Glaucoma Recogination Using Superpixel Classification and Artificial Neural Network

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Abstract
Glaucoma is an incurable eye disease which causes damage to the optic nerve and leads to progressive and irreversible loss of vision. So earlier detection of glaucoma is very important. The clinical examination of Cup Disc Ratio (CDR) could be a standard procedure used for glaucoma screening. But the recent existing methods are not sensitive enough for population based glaucoma screening.
The paper proposes an optic disc and optic cup segmentation using Simple Linear Iterative Clustering (SLIC) algorithm of super pixel classification. It automatically locates the optic cup and optic disc from retinal 2D fundus images. In optic disc segmentation, Center Surround Statistics (CSS) are used to classify each super pixel as disc or non-disc. In optic cup segmentation, in addition to the center surround statistics, the location information is also included into the feature space to increase the performance. ANN classifier with GDM (Gradient descent with momentum) algorithm is used to train the images. The segmented optic disc and optic cup are then used to compute the area and find the CDR for glaucoma screening. The result is further classified into glaucoma detected or not based on the CDR value. The results obtained show that the methodology successfully classifies the retinal image. The accuracy obtained was 99%, sensitivity was 99.6% and specificity was 99.2%. The ROC and confusion matrix was plotted from the analysis.

Keywords
Glaucoma Screening; Optic Cup Segmentation; Optic Disc Segmentation; Superpixel Generation

I. Introduction
GLAUCOMA is an incurable eye disease which damages the optic nerve. It is a major disease which causes blindness for people over 60 years, and is predicted to affect around 80 million people by 2020. The disease leads to loss of vision, gradually over a long period of time. As the symptoms only occur when the disease is quite advanced, glaucoma is called the silent thief of sight. As per the study, Glaucoma is incurable, but it can often be prevented with early treatment. Therefore, the detection of glaucoma in time is critical. However, most of the glaucoma patients are unaware of the disease until it has reached its advanced stage. In Singapore, more than 90% of patients are unaware of this disease and in Australia, about 50% of people with glaucoma are undiagnosed. Since glaucoma is a disease which shows only few signs or symptoms and also is too dangerous that it causes loss of vision forever, the detection of glaucoma among people at the preliminary stages is vital.
This paper focuses optic disc and optic cup segmentation using super pixel classification. It automatically locates the optic cup and optic disc from retinal 2D fundus images. Optic disc and optic cup are segmented by using feature extraction. ANN classifier with GDM (Gradient descent with momentum) algorithm is used to train the images. The segmented optic disc and optic cup are then used to compute the area and find the CDR for glaucoma screening. The result is further classified into glaucoma detected or not based on the CDR value.
This paper is structured as follows. Section II risk factors of glaucoma. Proposed work is presented in Section III. Section IV describes experimental results. Conclusion and future scope are discussed in Section V. Acknowledgment is drawn in Section VI.

II. Risk Factors of Glaucoma
Because chronic forms of glaucoma can destroy vision before any signs or symptoms are apparent, be aware of these factors:
(a) Elevated internal eye pressure (Intraocular pressure)- If your internal eye pressure (intraocular pressure) is higher than normal, you're at increased risk of developing glaucoma, though not everyone with elevated intraocular pressure develops the disease.
(b) Age- You're at a higher risk of glaucoma if you're older than age 60. You may be at higher risk of angle-closure glaucoma if you're older than age 40
(c) Medical conditions- Several conditions may increase your risk of developing glaucoma, including diabetes, heart diseases, high blood pressure and hypothyroidism.
(d) Other eye conditions- Severe eye injuries can cause increased eye pressure. Other eye conditions that could cause increased risk of glaucoma include eye tumors, retinal detachment, eye inflammation and lens dislocation. Certain types of eye surgery also may trigger glaucoma. Also, being near sighted or farsighted may increase your risk of developing glaucoma.
(e) Long-term corticosteroid use-Using corticosteroid medications, especially eye drops for a long period of time may increase your risk of developing secondary glaucoma.

III. Proposed Method
This paper put forward the SLIC algorithm for identifying the Glaucoma by segmentation on the basis of optic disk and optic cup. The input is the fundus image of Human retina where the generation of super pixel, optic cup and optic disk are used for the segmentation process is taking by using region based segmentation. ANN classifier classifies the images. The CDR (cup –to-disk ratio) value is being calculated by using the areas optic cup and optic disk through segmentation technique. If the value of CDR is greater than the threshold value Glaucoma is identified, otherwise it is normal.

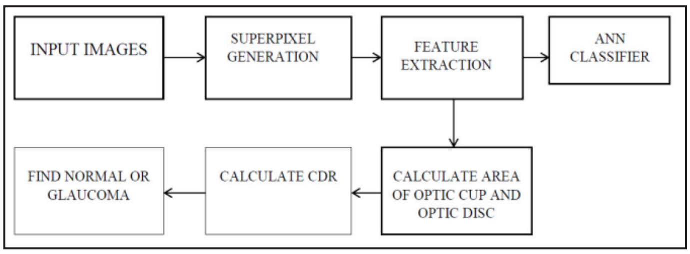

Fig. 1: Block Diagram

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A. OPTIC Disc Segmentation

In many computer aided glaucoma diagnosis systems segmentation of disc and cup are very important, The localization focuses on finding a disc pixel, very often the centre. Our work focuses on the segmentation problem and the disc is located by our earlier method ,which works well in our data set for glaucoma screening .The segmentation estimates the disc boundary, which is a challenging task due to blood vessel occlusions, pathological changes around disc, variable imaging conditions, etc. Some approaches have been proposed for disc segmentation, which can be generally classified as template based methods, deformable model based methods and pixel classification based methods.

Both the template and deformable model based methods are based on the edge characteristics. The performance of these methods very much depends on the differentiation of edges from the disc and other structures, especially the PPA [1]. The PPA region is often confused as part of disc for two reasons:

1) it looks similar to the disc

2) Its crescent shape makes it to form another ellipse (often stronger) together with the disc.

Deformable models are sensitive to poor initialization. To overcome the problem, a template based approach with PPA elimination is proposed. This method reduces the chance of mistaking PPA as part of the disc [2]. However, the approach does not work well when the PPA area is small, or when the texture is not significantly predominant.

Pixel classification based methods use various features such as intensity, texture, etc. from each pixel and its surroundings to find the disc. The number of pixels is high even at moderate resolutions, which makes the optimization on the level of pixels intractable. To overcome the limitations of pixel classification based methods and deformable model based methods, a super pixel classification based method and combine it with the deformable model based methods is used.

In the proposed method, super pixel classification is used for an initialization of disc boundary. The segmentation comprises: a super pixel generation step to divide the image into superpixels; a feature extraction step to compute features from each super pixel; a classification step to determine eachsuperpixel as a disc or non-disc super pixel to estimate the boundary.

B. Superpixel Generation

Many algorithms have been put forwarded for super pixel classification and they are proved to be useful in segmentation of images in various images of scene, human, animal, etc. In this paper it is used the simple linear iterative clustering algorithm (SLIC) to aggregate nearby pixels into super pixels in retinal fundus images. SLIC [4] is fast, memory efficient and has excellent boundary adherence when compared with other super pixel methods. It is also used with only one parameter, i.e., the number of desired super pixels. Here represents a brief introduction of the SLIC algorithm. In SLIC, initial cluster centers are sampled on a regular grid spaced by pixels apart from the image with pixels. In a neighborhood gradient position the centers are first moved. Then Clustering is applied. Based on color and spatial proximity, for each, SLIC repeatedly searches for its best matching pixel from the neighborhood around and then based on the found pixel computes the new cluster center. Until the distance between the new centers and previous ones is small enough, the iteration continues. Finally, to enforce connectivity, a post processing is applied. The PPA region seems to be close to the disc. Importantly features that reflect the difference between the PPA region and the disc region are to be included. Except for the texture, the super pixels from the two regions often appear similar: the PPA region contains blob like structures while the disc region is relatively more homogeneous. As the texture variation in the PPA region is often from a larger area than the super pixel, the histogram of each super pixel does not work well.

This is because the superpixel often contains a group of pixels with similar colours. Inspired by these observations, Kmeans clustering where all cluster centers must be compared with each pixel, this is the key to *speeding up the algorithm because the number of distance calculations can be reduced significantly by limiting the size of the search region significantly reduces, and results in a significant speed advantage over conventional [6]. In each pixel it is possible through the introduction of a distance measure D nearest cluster center Since the expected spatial extent of a super pixel is a region of approximate size and the search for similar pixel is done in a region around the super pixel center are S X S and 2S X 2S. Once, the nearest cluster center from associated with each pixel, an update step adjusts the cluster centers to be the mean [l a b x y] T vector of all the pixel s belonging to the cluster. They compute a residual error using L2 norm with two different location between the new cluster center location and previous cluster centre locations in E [10]. Similarly, reassigning disjoint pixel to nearby super pixels using post processing steps enforces connectivity.

C. Feature Extraction

Features from each super pixel is computed using feature extraction .Many features such as colour, appearance, location and texture can be extracted from super pixels classification, with this Centre surround statistics also computed for increase accuracy.

1. Center Surround Statistics

It is important to include features that reflect the difference between the PPA region and the disc region. The super pixels from the two regions often appear similar except for the texture: the PPA region contains blob-like structures while the disc region is relatively more homogeneous. The histogram of each super pixel does not work well as the texture variation in the PPA region is often from a larger area than the super pixel . This is because the super- pixel often consists of a group of pixels with similar colors. Inspired by these observations, centre surround statistics (CSS) [7] from super pixels as a texture feature can be included. To compute CSS, nine spatial scale dyadic pyramids are generated. The dyadic Gaussian pyramid is a hierarchy of low-pass filtered versions of an image channel, so that successive levels correspond to lower frequencies. It is accomplished by convolution with a linearly separable Gaussian filter and decimation by a factor of two. Then center surround operation between center (finer) levels and surround levels (coarser) is performed [8]. Denote the feature map in center level c as I(c) and the feature map in surround level s as I(s) and the interpolated map is denoted as I(c) , where, fs-c(I(s) denotes the interpolation from the surround level to the center level . The center surround difference is then computed as /I(c)-fs-c(I(s)/ .All the difference maps are resized to be the same size as the original. As we tend to delineated earlier, the PPA region appearance to be close to the disc. It is vital to incorporate features that reflect the distinction between the PPA region and the disc region. The histogram of each super pixel does not work well because the texture variation within the PPA region is often from a larger area than the super pixel [9]. This is because the super pixel often consists of a group of pixels with similar colours. Inspired by these observations, we tend to propose Center Surround Statistics (CSS) from super pixels as a texture feature. The Center Surround Statistics (CSS) consists of the

- Mean
- Variance

D. Optic Cup Segmentation

In 2-D images of fundus identifying the boundary of cup is a critical task without having depth information, because depth is important indicator of cup boundary. One landmark is used to determine cup region in 2-D fundus images is pallor [3]. It describes highest color contrast in inside area of the disc. The main challenge in cup segmentation is to determine the cup boundary when the pallor is nonobvious or weak. We present a super pixel classification based method for cup segmentation [5]. The procedure for the cup segmentation is similar to that for disc segmentation with some minor modifications.

E. Thresholding

Thresholding is very simple technique for image segmentation. From a gray scale image, thresholding can be used to create binary images. During the thresholding process, individual pixels in an image are marked as "object" pixels otherwise mark as the "background" pixels. This convention is known as threshold above. Variants include threshold below, which is opposite of threshold above; threshold inside, where a pixel is labeled "object" if its value is between two thresholds; and threshold outside, which is the opposite of threshold inside .Typically, an object pixel is given a value of “1” while a background pixel is given a value of “0.” Finally, a binary image is created by colouring each pixel white or black, depending on a pixel's labels.

F. CDR Calculation and Diagnosis

After obtaining the disc and cup, various features can be computed. The cup to disc ratio (CDR) compares the diameter of the cup portion of the optic disc with the total diameter of the optic disc. The hole represents the cup and the surrounding area the disc. Based on the segmented disc and cup boundary, we can calculate the disc area diameter and cup area diameter. Then the cup to disc ratio (CDR) is computed as

$$CDR = \text{Area of Cup}/\text{Area of Disc} \qquad (1)$$

The computed CDR is used for glaucoma screening. When CDR is greater than a threshold, it is glaucomatous, otherwise it will be considered as a healthy one. Here the threshold is taken as 0.45 by referring many papers as the same database used. Generally, the normal cup to disc ratio (CDR) is 0.45. The cup to disc ratio is above 0.45, then it suggests glaucomatous, otherwise normal.

G. Artificial Neural Network

An artificial neural network (ANN) is a computational model based on the structure and functions of biological neural networks. These are generally presented as systems of interconnected "neurons" which can compute values from inputs, and are capable of machine learning. ANN is also called as neural network processor made up of simple processing units which have natural propensity for storing experiential knowledge and making it available for use. Its working is similar to brain in two ways [12]. First, Knowledge is acquired by the Network from its surroundings through a learning process. Second, Interneuron link strength is used to store acquired knowledge. The word network in 'artificial neural network' refers to the inter–connections between the neurons in the different layers of each system. Figure shows a neural network.

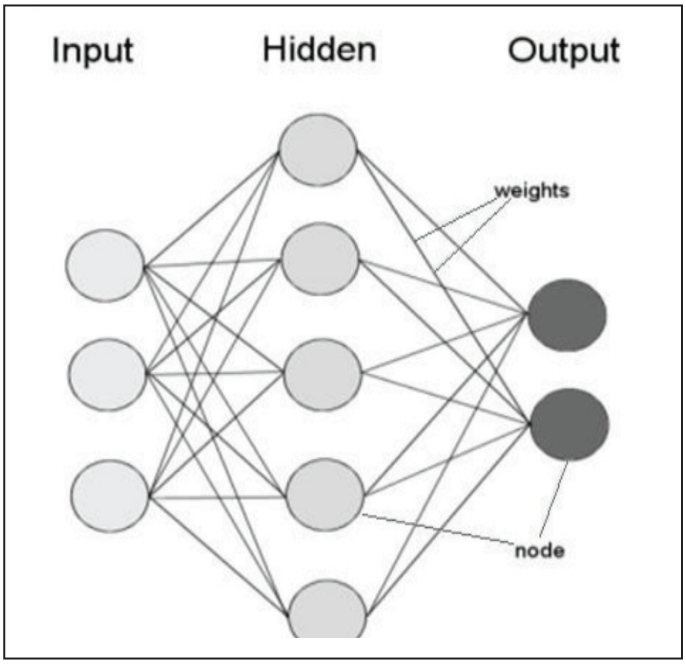

Fig. 2: Artificial Neural Network (ANN)

1. Learning Algorithm for ANN

The learning (or training) for ANN is not simply a matter of memorizing the mapping relationship between the inputs and outputs among the learning samples, but of extracting the internal rules about the environment which are hidden in the sample by learning the finite sample data. Up to now, there are many learning algorithm of neural networks among which are error back-propagation algorithm (BP algorithm) and its various improved patterns are most 26 extensively and effectively applied. MLP model which adopts the BP algorithm is generally called a BP network, and its learning process is made up of two parts: forward-propagation of input information and error back-propagation. Forward-propagation input information is transferred to the output layer from the input layer after being processed in the hidden layer. The state of each layer neuron influences only the state of neurons in the next layer. If it does not obtain the expected output in the output layer, it shifts to back-propagation, and error signals are shown along the original pathway of the neural connection, in return the connection weight of each layer is modified one by one. Through successive iterations, the error between the expected output signals of the network and practical output signals of the system reaches an allowable range. A learning algorithm for an ANN is often related to a certain function approximation algorithms, especially to some iterative algorithms that make the approximation error gradually smaller. In fact, the above-mentioned BP algorithm corresponds to gradient descent algorithms; such as gradient descent, gradient descent with momentum and gradient descent with adaptive learning rate in function approximation. Once this principle is known, it can construct various learning algorithms for neural networks according to different function approximation algorithms. In that Gradient Descent with Momentum back propagation (GDM) is used.

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(i). Gradient Descent with Momentum Back Propagation

GDM allows a network not only to respond to the local gradient, but also to track recent trends in the error surface. It acts like a low pass filter, a momentum α which allows the network to disregard small features in the error surface [16]. Without 17 momentum a network can get stuck whereas, with momentum a network can slide through such a minimum. GDM depends on two 27 training parameters. The parameter learning rate is similar to the simple gradient descent. The parameter momentum is the momentum constant that defines the amount of momentum, as in Equation

$$\Delta wij(r) = \eta .\delta j .xij + \alpha . \Delta wij(r-1) \qquad (2)$$

Where α is the momentum parameter and r is iteration. The methodology used in this study briefly involves the following steps

Where α is the momentum parameter and r is iteration. The methodology used in this study briefly involves the following steps

1. The first step is data selection which will be deliberated in the network simulation
2. The pre-processing procedure which is used to remove the inconsistencies of the data
3. The data partition that segregates the data into 2 parts; training and testing
4. Network model topology which maps the interconnection between nodes and selection of network structure, which entail the number of input output nodes, hidden nodes and transfer function. Here used main performance method is mean square error. The input layer is 1, output layer is 1, hidden layer is 2 and number of neuron in hidden layer is 50.
5. Training of the network which considers the experiments being made in order to validate the proposed network model by using the back-propagation algorithm. Training stops when any of these conditions occurs:
    - The maximum number of epochs (repetitions) is reached.
    - The maximum amount of time is exceeded.
    - Performance is minimized to the goal.
    - The performance gradient falls below min_grad. 28
    - Validation performance has increased more thanmax_ fail times since the last time it decreased (when using validation).
6. Model selection which entails the method of model selection based on overall performance.

IV. Experimental Results

An online database with retinal fundus images has been developed in order to be a reference for the design of optic nerve head segmentation algorithms. Here used RIM-ONE data set [15]. RIMONE is exclusively focused on ONH segmentation; it has a relatively large amount of high-resolution images 138.

Image acquisition

Database is available online at rimone.isaatc.ull.es and it can be used for research and educational purposes, without requesting permission to the authors. The camera used to capture these images is a fundus camera Nidek AFC-210 with a body of a Canon EOS 5D Mark II of 21.1 megapixels.

The images are classified in different subsets, as domain experts have indicated: • Normal eye (non-glaucomatous): 99 images. • Glaucomatous: 39 images. .

This image set was designed in collaboration with glaucoma domain experts of these hospitals: 5 Ophthalmologists and 1 optometrist. They selected the patients (for glaucoma samples) and the volunteers (for healthy eyes samples), the final image set and the associated diagnosis. All of the studied subjects were selected arbitrarily and do not belong to longitudinal cases. The database does not provide further clinical information about the imaged subjects because this information was not relevant to the segmentation of the ONH. 30. The database is stored in a zip file, divided in 2 directories, according to the 2 diagnostic categories in which images are classified. These directories are: Normal and Glaucoma

This experiment is conducted on MATLAB on a machine with 2.10 GHz core i3 2310M processor and 4 GB RAM.

Output Image

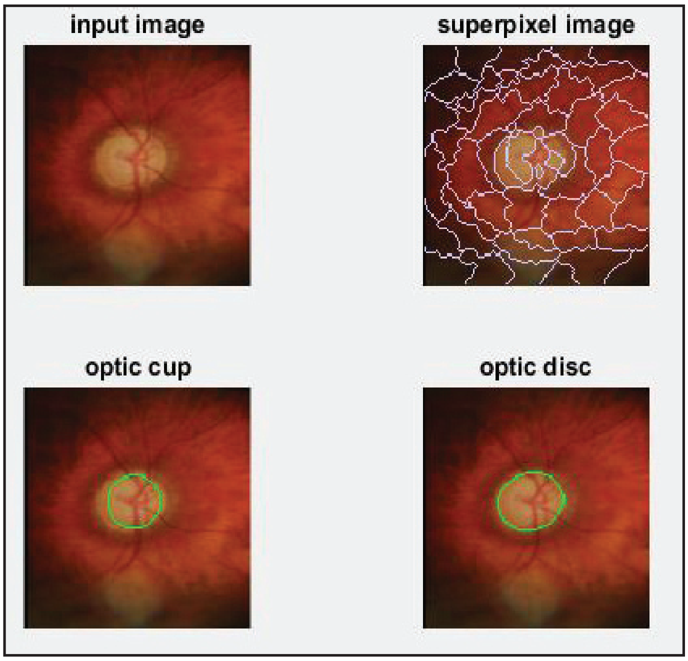

Fig. 3: Output images, 1- input image, 2- superpixel generated in input image, 3-optic cup segmented, 4- optic disc segmented

Accuracy obtained around 99%

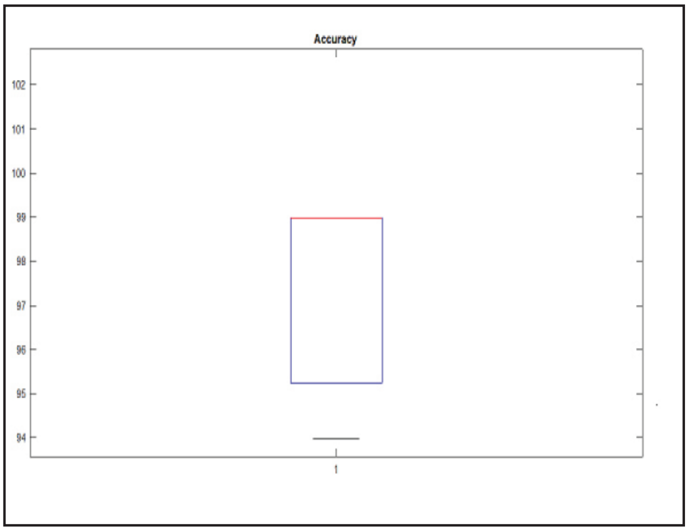

Fig. 4: Box Plot of Accuracy

Confusion Matrix

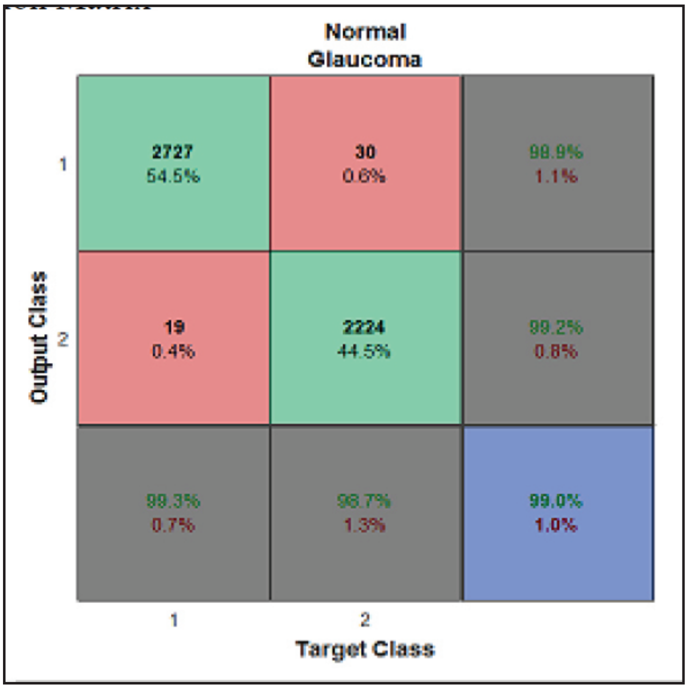

Fig. 5: Confusion Matrix (ANN Classification)

ROC Plot

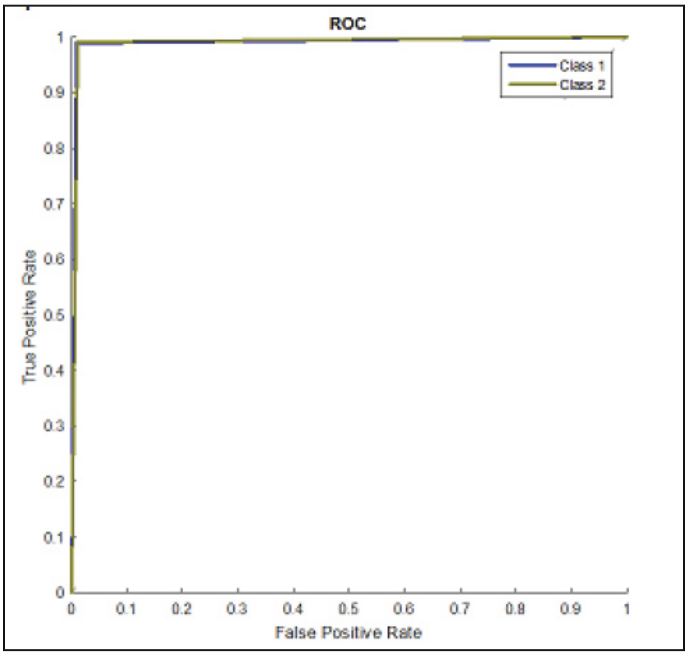

Fig. 6: ROC Plot

Table 1: Performance Analysis of ANN Classifier

Performance Parameters	ANN Classifier
Specificity	99.2%
Sensitivity	99.9%
Accuracy of classification	99%

V. Conclusion and Future Scope

This paper is presenting the SLIC technique for identification of the Glaucoma which is the main causes for the blindness. The treatment of the Glaucoma is not easy but the prevention is a main step for avoiding this diseases so earlier detection is most important. This paper is based on super pixel generation for which SLIC algorithm is used. SLIC algorithm a is fastest one among super pixel generation. This is used as preprocessing part also. The SLIC algorithm is providing a better way to identify the Glaucoma symptoms before affecting the eye. For identifying the Glaucoma, the Super Pixel and Disk-cup segmentation process are required. The Super Pixel is generating the image as per the required number of pixels. The superpixel image is being transformed segmentation process, where the image is separated by the background surface by extracting features by CSS method and classify by using ANN classifier. Through this process Optic disk and Optic cup segmented. The segmentation process is generating the Cup to Disk Ratio (CDR). Using optic Cup and Disk value we can find the Cup to Disk Ratio (CDR). The CDR value is representing the Glaucoma existence in the eye. If the CDR ratio is greater than or equal to threshold, Glaucoma detected and the less than threshold is representing that normal patient. In future, this paper is extended to classify what type of glaucoma and different stages of glaucoma.

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