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Corneal Feature Extraction for Diagnosis of Cataract

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ABSTRACT: Eye cataract is a condition in which the lens of the eye becomes clouding or less transparent. This affects the clear vision and is the most prevailing causes of blindness. Therefore, early cataract detection and prevention may reduce the blindness rate and surgery pain of the patients. This paper presents an eye cataract detection system using feed forward neural network .cataract and Non-cataract Detection and Segmentation of eye using boundary extraction and also Feature of the eye images extracted by using GLCM algorithm and classified using feed forward neural network and also find the centroid and radius of the pupil and iris. To extract features from the segmented region of the images. To classify the cataract and non-cataract of the eye images using feed forward neural network.

I. INTRODUCTION

The disease that affects the cornea is the leading cause of corneal blindness. One of the major causes of corneal blindness is corneal ulcer. The corneal ulcer detection and segmentation is still a challenging task due to accurately detect its ulcer location, size measurement, and visual acuity. However, the segmentation of corneal ulcer generally depends on physician subjective experience. It provides different segmentation results because of physician different professional knowledge and also time-consuming. Therefore, how to efficiently and accurately segment the corneal ulcer by digital image processing and machine learning techniques, becomes an important research direction in future. A corneal ulcer is an epithelial defect that encompasses a wide variety of inflammatory, degenerative and infectious of the cornea, the thin clear membrane in front of the pupil and iris. Corneal ulcers are caused by infections with viruses, bacteria, fungi, vitamin A deficiency, chronic allergic conjunctivitis, keratinis e, dry eyes, ocular herpes, extended wear contact lenses, pterygium, chemical burns, or parasites like Acanthamoeba, etc. Significant corneal scarring ultimately leads to visual impairment and therefore soon results in necrosis of corneal tissue. The prese nce of corneal scar tissue may cause pain, redness, aching, tearing sensitivity to light, blurred vision, swollen eyelids, foreign body sensation, and spot-on cornea i.e. greyish, white or dull spot. Mostly the ophthalmologist diagnosis corneal ulcer by slit-lamp examination with appropriate fluorescein. Fluoresce in stain is the most widely used to highlight any epithelial defect in the cornea to check whether the damaged area is an

Several methods for corneal ulcer detection andSegmentation is found in the literature [3-5]. L. Deng et al.[3] proposed a method for corneal ulcer segmentation using simple linear iterative clustering (SLIC) which Automatically extracting ulcer areas from ocular staining Images. SLIC superpixel based segmentation was applied to segment corneal ulcer which is a clustering method that clusters pixels according to their similarities. They validated their proposed system with 150 clinical images. The classification is done by using liner SVM using 5-fold cross validation. And the mean accuracy rate is 98.40%.

Kim, K., Bang, S., Kim. [4] proposed a color-based segmentation method to detect and segment corneal ulcers. They have used traditional slit-lamp imaging systems with an appropriate dye. The proposed methodology analyzed the corneal image in HSV color space and removes the light reflection area from the ulcer. They proposed a semi automated corneal boundary segmentation approach.

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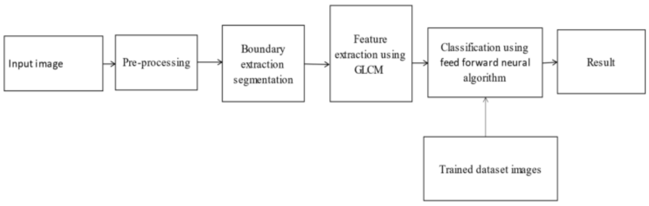
II. METERIALS AND METHODS

The entire procedure of developing the system for corneal ulcer detection using CNN and also ulcer segmentation are described further in detail. The proposed architecture is shown in Fig. 1.

BLOCK DIAGRAM



A. Dataset

There is a lack of publically available datasets for corneal ulcer disease detection. An appropriate visual content-based dataset is required to detect corneal ulcers accurately, starting from the training phase to evaluating the overall detection performance.The dataset is composed of 239 images of corneal ulcer. In order to distinguish other eye diseases and healthy eye from corneal ulcer diseased ones, one more non-corneal ulcer class was included in the dataset. It contains 187 images of noncorneal ulcers such as healthy eyes and several eye diseaese(i.e. cataracts, trachomatous, conjunctivitis, ectropion,periorbital cellulitis, and bitot spot of vitamin A deficiency).The dataset is used for training and testing our corneal ulcer detection model, based on this method. In this paper, we also apply several data augmentation techniques to expand the dataset with augmented images. Table 1 shows all the original corneal ulcer, non-corneal ulcer and augmented images that are used as training and validation dataset.In this section, we briefly review the existing VOD systems. Generally, VOD[13] systems can be categorized into True-VOD(TVOD), which is based on unicast [2] transmission, and Near-VOD (NVOD), which is based on broadcast or multicast transmission, [4]-[7] how videos are delivered . In TVOD, the system reserves dedicated transmission channels from server resources to each client so that clients can receive video data without any delay via dedicated transmission channels as if they use their own VCR. However, may easily run out of the channels because the channels can never keep up with the growth in the number of clients. On the other hand, in NVOD, clients have to wait by some delay time because content is multicast over several channels with periodical cycle.

B. Image Preprocessing

Images are collected from the Internet were in different formats along with different quality and resolutions. In order to enhance image quality and get better feature extraction, the dataset of original images is preprocessed for further analysis. Initially, the original eye images are resized to 256×256 pixels. Some sources contain full faces images with disease. We crop the eye part from a facial image and resize the images. All the images are smoothedusing median filter. This technique is used to reduceImpulsive noise that can preserve the suitable features and image edges. In other words, the median filter works by replacing each pixel of image with median of the intensity value of its neighbouring pixels. Then the preprocessed images are used as training samples for CNN, so that the system automatically classifies corneal ulcer disease or noncorneal ulcer.

C. Feed forward Neural Network

A **feed forward neural network** is an artificial neural network wherein connections between the nodes do *not* form a cycle.[1] As such, it is different from its descendant: recurrent neural networks.

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The feedforward neural network was the first and simplest type of artificial neural network devised.[2] In this network, the information moves in only one direction—forward—from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network

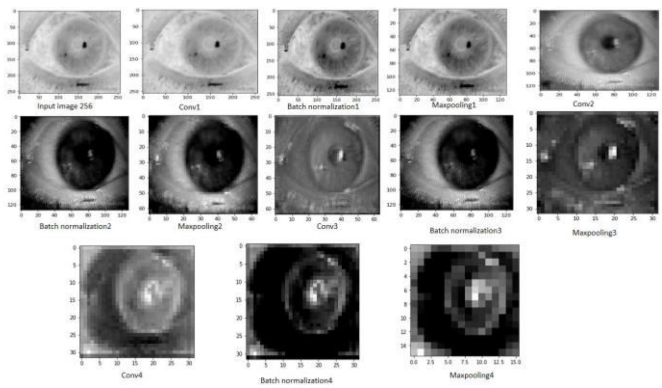
Single Layer Perception

The simplest kind of neural network is a *single-layer perceptron* network, which consists of a single layer of output nodes; the inputs are fed directly to the outputs via a series of weights. The sum of the products of the weights and the inputs is calculated in each node, and if the value is above some threshold (typically 0) the neuron fires and takes the activated value (typically 1); otherwise it takes the deactivated value (typically -1). Neurons with this kind of activation function are also called *artificial neurons* or *linear threshold units*. In the literature the term *perceptron* often refers to networks consisting of just one of these units. A similar neuron was described by Warren McCulloch and Walter Pitts in the 1940s.A perceptron can be created using any values for the activated and deactivated states as long as the threshold value lies between the two.

Perceptrons can be trained by a simple learning algorithm that is usually called the *delta rule*. It calculates the errors between calculated output and sample output data, and uses this to create an adjustment to the weights, thus implementing a form of gradient descent.

Single-layer perceptrons are only capable of learning linearly separable patterns; in 1969 in a famous monograph entitled *Perceptrons*, Marvin Minsky and Seymour Papert showed that it was impossible for a single-layer perceptron network to learn an XOR function (nonetheless, it was known that multi-layer perceptrons are capable of producing any possible boolean function).

Although a single threshold unit is quite limited in its computational power, it has been shown that networks of parallel threshold units can approximate any continuous function from a compact interval of the real numbers into the interval [-1,1]. This result can be found in Peter Auer, Harald Burgsteiner and Wolfgang Maass "A learning rule for very simple universal approximators consisting of a single layer of perceptrons".[3]



1.Corneal Ulcer Detection:

In our automatic corneal ulcer detection and segmentation system, we designed an automated platform where the human eye part is obtained from facial images. This facial image capturing is done by high-resolution digital camera. In our approach, the system automatically detects face and the eye region using Haar Feature-based Cascade Classifiers [11]. After segmenting the eye part from the face part, these features are applied to the CNN model to classify corneal ulcer or non-corneal ulcer.

The corneal ulcer disease is recognized by using CNN described the model in Heading 2 Section D. Once the system detect corneal ulcer disease by CNN, itAutomatically segments the ulcer area from the eye image.

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2)Sclera and Iris Segmentation:

In this phase, we apply the Grab Cut method to exclude outer skin area from the eye image. During the Grab Cut [12] segmentation process, we used a rectangular mask in order to remove skin area andeyelid borders accurately. The upper and lower eyelids and iris locations are determined using the canny edge detection technique [13]. We also apply Hough transform to determine the center of the pupil and its radius. After the determination of the inner and outer boundaries of the iris, we apply binary thres holding to identify the glare from reflections (bright spots) of the image. Then we apply active contours to segment iris and sclera. Active contour technique can be described as the process of segmentation of pixels from the essential region of interest (ROI) that is performed to achieve the outcome for further processing andAnalysis [14]. And contours act as a collection of points(Boundaries) which is designed for the ROI required in an image [14]. The corneal ulcer segmentation procedures are shown in Fig.5.Fig.5. The corneal ulcer segmentation of all steps, obtained from theProposed methodology. Experimental Results: (a) original eye images; (b) Exclude skin area from eye region; (c) and (d) sclera and iris segmentationRespectively; (e) ulcer area detection.

3) Corneal ulcer area segmentation:

In certain cases, after the aforementioned steps, there may still be non-ulcer areas left exhibiting the same white or grayish color, in such Cases, we performed erosion followed by dilation to Remove the unwanted areas.The combination of two morphological operations erode apply on the segmented iris image and then dialtes the erode iris image. The dilation operation is used to add pixels to the boundaries of objects in an image, while erosion operation is used to remove pixels on object boundaries [3]. Then we apply active contours to localize the ulcer area from cornea. Also to find out the severity of the corneal ulcer, we calculated the affected area. Affected ulcer area is calculated by ratio between the area of the whole iris area and the ulcer affected area.

TABLE 3. COMPARISON STATISTICAL RESULTS

	Sensitivity	Specificity
Corneal ulcer (Number of original images)	97.92%	95.87%
Corneal ulcer (Augmented images)	98.78%	98.60%

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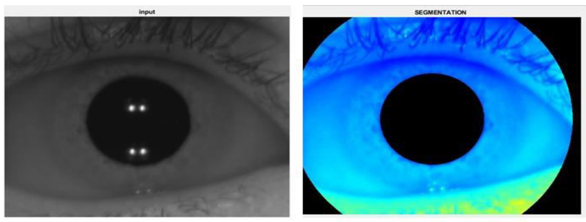
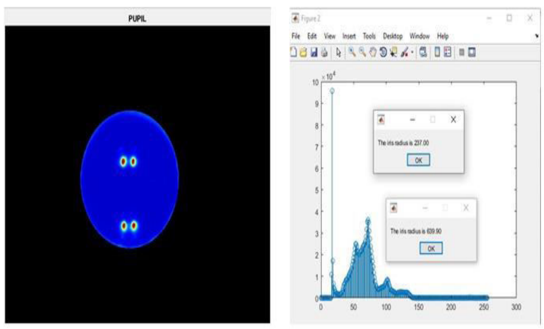
III. EXPERIMENTAL ANALYSIS

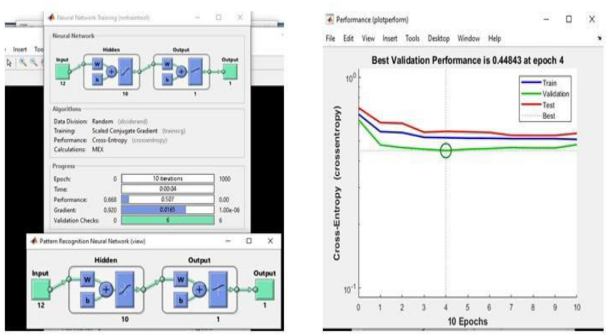
1.Input and segmentation

OUTPUT IMAGES FOR CATARACT



2.Centroid and radius of pupil





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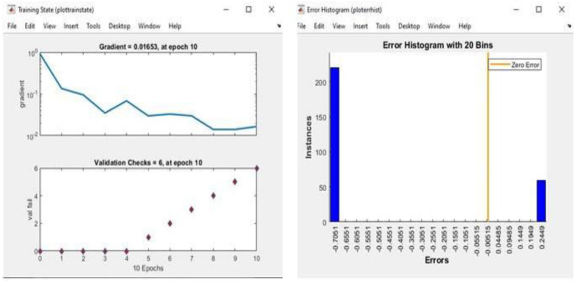
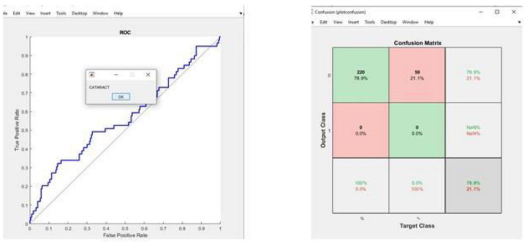
3.Training state and Error histogram



IV. SIMULATION RESULT



V. CONCLUTION AND FUTURE WORK

This article first introduces the background and significance of cataract diagnosis. The automatic diagnosis of cataract can improve the accessibility of cataract examination and provide an important reference for underdeveloped areas with scarce medical resources to prevent blindness caused by cataract. This study proposed a unified framework to perform automated nuclear cataract severity classification using feedforward neural network.. Experimental results show that the framework is competitive among many existing cataract grading methods. This method simplifies the complicated operation in cataract screening process, reduces the difficulty of screening by artificial intelligence technology, improves the accuracy rate, reduces the misdiagnosis rate and greatly improves the accessibility of medical treatment

Corneal feature extraction for diagnosis of cataract has lot of advantages. The advantages are it will learn more complex function and it looks cool when you make your network deeper. The future scope should have chance to replace this method with Real time automated prediction system which use software and camera combined process instead of manual process.

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