

## Classification of Corneal Pattern Based on Convolutional Neural Network

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**Abstract**—The early discovery of the disease is a great achievement in management of the cornea. This paper presents an efficient approach for the classification of normal and abnormal corneal patterns based on deep learning. Convolutional Neural Networks (CNNs) are utilized for this purpose. The CNN model built for this purpose comprises 5 layers. The classification process is achieved through two stages. Automatic feature extraction based CNN is applied in the first stage, followed by sequence of processing layers includes: pooling layer, dropout layer and fully connected layer resulted in a diagnosis of the condition of the patient in terms of normal or abnormal. The proposed technique was tested and evaluated based MATLAB environment on a set of corneal images. These images were collected for patients based on confocal microscopy. The CNN classification results on corneal fundus images recorded an accuracy of 100 %.

**Keywords:** Deep learning, Convolutional neural network (CNN), Normal and abnormal corneal images and model accuracy.

### 1. Introduction

Cornea is the transparent layer that face the light which enters the eye. Cornea and Sclera form the outer tunic of the eye and are mechanically strong. They protect the eye from any foreign object to enter it. Cornea has 5 main layers, namely: 1) Epithelium 2) Bowman's layer 3) Stroma 4) Descemet's membrane and 5) Endothelium. The main function of the endothelium is to pump the excess water out of the stroma to preserve its mechanical structure and optical clarity. In this paper we will use the corneal endothelium patterns for the classifications. The corneal endothelium is an important impact at the human vision because of the directly relationship between the cornea healthy and the endothelium cells [1-3].

M.Tang 2005, V. Girisha 2016, Iman Mohammed 2006 display the corneal disease that can cause some disaster cases such as clouding, distortion or blindness. The major types of the endothelium diseases are the following: 1) Keratoconus is weakening and thinning of the central cornea. 2) Corneal endothelial cells (CECs) are terminally differentiated cells and transparency. 3) Fuchs' endothelial dystrophy is effect at the inner layer for the cornea which called the endothelium. 4) Bullouskeratopathy is a condition in which the cornea becomes permanently swollen. This occurs because the inner layer of the cornea, the endothelium, has been damaged and can't pumping fluids out of the tissue, various techniques used at this article such as histogram, enhancement and segmentation for the images for enhance the quality of the images. The results from this classification with accuracy 83% for Fuchs' dystrophy, 77% for Guttation, 82% for Iridocorneal, 82% for Posterior dystrophy [4-6].

G.Ayala 2001, R.Nadachi 1992, F.Sanchez 1999, the image preprocessing techniques are presented to improve the image quality. Several previous solutions for segmentation of endothelial image have already been introduced. Their aim is to delineate cell borders using such techniques as: Numerical measures for corneal cells using Wavelet transform, Local greyscale thresholding followed by scissoring and morphological thinning [7-9].

M. Mahzoun 1996, K. Habrat 2016 and A. piokowski 2017 used some techniques such as active contours, or analysis local pixel levels aimed at finding intensity borders between cells, calculating the corneal cells and their inter relationship, cell density, coefficient of variation, hexagonally, exploits the features that endothelium cells are approximately laid out as a regular tessellation of hexagonal shapes. These techniques estimate the inverse transpose of a matrix generating the cellular lattice [10-12].

Rajendra Acharya and kannathal N2006 presented a comparison between three classifiers for corneal images, artificial neural network ANN with accuracy 89% and fuzzy classifier 92.94 % and adaptive neuro fuzzy classifier 92.94% and they trained 30 image normal and 50 image abnormal Magdalena Habrat, Adam Piorkowski, 2016 based on automated analysis of cornea endothelial cell images. It presented a method for corneal endothelial images segmentation. A preprocessing step was done for edge regularization by using filtering technique. The cell's borders are then determined using the directional filter [13-14].

Alferdo Ruggeri, Enrico Grisan, 2005 and Marco 2002 presented a solution to the problem of automatic estimation of endothelial sell density from corneal images. They proposed methods that the spatial frequency existed in digital endothelium images is extracted with a 2-D discrete fourier transform (DFT) technique. The cell density is related to a circular band in the DFT of the images which contain the frequency information and the goal of Gavet article, 2008 to compute the borders of the cornea cells based on NN technique. Greyscale specular microscopic images of corneal endothelial cells are used for evaluating this algorithm. The disadvantage of the neural network technique is the use of fixed-size mask which needs to expert to perform the necessary corrections while Gavet article compute the borders of the cornea cells automatically [15-17].

Enrico Grisan and Anna Paviotti 2005 proposed a new method to calculate endothelium cell density which is one of the main indicators of cornea health state and quality. This article exploits the property that endothelium cells have approximately a regular tessellation of hexagonal shapes. This approach evaluates the inverse transpose of a matrix creating this cellular lattice and then from this cellular lattice the cell density can be easily obtained. This information could be easily extracted if the cell contours are well defined in the image. There are other methods to classify the corneal images based on the corneal curvature [18-20].

Fabijańska 2019, introduced an approach to study the corneal health status based efficient automatic segmentation of corneal endothelial images. They used a combination of neural network to determine the pixel location at the cell boundaries with post processing stage to obtain the edginess map. They exploited morphological operations with local thresholding for images segmentation. They achieved acceptable results compared with ground truths [21].

Table 1 shows a comparison between different classification techniques according the accuracy:

Table 1: Comparison between different classification techniques

Classification methods	accuracy
ANN [13]	89%
Fuzzy classifier [13]	92.94
Neuro Fuzzy classifier [13]	92.94
Automated neural networks model [22]	80%
Segmentation Cell density [18]	90%
NN [16]	90%

This paper gives an efficient approach for automatic corneal image classification based on deep learning. The objective is to detect anomalies in corneal patterns for efficient diagnosis of different diseases. Also, the grading of diseases is of large importance for patients and technicians.

The paper is organized as follows. Section 2 gives the traditional approach based on automatic feature extraction. Section 3 shows the proposed approach based on deep learning which estimated by equations matrices in section 4. Section 5 presents the simulation results. In section 6, the concluding remarks are spotted.

## 2. Approach Based on Automatic Feature Extraction

In the traditional method for identifying the corneal disease, an image enhancement of fundus images is applied to enhance contrast for better representation of objects. Fig.1 shows samples of normal and abnormal corneal images. Fig.2 displays a simplified diagram of traditional method to classify the corneal images. Fig.3 shows a block diagram of the proposed CNN system to classify between the normal and abnormal images.

The CNN is a deep neural network for image recognition. CNN includes the feature extractor in the training process. The convolutional layers followed as an activation function, pooling layers, dropout layers and fully connected layers. The convolutional layer is contained filters that are used to perform a two dimensional (2D) convolution with the input image. Feature maps are generated from the convolution layer. The pooling layer decreases the size of the image. The used value is the maximum or mean value of the pixels. The max-pooling layer is used in this technique. The inclusion of a dropout layer is used a regularization technique for reducing over fitting [22-24].

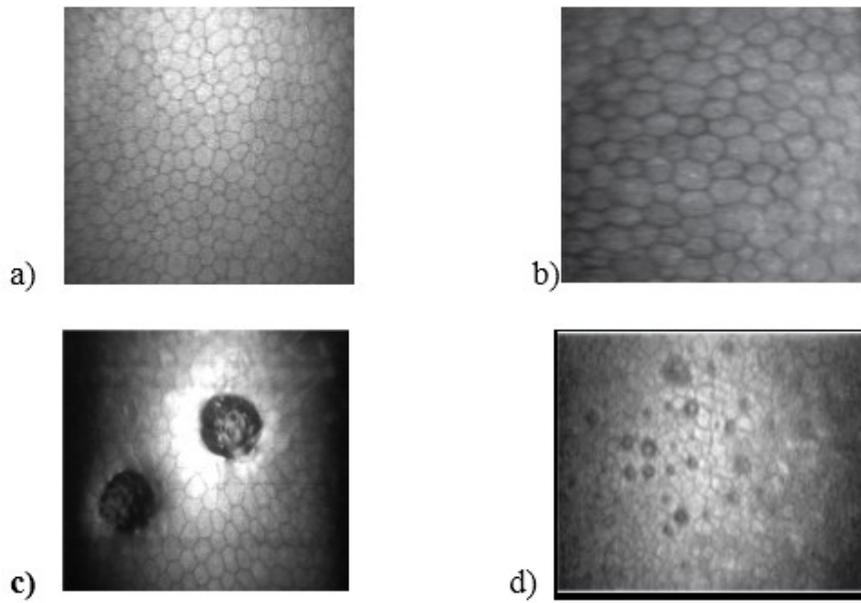


Fig.1 Sample frames of corneal images. a, b are normal images. c, d are abnormal images [5].

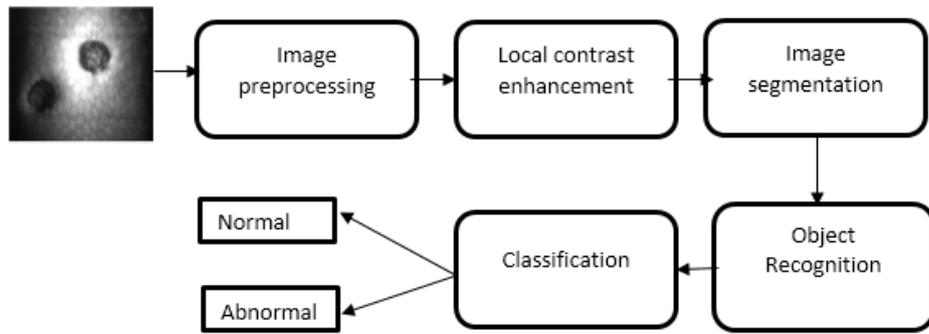


Fig.2 Block diagram of traditional method for identification of corneal status [5].

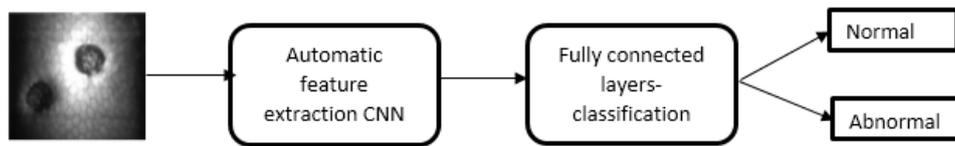


Fig.3 Block diagram of the proposed system

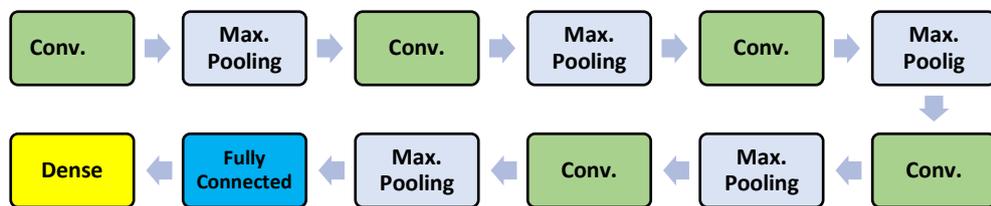


Fig.4 Layers of the Proposed Deep Learning Model.

### 3. Proposed Approach Based on Deep Learning

This approach is based on building an efficient deep learning model that can distinguish between both normal and abnormal states of person's cornea. The proposed model consists of 5 Conv. layers followed by 5 max pooling layers. Finally a global average pooling is used. Table 1 shows the model summary for each layer and its output shape. Images are input in  $224 \times 224$ . Layers have number filters of 16, 32, 64, 128 and 256 for layers 1, 2, 3, 4, 5 respectively. Finally two dense layer will be used. Figure 4 illustrates the steps of the proposed model.

This model is implemented for 50 corneal images dataset. The dataset is divided into 80% training and 20% for testing. The proposed convolutional neural network (CNN) is summarized in table 2. This table shows the output of each layer of the proposed deep learning CNN model.

Table 2: Classifications of Proposed Deep Learning Model.

Layer Type	Output Shape
CNV	(222, 222, 16)
Pooling	(111, 111, 16)
CNV	(109, 109, 32)
Pooling	(54, 54, 32)
CNV	(52, 52, 64)
Pooling	(26, 26, 64)
CNV	(24, 24, 128)
Pooling	(12, 12, 128)
CNV	(10, 10, 256)
Pooling	(5, 5, 256)
Global Average Layer	(256)
Dense	(2)

### 4. Evaluation metrics:

4. In this proposed approach, accuracy and cross entropy are used to estimate the strength of the CNN model. Accuracy knowing as recognition rate is calculated as follows:

The Recognition Rate:

$$\text{Recognition rate} = \frac{\text{The number of success identifications}}{\text{The total number of identification}}$$

- **Loss (cross entropy)%** =  $\text{Log}(\text{estimated}) - \text{Log}(\text{target})$

### 4. Results

The proposed approach is implemented for the 50 corneal images and the accuracy and loss are estimated as the following: figure5 and 6 show the accuracy and loss during the training phase of the benchmark model using one Max pooling layer, figures 7 and 8 show the accuracy and loss during the training phase. It can be observed that the

accuracy reached 100 % and the loss decreased near to be zero.

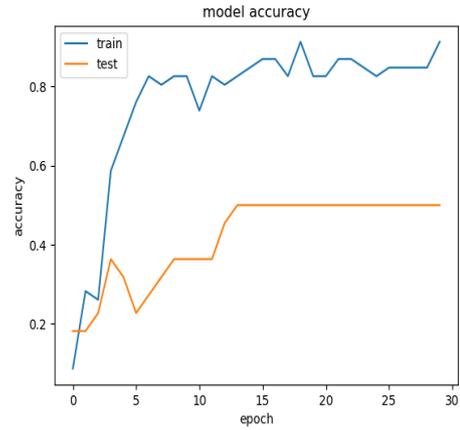


Fig.5. Resulting accuracy of the benchmark model.

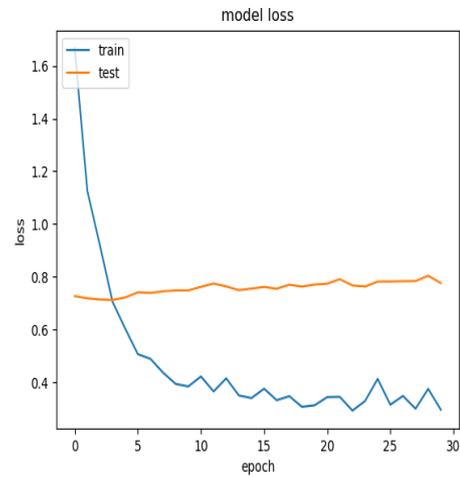


Fig.6. Resulting loss of the benchmark model.

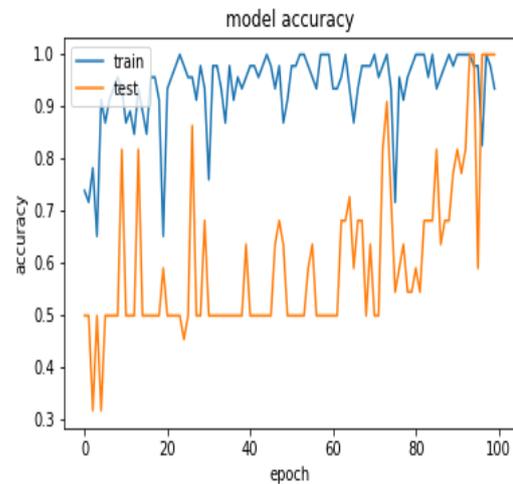


Fig.7. Resulting accuracy of the proposed deep learning model.

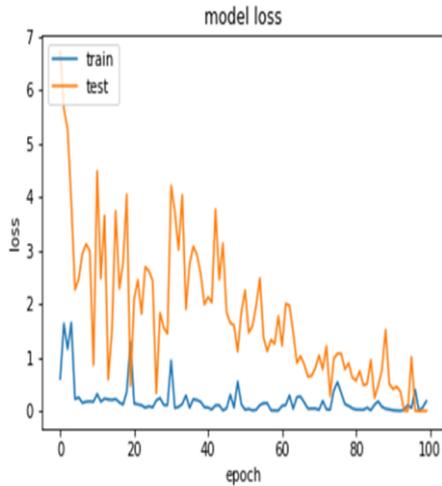


Fig.8. Resulting **loss** of the proposed deep learning model.

Table 3 shows the difference between ANN, SVM and the proposed solution

**6. Conclusion**

This paper represented an automatic feature extraction and classification of corneal images based on deep learning using convolutional neural networks. The proposed approach presents high performance classification of normal and abnormal states of cornea. The evaluation results reveal that the proposed approach realizes an accuracy of 100 % and zero % loss.

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Table 3. Difference between ANN, SVM and the proposed solution

	<b>ANN</b>	<b>SVM</b>	<b>Deep learning (CNN)</b>
<b>Adv.</b>	<ul style="list-style-type: none"> <li>- High efficiency and throughput</li> <li>- Learn itself to do tasks depended on the given data for training</li> </ul>	SVM takes less time than ANN in the all cases of the time of features extracted from the signals.	<ul style="list-style-type: none"> <li>-High efficiency and throughput with high accuracy for image classification.</li> <li>-No need feature extraction layer.</li> <li>-Low loss at the recognition at the images.</li> </ul>
<b>Disadv.</b>	<ul style="list-style-type: none"> <li>- Difficulty of showing the problem to the network</li> <li>- The duration of the network is unknown because of the feature extraction layers.</li> </ul>	Several key parameters that need to be set correctly to achieve the best classification results for any given problem	More complex
<b>Process time</b>	0.3 sec	0.2 sec	0.5 sec
<b>Accuracy</b>	- 75%	79%	100%

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