to the algorithm is preprocessed as all the images should have the same resolution, size and pixel level.

Hence data preprocessing is a much-needed step. Next, the dataset is divided into three sets - training, validation and testing. Training dataset is used for training and learning by CNN, the results are validated by validation dataset and the implemented algorithm’s accuracy is tested by testing dataset. CNN is trained on train dataset and as the accuracy obtained is acceptable, test data is applied as input to the algorithm. Accuracy serves as a final parameter to test the implemented algorithm to classify eye using corneal topographies into a Keratoconus-affected eye or a healthy-normal eye. The colors used in the topography shows the changes in the elevation parameter of cornea.

5. PERFORMANCE EVALUATION OF KERATOYE DETECTION ALGORITHM

Gathering a large dataset of eyes is quite challenging as it belongs to clinical data. Hence, we have used a model called SyntEyes KTC to automatically generate a large set of corneal topographies which can be used as input to our CNN algorithm. SyntEyes uses Scheimpflug tomographies [10] baseline 145 to generate the information. Multivariate Gaussian analysis is used to produce the stochastic model of KTC eyes and no. of integrated parameters are reduced for further processing. All the incorrect topographies produced by this model is removed. The KeratoEye algorithm uses 1000 samples of non-KTC eyes and 1000 samples of KTC eyes, training set includes 750 samples while validation and test set include 150 and 200 samples.

Figure 5 represents the detailed layers of our KeratoEye CNN algorithm. At first, we have input layer that contains the data in layered format. At convolutional layer, padding is performed to create feature maps. In our algorithm padding of 1 is used to make spatial output size same as input size.

At normalisation layer, normalisation of layers is done to ensure optimisation of the network. At the rectified linear unit layer, training time of CNN is reduced and sensitivity is lowered as well as non-linearity is added. At max pooling layer, all the redundant information is removed from all the layers. In the next step number of filters is increased from 16 to 32 and normalization, linear rectification and redundancy removal is performed. The process is again repeated using 64 filters. Since a very slight difference was observed in the outputs of 64-neuron and 128-neuron convolutional layers, we restricted our implementation to 64 layers only.

At fully connected layer, all the neurons from different layer connects to interact with each other and exchange information. This information helps CNN to identify all the extracted features from input data. The size of this layer is kept equal to number of classes we want to classify the data, so it is two here one for Keratoconus eye and other for normal eye.

At SoftMax layer [11], probabilities of classification are determined which is used by full classification layer. At classification layer, we have activation function which classifies the input into one of the two class.

The results obtained can be observed in Figures 3,4,5. Figure 3 represents training loss/accuracy. Figure 4 shows confusion matrix with precision, recall, f1-score, support and accuracy and Figure 5 represents each layer by layer output.

<table>
<thead>
<tr>
<th>precision</th>
<th>recall</th>
<th>f1-score</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.67</td>
<td>0.80</td>
<td>0.73</td>
</tr>
<tr>
<td>1</td>
<td>0.75</td>
<td>0.60</td>
<td>0.67</td>
</tr>
</tbody>
</table>

| accuracy  | 0.70   | 10       |
| macro avg | 0.71   | 0.70     | 0.70    | 10      |
| weighted avg | 0.71  | 0.70     | 0.70    | 10      |

Figure 3: Training Loss/Accuracy representation.

Figure 4: Confusion matrix of result.
6. CONCLUSION

The algorithm implemented is solely proposed for diagnostic purpose and assisting ophthalmologists for Keratoconus detection. From the results obtained for our KeratoEye Algorithm, we ensure a high level and good accuracy performance. Machine learning algorithms are quite good enough in medical science as they provide good results in short time with nearly accurate results and thereby benefits patient health and care. The contribution of the paper is applying machine learning techniques to detect Keratoconus eye using corneal topographies. Once the implemented algorithm goes live with sufficient training, it will help ophthalmologist to diagnose a patient by inputting his corneal topography to KeratoEye Algorithm of is suffering from Keratoconus or not. The algorithm when incorporated as diagnostic tool, it will surely help in Keratoconus diagnosis and help in reducing corneal transplants.

REFERENCES