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Prediction for Glaucoma Image Feature Extraction Using Classification Mining Model

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ABSTRACT

Glaucoma is the major cause of blindness in working population. Glaucoma is characterized by increased intra-ocular pressure inside the eye leading to changes in the optic disc and optic nerve. It does not reveal its symptoms until later stage. In this paper image dataset consists of 30 images, out of which 15 are normal images and 15 are Glaucoma affected images. The implementation of the proposed work was done through Matlab 2013a. The results first project the efficiency of disc segmentation and six feature extraction. Then, results show the Glaucoma detection without eliminating instance with NBC algorithm. Then the classification accuracy obtained after eliminating instances through NBC are reported. The SVM and NBC classification results are reported on features with and without feature selection.

Keywords:- Glaucoma Image, SVM, NBC, Disc Segmentation, Feature Extraction

I. INTRODUCTION

Glaucoma is a corporate terminus for a composite radical of circumstances that have reformist ocular pathology ensuing sight loss [1].Essential angle-open glaucoma is a reformist ophthalmic pathology regarding nerves qualified by permanent loss of retinal ganglion cells, decadence of their ax seed within optic nerve and also affects field of vision [2].High amount of intra-ocular pressure (IOP) is one of the major danger components of glaucoma disease. Accusative of present medicament accesses is to reduce (IOP) inside eyes to prevent structural anthropology damage [3]. Glaucoma has several types but the main two types are open-angle and close angle glaucoma because both these types have high intraocular pressure inside the eyes. Open-angle glaucoma is common as compared to angle-closure. There are no clear symptoms for open-angle glaucoma because it develops gradually while close-angle glaucoma is very painful and needs immediate treatment [4].Valuation of retinal nerve fiber layer (RNFL) heaviness and ocular field arguments are important for the detection of glaucoma [5]. A variety of various possibilities admitting mechanical and vessel frameworks has been utilized for pathological process of glaucoma [6].Glaucoma, a proceeding stimulate of blindness strikes least wise 67 million people worldwide [7] and it is a radical of diseases that causes permanent impairment to the ocular nerve and ultimately vision loss.

In the recent past, a prominent scurf order wide affiliation subject has been carried on to represent the factors for Glaucoma [8]. Glaucoma mainly strikes the ganglion cell complex (GCC) which is the aggregate of three inner most layers such as retinal nerve fiber layer, ganglion cell layer and inner plexiform layer [9]. Most of these diseases are qualified by lifted intraocular pressure [10].Ocular area examining is one of the significant methods for monitoring of glaucomatous patients [11]. With the help of Fourier domain optical coherence tomography (FD-OCT) we can achieve relationship among ocular function and heaviness of macular (GCC) which is composed of three inner most layers. Through the measurement of symptomatic value macular (GCC) we can easily detect normal, moderate and severer glaucoma [12].

In this paper, Glaucoma is the major cause of blindness in working population. Hence, regular screening of the patients is required to identify the disease, thus demanding high labor, time and expertise. Thus, computational techniques are sought for their analysis. In this paper, identification of Glaucoma is carried out through computational techniques namely image processing and mining. As the changes in the profile of optic disc act as biomarker for the onset of the disease, optic disc is segmented through image processing techniques. Optic disc is the brightest part portrayed as oval structure in the retinal fundus image. It encompasses optic cup, which is the brightest central part, optic rim, the surrounding pale part and the blood vessels. All these structures are segmented and their properties are elicited. Then, properties of the disc, cup and blood vessels within optic disc are mined to design a learning model for prediction of Glaucoma.

II. LITERATURE SURVEY

Glaucoma is one of the major causes for blindness. Automated identification of Glaucoma can be of great help to the Ophthalmologists and the society. The existing approaches towards Glaucoma diagnosis is concisely presented here. Generally, the process of Glaucoma detection involves the extraction of optic disc and cup followed by elicitation of its properties such as cup to disc ratio and ISNT ratio to distinguish normal images from Glaucoma affected images.

Automatic Identification of Glaucoma plays a major role in retinal image analysis it could prevent vision loss in many patients when detected at the appropriate time. The existing methodology consists of two phases namely image processing phase and data mining phase

Some of the approaches are briefed here. In 2009, Nayak et al [4] used Neural networks with Cup to disc ratio and ISNT ratio, computed from the extracted optic disc and blood vessels as features and achieved a sensitivity and specificity of 100% and 80% respectively.

In 2011, Acharya et al [5] incorporated texture and Higher Order Spectra features after z-score normalization and feature selection, and classified with a random-forest classifier, correctly identifying the glaucoma images with an accuracy of more than 91%. Again in 2011, Ganesh abu and Shenbagadevi [6] proposed the usage of K means clustering for extraction of optic disc and hence in CDR calculation revealing 90% match with clinical CDR.

Yet another attempt in 2011, Ho et.al, [7] proposed a system that involved vessel detection, vessel in painting, CDR calculation and neuroretinal rim for ISNT rule. K-Nearest Neighbor, SVM and Bayes Classifier with CDR and ISNT ratio yielded a classification accuracy of 95%.. In 2014, GeethaRamani et al [8] proposed a framework based on image features to detect Glaucoma.

The methodology incorporated Conversion to various color spaces, channel extraction, statistical, histogram, GLCM based feature extraction and classification through Grafted C4.5 yielding an accuracy of 86.67% on HRF images with cross validation of 3 folds. Again in 2014, Vijapur [9] proposed a data driven workflow for detection of Glaucoma through extraction of energy features from detailed co-efficient images obtained through application of daubechies, symlets and bioorthogonal wavelet filters and computation of cup to disc ratio feature through optic disc attained through disc prediction and cup.

III. METHODOLOGY

1. Support Vector Machines (SVMs)

Support Vector Machines (SVMs) a supervised machine learning technique. There are a number of examples of where it has been used in the agricultural domain. To minimize the generalization error bound and to achieve generalized performance, SVM is used in this existing.

The SVM (Support Vector Machine) approach is used to create functions from a set of labeled training data. These functions can be a classification function or it can be general regression function. In this module, the algorithm is used to study the performance of this approach on the dataset used for the proposed system. The results are generated by using this algorithm.

The number of patients suffering from glaucoma in the world is over 100 million. Glaucoma is a multi-factorial disease in which, Primary open-angle glaucoma - a chronic eye disease characterized by an increase in the intraocular pressure (IOP) levels, damaging the optic nerve, causing a violation of the visual fields and leads to irreversible blindness if untreated quickly. Early detection of glaucoma can limit the progression of disease. The ratio of the size of the optic cup to the optic disc, also known as the cup-to-disc ratio (CDR), is one of the important clinical indicators of glaucoma, and is currently determined manually by trained ophthalmologists, limiting its potential in mass screening for early detection

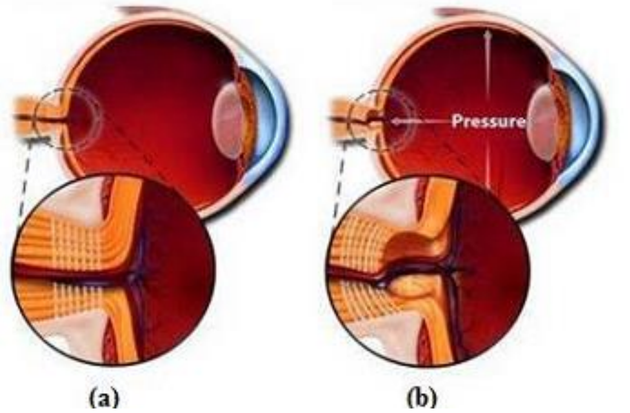


Figure 3.1: (a) Normal Eye (b) Glaucoma Eye

Primary glaucoma has three basic forms:

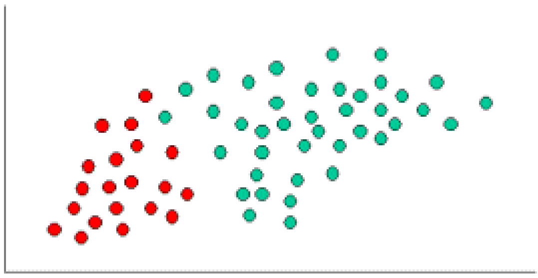
a) Closure form
b) Open form
c) Mixed form

Closure form of glaucoma is characterized by a narrow or closed structure of the angle of the anterior chamber. The main link in the pathogenesis of primary angle-closure glaucoma is an indoor unit drainage system of the eye, which is blockage of the anterior chamber angle of the iris root. Open-form of glaucoma, as the name implies, it has an open profile or a wide angle of the anterior chamber and the free access of aqueous humor drainage to the area.

The main resistance to outflow is directly in the most profound ways of outflow - trabeculae, scleral sinus, and collector channels intrascleral plexus. Mixed form of glaucoma combines a narrow structure of the anterior chamber angle (liquid difficulty of access to the drainage system of the eye) and the deterioration of the permeability for ocular moisture filtration zone. In addition to primary glaucoma significantly rarer congenital, vascular, hypersecretory, low and high pressure form of secondary glaucoma. Clinically, the diagnosis of Glaucoma can be done through measurement of CDR. It is defined as the ratio of the vertical height of the optic cup to the vertical height of the optic disc. A CDR value that is greater than 0.65 indicates the high glaucoma risk.

2. Naive Bayes Classifier Introductory Overview

The Naive Bayes Classifier technique is based on the so-called Bayesian theorem and is particularly suited when the dimensionality of the inputs is high. Despite its simplicity, Naive Bayes can often outperform more sophisticated classification methods.



To demonstrate the concept of Naïve Bayes Classification, consider the example displayed in the illustration above. As indicated, the objects can be classified as either GREEN or RED. Our task is to classify new cases as they arrive, i.e., decide to which class label they belong, based on the currently exiting objects.

Since there are twice as many GREEN objects as RED, it is reasonable to believe that a new case (which hasn't been observed yet) is twice as likely to have membership GREEN rather than RED. In the Bayesian analysis, this belief is known as the prior probability. Prior probabilities are based on previous experience, in this case the percentage of GREEN and RED objects, and often used to predict outcomes before they actually happen.

Thus, we can write:

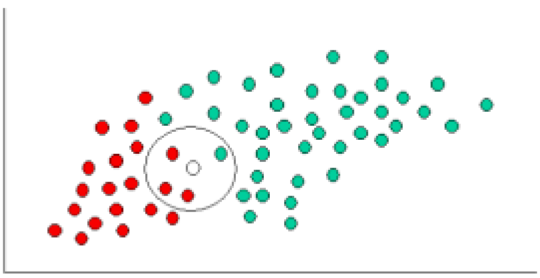
$$\text{Prior probability for GREEN} \propto \frac{\text{Number of GREEN objects}}{\text{Total number of objects}}$$

$$\text{Prior probability for RED} \propto \frac{\text{Number of RED objects}}{\text{Total number of objects}}$$

Since there is a total of 60 objects, 40 of which are GREEN and 20 RED, our prior probabilities for class membership are:

$$\text{Prior probability for GREEN} \propto \frac{40}{60}$$

$$\text{Prior probability for RED} \propto \frac{20}{60}$$



Having formulated our prior probability, we are now ready to classify a new object (WHITE circle). Since the objects are well clustered, it is reasonable to assume that the more GREEN (or RED) objects in the vicinity of X, the more likely that the new cases belong to that particular color. To measure this likelihood, we draw a circle around X which encompasses a number (to be chosen a priori) of points irrespective of their class labels. Then we calculate the number of points in the circle belonging to each class label. From this we calculate the likelihood:

$$\text{Likelihood of } X \text{ given GREEN} \propto \frac{\text{Number of GREEN in the vicinity of } X}{\text{Total number of GREEN cases}}$$

$$\text{Likelihood of } X \text{ given RED} \propto \frac{\text{Number of RED in the vicinity of } X}{\text{Total number of RED cases}}$$

From the illustration above, it is clear that Likelihood of X given GREEN is smaller than Likelihood of X given RED, since the circle encompasses 1 GREEN object and 3 RED ones. Thus:

$$\text{Probability of } X \text{ given GREEN} \propto \frac{1}{40}$$

$$\text{Probability of } X \text{ given RED} \propto \frac{3}{20}$$

Although the prior probabilities indicate that X may belong to GREEN (given that there are twice as many GREEN compared to RED) the likelihood indicates otherwise; that the class membership of X is RED (given that there are more RED objects in the vicinity of X than GREEN). In the Bayesian analysis, the final classification is produced by combining both sources of information, i.e., the prior and the likelihood, to form a posterior probability using the so-called Bayes' rule (named after Rev. Thomas Bayes 1702-1761).

$$\text{Posterior probability of } X \text{ being GREEN} \propto$$
$$\text{Prior probability of GREEN} \times \text{Likelihood of } X \text{ given GREEN}$$
$$= \frac{4}{6} \times \frac{1}{40} = \frac{1}{60}$$

$$\text{Posterior probability of } X \text{ being RED} \propto$$
$$\text{Prior probability of RED} \times \text{Likelihood of } X \text{ given RED}$$
$$= \frac{2}{6} \times \frac{3}{20} = \frac{1}{20}$$

Finally, we classify X as RED since its class membership achieves the largest posterior probability.

The above probabilities are not normalized. However, this does not affect the classification outcome since their normalizing constants are the same.

IV. RESULTS AND DISCUSSION

The proposed framework is evaluated on HRF [25] image dataset. The dataset consists of 30 images, out of which 15 are normal images and 15 are Glaucoma affected images. The implementation of the proposed work was dome through Matlab 2013a . The steps in image processing phase were carried out in Matlab. The results first project the efficiency of optic disc segmentation. Then, results show the Glaucoma detection without eliminating instance with SVM clustering. Then the classification accuracy obtained after eliminating instances through NBC are reported. The classification results are reported on features with and without feature selection.

Image	SVM Rate	NBC
1.jpg	0.7994	0.6658
2.jpg	0.8223	0.6982
3.jpg	0.7126 0.5535	0.5535
4.jpg	0.8870	0.7969
5.jpg	0.8248	0.7018

Table 4.1 Performance Table

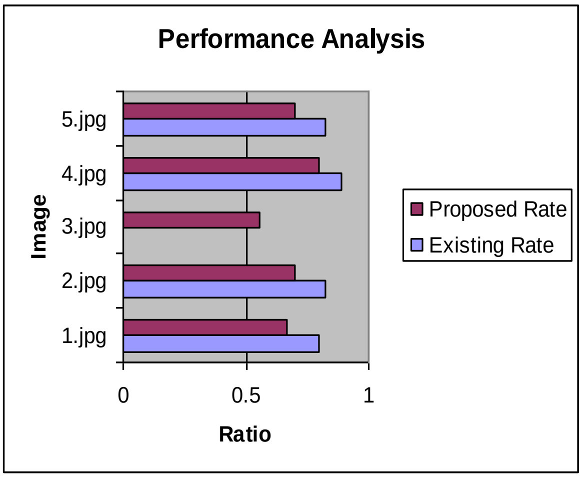


Fig 4.1 Performance Table

The following table 4.2 and 4.3 describe training and test dataset for feature extraction model.

Table 4.2 Training dataset

S.No	Training Dataset	Normal Image	Dieses Image
1	150	55	95
2	300	74	226
3	450	116	334
4	600	124	476

Table 4.3 Test Dataset

S.No	Test Dataset	Normal Image	Dieses Image
1	100	39	61
2	200	65	135
3	300	92	208
4	400	115	285

Table 5.5 Training Dataset Metrics Analysis

	Dieses Detection		Precision	Recall	F-measure	Accuracy
	No. of Instances	No of Attributes				
SVM	600	6-Including class Label	0.615	0.754	0.677	0.682
NBC	600	6 - Including class Label	0.655	0.798	0.718	0.723

IV. CONCLUSION

Glaucoma detection we can conclude that Glaucoma have structural changes on ONH and its features. These structural changes can be analyzed using morphological operations and some other image processing techniques Glaucoma is a major cause of blindness in the society. Computational techniques are sought for detecting Glaucoma. This work involves extraction of blood vessels through symmlet wavelet transformation, extraction of optic disc through maximum voting of three segmentation algorithms, cup segmentation through intensity thresholding, extraction of blood vessels within the optic disc, elicitation of features associated with these structures, feature selection, classification through hybrid model involving SVM followed by ensemble classification of Reduced Error Pruning tree reporting an accuracy of 95.42%. The methodology serves the society.

Table 5.5 Test Dataset Metrics Analysis

	Dieses Detection		Precision	Recall	F-measure	Accuracy
	No. of Instances	No of Attributes				
SVM	600	6-Including class Label	0.777	0.681	0.7258	0.729
NBC	600	6 - Including class Label	0.792	0.688	0.736	0.738

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