ISSN No. 0976-5697

Volume 3, No. 4, July- August 2012

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

A Thorough Investigation on Automated Diagnosis of Glaucoma

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Abstract--- Protective drug and major screenings has become an essential aspect due to high treatment costs and moreover at a later stage, disease treatment may no longer be effective. This is the scenario with glaucoma, in which the considerable loss of optic nerve fibers results in irreversible vision loss, making glaucoma one of the major causes of blindness. This disease is characterized by the increase in fluid pressure which in turn affects the optic nerve and cause vision loss. Automatic retina image analysis has become an essential screening tool for early detection of diseases. There are a number of techniques of treatment which can obstruct progression of the glaucoma. This paper provides a thorough investigation of the existing techniques and the characteristics of the techniques are analyzed for the betterment of the existing techniques for the diagnosis of glaucoma.

Keywords--- Glaucoma, Optic Nerve Head, Support Vector Machine, Short-Wavelength Automated Perimetry (SWAP),Fundus image

I. INTRODUCTION

GLAUCOMA is one of the well known reasons of blindness with a mean occurrence of 4.2% for the people above 60 years. This disease is featured by transformations in the eyeground (fundus) in the region of the Optic Nerve Head (ONH):

(i) enlargement of the excavation,
(ii) disc hemorrhage,
(iii) thinning of the neuroretinal rim,
(iv) asymmetry of the cup between left and right eye,
(v) loss of retina nerve fibers,
(vi) Appearance of parapapillary atrophy.

The progressive loss of retinal nerve fibers in the parapapillary region provokes the glaucoma. Though, those lost fibers cannot be rejuvenated and there is no probability for healing glaucoma, the development of the disease can be controlled [1].

A diagnosis of glaucoma needs a clinical triad: elevated intraocular pressure, structural adjustment of the optic disc, and visual field problems. As a psychophysical test of optic nerve function, visual field testing plays a vital role in the evaluation of glaucoma. For the past few decades, white-on-white automated perimetry (W-W) has been taken up for the test of reference for glaucoma diagnosis and monitoring. But, as demonstrable visual field problems occur after structural alterations in the optic disc [2] it is now regarded subordinate to optic nerve head description. In [3], optic nerve fiber size damage due to glaucoma was determined. In the superior and inferior of glaucomatous eye, there was a greater atrophy of fibers of all sizes. The areas that suffer loss of fibers in glaucoma contain a high proportion of larger diameter fibers. Larger fibers were lost in areas of the optic nerve with mild damage, indicating the inherent susceptibility to injury by glaucoma.

In recent times, a number of investigations have shown that foveal blue and blue-yellow color vision problems are seen in patients with ocular hypertension and glaucoma, and these problems emerge to be early markers of glaucomatous damage [4-8]. Patients with ocular hypertension who had blue and blue-yellow color vision problems had much higher probability occurrence of glaucomatous visual field loss in later years, compared with the patients with normal color vision results [8]. By means of special approaches that selectively investigate the sensitivity of short-wavelength-sensitive cones, it is easy to detect glaucomatous visual field problems at an earlier stage. A number of investigations have shown that Short-Wavelength Automated Perimetry (SWAP) is more sensitive than W-W in discovering early glaucomatous problems and it also shows greater progression of existing glaucomatous problems [4, 9, 10].

But, still there is a great challenge in knowing and realizing the cause, types and the natural course of glaucoma. The usage of advanced imaging technologies, such as Confocal Scanning Laser Tomography (CSLT), captures 3-dimensional images of the optic disc that are utilized for diagnostic purposes [11].

But, the analysis of CSLT images is a manual procedure in which a trained person has to manually define the margins of the optic nerve and then categorize whether the optic nerve is normal or glaucomatous. The existing techniques results in misjudgments/errors in the analysis of the CSLT image, failure to distinguish between actual and noisy images and variance in the diagnostic recommendations over a group of practitioners. Therefore the main challenge is to automate the analysis of diagnosis of glaucoma in a quantifiable manner.This paper investigates the existing techniques for the diagnosis of glaucoma. This paper focuses on bringing out the analysis of the characteristic features of the existing approaches, its advantages and disadvantages.

II. LITERATURE SURVEY

There are several approaches available in the literature for the diagnosis of glaucoma. All these existing techniques have their unique features and characteristics. This section analyzes the most important existing techniques for the diagnosis of glaucoma.

A. A Data Mining Framework:

In the application of retina image analysis, automated techniques are already available for certain operations, for example, determination of components of the eyeground (e.g. segmenting the vessels [12] or the ONH [13,14]. These factors can be utilized for automated diagnosis of diseases such as diabetic retinopathy or glaucoma. In [15[, texture and Higher Order Spectra features are combined to extract features from fundus images for diagnosis of glaucoma. These features had a low *p*-value that classifies normal and abnormal classes. Existing image-based glaucoma detection techniques is performed on HRT images. A smooth two-dimensional surface that is fitted to the optic nerve head in topography images has been formulated in [16, 17]. In [18], Glaucoma was detected using confocal scanning laser image by considering the nine structural optic nerve head parameters viz. cup area, cup to disc area ratio, rim area, height variation contour, cup volume, rim volume, cup shape measure, mean retinal nerve fiber layer thickness, and retinal nerve fiber layer cross-section area and the performance was evaluated with linear multivariate analysis and a neural network. Detection of glaucomatous damages can be carried out through global shape measures of the optic disc (cup and disc area, height variation in HRT images).

This global shape technique is compared with a sector-based analysis in [19]. Optic disc parameters and additional parapapillary parameters were calculated using Support Vector Machine (SVM) to detect glaucoma[20]. It has been stated recognition of glaucoma through separately applied, shape-based techniques on different modalities (confocal laser scanning ophthalmoscopy, scanning laser polarimetry, optical coherence tomography) is not better than qualitative assessment of the optic disc by ophthalmologists [21]. All these shape based techniques assumed a valid segmentation of the optic disc. But, segmentation based approaches have the major limitation that small errors in segmentation may result in considerable alteration in the measurements which would in turn affect estimation and diagnosis.

A robust, automated glaucoma detection system through color fundus images in a data-driven way was presented in [22]. Thus, image-based features that are novel in the domain of glaucoma detection are given. This, so called appearance based technique is well-known from object and face recognition [23, 24]. The approach is based on statistical assessment of the data and is not based on clear outlining of the optic disc, as needed for global or sector-based shape analysis. As a result, preprocessing and image-based feature extraction has key control on the classification process. This effort indicates the control of different image-based features on the accuracy of glaucoma classification from fundus images. Different types of features are examined (pixel intensity values, textures, spectral features, and parameters of a histogram model) that are planned to capture glaucomatous structures and estimate the results through three different classifiers namely naive Bayes classifier, k nearest neighbor and Support Vector Machine. They were used to categorize the computed features as is, in integration with an attribute pre-selection technique and with an iterative attribute selection by Ada Boosting.

The integration of features is also taken into consideration. Researchers have examined optic nerve data and CSLT based images with changeable results. In [25] forward and backward feature selection techniques operating with retinal tomography images applied for training Multi Layer Perceptron (MLP), Support Vector Machine (SVM) and linear discriminant functions. A correlation analysis and forward wrapper model to choose features from optic disc data for training SVM classifiers were employed as in [26]. A wrapper model was utilized in [27] for feature selection to train SVM classifiers.

A data-driven Glaucoma Diagnostic Support (GDS) system which is presented in [28] features the automatic interpretation of CSLT topography images of the optic nerve to support the following aspects.

i. The categorization of the optic disc images to differentiate between healthy and diseased optic discs.
ii. The discovery of the sub-types of glaucomatous optic disc damage. This is to further sub-classify the glaucoma patients to offer treatments in line with the definite morphological patterns of damage [29].
iii. The visualization of the temporal progression of the disease for a patient over a period of time.

This multi-stage technique is a hybrid of image processing and data mining approaches. In Stage 1, image-processing approaches are applied to CSLT images to obtain image-defining features. In Stage 2, data classification approaches are applied to the image's shape-defining features to establish classifiers that can differentiate between healthy and glaucomatous optic discs. An essential operation at this stage is feature selection whereby an optimal subset of image feature with high image classification capabilities is chosen. In Stage 3, data clustering approaches are employed to the optimal subset of image-defining features to categorize the different sub-types of glaucomatous images in the image data-set.

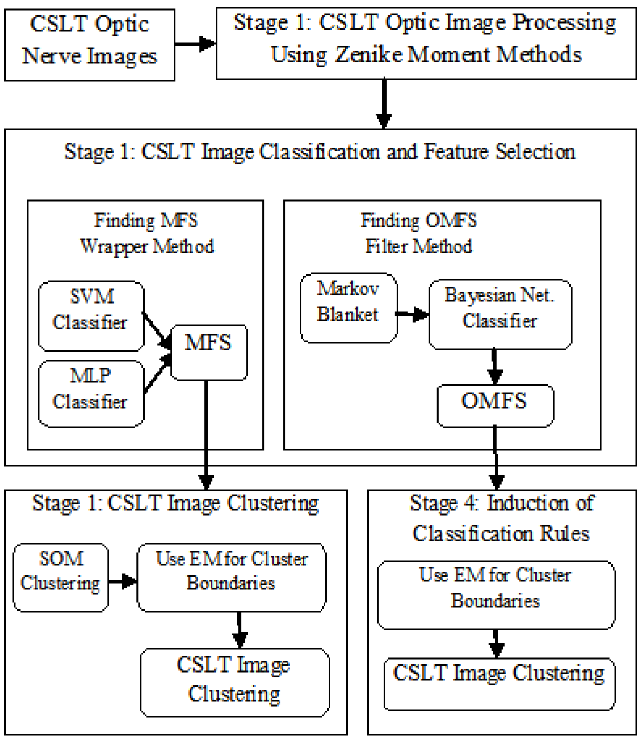

Figure 1: Functional design of our GDS system

The emergent image clusters are then utilized to both notice the progression of the disease and the recognition of noisy optic nerve images. In Stage 4, rule-induction approaches are employed to the optimal subset of features to provoke classification rules. Fig 1 illustrates the functional design of our GDS system. A novel automated classification system for glaucoma, based on image features from fundus photographs was described in [30]. This novel data-driven technique needs no manual support and does not depend on clear structure segmentation and measurements. Initially, non-uniform illumination, size differences and blood vessels which are not essential for disease recognition are removed from the images. Subsequently, the extracted high-dimensional feature vectors are compressed via PCA and are integrated before SVM classification. The approach attains significant accuracy of recognizing glaucomatous retina fundus images when compared with human experts. The "vessel-free" images and intermediate output of the techniques are novel depictions of the data for the doctors that may offer new insight into and assist to better understand glaucoma

This system comprises of a standard 3-step image analysis pipeline as shown in Fig 2. The steps are:

a. preprocessing,
b. image-based feature extraction
c. classification

Neuro-retinal rim which is a roughly circular region around the ONH is the most essential region when diagnosing glaucoma [31]. This automated approach is based on statistical ssessment of the data and does not depend on clear measurements from the optic disc segmentation, as needed for global or sector-based shape analysis. This appearance-based approach is very common in object and face recognition [32,33], but it is novel in the field of retina imaging. In such systems, data preprocessing and feature extraction has main influence on the classification. As in [34] which indicate that this approach performs better on images with less disease-independent variations

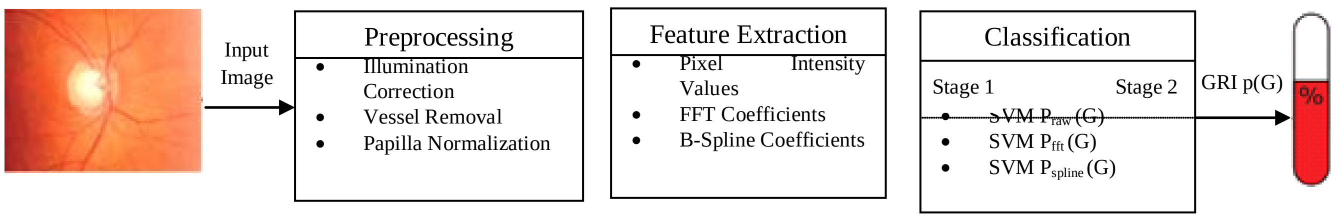

Figure 2: GRI processing pipeline: (i) preprocessing eliminates disease-independent variations from the input image, (ii) feature extraction transforms the preprocessed input data to characteristic and compact representation, and (iii) a 2-stage probabilistic SVM classification generates the Glaucoma Risk Index (GRI)

B. Comparison of the Two Automated Glaucoma Diagnostic Approaches:

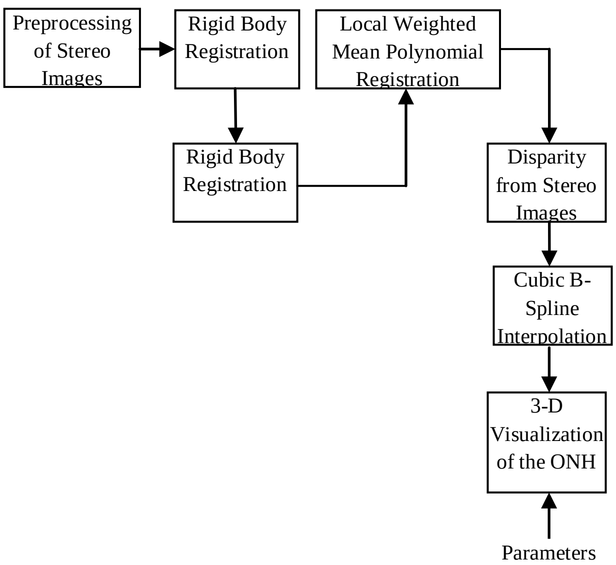

Figure 3: Process implemented by Enrique Corona

Fig 3 show the sequence of steps implemented in a highly-abridged format as in [35]. The steps used are:

a) Preprocessing
b) Rigid registration
c) Nonrigid polynomial registration
d) Stereo analysis
e) Interpolation
f) Computation of results

There a number of subtle issues pertaining to each step that is missing from the diagram. These issues may need further explanation, evaluation, clarification, or even correction in certain scenarios.

An automated approach for the detection of glaucoma from fundus images was explained in [36]. This process uses such approaches as pyramidal stereo-matching, fuzzy clustering, active contours, feature extraction, and others. The results of sensitivity and specificity calculations showed better accuracy of the approach within the digital fundus images when compared with the approach in [35].

Fig 4 illustrates the high-level block diagram of the Philip's approach. It is to be observed that two high-level blocks are introduced in [35] denote an optic disk segmentation routine and an optic cup segmentation routine.

It is to be observed that in [35] approach, all processing was carried out on the green image plane as it offered the greater part of information. However, considerable information clearly exists in the other color channels. So, this approach uses all the channels.

The non-uniform illumination correction approach presented is classical background subtraction which is more robust for various image capture conditions than the existing approach. This approach provides a number of benefits over the approach proposed in [35] statistical technique such as independence of the direction of the illumination gradient, fast processing, as the greater part of the computations involve low-pass filtering, and robustness against misalignments between the images.

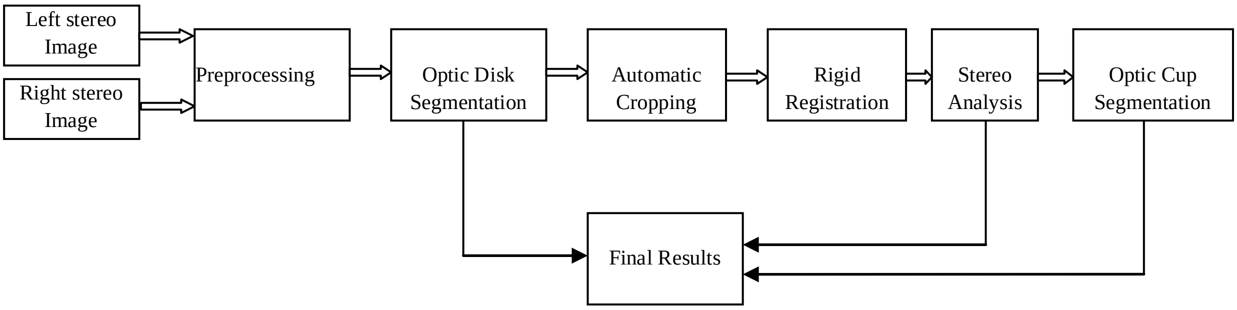

Figure 4: High-level block diagram of the Philip's Approach

There are certain limitations in this approach. These comprise a possible loss of usage contrast after adjustment and border effects caused by the large low-pass filter needed for evaluating the background of the image. The loss of contrast is inevitable as only an estimate of the non-uniform illumination is possible without calibrated test equipment and static image capture conditions.

C. Detection of Glaucoma Using Fundus Image:

An automatic segmentation of the papilla in a fundus image based on the Chan-Vese model and a shape restraint method was proposed in [37]. The experimental results revealed that this approach illustrates a significant performance in identifying the papilla shapes and computing the shape feature parameters. It also indicates that the approach is robust to noise and object deformity.

A preliminary examination on the association of vessel diameter variation and glaucoma was proposed as in [38]. This involves the extraction of vessel centerlines through differential calculus and the geometrical alignment (registration) of the images by means of the chamfer matching algorithm. The evaluation of vessel diameters by fitting a Gaussian function to intensity profiles.

An automated localization of retinal optic disc through fundus image for the identification of glaucoma was proposed in [39]. This approach comprises of morphological processing for separating the brightest area in the image and Hough transform for identifying the key circular feature within the positive horizontal gradient image within this region of interest.

A level set based automatic cup to disc ratio determination through retinal fundus images in ARGALI is proposed in [40]. In this approach, variational level set is used for disc segmentation and threshold level set for cup segmentation. An ellipse fitting is also employed for boundary smoothening.

An optic cup and disc extraction from retinal fundus images for determination of cup to disc ratio is described in [41]. The cup to disc ratio can be obtained by deriving cup and disc from the retinal fundus images. Threshold approach is used for extracting the cup and a variational level set technique is employed for extracting the disc.

In the approach proposed in [42] , the ratio of optic Cup to Disc (CDR) is computed through fundus photograph where CDR, is an essential indicator of glaucoma [43]. Vital anatomical structures captured in a fundus image are blood vessels, optic cup, optic disc and macula for a normal retina. The color fundus images are employed to track the eye diseases by the ophthalmologists and it offers early signs of certain diseases such as diabetes, glaucoma etc.

The optic cup and optic disc are shown in Fig 5. The optic disc measures about 1.5 mm in diameter.

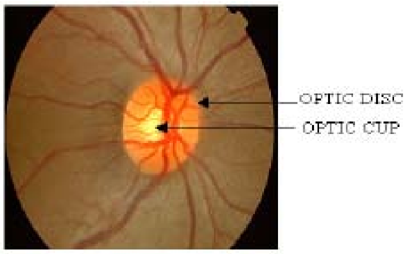

Figure 5: Fundus Image

In the approach used in [42], Optic Disc is extracted by Hill Climbing Algorithm [44], and optic Cup is extracted using Fuzzy C-Mean clustering [45]. Cup segmentation is a challenging task compared to disc segmentation because of the presence of high density vascular architecture in the region of the optic cup. As glaucoma advances, the cup enlarges until it occupies most of the disc area. The cup-to-disc ratio compares the diameter of the "cup" segment of the optic disc with the total diameter.

D. Recent Techniques for the Diagnosis of Glaucoma:

Glaucoma is a disease in which fluid pressure in the eye increases continuously, affecting the optic nerve and resulting in vision loss. Computational decision support systems for the prior detection of glaucoma can prevent this difficulty. The retinal optic nerve fiber layer can be evaluated through optical coherence tomography, scanning laser polarimetry and Heidelberg retina tomography scanning approches. A novel approach for glaucoma detection through integration of texture and Higher Order Spectra (HOS) features from digital fundus images is given in [46]. Support vector machine, sequential minimal optimization, naive Bayesian, and random-forest classifiers are employed to carry out supervised classification. The results illustrate that the texture and HOS features after z-score normalization and feature selection, and when integrated with a random-forest classifier, provides significant performance when compared with other classifiers and identifies the glaucoma images with an accuracy of more than 91%. The influence of feature ranking and normalization is also examined to enhance the results. This novel features are significant and can be used to detect glaucoma accurately.

Optical Coherence Tomography (OCT) has become an efficient ocular imaging technique under the framework of Computer-Aided Diagnosis that can be utilized in glaucoma diagnosis by evaluating the retinal nerve fiber layer thickness. An automated retinal layer segmentation approach for OCT images is given as in [47]. In this approach, an OCT image is initially cut into multiple vessel and non vessel sections by the retinal blood vessels that are detected via an iterative polynomial smoothing process. The nonvessel sections are then filtered by a bilateral filter and a median filter that suppress the local image noise but keep the global image variation across the retinal layer boundary. Ultimately, the layer boundaries of the filtered non vessel sections are detected, which are further categorized to different retinal layers to find out the complete retinal layer boundaries. Experiments over OCT for four subjects indicate that this technique segments an OCT image into five layers accurately.

Optic disc (OD) detection is a vital step in automated diagnosis of various ophthalmic pathologies. A new template-based technique for segmenting the OD from digital retinal images is presented in [48]. This approach employs morphological and edge detection techniques followed by the Circular Hough Transform to attain a circular OD boundary approximation. It needs a pixel positioned within the OD as initial data. For this reason, a location technique based on a voting-type algorithm is also presented. The approaches were evaluated on the 1200 images of the publicly available MESSIDOR database. The location process succeeded in 99% of cases, taking an average computational time of 1.67 seconds with a standard deviation of 0.14 seconds. Alternatively, the segmentation algorithm offered an average common area overlapping between automated segmentations and true OD regions of 86%.

There are two common types of glaucoma:

i. open angle glaucoma
ii. angle closure glaucoma

Glaucoma type classification is essential in glaucoma diagnosis. Clinically, ophthalmologists investigate the iridocorneal angle between iris and cornea to find out the glaucoma type and the degree of closure. But, manual grading of the iridocorneal angle images is a time consuming process. A focal edge for automated iridocorneal angle grading is proposed in [49]. The iris surface is positioned to determine focal region and focal edges. The association between focal edges and angle grades is constructed via machine learning. A modified grading system with three grades is adopted. The experimental results indicate that this approach can correctly classify 87.3% open angle and 88.4% closed angle.

It is very essential to diagnose glaucoma as early as possible to reduce the damage to the optic nerve. There are several tests employed to detect the damage caused by glaucoma, but, none of tests is suitable for all the possible effects. In [50] an approach is presented using fuzzy set theory to integrate these results into one diagnosis. The technique comprises of two variations of three different approaches resulting in six different algorithms. The algorithms were verified with a set of patient data and the supplementing the diagnosis of doctors. The results of the algorithms were compared to determine the ones with a higher degree of correlation to the diagnosis of the doctors.

In [51] a technique is proposed to automatically extract the key features in color fundus images. The optic Cup-to-Disc Ratio (CDR) in retinal fundus images is one of the standard physiological features in the diagnosis of glaucoma. The least square fitting algorithm mainly focuses to enhance the accuracy of the boundary estimation. The approach employed is a core component of Automatic cup-to-disc Ratio measurement system for Glaucoma detection and AnaLysIs (ARGALI), a system for automated glaucoma risk evaluation. The performance of the algorithm is illustrated manually on segmented retina fundus images. It is observed that the approach accurately detected neuro-retinal cup height by comparing the automatic cup height measurement to ground truth. This approach enhances the efficiency of clinical interpretation of Glaucoma in fundus images of the eye.

The diagnostic criteria for glaucoma comprises of intraocular pressure measurement, optic nerve head evaluation, retinal nerve fiber layer and visual field defect. The thorough study of ONH, CDR and neural rim configuration are essential for early detection of glaucoma. But, the broad range of CDR is tough to recognize early changes of ONH and various ethnic groups have various features in ONH structures. Therefore, it is still essential to build various detection approaches to support doctors to diagnose glaucoma at early stages. An automatic detection system which comprises of two major phases [52]:

a) ***First phase:*** performs a series modules of digital fundus retinal image analysis which includes vessel detection, vessel in painting, CDR calculation, and neuro-retinal rim for ISNT rule,

b) ***Second phase:*** determines the abnormal status of retinal blood vessels from different perspective.

Several clinical fundus retinal images comprising of normal and glaucoma images were applied to this system for illustration

Min-Redundancy Max-Relevance (mRMR) is a feature selection technique based on information theory. The mRMR principle for automatic glaucoma diagnosis is investigated in [53]. Optimal candidate feature sets are obtained from a composition of clinical screening data and retinal fundus image data. An mRMR optimized classifier is further trained through the candidate feature sets to identify the optimized classifier. This approach is tested on eye records of 650 subjects collected from Singapore Eye Research Institute. The results illustrate that this classifier is much compact by using less than one-fourth of the initial feature set. The ranked feature set also facilitates the doctors to better access the diagnostic process of the algorithm.

Automatic computation of optic cup boundary is tough due to the interweavement of blood vessels with the surrounding tissues around the cup. A multimodality fusion technique for neuroretinal cup detection enhances the accuracy of the boundary assessment [54]. The performance of the algorithm is illustrated on 71 manually segmented retina fundus images gathered from Singapore Eye Research Institute. It is observed from the experimental results that this approach accurately detected neuro-retinal cup height for 69 images and achieved 97.2% accuracy.

A computer-based glaucoma screening system [55] is presented in which optic nerve defects detection, visual field examination, and expert system rules are integrated to enhance the sensitivity and specificity. A variety of fundus image processing techniques are used and a histogram model is given particularly for combed hair retinal nerve fiber layer problem. A visual field test carried out on computer monitor is adopted to minimize the cost for other perimetry equipments. The assistant diagnostic module can offer a chief diagnosis based on a group of fuzzy rules. The system is cost effective and appropriate for detecting early stage glaucoma, particularly for large-scale screening.

Primary Open Angle Glaucoma (POAG) discriminated model using Support Vector Machine (SVM) method is presented to differentiate the primary open-angle glaucoma disease, which is not clear in early symptoms and comprises of various risk factors, furthermore easy to blind with prolonged intraocular hypertension. SVM classifier with a radial basis inner function was developed to predict and distinguish certain unknown patients [56]. Simultaneously, Bayes angle discriminated model and Logistic regression, which are standard statistical classification techniques are set up to compare with SVM methods in POAG diagnosis. The results revealed that SVM technique is reliable and superior in several aspects to statistical classification techniques in the POAG recognition.

The scanning laser ophthalmoscope is a device used by ophthalmologists to attain topographic images of ONHs of the patients. Measurements are taken from these images that illustrate the shape of the ONH. Glaucoma comprises of the loss of retinal nerve fibers, which in turn forms a transformation in the ONH shape. But, it is very challenging to observe which shape parameters are most relevant to the diagnosis of glaucoma. In order to solve this problem, a feed forward Artificial Neural Network (ANN) was designed to distinguish between patient data. Patients were first independently categorized using perimetry data (visual fields) into normal and abnormal (glaucomatous) groups. ANN was trained through error backpropagation (n=91 samples) and the classification model was cross validated using one normal, and one abnormal sample. The entire data set (45 normal and 46 abnormal) was used for cross validation and each time the error rate of the training set was needed to be less than 15%. ANN gave an overall classification rate of 86.7%, with a specificity (correct normal) of 88.9% and a sensitivity (correct abnormal) of 84.4%. The ANN classification model, with only two hidden units, generalized well which shows that the ONH measurements are valuable for the detection of glaucoma.

III. PROBLEMS AND DIRECTIONS

During eye investigations, ophthalmologists look for particular regions and patterns to recognize possible markers of diseases [57]. Automated techniques already exist for certain operations in this analysis (e.g., segmenting the vessels [58,59] or ONH, [60,61] locating and quantifying microaneurisms, [62] or drusens [63]. Although digital color fundus images were already taken into consideration, for instance, for automated analysis of diabetic retinopathy, in glaucoma evaluation, they are generally employed in visual inspection only. A number of existing image-based glaucoma detection techniques operate on HRT images. The topography images can be employed to fit smooth parametric surface models to, [64] detect glaucomatous damages via global shape measures of the optic disc, [65] perform sector based analysis, [66] or evaluate optic disc and additional parapapillary parameters via SVM for detecting glaucoma [67]. A comparative analysis indicated that the detection of glaucoma by quantitative shape-based analysis on different modalities (confocal laser scanning ophthalmoscopy, scanning laser polarimetry, optical coherence tomography) is not better than qualitative assessment of the optic disc by experienced ophthalmologists, yet the combination of those techniques can considerably enhance this ability [68].

A number of existing computer aided analysis of retina images for glaucoma evaluation are based on certain types of image segmentation, which is mostly done manually or by semi-automated techniques. The limitation of hard, segmentation-based approaches is that small errors in localization and/or delineation may result in considerable errors in the measurements and as a result in the diagnosis. The main goal is to attain robust classification based on high dimensional feature spaces, in which entire regions with their pixel values and derived texture features are taken into account. Digital fundus images are used for automatic glaucoma screening and imitate, by means of computer algorithms, the evaluation approach of the ophthalmologists. They have the capability to investigate the relevant structures (such as the ONH) while implicitly eliminating the others (e.g blood vessels and illumination artifacts). A complete retina image analysis process is developed that from the input fundus images automatically calculates a single probabilistic output value (Glaucoma Risk Index, GRI), that could be employed as an added filter in a screening situation.

Advanced neural network techniques can be used employed in the diagnosis of glaucoma. Moreover, an approach that integrates advanced computational intelligence/soft computing paradigms with thorough analysis and knowledge can be employed. Computational intelligence techniques including fuzzy logic, neural networks and genetic algorithms can be very effective in handling with imprecision, uncertainty and partial truth [69,70]. These algorithms are widely used in practical medical activities and in medical knowledge. Thus, these algorithms can be utilized to develop an advanced intelligent system for diagnosis and prediction of glaucoma. Neuro-fuzzy systems integrated with proper training algorithms can be utilized in this domain.

IV. CONCLUSION

Glaucoma is a serious ocular disease which would result in blindness if it couldn't be detected and treated in appropriate manner. There are several techniques available in the literature for the diagnosis of glaucoma. But, majority of the existing techniques do not provide efficient results in all the scenarios. This paper analyzes the characteristic features of various existing techniques for the diagnosis of glaucoma. From the survey, it is observed that advanced techniques are very essential for better performance in the diagnosis of glaucoma. This survey would be a platform for the future research work in the field of glaucoma diagnosis.

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