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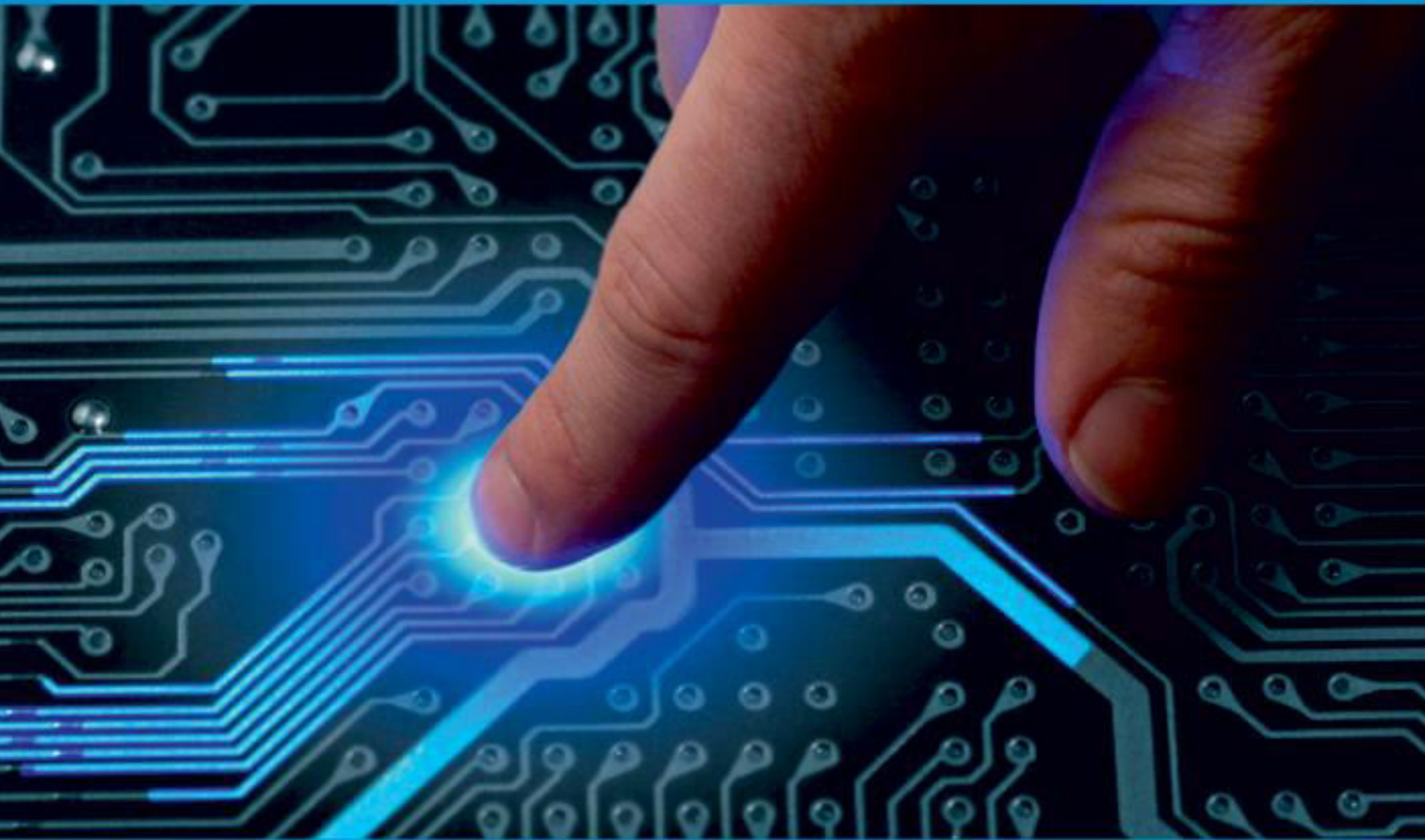

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Accurate Detection and Recognition of Glaucoma Using Image Processing

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ABSTRACT: This paper presents the classification of eye disease which may have clinical use in the description of the present eye state, in the assessment of treatment results, and in the choice of therapy. Requirements for any classification system should include simplicity, clinical nature (i.e., easily carried out by any physician equipped with ordinary non-invasive techniques), reproducibility and meaningfulness (i.e., objective and of clinical relevance to the patient). The image processing system is suitable for pure description. It is not very helpful in the assessment of treatment results. That outcome probably is best described by measuring disease types and stage. In existing system, the doctors manually diagnosed different disease. In our proposed method different machine learning techniques were used to detect a particular disease.

KEYWORDS: Machine Learning, Glaucoma Detection, Image Processing, buzzer.

I. INTRODUCTION

The term digital image refers to processing of a two-dimensional picture by a digital computer. In a broader context, it implies digital processing of any two-dimensional data. A digital image is an array of real or complex numbers represented by a finite number of bits. An image given in the form of a transparency, slide, photograph or an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or displayed on a high-resolution television monitor. For display, the image is stored in a rapid-access buffer memory, which refreshes the monitor at a rate of 25 frames per second to produce a visually continuous display. Diabetic retinopathy (DR) is a complication of diabetes, and it constitutes a leading cause of blindness worldwide. In 2030, 552 million people are expected to suffer from diabetes. The majority of visual loss cases can be prevented with early detection and adequate treatment. The earliest diabetes-related changes in the retina are often imperceptible and have minimum impact in the vision, Regular check-ups via DR screening programs are essential fordetecting the disease as early as possible and determining the adequate treatment.

Specialists search for abnormalities in the retina and classify the severity of the disease according to the findings. However, the diagnosis process is prone to errors due to the large number of patients to be observed, poor image acquisition and variety of lesions to analyze. Computer-aided diagnosis (CAD) systems can improve the DR screening pipeline both reducing the burden and providing a second opinionto the ophthalmologists, reducing diagnosis' subjectivity. Deep learning has recentlyallowed for CAD systems to achieve near-human performance in DR detection. DR grading, i.e., staging of the pathology according to its severity, is a more complex task since it requires the identification and integration of different lesions.

Generally, DR is classified accordingly to the international DR scale as mild non proliferative DR (NPDR) (R1), moderate NPDR (R2), severe NPDR (R3) or PDR (R4), ordered according to their risk of progression. Despite the task's complexity, several works have shown promising performance. a model (DR Graduate) that not only produces a grade but also an uncertainty associated with the predictions.

Machine learning teaches computers to do what comes naturally to humans: learn from experience. Machine learning algorithms use computational methods to "learn" information directly from data without relying on a predetermined equation as a model. The algorithms adaptively improve their performance as the number of samples available for learning increases.

The aim of supervised machine learning is to build a model that makes predictions based on evidence in the presence of uncertainty. A supervised learning algorithm takes a known set of input data and known responses to the data (output) and trains a model to generate reasonable predictions for the response to new data. Supervised learning uses classification and regression techniques to develop predictive models.

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II. LITERATURE SURVEY

[1]WheymingTinaSong:Latestframeworkcombinestheuseofconvolutionalneuralnetworks(CNN)withtheproposedgeneralizedlossfunction,robustdesignofexperiment (DOE),and Retinal theory to improve the results of fundus photography flash by restoring theoriginalcolorsviaremovingthelighteffect.

[2]PaulY.Kim,KhanM:Sensitivity,specificity,andareaunderreceiveroperatingcharacteristiccurve(AUROC)arecomputedfortheFFAfeaturesandformetricsobtainedusingwavelet-Fourier analysis (WFA) and fast-Fourier analysis (FFA)

[3]FaizanAbdullah:Glaucomaisanincurableeyediseasethatleadstoslowprogressivedegenerationoftheretina.Itcannotbefullycured;however,itsprogressioncanbecontrolledincaseof early diagnosis. Unfortunately, due to the absence of clear symptoms during theearly stages, early diagnosis are rare. Glaucoma must be detected at early stagessince late diagnosis can lead to permanent vision loss. Glaucoma affects the retinaby damaging the Optic Nerve Head (ONH)

[4]**RicardoCarreño:**ThemostwidelyusedfunctionisMax-pooling,whichconsistsoftakingthehighestvalueofaneighborhoodofpixelsinanimage. Preprocessing typically deals with enhancing, removing noise, isolating regions, etc. Segmentation partitions an image into its constituent parts or objects.

[5] **O. C. Devecioglu:** Glaucoma leads to permanent vision disability by damaging the optical nerve that transmits visual images to the brain. The fact that glaucoma does not show any symptoms as it progresses and cannot be stopped at the later stages, makes it critical to be diagnosed in its early stages. Although various deep learning models have been applied for detecting glaucoma from digital fundus images, due to the scarcity of labeled data, their generalization performance was limited along with high computational complexity and special hardware requirements, and their performance is compared against the conventional (deep) Convolutional Neural Networks (CNNs) over three benchmark datasets: ACRIMA, RIM-ONE, and ESOGU.

[6] **M. T. Islam:** Glaucoma is an irreversible neurodegenerative disease, where intraocular hypertension is developed due to the increased aqueous humor and blockage of the drainage system between the iris and cornea. As a result, the optic nerve head, which sends visual stimulus from our eyes to the brain, is damaged, causing visual field loss and ultimately blindness

[7]**O. J. Afolabi:** Glaucoma has been credited to be the foremost cause of preventable loss of sight in the world second only to cataract. Its effect on the eye is usually irreversible and can only be prevented by early detection. In this journal, they developed a glaucoma detection technique

[8]**R. B. Bharathi:** Tonometry, a procedure of glaucoma investigation is carried out effectively in all eye care clinics. The other testing method namely gonioscopy requires professional expertise and experience due to which optometrists/ophthalmologists avoid this test. Hence the proposed technology would let these two important glaucoma testing procedures be performed simultaneously with a common instrument "Ton goniometry" and making detection easier, timesaving, and lowering uneasiness to the patient

III. IMAGE PROCESSOR

An image processor does the functions of image acquisition, storage, pre-processing, segmentation, representation, recognition and interpretation and finally displays or records the resulting image. The following block diagram gives the fundamental sequence involved in an image processing system.

As detailed in the diagram, the first step in the process is image acquisition by an imaging sensor in conjunction with a digitizer to digitize the image. The next step is the pre-processing step where the image is improved being fed as an input to the other processes. Pre-processing typically deals with enhancing, removing noise, isolating regions, etc. Segmentation partitions an image into its constituent parts or objects. The output of segmentation is usually raw pixel data, which consists of either the boundary of the region or the pixels in the region themselves. Representation is the process of transforming the raw pixel data into a form useful for subsequent processing by the computer. Description deals with extracting features that are basic in differentiating one class of objects from another. Recognition assigns a label to an object based on the information provided by its descriptors. Interpretation involves assigning meaning to an ensemble of recognized objects. The knowledge about a problem domain is incorporated into the knowledge base. The knowledge base guides the operation of each processing module and also controls the interaction between the modules. Not all modules need be necessarily present for a specific function. The composition of the image processing system

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depends on its application. The frame rate of the image processor is normally around 25 frames per second. Image enhancement operations improve the qualities of an image like improving the image's contrast and brightness characteristics, reducing its noise content, or sharpen the details. This just enhances the image and reveals the same information in more understandable image. It does not add any information to it.

Image compression and decompression reduce the data content necessary to describe the image. Most of the images contain lot of redundant information, compression removes all the redundancies. Because of the compression the size is reduced, so efficiently stored or transported. The compressed image is decompressed when displayed. Lossless compression preserves the exact data in the original image, but Lossy compression does not represent the original image but provide excellent compression.

Digital image processing has a broad spectrum of applications, such as remote sensing via satellites and other spacecraft, image transmission and storage for business applications, medical processing, radar, sonar and acoustic image processing, robotics and automated inspection of industrial parts.

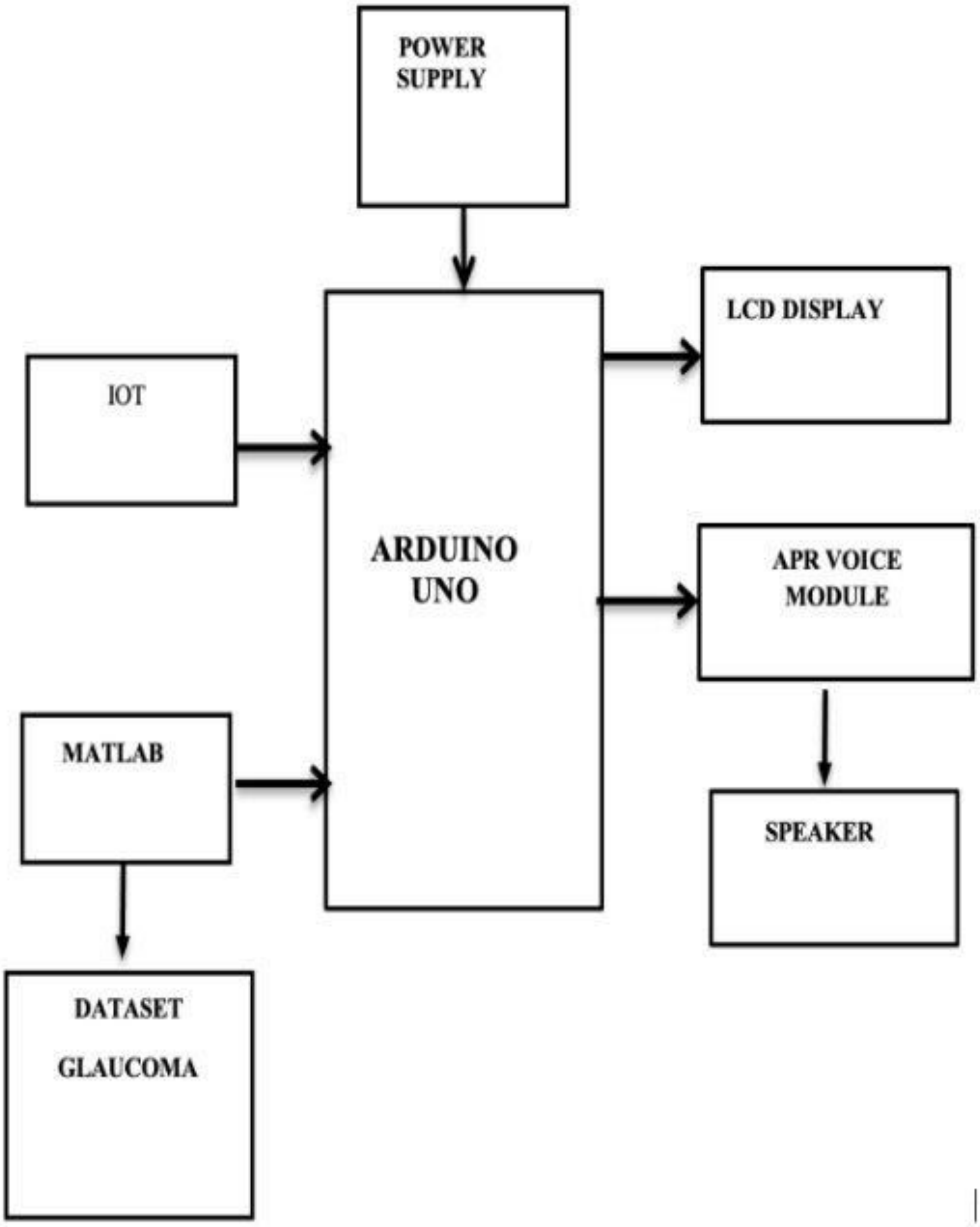

Figure 1 : Block diagram of Glaucouma Detection and Accuration

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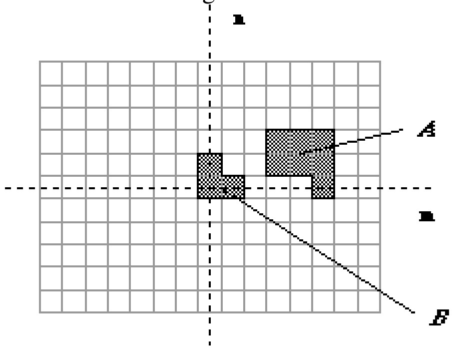
IV. MORPHOLIGICAL OPERATIONS

It is defined an image as an (amplitude) function of two, real (coordinate) variables a(x,y) or two, discrete variables a[m,n]. An alternative definition of an image can be based on the notion that an image consists of a set (or collection) of either continuous or discrete coordinates. In a sense the set corresponds to the points or pixels that belong to the objects in the image. This is illustrated in figure below which contains two objects or sets **A** and **B**.



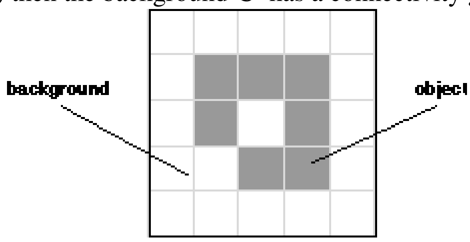
A binary image containing two object sets C and **D**.
The object **C** consists of those pixels a that share some common property:

$$A = \{\alpha | property(\alpha) == \text{TRUE}\}$$

As an example, object C consist of {[0,0], [1,0], [0,1]}.
The background of **C** is given by **C**^{c} (the complement of **C**) which is defined as those elements that are not in **C**:

$$A^c = \{\alpha | \alpha \notin A\}$$

We introduced the concept of neighborhood connectivity. We now observe that if an object **C** is defined on the basis of C-connectivity (C=4, 6, or 8) then the background **C**^{c} has a connectivity given by 12 - C.



A binary image requiring careful definition of object and background connectivity.

3.1.1 Dilation and Erosion

An arbitrary binary image object (or structuring element) **C** can be represented as:

$$A \leftrightarrow \sum_{k=-\infty}^{+\infty} \sum_{j=-\infty}^{+\infty} a[j,k] \bullet \delta[m-j, n-k]$$

where Σ and * are the Boolean operations OR and AND as defined in eqs. (81) and (82), a[j,k] is a characteristic function that takes on the Boolean values "1" and "0" as follows:

$$a[j,k] = \begin{cases} 1 & a \in A \\ 0 & a \notin A \end{cases}$$

and d[m,n] is a Boolean version of the Dirac delta function that takes on the Boolean values "1" and "0" as follows:

$$\delta[j,k] = \begin{cases} 1 & j = k = 0 \\ 0 & otherwise \end{cases}$$

Dilation for binary images can therefore be written as:

$$D(A,B) = \sum_{k=-\infty}^{+\infty} \sum_{j=-\infty}^{+\infty} a[j,k] \bullet b[m-j, n-k] = a \otimes b$$

which, because Boolean OR and AND are commutative, can also be written as

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$$D(\mathtt{A},\mathtt{B}) = \sum_{k=-\infty}^{+\infty} \sum_{j=-\infty}^{+\infty} a[m-j, n-k] \bullet b[j,k] = \mathtt{b} \otimes \mathtt{a} = D(\mathtt{B},\mathtt{A})$$

Thus, dilation and erosion on binary images can be viewed as a form of convolution over a Boolean algebra.

3.1.2 Morphological filtering of gray-level data

For a rectangular window, J x K, the two-dimensional maximum or minimum filter is separable into two, one-dimensional windows. Further, a one-dimensional maximum or minimum filter can be written in incremental form, this means that gray-level dilations and erosions have a computational complexity per pixel that is O(constant), that is, independent of J and K.

The operations defined above can be used to produce morphological algorithms for smoothing, gradient determination and a version of the Laplacian. All are constructed from the primitives for gray-level dilation and gray-level erosion and in all cases the maximum and minimum filters are taken over the domain $[j,k] \in \mathtt{B}$.

For linear filters the gradient filter yields a vector representation (eq. (103)) with a magnitude (eq. (104)) and direction (eq. (105)). The version presented here generates a morphological estimate of the gradient magnitude:

$$\begin{aligned} Gradient(\mathtt{A},\mathtt{B}) &= \frac{1}{2}\left(D_G(\mathtt{A},\mathtt{B}) - E_G(\mathtt{A},\mathtt{B})\right) \\ &= \frac{1}{2}\left(\max(\mathtt{A}) - \min(\mathtt{A})\right) \end{aligned}$$

The morphologically-based Laplacian filter is defined by:

$$\begin{aligned} Laplacian(\mathtt{A},\mathtt{B}) &= \frac{1}{2}\left(\left(D_G(\mathtt{A},\mathtt{B}) - \mathtt{A}\right) - \left(\mathtt{A} - E_G(\mathtt{A},\mathtt{B})\right)\right) \\ &= \frac{1}{2}\left(D_G(\mathtt{A},\mathtt{B}) + E_G(\mathtt{A},\mathtt{B}) - 2\mathtt{A}\right) \\ &= \frac{1}{2}\left(\max(\mathtt{A}) + \min(\mathtt{A}) - 2\mathtt{A}\right) \end{aligned}$$

V. SUMMARY OF MORPHOLOGICAL

The effect of these filters is illustrated below. All images were processed with a 3 x 3 structuring element as described in eqs. through. Figure 46e was contrast stretched for display purposes and the parameters 1% and 99%.

figure 2**d)** Gradient **e)** Laplacian

Examples of gray-level morphological filters

4.1.1 Border Corrected Mask

A mask is a filter. Concept of masking is also known as spatial filtering. Masking is also known as filtering. In this concept we just deal with the filtering operation that is performed directly on the image. In image processing, a kernel, convolution matrix, or mask is a small matrix useful for blurring, sharpening, embossing, edge-detection, and more. This is accomplished by means of convolution between a kernel and an image. The mask is created to find the exact operations in an image. So that we can identify the problems or the features which we need to find in an image. The border corrected mask is a mask in which the edges are closed to find all the features of an image.

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Example of border corrected mask is given below

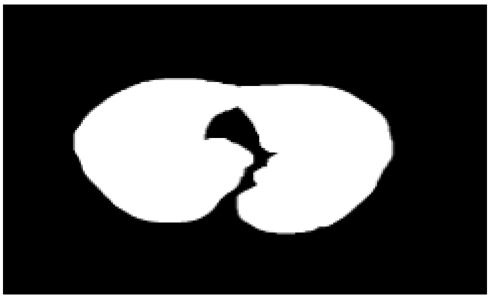


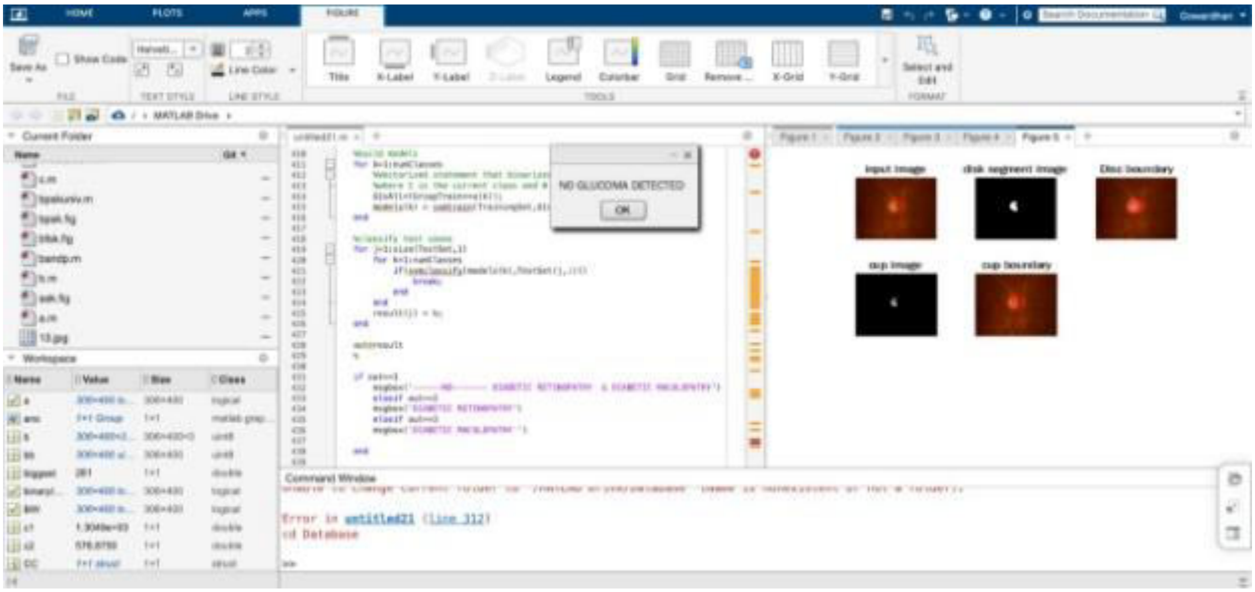
Figure 3 : Border corrected mask

4.1.2 Segmentation

In computer_vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge_detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). When applied to a stack of images, typical in medical_imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching_cubes..

VI. RESULTS



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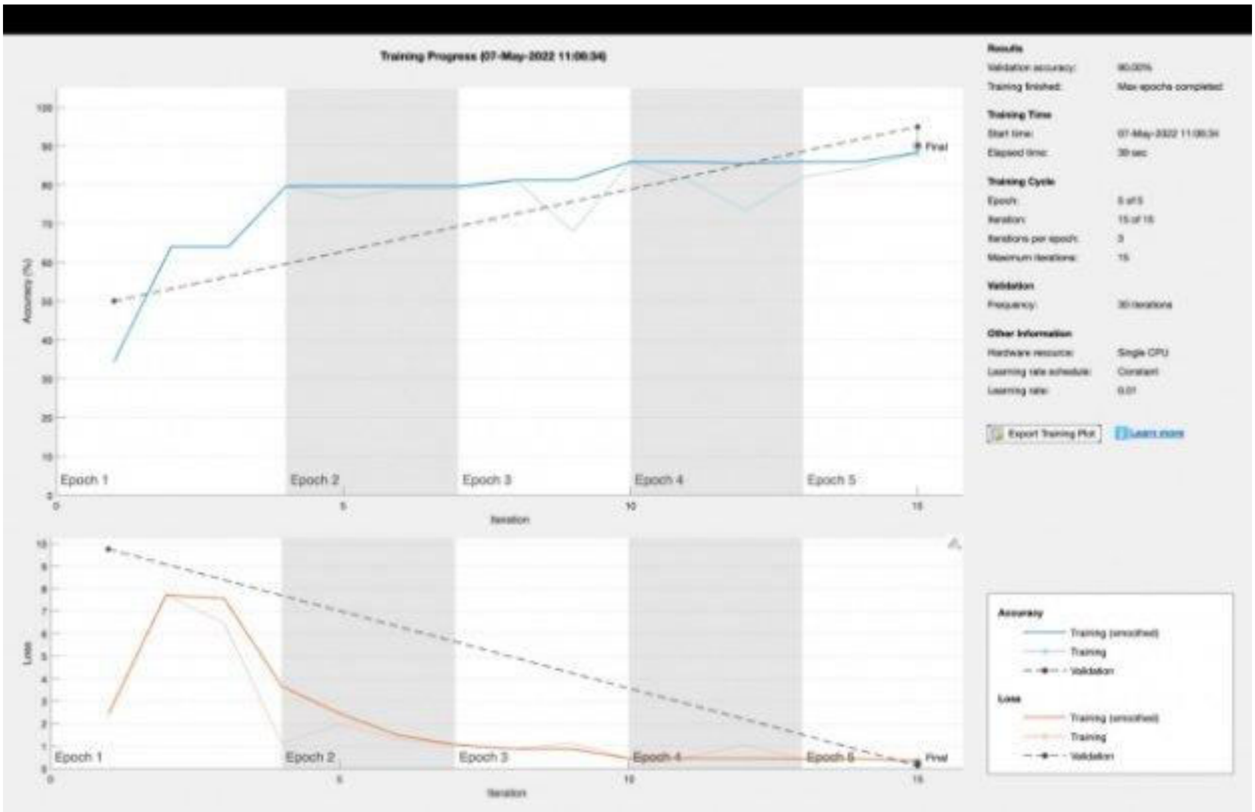

Figure 4 : Output results

VII. CONCLUSION

Classification of the eye disease may have clinical use in the description of the present eye state, in the assessment of treatment results and in the choice of therapy.Requirements for any classification system should include simplicity, clinical nature(i.e., easil y carried out by any physician equipped with ordinary non-invasive techniques), reproducibility and meaningfulness (i.e., objective and of clinical relevance to the patient). The im age processing system is suitable for pure description of detecting the diseases. It is not very helpful in the assessment of treatment results. That outcome probably is best described by measuring disease types and stage. Deep learning systems, such as convolutional neural networks (CNNs), can infer a hierarchical representation of images to discriminate between norma l and diseased eye patterns for diagnostic decisions. The proposed system visualizes the filters in CNN and observe that CNN can capture the differences between WS and BA networks. Furthermore, the system tests the robustness of the model by setting different sizes for training and testing. It also compares our model with baseline methods, and the result shows that our model performs well on large-scale networks. The biggest advantage of our model is that it can deal with networks with different structures and sizes.

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