

Comparitive Study of Glucoma Detection using Different Classifiers

Priya Singh,

PG Student, Department of EXTC

Thakur College of Engineering and Technology, Mumbai, India

Bijith Marakarkandy,

Associate Professor, Department of Information Technology

Thakur College of Engineering and Technology, Mumbai, India

ABSTRACT

The Glaucoma is a condition of eye disease of optic nerve, in which the nerve cells in front of the optic nerve die and sometimes it results in blindness. The two techniques to diagnose glaucoma are optical coherence tomography (OCT) and heidelberg retinal tomography (HRT) are very expensive. The early detection of glaucoma is major key to start proper treatment and to reduce the irreversible visual field loss. This Paper proposes a new method to diagnose glaucoma using digital fundus image. The best method is to involve image processing and Image classification techniques for early diagnosis of glaucoma. Image classifiers such as support vector machine (SVM), K-Nearest Neighbor (KNN), and Bayesian for Image Classification are used here. All these classification techniques are implemented in Matlab 2016. The classification accuracy for SVM, KNN and Bayesian are 97%, 92% and 89% respectively. A batch of High Resolution Fundus (HRF) image database obtained from the Technische Fakultat is used to assess the performance of proposed system and best classification rate with SVM of 97% is achieved.

KEYWORDS

Support Vector Machine (SVM), K-Nearest neighbor (KNN), Bayesian Classification, Intraocular pressure (IOP),

INTRODUCTION

In our human body, eyes with which we see the world are most delicate and sensitive organ. Glaucoma is a condition of eye disease of optic nerve, in which the nerve cells in front of the optic nerve die and sometimes it results in blindness. The fluid which is always found in eye is called aqueous and it has stable pressure called as intraocular pressure (IOP). This fluid is continuously formed within the eye and is also simultaneously drained out to maintain a stable IOP. IOP is increased due to the blockage of the normal outflow mechanism. This situation damages the optic nerve of the eye. This fluid is continuously formed within the eye and is also simultaneously drained out to maintain a stable in IOP. IOP is increased due to the blockage of the Normal outflow mechanism. This situation damages the optic nerve of the eye. It was previously assumed that glaucoma was almost always due to increased intraocular pressure but this can occur with normal and even low eye pressure in patient. Therefore now key for diagnosis of glaucoma is damage to optic nerve. Glaucoma is the diagnosis given to a group of ocular conditions that contribute to the loss of retinal nerve fibers with a corresponding loss of vision.

Glaucoma therefore is a disease of the optic nerve, the nerve bundle which connects the eye to the brain and relays the visual signal. As lost capabilities of the optic nerve cannot be recovered, it is necessary to detect glaucoma at an early stage.

Thus early detection followed by the treatment is the key to preventing vision loss from glaucoma. The need for early glaucoma detection is due to the facts:

1) No noticeable symptoms in its early stages

- 2) Damage caused by it is irreversible
- 3) Leads to permanent loss of vision if not treated on time.

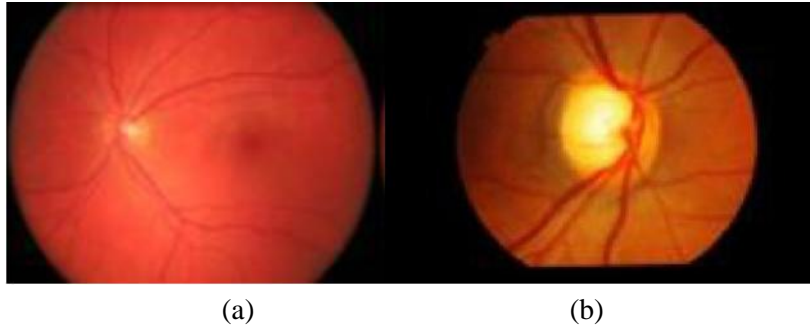


Figure 1 Standard fundus images (a) normal (b) glaucoma.

Subsequent treatment is essential for affected patients to preserve their vision. Manual analysis of the eye is time consuming and the accuracy of the parameter measurements also varies with different clinicians. Now, the classifier can distinguish between a normal eye fundus and a glaucoma affected eye fundus up to a certain level of accuracy.

The method such as Optical Coherence Tomography (OCT) and Heidelberg Retinal Tomography (HRT) are used in glaucoma detection but the cost of these methods are very expensive. As an alternative, many ophthalmologists use fundus cameras to diagnose glaucoma. Image processing techniques allow extracting the features that can provide useful information to diagnose glaucoma.

This paper presents a novel method for to detect glaucoma using digital fundus images. At first stage, the images of fundus eye are pre-processed. Then, Feature extraction technique is used in which R (Red), G (Green), B (Blue) value of images is found and feature vectors are created. The creation of data sets are used to categories the different class. After Feature extraction technique, the modified images are fed into various classifiers techniques such as SVM, KNN and Bayes. Using Graphical user Interface (GUI) it integrated with Matlab and used for finding different classifiers output. Accuracy of all classifiers is calculated using confusion matrix and displayed using GUI.

II. Literature Survey

Several of the techniques used in prior research are utilized for the experiments are described in this chapter.

Atheesan S., Yashothara S. published a paper on Automated Glaucoma Detection using Fundoscopic Images. This paper presents a detailed analysis on an automatic system to identify glaucoma disease from fundoscopic images using digital image processing. Here glaucoma is identified through cup (optic disc's inner circle) to disc (outer circle) ratio (CDR) calculation and by the orientation of the blood vessels. If the CDR value is between 0.0 and 0.3, then image is normal and if it is greater than 0.3, then it is glaucomatous. Blood vessel orientation is identified by the distribution of the extracted blood vessels in four equal quarter circles. If most of the blood vessels are belonged to only one or two quarter circles then it is advanced glaucomatous and if the blood vessels spread into three or all four quarter circles, then it is early glaucomatous or normal.

Abhishek Dey and Samir K. Bandyopadhyay have come out with a paper on Automated glaucoma selection using support vector classification method. Images pre-processing techniques such as noise removal and contrast enhancement, Principal Component Analysis (PCA) method for feature extraction and Support Vector Machine (SVM) method for image classification are used in the proposed method. In our work, after cross validation trained SVM classifier has accuracy rate 96%, sensitivity 100%, specificity 92%, positive predictive accuracy 92.59% and negative predictive accuracy 100%.

Annapoorani R, Karthik R have presented paper Classification of glaucoma using fundus image. The types of glaucoma disease is identified using the bayesian classifier and SVM classifier are compared and studied

using existing logic based image processing architecture has been verified and designed by using LabVIEW system and the Vision Development Module. This could be an effective and the efficient image processing based logic implementation for the DCT based image classification.

Kartikeyan Sakthivel, Rengarajan Narayanan have proposed the work on an automated Glaucoma detection using Histogram features. In this paper, a novel method is proposed for the early detection of glaucoma using a combination of magnitude and phase features from the digital fundus images. Local binary patterns (LBP) and Daugman's algorithm are used to perform the feature set extraction. The performance of the proposed method is compared with the higher order spectra (HOS) features in terms of sensitivity, specificity, classification accuracy and execution time. The proposed system results 95.45% output for sensitivity, specificity and classification.

Shishir Maheshwari, Ram Bilas Pachori, and U. Rajendra Acharya have published paper on automated diagnosis of glaucoma using empirical wavelet transform and correntropy features from fundus images. To decompose the image and correntropy features are obtained from decomposed EWT components EWT is used. These extracted features are ranked based on t value feature selection algorithm. Then, these features are used for the classification of normal and glaucoma images using Least Squares Support Vector Machine (LS-SVM) classifier. The LS-SVM is involved for classification with Radial Basis Function (RBF), Morlet wavelet and Mexican-hat wavelet kernels. The classification accuracy of proposed method is 98.33% and 96.67% using three-fold and ten-fold cross validation respectively.

Yuchao Ma, Ramin Fallahzadeh, and Hassan Ghasemzadeh, have come out with the work named as Glaucoma- Specific gait pattern assessment Using body worn sensors. We perform machine learning algorithms to distinguish glaucoma patients from healthy controls, and identify several prominent features with high discriminability between the two groups. The results indicate that classification algorithms can be used to identify gait patterns of glaucoma patients with accuracy higher than 94% in a 10-meter-walk test. Our results demonstrated that there are prominent features in gait patterns which yield significant differences between glaucoma patients and healthy controls ($p < 0.001$).

Javeria Ayub, Jamil Ahmad, Jan Muhammad, Lubna Aziz, Sara Ayub have published paper on Glaucoma detection through optic disc and cup segmentation using k-mean clustering. Region of interest (ROI) extraction through intensity weighted centroid method which is followed by preprocessing and recursively applied k-mean clustering segmentation for the detection of Optic cup (OC) and optic disc (OD). Ellipse fitting is implied for boundary smoothening of OC and OD. Performance of the proposed technique is assessed on 100 fundus images collected locally. Proposed approach gives an accuracy of 92% for glaucoma and Mean square error of 0.002 for CDR.

III. Proposed Methodology

The Figure 1 shows the block diagram of the proposed system for the detection of glaucoma. The various stages in my proposed method i.e. image pre- processing; feature extraction and image classification are detailed in the following section.

A. Data Acquisition

One important requirement of the classification systems is to have enough amounts of the required data. That is at least 10 times more the data used for training. In this study I have used databases which are public. The proposed method has been applied on these public databases. These Public databases are obtained from Technische Fakultät and are available online publicly at <http://www.tf.fau.de/>. It consists of 110 normal and 110 glaucoma images. The images are stored in JPG file format at various resolutions.

B. Feature Extraction

In order to classify the fundus images, the first step is feature extraction. This paper is based on the impact of feature on the classification here two types of training data set are prepared. The first training data set consists of the R (Red), G (Green), B (Blue) color features of each pixels which shows i.e. normal image of eye. The second training data set consists of R (Red), G (Green), B (Blue) color features of each pixels glaucoma

image. The training pixels are collected from the different regions of the image for the specific class and that class is assigned by the unique value. Based on the features of known classes the Training vectors are trained. During testing when the features are provided for pixels which are not having the classes then it will give the class based on their learning. The vectors are then further used for finding accuracy.

C. Pre-Processing

The retinal images which are acquired with a digital fundus camera that captures the illumination reflected from the retinal surface. In these images many retinal images suffer from non-uniform illumination given by several factors. The curved surfaces of retina, pupil dilation or presence of disease among others are some factors. Here camera leads to a poorly illuminated peripheral part of the retina with respect to the central part. Pre Processing is major step taken for image processing task. Pre- processing can help to improve the performance of image processing methods such as Feature extraction, Image segmentation, and image transform and disease selection. These are the several techniques have been used to enhance retinal images. Preprocessing also remove disease independent variations from the input image.

In our proposed method, 110 digital eye fundus images are taken for training the SVM classifier and other classifiers also. This paper also suggests that instead of preprocessing some particular regions of images, entire images are preprocessed before feature extraction and image classification task.

D. Classification Algorithm

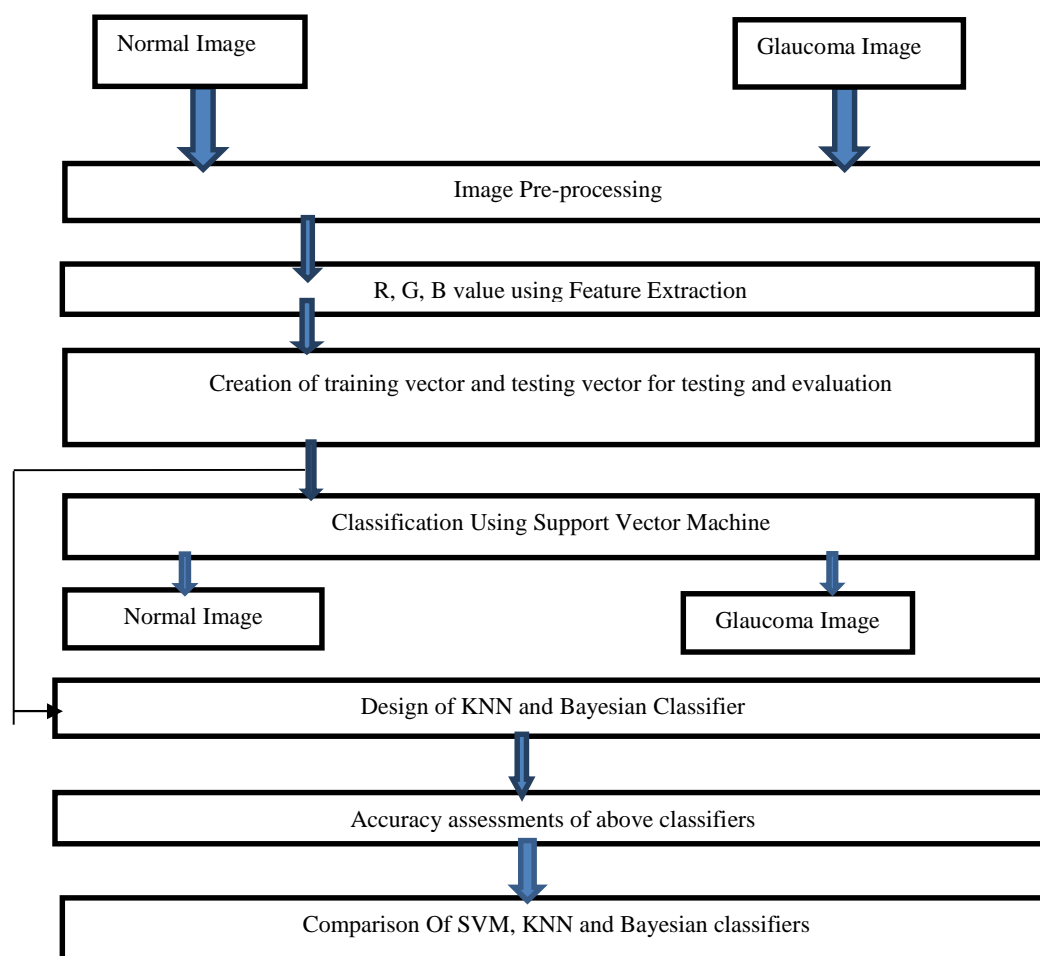


Figure 2Flow Chart of methodology

Classification is technique of grouping different object into similar classes which consist of similar features. Classification can be done for both data and the images. Usually classification involves three parts namely

training testing and validation. In training period, properties of the features are separated and based on this training class is created. Finally in testing period, these feature space partitions are being used to classify the features. The required information can be retrieved by classifying the things into distinct classes without consuming much time. The purpose of classification is to help the readers and its idea is to reduce the complication of search for those who seek the information. There are basically two types of classification techniques are available which are called as supervised and unsupervised classification. In supervised classification at the initial stage the trainer knows about the classes i.e. what are the features which are belongs to different classes whereas the things are opposite in the case of unsupervised classification where the features are classified into different classes based on its feature similarity. So, classes in unsupervised classification are called as cluster. So the tools which do the classification are known as classifiers. Some of the classifiers are K Nearest Neighbor (KNN), Bayesian and Support Vector Machines (SVMs). Here three types of supervised classification techniques are adopted and combined to improve accuracy of the classifier which is in Fig 2:

i) Support Vector Machine (SVM):

Support Vector Machine is a linear classifier which is also called as binary classifier. It is very strong compared to the other classifiers because of its simple structure and it needs less number of features. Some of the basic definitions involved in SVM are hyper plane, Margin and Support vectors.

- Hyper plane: It is a line which separates D dimensional space into two half classes. Hyper plane is given by the Equation 3.1

$$wx + b = 0 \dots\dots\dots (3.1)$$

Where w is the weight vector which represents the orientation of the hyper plane.

b is the bias term which represents the position of the hyper plane.

x is the input feature vector.

- Margin: It is the distance between the support vectors of each class. It is given by the Equation (3.2)

$$M = \frac{2}{|w|} \dots\dots\dots (3.2)$$

- Support vectors: Support vectors are the points on the margin which are necessary for finding the hyper plane. These are determined by finding the distance between each pair of the classes. The position of the support vectors depends on these support vectors. The removal of other samples in the training set will not alter the position but, if the support vectors are removed, the position of the hyper plane will differ. SVM design is greatly influenced by the position of the hyper plane.

SVM is designed to separate a set of training images into two different classes, $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ where x_i in R^d , d -dimensional feature space, and y_i in $\{-1, +1\}$, the class label, with $i=1..n$. SVM builds the optimal separating hyper planes based on a kernel function (K). All images, of which feature vector lies on one side of the hyper plane, belong to class -1 and the others are belong to class +1

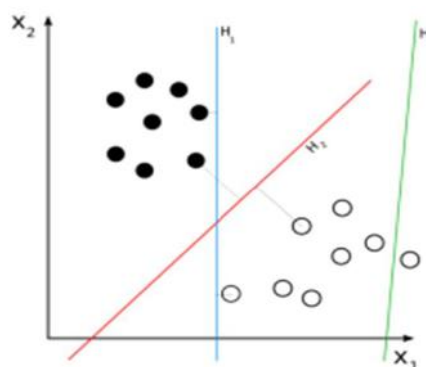


Figure III-3 Separating hyper planes between two classes

As we can see from Fig. 3-1, H3 does not separate the two classes while H1 separates the two classes with a small margin, only H2 gives a maximum margin between two classes, therefore it's the right hyper plane used by support vector machine. If the data of various classes can be separated as in Fig. 3-1, then the linear SVM is used. Otherwise if the data of the classes cannot be separated, then the non-linear SVM classifier is used. However, instead of defining a function for the hyper plane itself; we define the margin in between the two classes. From Fig 3-2., we can see that the position of our hyper plane depends on the value of w where w is the (not necessarily normalized) normal vector to the hyper plane. More formally, linear SVM classifier function can be defined as,

$$f(x) = w^T x + b \dots \dots \dots (3.3)$$

Such that for each training sample x_i the function gives $f(x_i) > 0$ for $y_i = +1$, and $f(x_i) < 0$ for $y_i = -1$. In other words, training samples of two different classes are separated by the hyperplane $f(x) = w^T x + b = 0$, where w is weight vector and normal to hyperplane, b is bias or threshold and x_i is the data point. The nonlinear SVM classifier is defined as,

$$f(x) = w^T \phi(x) + b \dots \dots \dots (3.4)$$

The transformation from non-linear to linear separating hyperplane in higher dimensional feature space is done by taking help of kernel functions. A kernel function on two samples, represented as feature vectors in some input space, is defined as

$$k(x_i, x_j) = \phi(x_i)^T \phi(x_j), \dots \dots \dots (3.5)$$

is the feature vector.

Most commonly used kernels are

$$\text{Linear kernel: } k(x_i, x_j) = x_i^T x_j \dots \dots \dots (3.6)$$

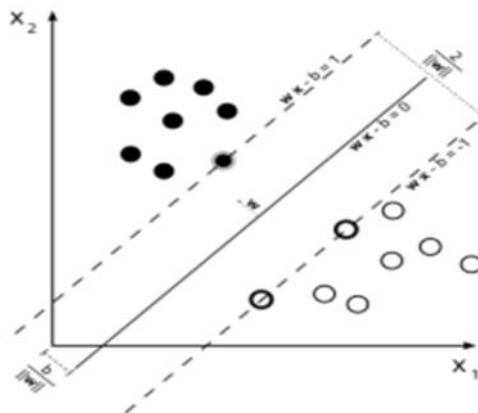


Figure III-4 Maximum-margin hyper plane and margins for an SVM trained with samples from two classes

SVM is a binary linear classifier but it can be extended for multiclass problems also. However, our problem is a two class prediction problem where normal healthy eye fundus images will belong to one class (say positive class) and glaucoma affected eye fundus images will belong to another class (say negative class).

ii) K-Nearest Neighbor (KNN):

KNN is a simple classification method with good accuracy. It depends on the majority vote of the k -nearest neighbor classes. Thus the result can be considered as the best fit class for that point. For example if $k = 5$, the algorithm will take a call of its 5 nearest neighbor. Consider the figure (3-3 a) here the point X belongs to class 3. If $k = 5$ as in figure (3-3 b) the point X belongs to class 1 because of the majority vote from the five nearest points. Euclidean distance is the parameter used to determine the distance between the target point and cases from the example classes.

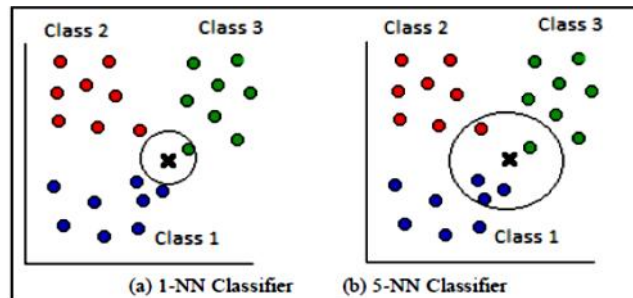


Figure 3-3 K Neighbor Classification

The KNN is one of the very basic and easy classification technique is available for the classification. It is supervised classification technique which is not complex like other classification techniques *i.e.* ANN, SVM, Random forest etc. This algorithm simply creates and uses the different instances created from the training data dataset and these instances are used to classify the testing datasets into different classes. The KNN classification techniques never create the internal model like other classifiers such as ANN and SVM etc. Therefore it is very simply to implement and provides the fast processing of the data.

iii) Bayesian classification Method

Bayesian classifiers are popular statistical classifiers and the Bayesian classification is done via Bayes' theorem. Membership probabilities of a Class including the probability of a specific class to which a given tuple belongs can be predicted by Bayesian classifiers.

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)} \dots \dots \dots (3.7)$$

Where $P(c|x)$ = Posterior Probability

$P(x|c)$ = likelihood

$P(c)$ = class prior probability

$P(x)$ = Predictor prior Probability

$$P(c|x) = p(x_1|c) * p(x_2|c) * \dots * p(x_n|c) \dots \dots \dots (3.8)$$

In classification of statistical the Bayes classifier minimizes the probability of misclassification. Suppose a pair (X, Y) takes values in $R^d \times \{1, 2, \dots, K\}$, where Y is the class label of X . This means that the conditional distribution of X , given that the label Y takes the value r is given by

$$X|Y = r \sim P_r \quad \text{for } r = 1, 2, \dots, K \dots \dots \dots (3.9)$$

Where “ \sim ” means “is distributed as”, and

P_r Denotes a probability distribution

A classifier is a rule that assigns to an observation $X=x$ a estimate of what the unobserved label $Y=r$ actually was. In theoretical terms, a classifier is a measurable function $C: \rightarrow \{1, 2, \dots, K\}$, with the interpretation that C classifies the point x to the class $C(x)$. The probability of misclassification, or we can say risk, of a classifier C is defined as

$$R(c) = P\{c(X) \neq Y\} \dots \dots \dots (3.10)$$

The Bayes classifier is

$$C^B(x) = \arg \max_{r \in \{1, 2, \dots, K\}} P(Y = r | X = x) \dots \dots \dots (3.11)$$

Where r is $\{1, 2, \dots, K\}$

In practice, as in most of statistics, the difficulties and subtleties are associated with modeling the probability distributions effectively—in this case, $P(Y=r | X=x)$. The Bayes classifier is a useful benchmark in statistical classification. The excess risk of a general classifier C (possibly depending on some training data) is defined as $R(C) - R(C^B)$. Thus this non-negative quantity is important for assessing the performance of different

classification technique. When training data size attains infinity, excess risk concurs to zero. This state of classifier is known to be consistent.

IV. Experimental Results

The proposed algorithm is tested on 15 normal fundus images and 15 glaucoma affected images are obtained from glaucoma patients. In my proposed method for all images preprocessing, feature extraction and classification techniques are simulated in Matlab R2016. These images are preprocessed in multiple but series of stages as described in III section. Then these preprocessed images are modified by feature extraction. After this, these modified images are fed into classifier known for purpose of training. After getting training vector classification is done in to different classes. The training vectors which are from the first set of samples are given as class1 or called as glaucoma image are and the training vectors which are found from second samples of set are given as Class 2 or called as normal image. After separation of classes the classification of images are obtained. The KNN classifier classify data using nearest neighbour method .It uses testing label and training vector and group to calculate accuracy. In Bayes classifier, normal Gaussian distribution is used to fit or model the feature base and it calculates prior probabilities from the relative frequencies of the classes in training. In SVM classifier, linear kernel is used to map the training data into kernel space. It can also be enhanced using other kernel function. Further validation process is done and accuracy rate is found. The Confusion matrix is taken and accuracy is calculated.

Accuracy rate = correctly classified samples / Classified samples

It can be observed that the proposed method has a higher classification rate while using SVM classifier. There are many hyperplane that might classify the data. The best hyperplane is chosen that represents the largest separation, or margin, between the two classes which results in higher classification rate. In KNN classifier, only the distance measure between the training set and testing set is used for the classification which results in misclassification if the feature scales are inconsistent. The imbalance between the numbers of training samples per class in Bayes classifier, results in poor choices of weights for linear decision boundary that leads in misclassification. Experimental results show that the maximum classification rate 97% for glaucoma is achieved while using the SVM classifier. This project work presents a detection of affected glaucoma disease, image segmentation and image classification. The proposed technique is implemented on MATLAB 2016 combined with GUI.

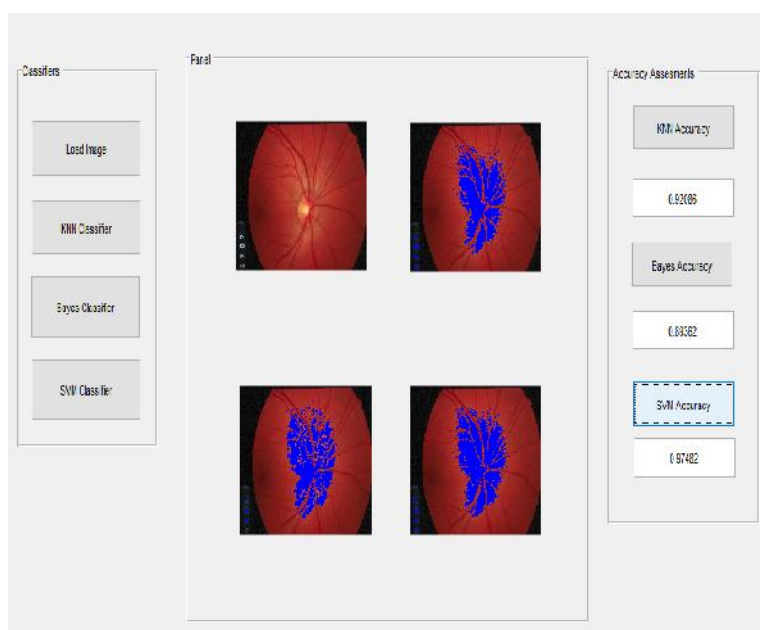


Fig 4-1Result of GUI image

Category	No. of Training set	No. of Testing set
Normal	10	10
Glaucoma	10	10

Fig. 4-2 Number of Training and testing sets

Classifier	Accuracy
KNN	92%
BAYES	89%
SVM	97%

Fig. 4-3 Classification Rates

V.FUTURE SCOPE

The detection of glaucoma can be classified by other classification technique such as Decision Tree, Random Test classifier and can be compared with SVM and KNN classifier. The different types of glaucoma disease such as Open angle glaucoma, Angle closure glaucoma, and Normal Tension glaucoma are identified and classified using SVM, KNN and Bayesian classifiers. These classification techniques can be also used for detection other eye diseases such as Age based Macular Degradation, Diabetic Retinopathy .It can also be used for non-eye disease such as Diabetes.

VI. CONCLUSIONS

In this paper, my aim is to develop a model which can classify glaucoma affected eye fundus images with greater accuracy. The damage done by glaucoma is irreversible. Early detection and treatment of glaucoma is the only solution. "Comparative study of Glaucoma Detection using different classifier" will provide better solution for the difficulties and drawbacks of current manual procedure of detecting glaucoma with naked human eyes, which is more time consuming, requires more effort and more human resources with an expert level knowledge and experience. Image classifiers such as support vector machine (SVM), K-Nearest Neighbor (KNN), and Bayesian for Image Classification. All these techniques are implemented in Matlab via Graphical user interface (GUI) to extract the related features and information from images. The classification accuracy for all proposed methods is 97%, 92% and 89% respectively. SVM takes few minutes of runtime for training SVM classifier. Hence the efficiency of computational is great. Even diagnosis of this kind of eye disease by a doctor is unreliable. Experimental results show that the maximum classification rate 97% for glaucoma is achieved while using the SVM classifier. So this proposed method can help the doctors in their decision making process for detection glaucoma.

REFERENCES

- [1] Atheesan S. and Yashothara S., "Automatic glaucoma detection by using fundusoscopic images," International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), Chennai, 2016, pp. 813-817
- [2] Abhishek Dey and Samir K. Bandyopadhyay, "Automated Glaucoma Detection Using Support Vector Machine Classification Method," 2016, British Journal of Medicine & Medical Research (BJMMR), Kolkata , DOI: 10.9734/BJMMR/2016/19617
- [3] ANNAPOORANI, R., and R. KARTHIK. "Classification System for Glaucoma Detection using Fundus Image." (2015), International Journal of Scientific Engineering and Technology Research (IJSETR), Vol.04, Issue.14, June-2015, Pages:2705-2709
- [4] Sharanagouda Nawaldgi, "Review of automated glaucoma detection techniques", Wireless Communications Signal Processing and Networking (WiSPNET) International Conference on, pp. 1435-1438, 2016.
- [5] S. Maheshwari, R. B. Pachori and U. R. Acharya, "Automated Diagnosis of Glaucoma Using Empirical Wavelet Transform and Correntropy Features Extracted From Fundus Images," in IEEE Journal of Biomedical and Health Informatics, vol. 21, no. 3, pp. 803-813, May 2017
- [6] Y. Ma, R. Fallahzadeh and H. Ghasemzadeh, "Glaucoma-Specific Gait Pattern Assessment Using Body-Worn Sensors," in IEEE Sensors Journal, vol. 16, no. 16, pp. 6406-6415, Aug.15, 2016.

-
- [7] J. Ayub et al., "Glaucoma detection through optic disc and cup segmentation using K-mean clustering," 2016 International Conference on Computing, Electronic and Electrical Engineering (ICECube), Quetta, 2016, pp. 143-147. doi: 10.1109/ICECUBE.2016.7495212
 - [8] A. Chakravarty and J. Sivaswamy, "Glaucoma classification with a fusion of segmentation and image-based features," 2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI), Prague, Czech Republic, 2016, pp. 689-692
 - [9] M. Lotankar, K. Noronha and J. Koti, "Detection of optic disc and cup from color retinal images for automated diagnosis of glaucoma," 2015 IEEE UP Section Conference on Electrical Computer and Electronics (UPCON), Allahabad, 2015, pp. 1-6.
 - [10] D. E. Kusumandari, ArisMunandar and G. G. Redhyka, "The comparison of GVF Snake Active Contour method and Ellipse Fit in optic disc detection for glaucoma diagnosis," 2015 International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT), Bandung, 2015, pp. 123-126
 - [11] X. Chen, Y. Xu, D. W. Kee Wong, T. Y. Wong and J. Liu, "Glaucoma detection based on deep convolutional neural network," 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milan, 2015, pp. 715-718
 - [12] Salam, Anum A., et al. "Automated detection of glaucoma using structural and non-structural features." SpringerPlus 5.1 (2016): 1519.
 - [13] Sharanagouda Nawaldgi, "Review of automated glaucoma detection techniques", Wireless Communications Signal Processing and Networking (WiSPNET) International Conference on, pp. 1435-1438, 2016.
 - [14] Harshvardhan G, Venkateswaran N and Padmapriya N, "Assessment of Glaucoma with ocular thermal images using GLCM techniques and Logistic Regression classifier," 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), Chennai, 2016, pp. 1534-1537