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Automatic Glaucoma Detection Using Sobel Edge Detection & Svm Classifier

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Abstract- **It is hard to diagnose the glaucoma from single routine test that is why it is supposed as one of the most complex disease for diagnosis. Glaucoma may affect the eyes that reach the deficiency towards either partial blindness or complete blindness. It cannot be treated once it occurred but it can be cured by routine examination. Diagnosing glaucoma on time may save the rest vision but it does not improve the eyesight by treating by any medical experts. An OCT scan is an important test in diagnosing and monitoring glaucoma. Here the system is based on Sobel Edge Detection and Support image processing and classification methods to detect glaucoma by comparing and measuring various parameters of the fundus images of glaucoma patients and general patients.Vector Machine (SVM) Classifier. Sobel can highlight the nerves or blood vessels and segment the fundus optic disc that may or may not affect by glaucoma. On the other hand SVM can classify the affected area or impaired cells that can resulted a better diagnostic system. It is an irregular or polynomial data classification that can work for Iris based fundus images. System acquired 94.45 % of accuracy with minimal false alarm rate and obtains less processing time.**

Keywords:- **Automatic Glaucoma Detection, Fundus Imaging, Optic Disc, Optic Cup, SVM, Sobel Edge Detection, Retinal Image, Hemorrhages**

I. INTRODUCTION

Glaucoma is a chronic disorder of the optic disc in which fluid pressure inside the optic nerve increases and is untreatable; Patients may lose their vision and they may become blind. Since glaucoma is untreatable, early detection and prevention can protect the fundus nerve from severe.

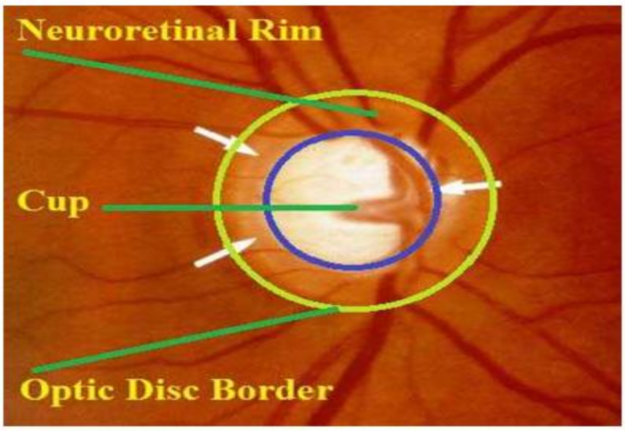

Fig 1. Glaucoma Architecture.[1]

Instinctive analysis of retinal images is now becoming an important screening tool. This method helps to identify vision loss. Glaucoma is known as "silent theft of vision".This is not an immediate result and vision loss occurs gradually over a long period of time. Glaucoma detection different types of diseases and ailments of the eyes. Glaucoma is one of the most common causes of blindness. The disease is caused by an increase in intraocular pressure. involves measuring the shape and size of the optic disc.

Glaucoma usually increases intra-ocular pressure (IOP) in the eyes and gradually destroys the visual field of the eye. Early detection of the disease is essential to prevent blindness. Screening for glaucoma based on digital images of the retina has been ongoing for the past few years. There are the term ocular-hypertension refers to individuals whose IOP is constantly increasing and whose nerve optics are not compromised. There are different types of glaucoma such as several approaches to detecting retinal abnormalities caused by glaucoma. Major image processing methods include image registration, image fusion, image segmentation, open angle, close angle, congenital and Normal tension glaucoma affects the destroys nerve optics.

The word angle general tension visual field and means the space feature extraction, image enhancement, morphology, pattern matching, image classification, analysis and statistical measurements. between the iris and the cornea; If this distance is large, it is called chronic glaucoma and if

International Journal of Scientific Research & Engineering Trends
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the space between the iris and the cornea is small, it is called close angle glaucoma. Figure shows the fundus image of the eye, which is the limit of the area. An important feature of this defect is the development of papillae excavation. In fact, the papilla or image processing and classification methods to detect glaucoma by comparing and measuring various parameters of the fundus images of glaucoma patients and general patients.

II. RELATED WORKS

Swethali M. Nikam [2017] et al. proposed a system that is based on CDR (cup to disk ratio) and separation by optical disc is a combination of fibers that make up the optical nerve, causing the optic nerve to disappear due to the depression found in the excavated optical disc. The "disc" report indicates the availability of glaucoma (usually around 0.3) between the excavated size and the optical disc. The main idea behind this paper is to describe a system based on threshold has been proposed to distinguish glaucoma from retinal images.

Glaucoma can be detected by analyzing the areas above the optic cup and optic disc retina image and the size of the optic cup and disc. The system localizes these areas here using the entrance and partition by measuring horizontally and vertically. If the size is larger than 0.3, the patient may have glaucoma. But by analyzing the size of the glaucoma; the size must be accurate or the fault alarm rate will increase. Early glaucoma cannot be detected using CDR because it only analyzes the optic cup and disk [2].

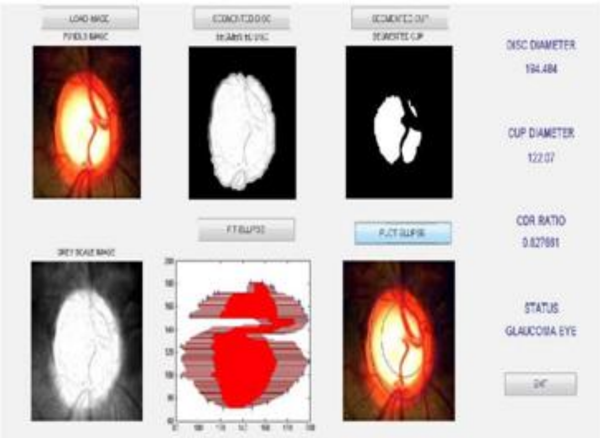

Fig 2. Graphical User Interface for Glaucoma Detection. [2]

Thus, the fit ellipse is used to determine the boundary between the optic cup and the optic disc. Using the cup-to-disc CDR ratio, we found that glaucoma or normal to a specific eye. This system is easy to use and we use the Matlab GUI, so it is user friendly. Matlab GUI provides numerical values for cup, disk diameter and CDR ratio along with graphical representation of the eye [2].

Namita Sengar [2017] et al. proposed a system which is based on optic disc detection and hemorrhages segmentation. Bleeding releases a portion of the blood from the ruptured vessels inside the retina image. But by determining whether the blood vessels are broken; that may not be sure if this is glaucoma. Normal eyes often have red blood vessels that look like broken vessels and are considered non-glaucoma retina [3].

Mrs. Pavitra G [2018] et al. proposed a system that is based on cup-to-disk ratio estimation and pixel brightness conversion, geometric conversion, and pre- processing of the desired area, such as a limited area of the processed image. The histogram equation is also part of it. The standard ratio from cup to disc is 0.3, which is considered if the ratio is larger than specified; this is glaucoma. This ratio is easily affected by the reflection of light and blood.

Shwetha C. Shetty [2018] et al. represents a system based on clustering and optic cup measurements. K- media clustering is used to separate the optic cup area from the fundus image. During the boundary detection phase, the morphological operation takes place after the automatic optic cup and edge detection. Clustering of similar cells from the retina image also affects blood vessels, reducing accuracy or optimal detection rate [5].

Juan Carrillo [2019] et al. represents a system that uses partitioning and access to hide unwanted background and divide the area of interest (ROI). It converts blood vessels and any area above the retina image into a grayscale image. If elimination or masking is done using the segmentation method, it can cause the loss of certain parts of the glaucoma and the sensitive information can be removed or removed from the image, which can degrade the optimal detection rate. Here the system achieves 88.5% accuracy, which may be slightly higher [6].

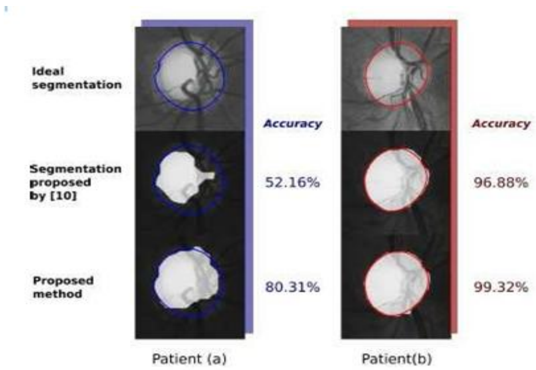

Fig 3. Disc Segmentation Results. [6]

Liu Li [2019] et al. served a system that is based on the convolutional neural network (CNN). To diagnose patterns of glaucoma, the system here must be trained with different models of glaucoma-affected retinal images. The

International Journal of Scientific Research & Engineering Trends
Volume 6, Issue 6, Nov-Dec-2020, ISSN (Online): 2395-566X

system does not successfully classify glaucoma if the optical disc and cup differ from the trained model [7].

Ali Serener [2019] et al. specifies the CNN based system and uses the histogram equation to preprocess the data. Resnet 50 and Googlenet are both in-depth learning methods for training systems with different conditions to detect glaucoma. Samples are limited, and complex blood vessels may not transmit the required accuracy and optimal detection rate. The performance of both models takes into account accuracy, precision, specificity and ROC curve range. Results show that Google has surpassed Resnet-50 for early, advanced and total glaucoma detection [8].

Sertan Serte [2019] et al. proposed a system which is based on the Deep Neural Network. Fundus created a simple in-depth study model to identify glaucoma in images. The model works on three in-depth learning structures: Resnet, Google Net and Resnet 152. Training is very expensive due to the complex data models. It uses a convincing algorithm. In-depth study requires expensive GPUs and hundreds of machines. Unlike previous works, the training here is conducted together in four different datasets and tested in one. Although the datasets are different from each other, the prototype of the five datasets tested and the three different structures display 80% of the time, comparable or better than the previous work [9].

III. PROBLEM IDENTIFICATION

Juan Carrillo et al. proposed a system that uses background subtraction using segmentation and thresholding for extracting the region of interest and classifies blood vessels. Segmenting only using thresholding and obtaining decision on the basis of that; is not a good approach because it may also erode the region of interest that affects the accuracy directly. The accuracy is often less that is recorded as 88.5% that may enhanced in future.

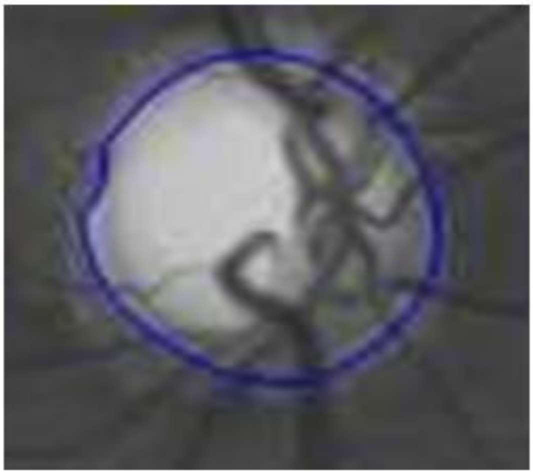

Fig 4. Retinal Boundary Extraction. [6]

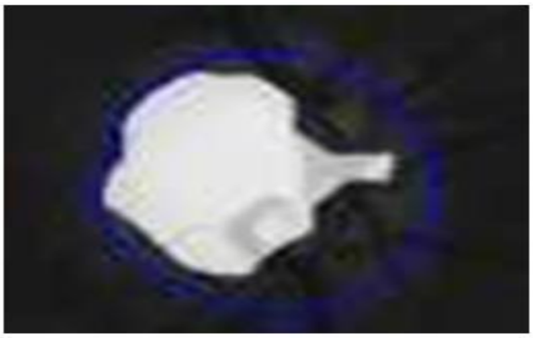

Fig 5. Erosion by Segmentation.[6]

IV. PROPOSED WORK

The proposed system is based on Sobel Edge Detection and SVM classifier. System uses fundus image that has been scanned from OCT scanncer and later ehanced with certain pre-processing techniques such as grayscalling, contrast adjustment etc. Here system can extract the edges of the fundus image that highlighted the nerves as well as the impaired regions then classifier segment the glaucoma and Input Matrix Output Matrix.

+1 0 -1
+2 0 -2
+1 0 -1

Sobel Kernel Matrix for Horizontal Axis,
b11 = a11*1+a12*0+a13*(-1)+a21*2+a22*0+ a23*(-2)+ a31*1+ a32*0+ a33*(-1)

Similarly, each pixel will be calculated according to the kernel matrix and finally Gx has been computed.
The example below shows the calculation of a value of Gy:

+1 +2 +1
0 0 0
-1 -2 -1
Sobel Kernel Matrix for Vertical Axis,
b11 = a11*1+a21*0+a31*(-1)+a12*2+a22*0+ a32*(-2)+ a13*1+ a23*0+ a33*(-1)

At each pixel in the image, the gradient approximations given by Gx and Gy are combined to give the gradient magnitude, using:

G = JG2 + G2 declare result accordingly. The Sobel-Feldman operators y relies on rolling the image horizontally and vertically with a small, separated and integer filter, so it is less costly in terms of calculations. On the other hand, the approximate gradient it produces is relatively raw, especially for high frequency frequency variations in the image.

+1 0 −1 +1 +2 +1

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Gx = [+2 0 −2] * I, Gy = [0 0 0] * I
+1 0 −1 −1 −2 −1

Where A as an input 2D image array or matrix, Gx and Gy - are the gradient kernel that will be multiplied with input image array A. Where Gx is the horizontal gradient and Gy is the vertical gradient. Negative gradients appear darker, and positive gradients appear brighter. Computing the value at each pixel and shifting the row towards right till the end row has been reached. The example below shows the calculation of a value of Gx:

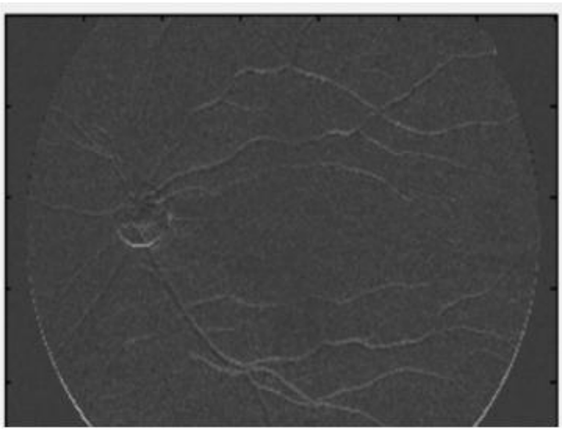

Fig 6. Sobel Edge Detection for Fundus Image.

An SVM model is basically the representation of different classes in a hyperplane in a multi-dimensional space. The error can be minimized as the hyperplane produces SVM in a repetitive manner. The goal of SVM is to classify datasets to find the maximum marginal hyperplane (MMH).

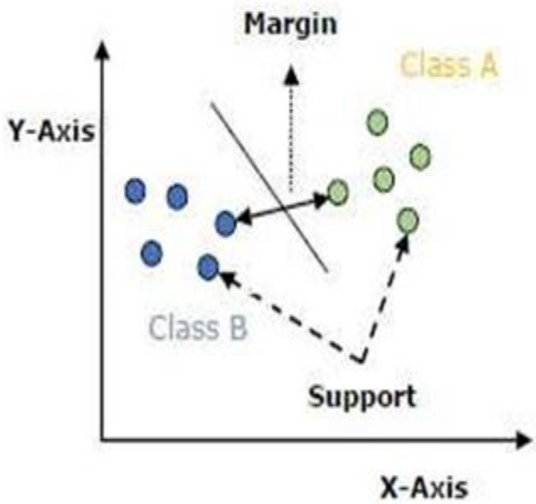

Fig 7. SVM Classification.

$$k(X,Xi)=1+sum(X*Xi)^\wedge d$$

Here d is the degree of polynomial, which we need to specify manually in the learning algorithm.

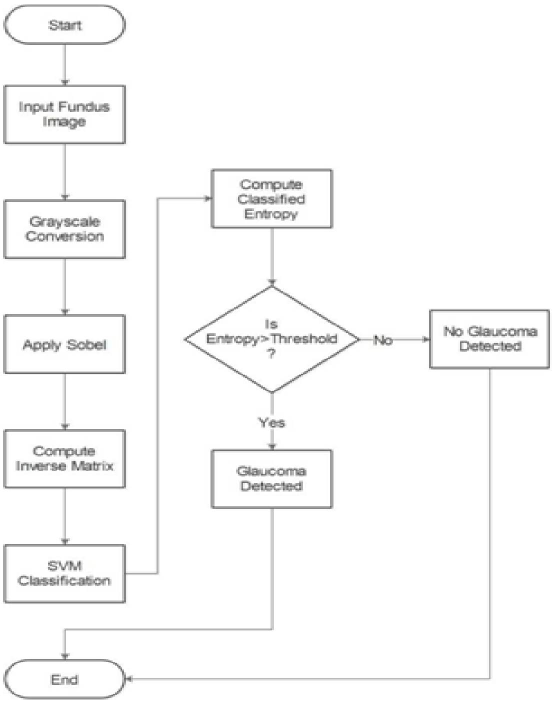

Fig 8. Flow Chart.

Flow chart represented the work flow model for managing Glaucoma detection from fundus images. First of all, a fundus image is to be imported for pre-processing such as grayscale conversion and sobel edge detection. Once the pre-processing has been done, SVM classification is to be used for clustering similar kinds of data in a particular class. Once the clustering has been done, entropy is calculated and if it is greater than the threshold value that means selected fundus image may contain impaired cells due to that glaucoma has been detected otherwise system declared it as a normal image.

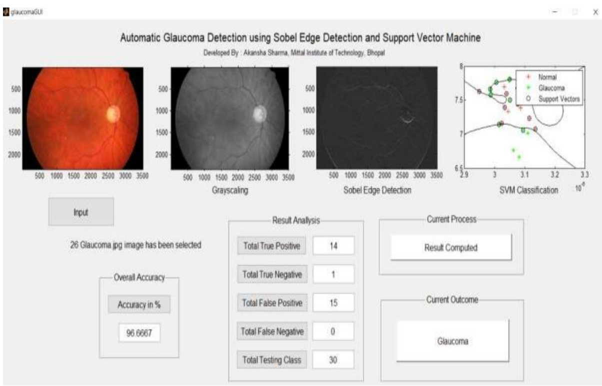

Fig 9. Proposed Work GUI.

1. Sobel & SVM Polynomial Kernel Algorithm

Input: I ← Input Fundus image as 2D array array Output: K ← Classified Glaucoma Cells
Step 1: Input 2-D image as an array

International Journal of Scientific Research & Engineering Trends
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Step 2: Convert RGB Fundus image into grayscale image
Step 3: Apply Sobel Edge Detection by gradient kernel operator mask Gx & Gy, where Gx is horizontal kernel mask & Gy as vertical kernel mask

+1 0 −1 +1 +2 +1
Gx = [+2 0 −2] * A, Gy = [0 0 0]* A
+1 0 −1 −1 −2 −1
G = JG2 + G2
s y

Step 4: Compute G-1
Step 5: Apply SVM by defining data points
(xn, yn)→ (x1, y1) (xn, yn)
Step 6: k(x, y) is a kernel function
k(x, y) = (xTy)2= (x1y1 + x2y2 + x3y3)23i,j=1xixjyiyj

Step 7: Classify Datapoints
Step 8: Compute Entropy
Step 9: if Entropy > Tr then
Glaucoma Detected;
else
No Glaucoma Detected;
end else end if
Step 10: End

V. RESULT ANALYSIS

The system has been tested with 30 OCT scanned fundus images of different patients that belong to infected traits or may not. System recorded 14 as true positive it means that there are 14 images contains glaucoma and system detected it positively and 1 as true negative that means there is an image contains glaucoma but system was not able to detect it. There are 15 tests are false positive where glaucoma has not been there and system didn't detect it as glaucoma and 0 as false negative. System acquired 96.66 % of accuracy with 3.34% of error rate.

Accuracy = TP+FP–(TN+FN) * 100 %TTC

Table 1. Result Analysis.

	Outcomes
True Positive	14
True Negative	1
False Positive	15
False Negative	0
Total Testing Class	30

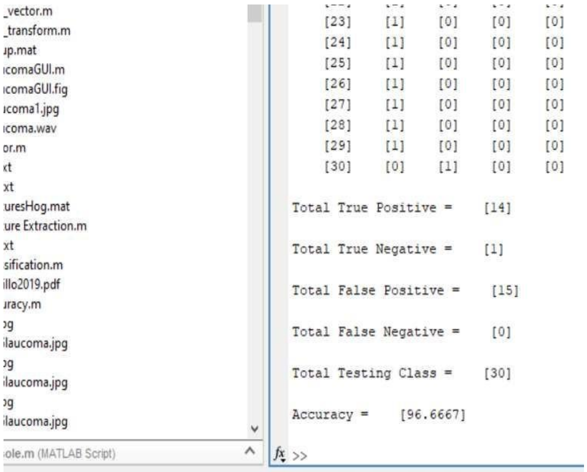

Fig 10. Console Result.

Fig 10. shows the result that has been obtained while testing with various samples.

Table 2. Result Comparison

Authors	Modality	Accuracy
Namita Sengar [3]	Gabor Filter & Segmentation by Thresholding	93.57%
Shwetha C. Shetty [5]	Fractal Analysis	92.00%
Juan Carrillo [6]	Background Subtraction using Segmentation by Thresholding	88.50%
Liu Li [7]	CNN	92.40%
Sertan Serte [9]	DNN	87.00%
Proposed	Sobel & SVM	96.66 %

VI. CONCLUSION & FUTURE SCOPE

Glaucoma detection is not an easy task for real world programs. Image processing tool can extract the severe information from various fundus optics and perform a diagnosis on the basis of that. It consumes less time and result is very effective. System effectively uses the Sobel operator and SVM classifier for classifying the glaucoma from various fundus imaging. System is able to classify the blood vessels and extract the impaired spot or cells that have been affected by glaucoma. If glaucoma can be detected timely then rest eye sight can be cured and defend the eyes from complete blindness. System achieved 96.66% of accuracy with no false acceptance rate. In future a classification method can be changed along with various pre-processing tools that can enhance the accuracy and save humans sight from the disease like glaucoma.

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