

## **A Novel Method to Improve the Detection of Glaucoma Disease Using Machine Learning**

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| Article History  | Abstract   |
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| Received: 22 January 2022<br>Revised: 14 April 2022<br>Accepted: 19 May 2022 | <p>Glaucoma is the subsequent driving reason for long-lasting visual impairment around the world. Early identification of glaucoma can restrict the infection movement. This infection is an asymptomatic neurological sickness. Early glaucomatous eyes and unusual seeming eyes that show no proof of sickness movement after some time (e.g., physiologic measuring). To stay away from obstruction, the veins are divided and prohibited toward the starting through in-painting. The cup division is more troublesome than the circle division because of the presence of high thickness vascular design in the district of the optic cup crossing the cup limit. So, this paper proposes the original technique to upgrade the exhibition of the cup division strategy by remembering a technique for vessel identification and vessel for painting. Likewise, machine learning procedures will be applied to find the reasonable boundaries in a few equations, including edge discovery approach and limit level set approach. Substitute elements of glaucoma from fundus picture and utilization of various classifiers for additional working on the presentation of the strategy. The trial examination has been completed as far as exactness, accuracy, review, F1 score, RMSE and Guide.</p> <p>Keywords: Glaucoma, segmentation, machine learning, edge detection, threshold level</p> |
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### **1 Introduction:**

Glaucoma is a corporate end for a composite extremist of conditions that have reformist visual pathology resulting sight misfortune. High measure of intra-visual tension is one of the significant peril parts of glaucoma infection. Accusative of present medicament gets to will be to lessen inside eyes to forestall primary human studies harm [1]. Through the estimation of suggestive value macular we can without much of a stretch identify typical, moderate and severer glaucoma. [2] There are different methodologies accessible for glaucoma diagnosis among which cup-to-plate proportion measurement is one of the significant fundamental psychological arguments for early determination of glaucoma. [3] This respective disease adjusts the retinal design. Diabetic maculopathy is the predominant reason for visual impairment all around the world like glaucoma and it is the repercussions of diabetes. Because of glaucoma optic cup shape enlarges and along these lines ophthalmologists can without much of a stretch distinguish glaucoma from fundus pictures. PC aided

diagnosis framework (computer aided design) is an office to the clinician's imprecise recognition of different sicknesses in less time. Vessel's extraction is a troublesome occupation since geometry, luminosity and reflectance qualities change from image to picture. In this manner vein division plays basic part in fundus pictures [4].

## 2 Literature review

Work [5] propose a strategy to compute the CDR consequently from no stereographic retinal fundus photos taken from a NIDEK AFC-230, which is a non-mydratic auto fundus camera. Creator [6] survey the connection between visual capability and macular ganglion cell complex (GCC) thickness estimated by Fourier-space optical lucidness tomography (OCT) and to assess the indicative worth of GCC thickness for recognizing early, moderate, and extreme glaucoma. Creator [7] form include space from heterogeneous information sources, i.e., retinal picture and eye screening information. An element choice structure is proposed by investigating various component positioning plans and a great many managed. Work [8] proposed an algorithm to automatically compute this accretion from the ultrasound images of the eye. Author [9] proposed CDR not entirely set in stone for both glaucoma impacted and typical fundus pictures. The strategy fizzles for a pictures because of the presence of different pathologies. The CDR esteem gives the movement about the illness. This approach can be further developed by some pre-handling steps [10].

## 3 Research Methodology:

In proposed method, the optic nerve image is taken as input which is specified to preprocessing stage to remove the unwanted noise, and then the preprocessed image is given as input of segmentation process based ROI segmentation the image is segmented. The segmented image is given to image scaling that can be calculated into disc diameter and cup diameter as CDR calculation then finally classification technique is used for classify the image as normal image and glaucoma image. The block diagram for this research proposal has been given below:

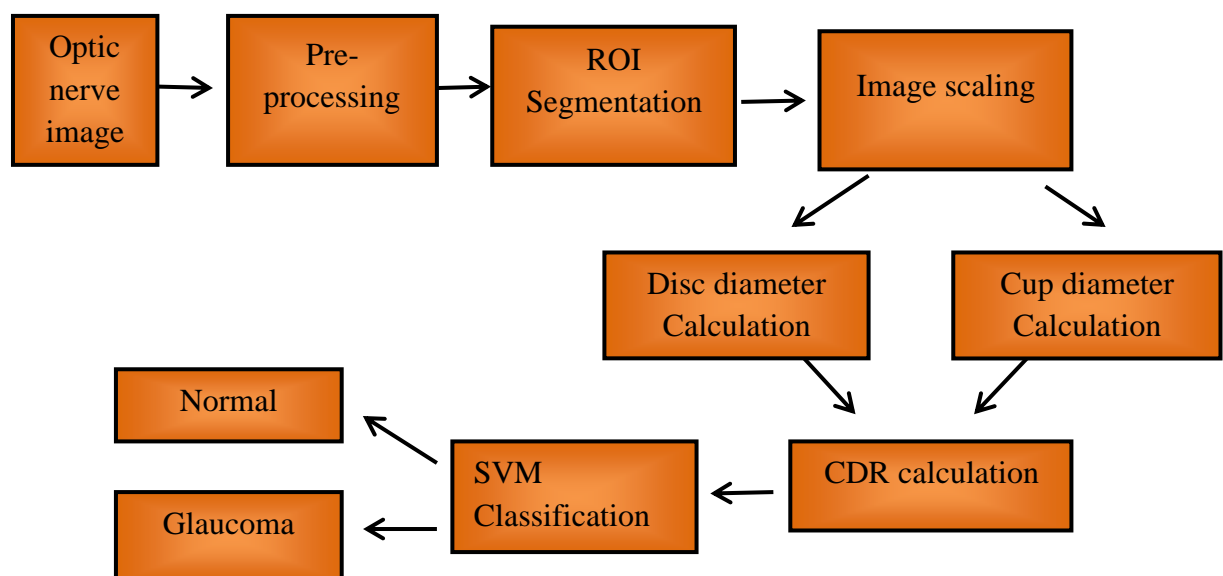


Figure-1proposed method

Since CDR is a significant pointer utilized for glaucoma location, this measurement is decided to assess our outcomes. The CDR is figured from the got cup and plate distance across from the picked technique. To assess the presentation of the methodology, the mistake E between the outcomes acquired from the robotized computation CDR Mechanized and the clinical ground truth CDR Facility is determined as:

$$E = \text{CDR Center} - \text{CDR Computerized}$$

The course of information implanting incorporates District of Interest (return for capital invested) division and pre-handling, trailed by implanting of the information into the return for money invested, and concealing the picture highlight bits behind the scenes. Commonly, a satellite picture comprises of a return for capital invested and a foundation. For the return on initial capital investment, it means a lot to upgrade the differentiation of the picture to plainly envision the subtleties more. For the foundation, the upgrade activity is pointless. Subsequently, a division activity is right off the bat performed to partition the picture into the return for capital invested and the foundation. For a given 8-digit dim scale picture  $H$ , the quantity of embraced top matches and the base pixel worth of the return on initial capital investment can be signified by  $M$  and  $RL$ , individually. All the pixel values inside are expanded by  $M$ , while those inside  $[256 - M, 255]$  are diminished by  $M$ . On the other hand, after the above interaction has been finished, visual disfigurement is completed as a pixel with an underlying worth  $L \in [1, MR]$  will become more brilliant contrasted with a pixel with an underlying worth  $L \in [MR, 255]$ . Consequently, a pixel with starting worth  $L \in [1, MR]$  is known as a turbulent pixel. Correspondingly, a pixel with an underlying worth of  $256 - M$  will be hazier contrasted with one with starting worth  $255 - M$ . To manage down this visual disfigurement, an improvement conspire is acted to decrease the quantity of turbulent pixels. The quantity of specific pinnacle matches to be extended,  $M$ , fulfills where  $RT$  is characterized as:

where indicates the ground surface capability. For a whole number the quantity of pixels inside separately, are counted up. At the point when the quantity of pixels in the span is least, it includes the base number of pixels in is viewed as the ideal  $p$ . The pixel values inside are expanded by  $M$ , by leaving out the initial sixteen pixels of the return for capital invested. The covering pixels inside the span are cluttered pixels. Since either the span has the base number of pixels, the quantity of pixels in the covering district is likewise a base. Also, the preprocessing of the return for capital invested pixels on the right-hand side is like the pre-handling of the return for capital invested pixels on the left-hand side. The pixel values inside the reach are diminished by  $M$ , by not thinking about the initial sixteen pixels of the return for capital invested. Moreover, taking into account the reclamation of the return on initial capital investment histogram at the less than desirable end, in the event that the stretch has the base number of pixels,  $p_0$  is expanded by  $RM$  as a sign. Further,  $q_0$  is expanded by  $RM$  as a sign if contains the base number of pixels.

where is the dropout dispersion. This outcome connotes that result of the model is acquired through Monte Carlo coordination over  $\tau$  stochastic results got through the model. Model vulnerability as caught by prescient difference is approximated as:

To inexact Bayesian deduction from RUnet, Dropout is utilized on every convolution layer (coming about design is named DRUnet). Subsequently, the model of the result at a specific emphasis is named as a stochastic result. For a test input is the model vulnerability. the result return for money invested division and model vulnerability are the mean and difference of  $\tau$  stochastic results.

SVM grouping is finished to recognize ordinary nerve picture and glaucoma nerve picture. Numerically talking, given a bunch of focuses  $x_i$  that have a place with two straightly divisible classes  $w_1, w_2$ , the distance of any case from the hyperplane is equivalent to SVM means to track down  $w, b$ , to such an extent that the worth of  $g(x)$  rises to 1 for the closest information directs having a place toward class  $w_1$  and - 1 for the closest ones of  $w_2$ . This can be seen as having an edge of

This prompts an enhancement issue that limits the goal capability dependent upon the limitation

At the point when an improvement issue — whether minimization or expansion — has imperatives in the factors being enhanced, the expense or mistake capability is expanded by adding to it the requirements, duplicated by the Lagrange multipliers. As such, the Lagrangian capability for SVM is framed by enlarging the goal capability with a weighted amount of the imperatives,

where  $w$  and  $b$  are called basic factors, and  $li$  's the Lagrange multipliers. These multipliers accordingly confine the arrangement's inquiry space to the arrangement of practical qualities, given the imperatives. Within the sight of disparity limitations, the Karush-Kuhn-Exhaust (KKT) conditions sum up the Lagrange multipliers. The KKT conditions are

The correlative slackness is the connection between the base and double definition: when added to imbalances, slack factors change them into uniformities. The double issue of SVM enhancement is to find

SVM is presently a delicate edge classifier; that is, SVM is characterizing the vast majority of the information accurately, while permitting the model to misclassify a couple of focuses nearby the isolating boundary. The issue in basic structure currently is a minimization of the goal capability

The regularization term or box imperative,  $C$ , is a boundary that shifts, contingent upon the improvement objective. As  $C$  is expanded, a more tight edge is gotten, and more accentuation is put on limiting the quantity of misclassifications. As  $C$  is diminished, more infringement are permitted, in light of the fact that amplifying the edge between the two classes turns into the SVM point.

#### 4 Performance analysis:

The presentation investigation of proposed strategy is outlined beneath. The boundary to be considered for assessment is exactness, accuracy, review, F1 score, RMSE and Guide. By utilizing U framework blunder pace of geographical mistake and afterward quantization blunder has been determined.

*Table- 1 Comparative analysis between proposed and existing technique based on Glaucoma dataset*

| Parameters | GCC | OCT | DGD_ML |
|------------|-----|-----|--------|
| Accuracy   | 85  | 89  | 96     |
| Precision  | 71  | 75  | 78     |
| Recall     | 55  | 59  | 61     |
| F1_Score   | 45  | 48  | 51     |
| RMSE       | 35  | 38  | 41     |
| MAP        | 42  | 44  | 46     |
| AUC        | 38  | 45  | 48     |

The above table-1 shows comparative analysis between proposed and existing technique based on Glaucoma dataset. Here the parametric analysis in terms of accuracy, precision, recall, F1 score, RMSE and MAP. Accuracy calculation is done by the general prediction capability of projected DL method. For calculating F-score, number of images processed are EEG signal for both existing and proposed technique. The F-score reveals each feature ability to discriminate independently from other features. For the first feature, a score is generated, and for the second feature, a different score is obtained. However, it says nothing about how the two elements work together. Here, calculating the F-score using exploitation has determined the prediction performance. It is created by looking at the harmonic component of recall and precision. If the calculated score is 1, it is considered excellent, whereas a score of 0 indicates poor performance. The actual negative rate is not taken into consideration by F-measures. The accuracy of a class is calculated by dividing the total items classified as belonging to positive class by number of true positives. Probability that a classification function will produce a true positive rate when present. It is also known by the acronym TP amount. In this context, recall is described as ratio of total number of components that genuinely fall into a positive class to several true positives. How well a method can recognise Positive samples is calculated by recall. Recall increases as more positive samples are determined. When training regression or time series models, RMSE is one of the most widely used metrics to gauge how

accurately our forecasting model predicts values compared to real or observed values. MSE squared root is used to calculate RMSE. The RMSE calculates the change in each pixel as a result of processing.

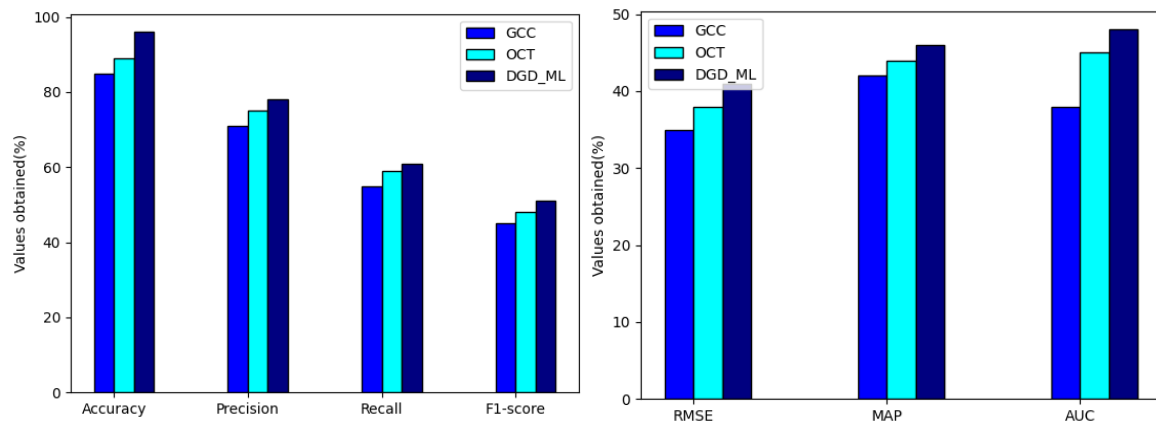


Figure 2: Overall comparison

From above figure 2 shows comparative analysis between proposed and existing technique. the proposed technique attained accuracy of 96%, precision of 78%, recall of 61%, F-1 score of 51%, RMSE of 41%, MAP of 46% and AUC of 48%. While the existing attained accuracy of 89%, precision of 75%, recall of 59%, F-1 score of 48%, RMSE of 38%, MAP of 44% and AUC of 45%.

## 5 Conclusion:

This research propose novel technique in enhance the presentation of the cup division strategy by remembering a technique for vessel recognition and vessel for painting. Alternate elements of glaucoma from fundus picture and utilization of various classifiers for additional working on the exhibition of the method. Comparing to cutting edge frameworks, the Nodular-Profound framework achieved huge higher outcomes. Subsequently, the Glaucoma-Profound framework can without much of a stretch perceive the glaucoma eye infection to take care of the issue of clinical specialists during eye-screening process for enormous scope conditions. The experimental analysis has been carried out in terms of accuracy, precision, recall, F1 score, RMSE and MAP. the proposed technique attained accuracy of 96%, precision of 78%, recall of 61%, F-1 score of 51%, RMSE of 41%, MAP of 46% and AUC of 48%.

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