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Original Research Article

Combination of clinical and multiresolution features for glaucoma detection and its classification using fundus images

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ABSTRACT

Glaucoma is a neuro-degenerative disorder of the eye and it leads to permanent blindness when untreated or detected in the later stage. The main cause of glaucoma is the damage of the optic nerve, which occurs due to the increase of eye pressure. Hence the early detection of this disease is critical in time and which can help to prevent further vision loss. The assessment of optic nerve head using fundus images is more beneficial than the raised intra ocular pressure assessment in population-based glaucoma screening. This work proposed a novel method for glaucoma identification based on time-invariant feature cup to disk ratio and anisotropic dual-tree complex wavelet transform features. Optic disk segmentation is done by using Fuzzy C-Means clustering method and Otsu's thresholding is used for optic cup segmentation. The results show the proposed method achieved an accuracy rate of 97.67% with 98% sensitivity using a multilayer perceptron model that is considered as clinically significant when compared to the existing works.

1. Introduction

Glaucoma is one of the most prominent chronic eye diseases which damage the optic nerve head. It is characterized by an increase in pressure within the eye, which is known as intra ocular pressure. This occurs when there is a blockage of drainage canals in the eye and it damages the delicate optic nerve fibers [1]. Our vision is possible by the optic nerve, which carries images from the retina to the brain. If the significant

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number of nerve fibers is damaged, it creates blind spots in the field of vision. Once nerve damage, it leads to permanent vision loss and it cannot be cured completely. Unlike many other diseases, its symptoms are not immediately noticed by patients. So it is a great health challenge in worldwide.

According to World Health Organization (WHO) statistics, it is found that glaucoma is the second leading cause of vision loss globally after cataract, especially in older people [2]. It is the third leading cause of blindness in India, whereas nearly 12 million people are suffering due to this disease [3]. The signs and symptoms of this eye disorder are only experienced at its advanced stages and this is the main challenge of glaucoma identification. Due to this, early detection of glaucoma is more relevant in the current society.

Glaucoma can be classified into two as open angle and angle closure glaucoma (Fig. 1). Open angle glaucoma is the most common one and it happens when the channels, which drain fluid inside the eye, become blocked due to the increase of intraocular pressure (IOP). It develops slowly and shows only a few signs. So the people may unaware about their sight loss for a long time. Angle-closure glaucoma (ACG) occurs very quickly and produces headaches, blurred vision and pain in the eye [4]. Since ACG happens by a closed or narrow angle between the iris and the cornea, an immediate medical attention is needed.

Through the regular and complete eye examination, glaucoma can be detected at its initial stage. Mainly three methods are available to detect this disease such as analysis of raising IOP, visual field evaluation, damaged Optic Nerve Head (ONH) analysis. The assessment of increased IOP by using tonometry is not an efficient screening tool because it may be present in normal IOP. The visual field test requires special equipment's and therefore it is unsuitable for screening. So, the evaluation of ONH is the most promising one. But the assessment of the automatic ONH is more beneficial in the sense of time-consuming and expensive. Almost all the glaucoma tests consume more time and need special talent. The devices such as Optical Coherence Tomography (OCT) and Heidelberg Retinal Tomography (HRT) contain almost identical details as the images taken by digital fundus camera [5]. Since the fundus images are more economical and are frequently used for glaucoma screening, most of the research works concentrate on digital fundus images to develop a reliable and large population-based screening algorithm for automatic glaucoma detection.

There is various state of the art methods are explored in the automated glaucoma detection and analysis as reported in the literature [6–10]. Narasimhan et al. [11] proposed a k-means clustering algorithm used to isolate the optical disk (OD) and optic cup (OC) separately. An elliptical fitting procedure is used to measure the cup to disk ratio (CDR) values. The OD blood vessels are extracted by using local entropy thresholding and calculated the inferior superior nasal and temporal (ISNT) ratio. Then, based on these features, evaluate the performance of this algorithm on Support vector machine (SVM), k-nearest neighbors (KNN) and Bayes classifiers. Dutta et al. [12] had developed a methodology for the glaucoma detection by using an adaptive threshold based segmentation algorithm. They only consider CDR, neuro retinal rim (NRR) area and blood vessels ratio in OD and also propose some preprocessing techniques to improve the segmentation quality.

Preethi et al. [13] proposed a new technique which consists of two processes, namely OD boundary detection, which is based on Linear Discriminant Analysis (LDA) and Contrast Limited Adaptive Histogram Equalization (CLAHE), and OC segmentation by using Watershed transformation. LDA is used in feature extraction and CLAHE is used for image enhancement. In that work, CDR has defined the vertical height of OC and OD. Kavitha et al. [14] adopted a new algorithm called super-pixel classification which is used to segment OD and OC for the screening of glaucoma. In that research work, center surround statistics, contrast enhanced histograms, K-Means clustering, simple linear iterative clustering and Gabor wavelet has been used for the evaluation of glaucoma detection in patients. Acharya et al. [15] introduced a glaucoma identification system by taking the advantage of texture and higher order spectra (HOS) features obtained from fundus images. The classifiers which are used to perform supervised classification are SVM, random-forest, Naive Bayesian classifiers and sequential minimal optimization. The segmentation of OD and OC is not required in this work, which is an advantage for classification.

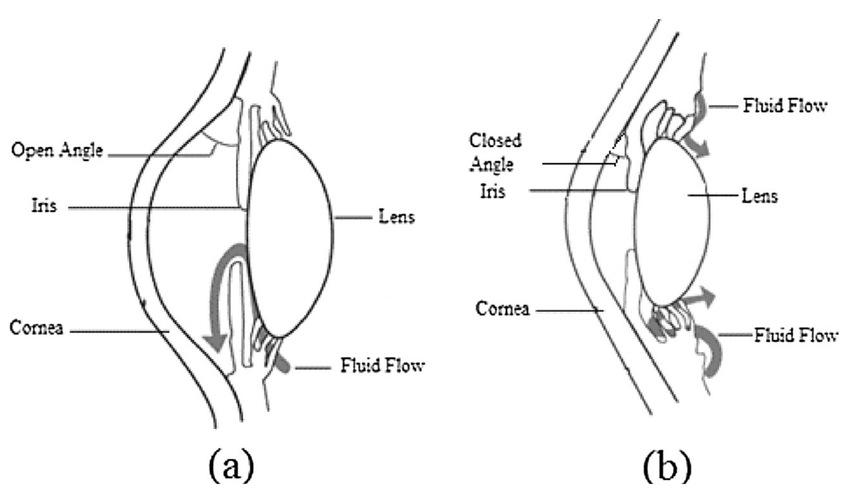

Fig. 1 – (a) Open angle glaucoma; (b) angle closure glaucoma.

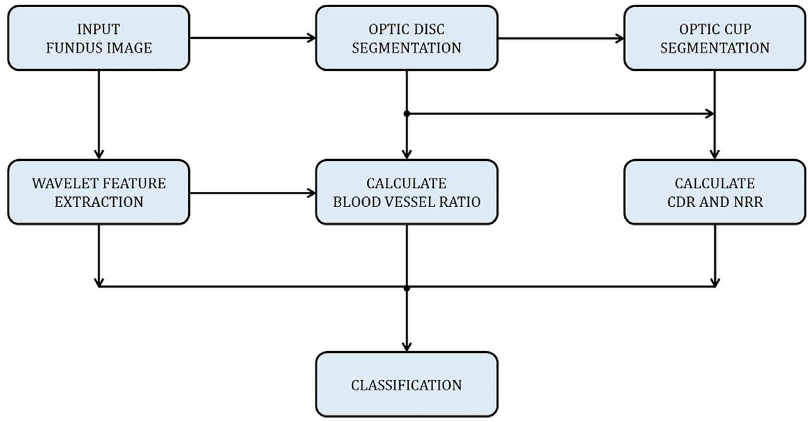

Fig. 2 – Block diagram of proposed glaucoma detection process.

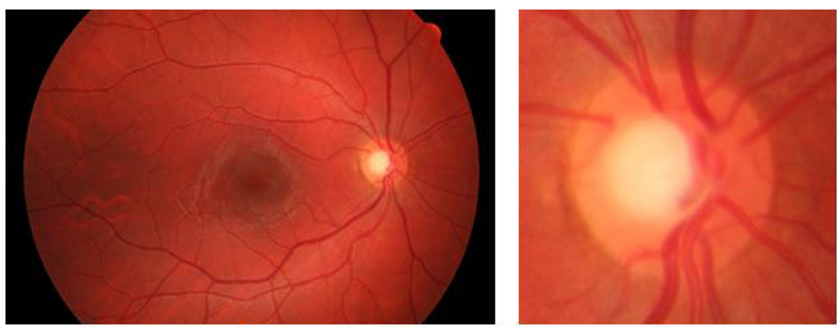

Fig. 3 – (a) Normal fundus image; (b) its ROI consists of optic disk.

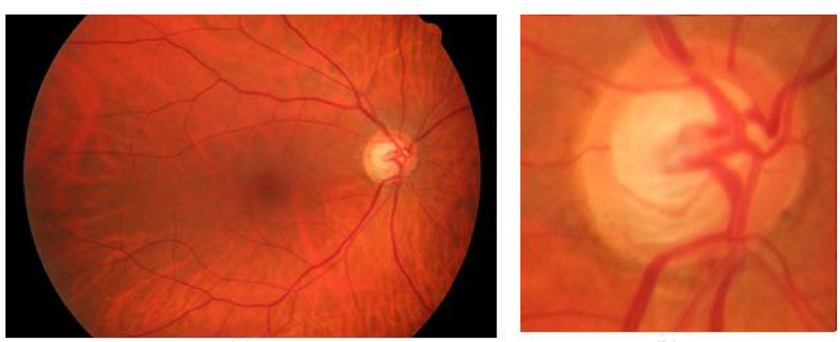

Fig. 4 – (a) Glaucoma affected fundus image; (b) its ROI consists of optic disk.

Dutta et al. [16] described an alternative methodology to diagnosis glaucoma by using the first level wavelet features of segmented OD. OD segmentation is done by using bit plane analysis. Here blood vessels are removed from the OD by increasing the identification accuracy. To choose prominent features also applies some feature selection methods like principal component analysis (PCA) and evolutionary attributes selection (EAS). The results reveal that wavelet features of OD are more significant compared to other clinical features in the glaucoma detection. Li Yun et al. [17] suggested a new method for the analysis of glaucoma; they extract the textural features by using fractal dimension and Hurst coefficient from Brownian motion. By using 2D discrete wavelet transform, extract the energy and entropy values of fundus images. Total 16 features are used for classification and found that SVM with the radial basis function kernel has the maximum efficiency.

This current work is envisaged to develop an efficient algorithm for glaucoma detection with improved accuracy rate. In order to achieve this goal, a new feature extraction method is proposed, which uses some clustering based segmentation techniques and Anisotropic Dual Tree-Complex Wavelet Transform (ADT-CWT) features. The major advantages of clustering based segmentation given the best result for the overlapped dataset and ADT-CWT provides an efficient representation of directional features in images [18]. Another contribution of this work is to find the minimum number of prominent features for the automatic diagnosis of glaucoma from retinal image. The rest of the paper consists of the following sections: Section 2 explains the brief descriptions of the proposed methodology, feature extraction methods and classifiers used in this work. Section 3 discusses the experimental results of the proposed method. Finally, Section 4 presents the conclusion of the work.

2. Proposed methodology

The various stages of the proposed method are explained in this section. Block diagram of the proposed glaucoma detection process is shown in Fig. 2. After the segmentation of OD and OC, then CDR and the ratio of NRR area measurements are obtained. Then extract the blood vessels in OD region separately to and blood vessel ratio in ISNT. In addition to these features, wavelet features such as mean, variance and energy are extracted by using ADT-CWT [19]. Based on different combination of these feature sets, classify the images into glaucoma or the normal one and found the prominent feature set to get maximum efficiency.

2.1. *Digital fundus image acquisition*

A dataset used for this work, are collected from Venu Eye Institute & Research Centre, New Delhi, India. From different aged patients, total 86 images were collected and used for this work, where 51 are healthy and 35 are glaucoma affected patients. These images were analyzed qualitatively and categorized by the expert ophthalmologists. A Fundus Camera (FF450plus) with VISUPAC from ZEISS was used to take the retinal images in JPEG format with a resolution of 2588 × 1958 pixels. For ease of processing, only taken the region of interest (ROI) from the images. In fundus images, OD is the brightest portion and analysis of glaucoma mainly concentrated on this area. The centroid of the optic disk is calculated by taking the mean of coordinates of pixels with maximum intensity. The image is chosen automatically as 300 × 300 by taking centroid as a center and consequently the region of interest (ROI) is extracted. Fig. 3 shows normal fundus images and its ROI consists of OD and Fig. 4 shows Glaucoma affected fundus images and its ROI consists of OD [20].

2.2. *Optic disk segmentation*

The detection of the position and shape identification of the OD in fundus images is essential for the glaucoma detection [21]. The block diagram of the OD segmentation process is shown in Fig. 5. The optic disk is the beginning of the optic nerve and it is covered by major blood vessels. Hence, in the segmentation process, it occurs gaps in the segmented OD boundary. In order to remove this region in the original image (in Fig. 6a), the morphological operation based on dilation is exploited (in Fig. 6b). For this dilation operation, a disk structuring element of diameter equal to

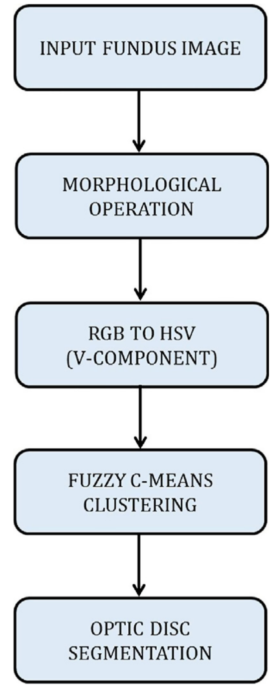

Fig. 5 – Optic disk segmentation process.

the primary blood vessel's width on the ONH is chosen with 20 pixels wide. The OD is the brightest area, looks like bright yellow or orange color in the fundus images and the OD boundaries are clearly distinguishable in V channel of the HSV plane. This can be used to isolate the OD pixels from its background and OD is segmented from the V channel as shown in Fig. 6c.

2.2.1. *Fuzzy C-Means clustering*

Clustering is an important unsupervised learning algorithm which deals with finding an object from an unlabeled data set. One of the main clustering algorithms is Fuzzy C-Means (FCM) algorithm [22,23] which gives better results for overlapped dataset compared to k-means algorithm. FCM means which allows one piece of data to belong to more than one cluster. The basic principle of this algorithm effectively minimizes the objective function which is given below:

$$J_m = \sum_{k=1}^{N}\sum_{l=1}^{C} \upsilon_{kl}^{m} y_k - c_l^2, \quad 1 < m < \infty \tag{1}$$

where m is an any positive real number, υ_{kl} is the degree of membership of y_k in the l cluster, y_k is the kth measured data with d dimension, c_l is the d dimension cluster center, $\|*\|$ represents the similarity between the center and measured data.

$$\upsilon_{kl} = \frac{1}{\sum_{j=1}^{C} \left[y_k - c_l / y_k - c_j \right]^{1/m-1}}$$

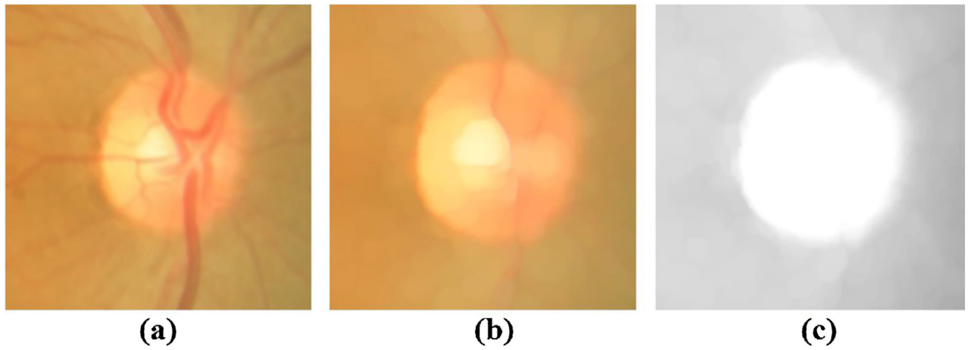

Fig. 6 – (a) Input fundus image; (b) after morphological operation; (c) V channel.

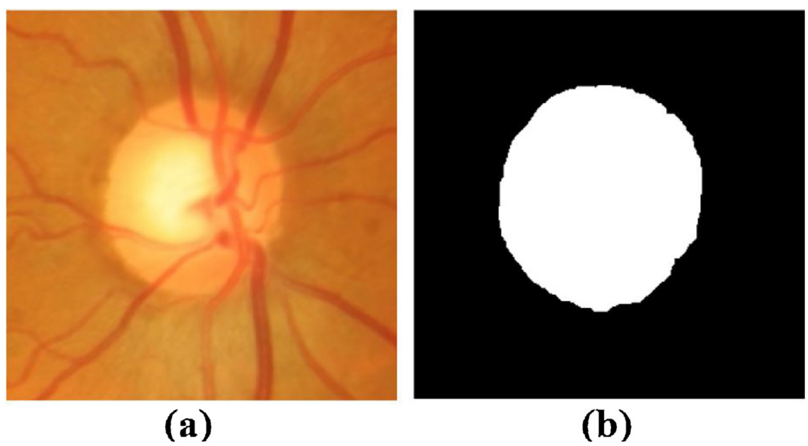

Fig. 7 – (a) Input fundus image; (b) segmented optic disk.

The algorithm consists of the following steps:

Step 1: Initialize $V = [\upsilon_{kl}]$ matrix, $V^{(0)}$

Step 2: At p-step: Find the centers vectors $C^{(j)} = [c_l]$ with $V^{(j)}$

$$C_l = \frac{\sum_{k=1}^{N} \upsilon_{kl}^{m} \cdot y_k}{\sum_{k=1}^{N} \upsilon_{kl}^{m}}$$

Step 3: Update $V^{(j)}$, $V^{(j+1)}$

Step 4: If $||V^{(j+1)} - V^{j}|| < \varepsilon$ then STOP; otherwise return to step 2.

MATLAB-Fuzzy Logic Toolbox function 'fcm' is used for generating clusters for this present application and it starts with an initial guess for the cluster centers, which are intended to mark the mean location of each cluster. Next, fcm assigns every data point a membership grade for each cluster. In this work, three clusters are generated with low, medium and high membership grades. The outputs obtained are three cluster centers C1, C2 and C3 and membership function matrix M with membership-grades, which are the intensity values of pixels. Thresholding is the operation of converting a multilevel image into a binary image i.e., it assigns the value of 0 (background) or 1 (objects or foreground) to each pixel of an image based on a comparison with some threshold value T (intensity or color value) [15]. As mentioned earlier the main feature of the OD is that it is having the highest intensity. The disk is extracted using the highest intensity and it is used as the threshold for the OD extraction. The threshold T is computed using the following method. From the generated clusters, first the cluster with maximum membership grade is found, and the corresponding grades are assigned with the same identification label. From the smoothed image, pixels with this gray level value are accessed, the average of the maximum and minimum intensity values are computed to obtain the threshold value T (where T = 1/2[Max (data (value)) + Min (data (value))]). In this T value calculation, data represents the data points of the smoothed image and label represents the cluster value with the highest membership grade. By applying the threshold T on the smoothed image I_S the image is converted to a binary image I_B. The following formula is used for the binary image extraction [15].

$$I_B(x,y) = \begin{cases} 1, & \text{if } I_s(x,y) > T \\ 0, & \text{if } I_s(x,y) \le T \end{cases}$$

Fig. 7 illustrates the segmented OD from the original input image.

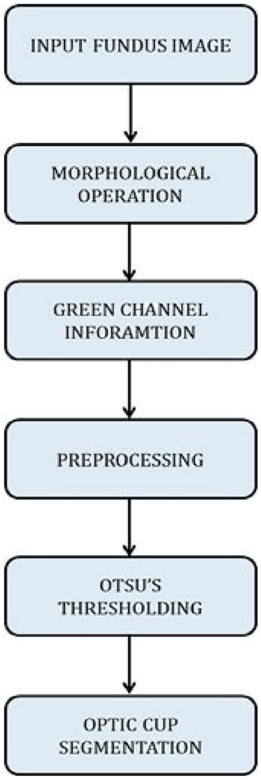

Fig. 8 – Optic cup segmentation process.

2.3. *Optic cup segmentation*

The OD can be separated into two areas; optic cup is a central bright cup-like area of the OD and neuro retinal rim is the peripheral region where optic nerves bend into the cup. The processes involved to find the cup region is shown in Fig. 8. Diagnosis of glaucoma using image processing techniques mainly focused the OD as well as OC regions. Here OC is segmented from the green channel because the cup is brighter than a disk. Through green channel, cup pixels can easily extract from OD. To improve the quality of the image, apply some preprocessing techniques to input fundus image as shown in Fig. 9. As a preprocessing, image standardization is used iteratively and it can be done by using Eq. (2).

$$G_{i+1} = G_i - (\mu_i + \sigma_i) \tag{2}$$

where G is the green channel image, i is the no. of iteration required, μ_i is the mean of the green channel image, σ_i is the standard deviation of the green channel image.

2.3.1. *Otsu's thresholding*

Thresholding is a method to extract an element from its background by using intensity value T. Based on this T value, each pixel is grouped as an object or a background. In Otsu's thresholding, found a threshold that maximizes the between-class variance and also minimizes the weighted within-class variance. This thresholding approach is applied to the preprocessed green channel of an input fundus image to get OC from disk region. Segmented optic cup by using Otsu's thresholding narrow-angle in Fig. 10b. Based on this segmented OD and OC, easily extract three clinical features like CDR, NRR area and blood vessels ratio in ISNT.

(i) Cup to disk ratio: It is the most common feature for glaucoma analysis. CDR [10] can be measured in terms of area of OD and OC by using Eq. (3). If the CDR value of the image is higher than 0.3, it is considered as glaucoma affected eye.

$$CDR = \frac{Area\ of\ segmented\ OC}{Area\ of\ segmented\ OD} \tag{3}$$

(ii) Neuro-retinal rim (NRR): OC is removed from the OD gets a disk-shaped area which is called NRR area shown in Fig. 11. For a healthy eye, NRR follows the ISNT rule. The mask used to measure the NRR in each quadrant is shown in Figs. 12 and 13. Its ratio (Eq. (4)) is smaller than unity for glaucoma affected eye.

$$NRR = \frac{NRR\ in\ Inferior\ quadrant\ area + NRR\ in\ Superior\ quadrant\ area}{NRR\ in\ Nasal\ quadrant\ area + NRR\ IN\ Temporal\ quadrant\ area} \tag{4}$$

(iii) Blood vessels ratio (BVR): Blood vessels are highly focused in the superior and inferior quadrants of the disk in a healthy eye. The blood vessels are extracted by applying the gray thresholding method. Use the same masks, as shown in Fig. 12, to measure the blood vessels in each quadrant as shown in Fig. 14. BVR in ISNT should be less for glaucoma eye compared to normal one.

$$BVR = \frac{BVR\ in\ Inferior\ quadrant\ area + BVR\ in\ Superior\ quadrant\ area}{BVR\ in\ Nasal\ quadrant\ area + BVR\ in\ Temporal\ quadrant\ area} \tag{5}$$

The mask used for both eyes are same. It has been illustrated in Figs. 13 and 14, from the masks affect the area of the neuro retinal rim and blood vessel (Figs. 13 and 14).

2.4. *Wavelet feature extraction*

The texture features of the image defined in the time domain are not enough for glaucoma classification because of hidden frequency information. The wavelet transform uses both frequency and spatial information. In the proposed method, the wavelet features are extracted by performing the Anisotropic Dual-Tree Complex Wavelet Transform (ADT-CWT) on the images. In anisotropic decomposition, sub-bands are only decomposed vertically or horizontally [18]. The DT-CWT sub-bands are directional. So adding anisotropic decomposition into the DT-CWT (ADT-CWT) will generate anisotropic and

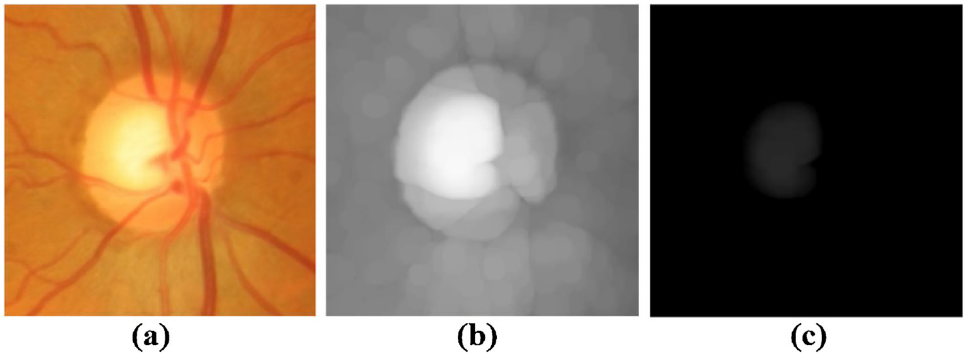

Fig. 9 – (a) Input fundus image; (b) green channel after the morphological operation; (c) pre-processed green channel.

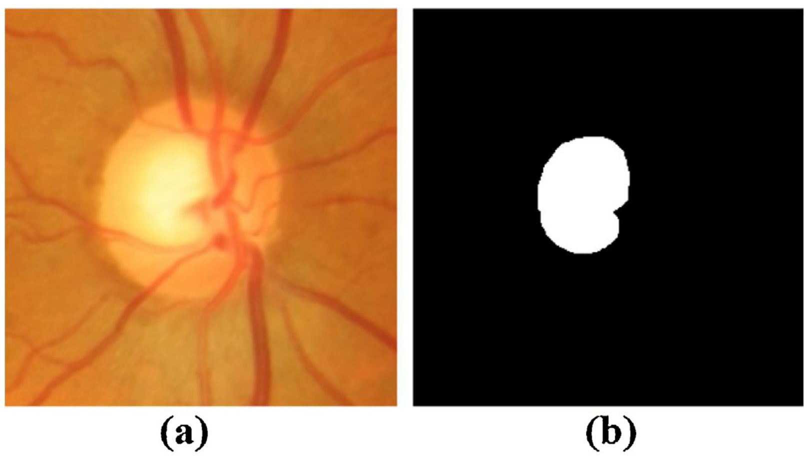

Fig. 10 – (a) Input fundus image; (b) segmented optic cup.

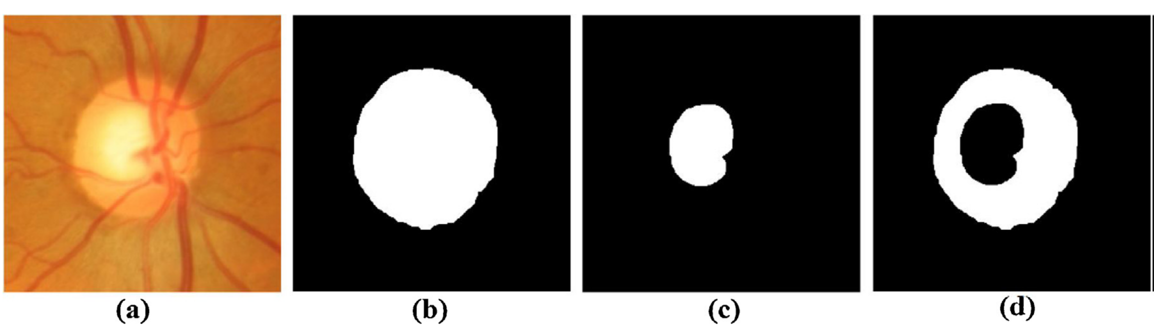

Fig. 11 – (a) Input fundus image; (b) segmented optic disk; (c) segmented optic cup; (d) neuro retinal rim.

also directional basis functions. In this application, 10 sub-bands information is used for the feature extraction. It is shown in Fig. 15. After decomposing the sub-bands, calculate the first order texture feature like mean (M), variance (V) and also second order texture feature the i.e., energy (E) from these 10 sub bands for classification.

2.5. *Classification*

People are always creating mistakes at the time of analysis or trying to find relationships between multiple features and become very difficult to attain a solution of particular problems. Machine learning can be effectively applied to such issues and it will improve the performance of systems. The Waikato Environment for Knowledge Analysis (WEKA) data mining tool is used [25,26] to select the optimal features using Minimum Redundancy Maximum Relevance (mRMR) feature selection technique for the classifier [8,9]. In this work, two class problems are investigated that is an image with glaucomatous or non-glaucomatous based on the feature set. Brief descriptions about each classifier used for our works are given below.

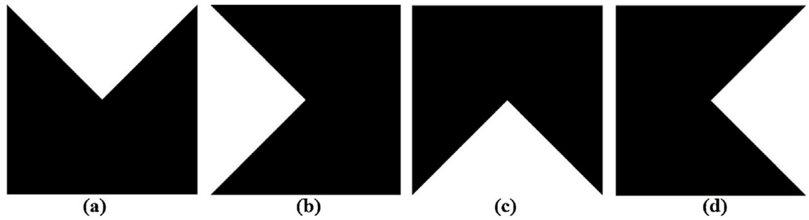

Fig. 12 – (a) Superior mask; (b) nasal mask; (c) inferior mask; (d) temporal mask.

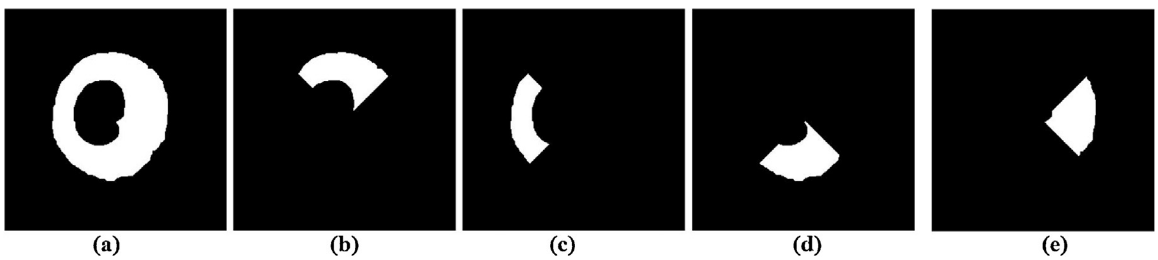

Fig. 13 – (a) Full NRR; (b) superior NRR area; (c) nasal NRR area; (d) inferior NRR area; (e) temporal NRR area.

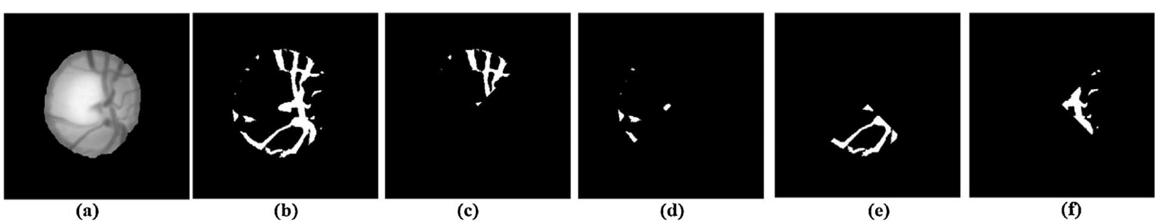

Fig. 14 – (a) Only disk portion in green channel; (b) blood vessels in OD; (c) blood vessels in superior; (d) nasal; (e) inferior; (f) temporal.

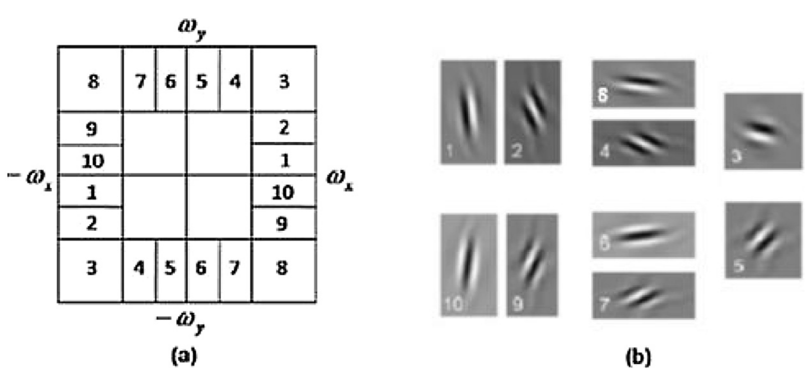

Fig. 15 – (a) Frequency-domain partition resulted from two level 2-D ADT-CWT decomposition; (b) basis functions of 2-D ADT-CWT.

2.5.1. *Multi-layered perceptrons (MLP) method*

MLP (Artificial Neural Networks) which is used to classify the instances which are not linearly separable. A multi-layer neural network consists of a large number of neurons combined together to form a pattern of connections. It is the combination of three classes: input units, output units, and units in between known as hidden units. In Feed-forward ANNs, signals travel through only one direction, from input to output [24].

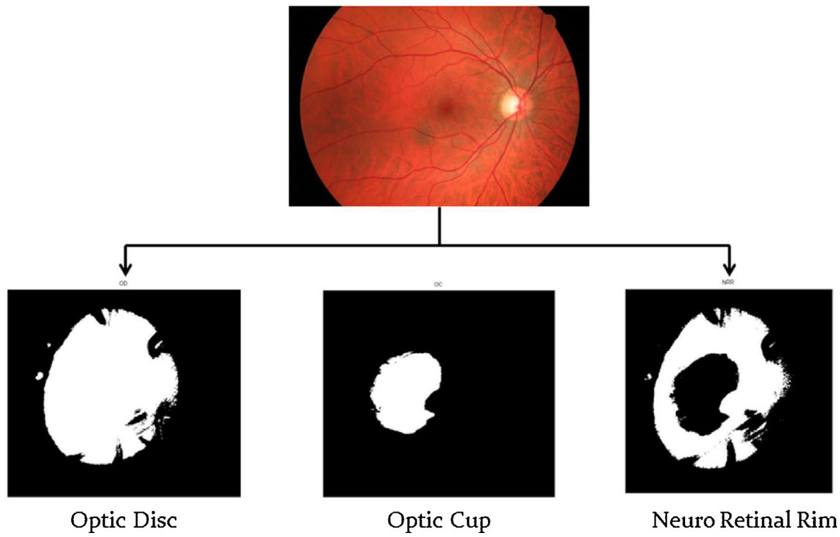

Fig. 16 – Segmented OD and OC results of healthy eye with CDR = 0.2581.

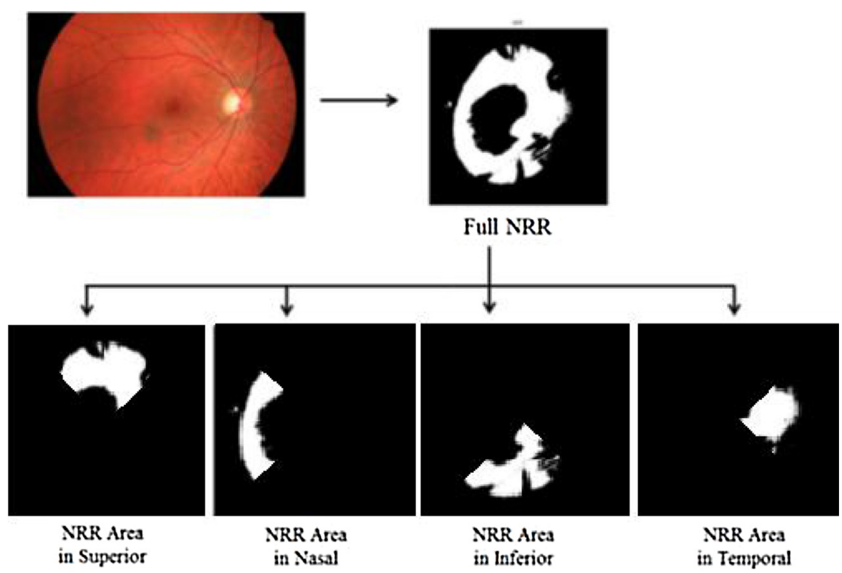

Fig. 17 – Segmented NRR area results of healthy eye with NRR area ratio = 1.4629.

2.5.2. *Support vector machine (SVM)*

SVM is a supervised learning algorithm and gets a better result for two class problems. The SVM complexity is unaffected by the number of features. In this paper, only consider linear polynomial as a kernel function [24].

2.5.3. *Random forest*

Random forests also known as random decision forests are used as ensemble learning for classification. It's correct for the decision tree's habit of over fitting to their training set. Its internal nodes are simple decision functions. For large databases, it works efficiently [8,9].

2.5.4. *Adaboost*

Adaboost means Adaptive Boosting, is a machine learning meta-algorithm and also resulting from a sequence of linear combination of weak classifiers. It can be used with other types of learning algorithms to increase their efficiency. But it is very sensitive to noisy data. Its outcome is close to sequential decision making [8,9].

3. Results and discussions

The performance of the proposed method is assessed using the dataset of 86 digital fundus images comprising 35 glaucomatous images and 51 normal images. The experiments were carried out on a PC with a 2.40 GHz Intel Core i3 CPU and 2 GB of memory. All algorithms except classification were implemented using Matlab R2013a. Classification is performed using data mining tool named as WEKA [26]. Tenfold cross-validation is used to split the samples into training and testing

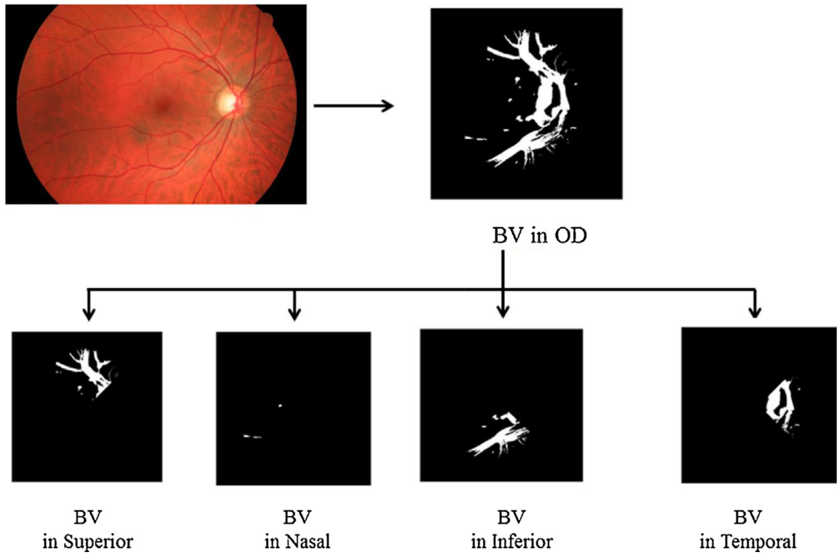

Fig. 18 – Extracted BVR in ISNT of healthy eye with BVR = 1.9721.

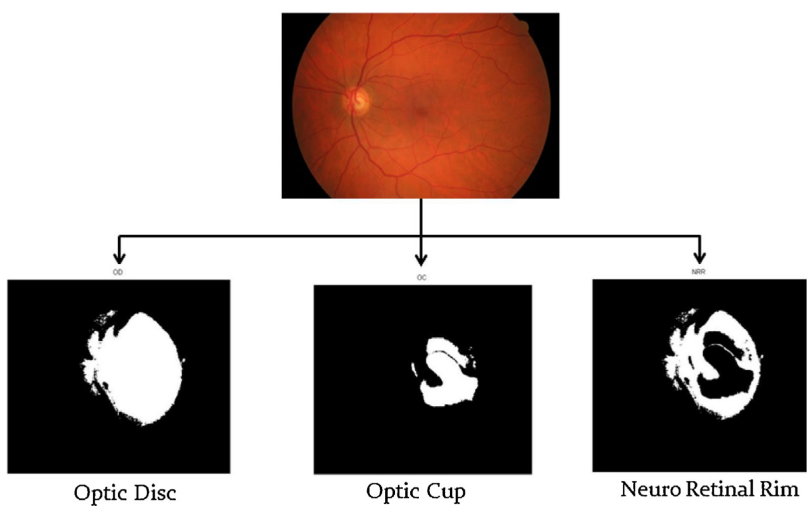

Fig. 19 – Segmented OD and OC results of glaucoma eye with CDR = 0.3354.

data. Once the ROI (300x300) is selected, segmentation of OD and OC are done using FCM clustering and Otsu's thresholding respectively. The segmentation results of the normal eye are shown in Figs. 16–18 and the glaucoma affected eye are also shown in Figs. 19–21. Then the feature such as CDR, NRR area and blood vessels ratio in ISNT are calculated. By using 2-D ADT-CWT the input image is decomposed into ten sub-bands (Fig. 15) and corresponding texture features such as mean, variance, and energy are calculated from each sub-band. Different combination of both clinical and wavelet features set is used for classification and the most prominent feature set is determined. The performance of the proposed algorithm is measured using the well-known parameter accuracy, sensitivity, and specificity which was widely used to evaluate the performance of classifiers. They can be defined by the following equations:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{6}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{7}$$

$$Specficity = \frac{TN}{FP + TN} \tag{8}$$

where *TP* is the number of positive instances identified correctly; *FN* is the number of positive instances rejected incorrectly; *TN* is the number of negative instances rejected correctly; *FP* is the number of negative instances identified incorrectly.

The observation results shown in Table 1, it is clear that different combination of feature set has dataset results. It is

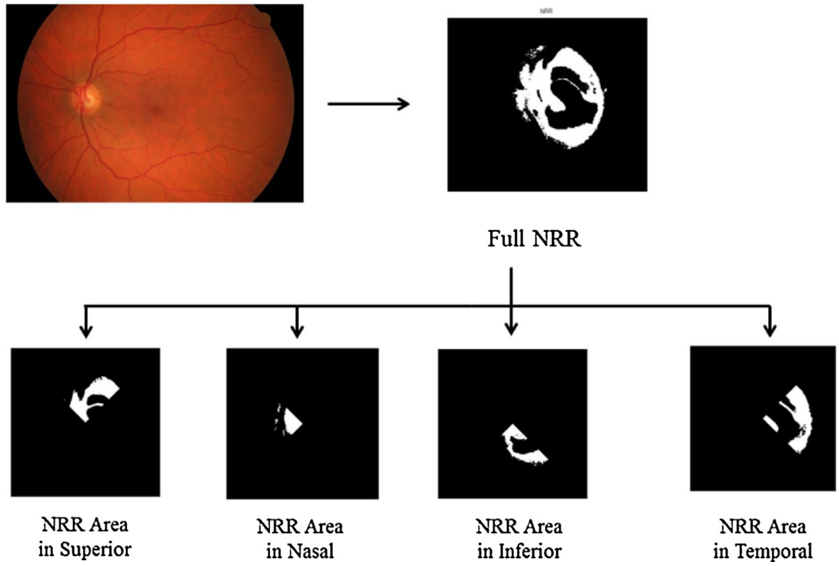

Fig. 20 – Segmented NRR area results of glaucoma eye with NRR area ratio = 0.9026.

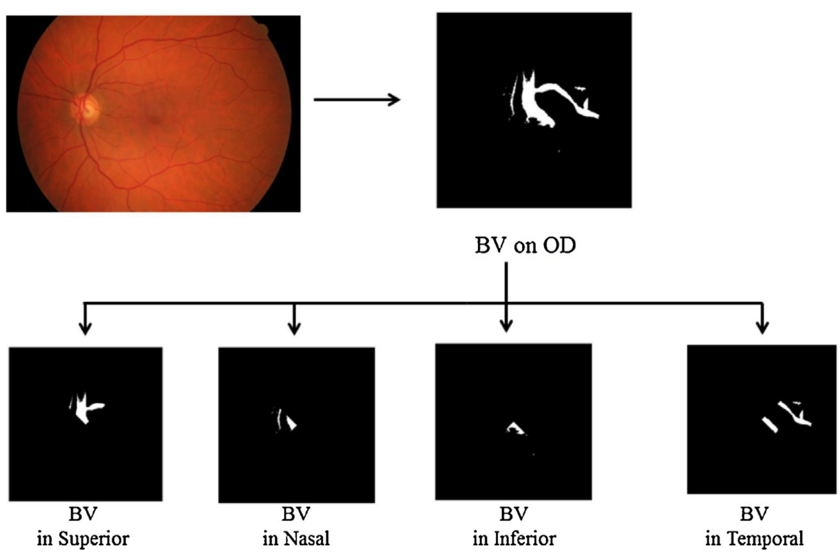

Fig. 21 – Extracted blood vessels results in ISNT of glaucoma eye with BVR = 0.9758.

also clear that the combination of CDR and Energy feature set provides a high accuracy rate of about 97.67% in the MLP classifier and also provides a high specificity of about 98% and better sensitivity rate of 97.1% in MLP classifier. The proposed method is also compared with some existing methods based on the feature set used and it is depicted in Table 2. In [12], it is achieved 94.11% accuracy by considering the clinical features such as CDR, NRR Area, and BVR. In this proposed method, a combination of both clinical and wavelet features (CDR and Energy) is used and it is achieved the accuracy rate of 97.67% with the use of the lesser number of features than in [12]. By using the proposed method, accuracy of 95.34% is achieved, with the combination of CDR, NRR, and BVR, which is better than [12] (see Table 1). From this, it is clear that our segmentation method is more efficient than in [12]. The comparison results reveal that the proposed method using MLP classifier achieved high-efficiency rate and considered as more clinically significant than existing methods.

4. Conclusions

A novel method has been proposed for glaucoma detection in digital fundus images. This method uses three classes FCM clustering technique for optic disk and Otsu's thresholding for cup segmentation. For wavelet feature extraction, 2-D ADT-CWT is also used. The classification has been performed with different combinations of the feature set using four types of classifiers namely MLP, SVM with linear polynomial kernel function, random forest and Adaboost. The proposed method

Table 1 – Efficiency rate of different combination of features in (%).

Feature combination	Best classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)
CDR, NRR, and BVR	Random forest	95.34	91.4	98
CDR, NRR, BVR, and V	SVM	96.51	94.3	98
CDR, NRR, BVR, and M	Adaboost	95.34	91.4	98
CDR, NRR, BVR, and E	SVM	94.18	91.4	96.1
CDR and M	SVM	94.18	96.1	91.4
CDR and E	MLP	97.67	98.0	97.1
CDR and V	Adaboost	95.34	91.4	98.0

Table 2 – Comparison of existing methodologies for glaucoma detection.

Features	No. of images	Accuracy (%)
CDR [13]	50	96.00
CDR and BVR [11]	36	95.00
5 HOS and 14 texture features [15]	60	91.70
18 wavelet features [16]	63	95.24
2 texture and 14 wavelet features [17]	200	98.00
CDR, NRR and BVR [12]	67	94.11
Proposed method (CDR and E)	86	97.67

shows the ability of glaucoma diagnosis with an accuracy of 97.67% using MLP classifier when compared with the existing methods. Future exploration could be stretched out by utilizing the publicly available database in order to validate the features. The method can be extended to the other eye disease detection like Diabetic Retinopathy, Macular Edema and Retinal Hemorrhage.

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