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Design & development of hybrid algorithms for glaucoma detection in humans –using local binary pattern (LBP) & the local multi-level binary pattern (LMBP)

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Abstract

In this paper, the overview of the design & development of hybrid algorithms for glaucoma detection in humans is presented using the concepts of the hybrid combination of LBP & LMBP algorithms. Matlab tool is being used to develop the algorithms and observe the simulation results of the 2 stages after the hybrid combination of the local binary pattern & the local multi-level binary pattern concepts. The simulation results shows the effectiveness of the method proposed.

Keywords: Glaucoma, Retina, CDR, IOP, , Fuzzy, Neural Network, PCA, DWT, GLCM

Introduction

The overall proposed block diagram corresponding to the software implementation of the glaucoma detection proceeds is presented in shown in figure no. 1. Also, a brief exhaustive review of each and every block is being presented with its functionality & it has to be noted that the entire detection process is divided into 3 stages, viz., stage-I, stage-II & stage-III to arrive at the end product after stage-III, i.e., glaucoma detection. Here, in this paper, we have presented only the **stage-I simulation results**.

Block-1 : The i/p to the algorithm proposed is the fundus pictures obtained from the database in which we have taken 60 image collection from various sources (we have created our own database).

Block-2 : From the fundus database, the inputted fundus image form the block – 1 is selected to determine whether it is affected with glaucoma or not affected.

Block-3 : Pre-processing of the fundus image is carried out next, where all the noises are removed and a noise free image is obtained.

Block-4 : Segmentation of the pre-processed image is carried out here in order to find the region of interest, i.e., the cup and the disc.

Block-5 : The Region of Interest, i.e., RoI which is the area of optical cup and area of optical disc will have to be extracted & are nothing but the RoI features, which is done using the hybrid concepts of LBP & LMBP algorithm, the output of which gives the entire features of the ROI.

Block-6 : At long last, the outcomes are processed utilizing the cup to the disc areas (which is the output of block - 5), using the hybrid combination of 3-level discrete wavelet transform and the principal component analysis.

Block-7 : The output of the block-6 is given as input to block 7, where the process is further refined using the concepts of gray level co-occurrence matrix in order to obtain the statistical texture features

Block-8 Here, the ratio of the cup to disc is calculated using the formula,

$$CDR = \frac{A_{cup}}{A_{disc}}.$$

Block-9 : The output of block-8 is given as input to the k-NN classifier, where the inputted & processed image is classified into healthy ones (normal) or unhealthy ones (moderate /severe) ones depending upon the cup to disc ratio, if the ratio is < 0.4, it is classified as normal case, if it falls in between 0.4 & 0.6, it is classified as moderate & if it is > 0.6, it is treated as a severe case.

Block-10 Here, all the inputted images from the block-1statistics are obtained where we can find how many are affected & how many are not affected.

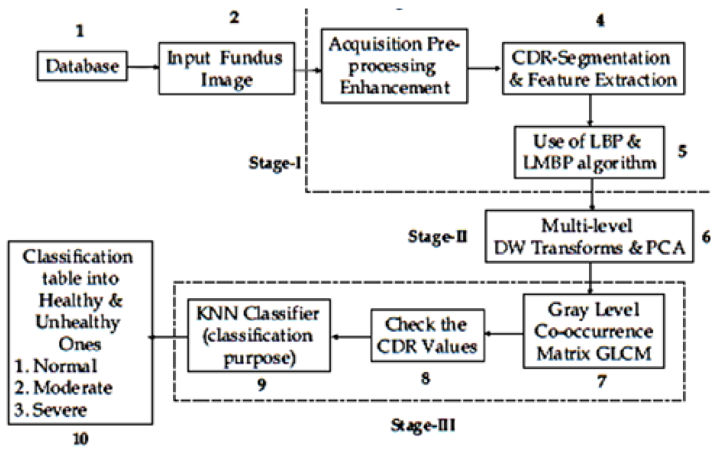

Fig. 1 : Proposed block-diagram of the hybrid representation of glaucoma detection using LBP, LMBP, DWT, PCA, GLCM & *k*-NN.

2. Database Collection

In order to build the algo., the 1st fundamental step is to acquire the databases of the images from a standard available datasets (may be from on-line or from hospitals). Thus, 60 fundus pictures (obtained from the fundus camera & stored in the database) were accumulated from different on-line datasets out of which, few pics were from the (HRF) - High Resolution Fundus image DB (www.optic-disc.org) also, remaining images were obtained from on-line database called as 'DROINS' and the left over from the IIT-Drishti website and a folder was made called as 'fundus DB', which was used as the input images to all the hybrid algorithm that was developed in this thesis. Few high resolution pictures were taken from the on-line database DRIONS, which consisted of a large number of fundus pictures obtained from the fundus camera. Few images were taken from hospitals.

Summary in process of glaucoma detection using IP

Generally, the complete glaucoma detection process in our proposed bio-medical system could be summarized as consisting of different blocks with each block having its own functionality & all the blocks are used in our research work [17].

- Database (general / generated one)
- Image acquisition/capturing
- Gray scale conversion
- Identification of ROI
- Pre-processing
- Re-sizing
- Boundary detection
- Segmentation
- Localization
- Normalization
- Noise removal

- Enhancement
- Feature processing
- Feature extraction
- Feature encoding
- Testing
- Decision taking
- Authentication
- Identification
- Recognition
- Classifiers
- Healthy / Un-healthy

3. Local Binary Pattern

Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Using the LBP combined with histograms we can represent the face images with a simple data vector. Local binary patterns (LBP) is a type of visual descriptor used for classification in computer vision. LBP is the particular case of the Texture Spectrum model & it has been found to be a powerful feature for texture classification, it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, it improves the detection performance considerably on some datasets. Firstly, we select the input test image from the database of 60 images and then perform pre-processing, segmentation and feature extraction process. This is what is discussed in the next sections.

4. Image pre-processing

The main aim of image pre-processing is to improve an image without any distortions and to increase appearance of an image. In colour retinal images, Optic disc appears to be the brightest part having pink or light orange colour and is considered to be Region of Interest (ROI). ROI is the region around the optic disc that must first be delineated, as the optic disc generally occupies less than 5% of the pixels in a typical retinal fundus image. While the disc and cup extraction can be performed on the entire image, localizing the ROI would help to reduce the computational cost as well as to improve the segmentation accuracy.

This preprocessing of the images is a method of processing the input image by removing the un-desirable distortions from it or improving few features of the inputted image so that it can be used for further processing, in the sense the image is refined. In the work considered, the fundus colour picture was obtained from the database of the fundus images. The ROI (optic cup and the optic disc), which is normally light pink or light orange in colour has to be removed so that their areas can be computed.

When the OC & OD extraction could be extracted from the fundus image, confining to the R O I (cup & disc) which can reduce the cost of computation (speed up the compiling process), consequently, increasing the accuracy of the process of segmentation to obtain the final outcome or the result. From the input image which is obtained from the image database, the region of the interest which is cup and disc will be cropped down and is resized to the standard size of (256 × 256).

5. Segmentation of optic cup and disc

Segmentation is defined as the process of isolating the foreground of the ROI from the background portion of the image. The region of interest is the optic cup and the disc, which has to be extracted. This process of separating out the ROI from the image taken as the input from the fundus database can be divided into multiple segments. The main aim of segmentation is to simplify and/or change the representation of an image into more meaningful and easier to analyse. Segmentation partitions an image into distinct regions containing each pixels with similar attributes. To be meaningful and useful for image analysis and interpretation, the regions should strongly relate to depicted objects or features of interest. Meaningful segmentation is the first step from low-level image processing transforming a grey-scale or colour image into one or more other images to high-level image description in terms of features, objects, and scenes.

The success of image analysis depends on reliability of segmentation, but an accurate partitioning of an image is generally a very challenging problem. Segmentation techniques are either contextual or non-contextual. The latter takes no account of spatial relationships between features in an image and group pixels together on the basis of some global attribute, e.g., grey level or colour. Contextual techniques additionally exploit these relationships, e.g., group together pixels with similar grey levels and close spatial locations.

6. Feature extraction

Feature represents a pattern or distinct structure of an image, i.e., extracting the important features of the ROI from the image is what is called as *feature extraction*, which is one of the important aspects of digital image processing. This helps us to find area, texture, resolution, edges, corners, centroid, moments, principal angle, orientation, etc… of the ROI in the image. This feature differs from its surroundings by texture, colour or intensity blobs, corners and edge

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pixels are the features of an image. These features are used for reconstruction of the images and for detection and classification of the images. neighbourhood highlights and their descriptors are the building squares of numerous vision calculations. Their applications incorporate picture enrolment, protest location and characterization with movement estimation. These calculations utilize nearby highlights to better deal with scale changes, revolution, and impediment, here we mainly consider the texture analysis of the image Image texture gives us the idea of how the colours are distributed. Image textures can be artificially created or found in natural scene When the pre-processing and the desired level of segmentation has been achieved, some feature extraction technique is applied to the segments to obtain features, which is followed by application of classification and post processing techniques.

It is essential to focus on the feature extraction phase as it has an observable impact on the efficiency of the recognition system. Feature selection of a feature extraction method is the single most important factor in achieving high recognition performance. Feature extraction has been given as '*extracting from the raw data information that is most suitable for classification purposes, while minimizing the within class pattern variability and enhancing the between class pattern variability*'. Thus, selection of a suitable feature extraction technique according to the input to be applied needs to be done with utmost care w.r.t. captured image which is taken from the database & given as input to our hybrid algorithm.

Now, we apply LBP, LMBP for the test images which is given as input to our algorithm. **LBP** stands for **Local Binary Pattern** is a simple yet very efficient texture operator. It mainly considers the neighbouring pixels and it compares each pixel with its neighbouring pixels of an image, it thresholds the neighbourhood of each pixel and considers the result as a binary number.

The local binary pattern (LBP) operator is a very powerful and gray-scale invariant method of analyzing textures. The LBP operator usually combines characteristics of statistical and structural texture analysis. It describes the texture with micro primitives, often called textons, and their statistical placement rules.

Ojala *et.al.* (1996) introduced the LBP texture feature to complement and improve the performance of the local image contrast measure. For each pixel in an image, a binary code is produced by thresholding its neighbourhood (8 pixels) with the value of the center pixel. A histogram is then constructed to collect up the occurrences of different binary patterns representing different types of curved edges, spots, flat areas etc. tons, and their statistical placement rules. The original 8-bit version of the LBP operator considers only the eight nearest neighbours of each pixel and it is rotation variant, but invariant to monotonic changes in gray-scale.

The dimensionality of the LBP feature distribution can be calculated according to the number of neighbours used. The basic 8-bit LBP can represent 28 different local patterns, so the dimensionality of the feature vector is 256. Later, the definition of the LBP was extended to arbitrary circular neighbourhoods of the pixel to achieve multi-scale analysis and rotation invariance (Ojala *et.al*. 2002). The neighbourhood of the center pixel is considered to be circular, and P neighbour samples are selected from the circular perimeter of radius R. Neighbour samples were interpolated on the circle with equal space. In the multi resolution model of the LBP, separate operators at different scales are constructed and the final feature vector is obtained by concatenating individual feature vectors one after another.

Maenpaa *et.al.* introduced the concept of 'uniform' patterns, where the maximum number of bit-wise changes from one to zero or vice versa in the circular neighbourhood is limited. Usually the maximum number of bit changes was allowed to be two. With this approach, the number of different binary codes is reduced dramatically, but the discrimination performance remained good. Existing LBP quantifies the occurrence statistics of individual rotation invariant patterns corresponding to certain micro-features such as spots, flat areas and edges.

It has become very popular because of its discriminative power and simplicity.it is used in many applications. It is possible to use this in real time challenges because of its computational simplicity. It can also be seen as the only approach for the texture analysis of the structural as well as the statistical models. They describe the neighbourhood of a pixel by making use of its binary derivatives.by using binary derivatives a short code can be formed which describe the neighbourhood of a pixel. LBP has variety of applications, it can be used in face recognition, pattern recognition and texture analysis. The local binary pattern operator generates a bit code that is used to describe the surroundings of a pixel.

The operator works on the grey scale images' LBP mainly takes (3 × 3) surrounding neighbours and gives a value 1 when the neighbour has larger value as compared to the centre pixel. And similarly, the operator

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generates a binary 0 if the neighbour has the value less than that of the centre pixel. The neighbours of the centre pixel are represented with an 8-bit number such as an unsigned 8- bit integer that makes it a very compact description. The figure no. 2 shows an example of an LBP operator how it could be used in our research work.

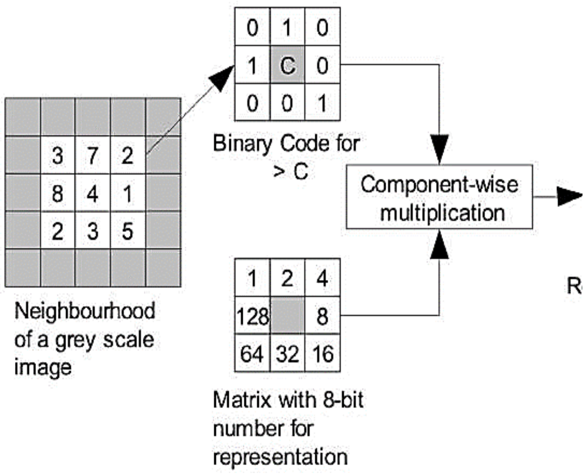

Fig. 2: LBP operator

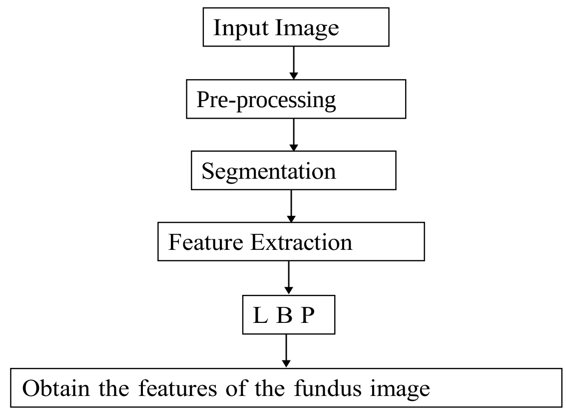

Fig. 3: Simplified flow chart of LBP

It has since been found to be a powerful feature for texture classification; it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, it improves the detection performance considerably on some datasets. A comparison of several improvements of the original LBP in the field of background subtraction

Algorithm Steps : The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells (e.g., 16 x 16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbours (on its left-top, left-middle, left- bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbour's value, write '0', otherwise, write it as '1'. This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each 'number' occurring (i.e., each combination of which pixels are smaller and which are greater than the center). This histogram can be seen as a 256- dimensional feature vector.
- Optionally normalize the histogram.
- Concatenate (normalized) histograms of all cells.
- This gives a feature vector for the entire window.

LBP is mainly used for the texture analysis of the histogram of an image. Usually when calculating a LBP code for an image, the edges are ignored as they do not have enough information and this would lead to produce false information. Firstly, The LBP component was calculated like the one shown in figure 1. Then, later the contrast component C was calculated by using the average of the pixels whose value is above the threshold value minus the average of the pixels whose value is under the threshold. In the case, the result would be (7+8+5)/3 □ (3+2+2+3+1)/5 ≈ 4.47. The feature vector can now be processed using the Support vector machine, extreme learning machines, or some other machine-learning algorithm to classify images. Such classifiers can be used for face recognition or texture analysis.

A useful extension to the original operator is the so- called uniform pattern, which can be used to reduce the

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length of the feature vector and implement a simple rotation invariant descriptor. This idea is motivated by the fact that some binary patterns occur more commonly in texture images than others. A local binary pattern is called uniform if the binary pattern contains at most two 0-1 or 1-0 transitions.

For example, 00010000 (2 transitions) is a uniform pattern, 01010100 (6 transitions) is not. In the computation of the LBP histogram, the histogram has a separate bin for every uniform pattern, and all non-uniform patterns are assigned to a single bin. Using uniform patterns, the length of the feature vector for a single cell reduces from 256 to 59. The 58 uniform binary patterns correspond to the integers 0, 1, 2, 3, 4, 6, 7, 8, 12, 14, 15, 16, 24, 28, 30, 31,32, 48, 56, 60, 62, 63, 64, 96, 112, 120, 124, 126, 127, 128, 129, 131, 135, 143, 159, 191, 192, 193, 195, 199, 207, 223, 224, 225, 227, 231, 239, 240, 241, 243, 247, 248, 249, 251, 252, 253, 254 and 255.

T. Ojala *et.al.* presented an equation to define the local neighbourhood of a pixel as given below for an arbitrary circular derivation for a LBP operator with any radius and centre threshold along with the neighbors.

$$T = t\,(g_c, g_o, g_{p-1})$$

where g_c is the grey-value of the center pixel ($g_0 - g_{P-1}$) represents the P number of neighbours with grey-value.

7. Flow-Chart for Stage-I

In our research work, the region of our interest is the cup to disc ratio so to extract the cup and the disc ratio we use LBP using the texture analysis, firstly we select the input image and then we apply LBP to extract the cup and the disc. In our research work, we have used hybridization method so as to extract all the features efficiently and obtain accurate results. The flow-chart for achieving this is shown in the Fig. 3 & 4 respectively.

1. We take the image from the database.
2. Select the test image.
3. The region of interest is the cup and the disc, so we extract the cup and disc.
4. Finally apply the LBP algorithm.

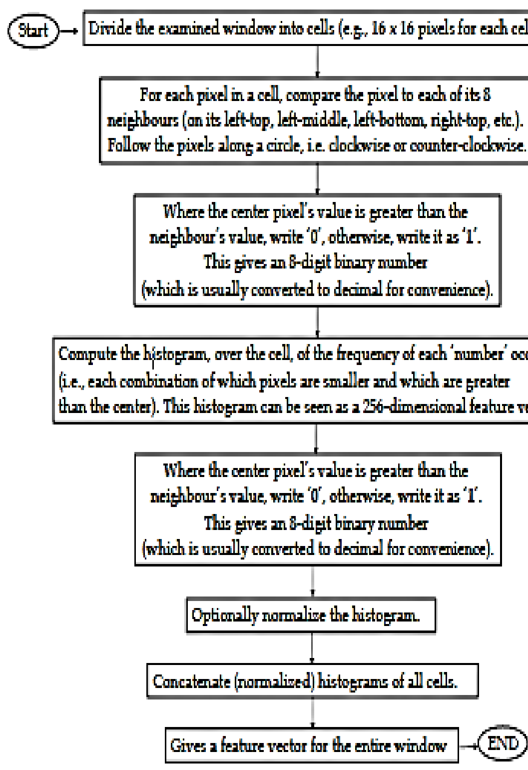

Fig. 4 : Data flow diagram for getting the features using the LBP concept

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8. Local Multi-Level Binary Pattern

In this section, the output of the stage-I from the previous section is given as input here so that the output of stage-I is a refined one with good efficiency and accuracy. "LMBP" stands for local multilevel binary pattern. Texture is the core element in numerous computer vision applications. The objective of this research work is to present a novel methodology for learning and recognizing textures. A local binary pattern (LBP) operator offers an efficient way of analysing textures. A multi-level local binary pattern operator which is an extension of LBP is proposed for extracting texture feature from the images. The operator finds the association of LBP operators at multiple levels. This association helps to identify macro features.

A local binary pattern (LBP) operator offers an efficient way of analysing textures. A multi-level local binary pattern operator which is an extension of LBP is proposed for extracting texture feature from the images. The classifier is trained with images of known texture class to build a model for that class. Depending on the size of the operator, octets are framed and LBP responses of the octets are noted. Their occurrence histograms are combined to frame the texture descriptor. The proposed operator is gray-scale invariant (GSI). The operator is computationally simple since it can be realized with few operations in the local neighbourhood. A non-parametric statistic named G-Statistic is used in the classification phase. The classifier is trained with images of known texture class to build a model for that class. Experimental results prove that the approach provides good discrimination between the textures.

Texture can be used as a measure for interpreting the images. Texture can be regarded as the visual appearance of a surface or material and the visual appearance of the view is captured with digital imaging and stored as image pixels. For a well-defined texture, intensity variations normally exhibit both regularity and randomness, and therefore texture analysis requires careful design of statistical measures. The degrees of randomness and of regularity will be the key measure when characterizing a texture. A surface is taken to be textured if there are large numbers of texture elements (or 'texels') present in it. The components of a texture, the texels, are uniform micro- objects that are placed in an appropriate way to form any particular texture. Image resolution is also very important in texture perception since low resolution images normally contain very homogenous textures. Textures provide discriminatory information and assists in pattern recognition and segmentation tasks.

Texture plays an important role in natural vision, and it has been widely applied to several surface characterization problems. Haralick et.al. applied texture analysis methods to remotely sensed images for doing terrain analysis. They attempted to classify regions of images to predefined classes to form a description of the sensed scene. Oliver used texture analysis and classified regions of SAR images to forest and non-forest classes. Texture has also been utilized for characterizing the surface of more concrete objects. Most of the real-world applications utilize texture analysis. In biomedical engineering and medical image analysis texture has been used for different purposes. Characterization of textured materials is usually very difficult and the goal of characterization depends on the application. The ultimate goal of texture characterization systems is to classify textures into different categories or to recognize different textures.

Typically, methods for texture analysis are divided into two main categories with different computational approaches: the stochastic and the structural methods. Structural textures are often man-made and have very regular appearance, for example, of line or square primitive patterns that are systematically located on the surface (e.g., brick walls). In structural texture analysis the properties and the appearance of the textures are described with different rules to specify the kind of primitive elements present in the surface and their location details. Stochastic textures are usually natural and consist of randomly distributed texture elements, which again can be, for example, lines or curves but placed at random (e.g., tree bark).

The analysis of these kinds of textures is based on statistical properties of image pixels and regions. There exists other categorization of textures, for example, artificial vs. natural, or micro textures vs. macro textures. Irrespective of the categorization, texture analysis methods try to describe the properties of the textures in a proper way. It depends on the applications what kind of properties should be sought from the textures under inspection and how to do that. This is rarely an easy task. Applications have different requirements for recognition: usually accuracy is the most important property, but sometimes also speed, usability and configurability should be prioritized.

There is no universal recognition method for different texture characterization tasks. In most general image analysis tasks, texture recognition methods must detect different textures in the images, but also consider images on a higher level. To exploit texture in applications, the measures should be accurate in detecting different texture structures, but still be invariant or robust with varying conditions that affect the texture appearance. Computational complexity should not be too high to preserve realistic use of the methods. Different applications set various requirements on the texture analysis methods, and usually selection of measures is done with respect to the specific application.

One of the major problems when developing texture measures is to include invariant properties in the features. In a real-world environment, it is very common that illumination changes over time, and causes variations in the texture appearance. Texture primitives may also rotate and locate in many different ways, which also causes problems. On the other hand, if the features are too invariant, they might not be discriminative enough. Texture plays an important role in numerous computer applications. A local binary pattern (LBP) operator is one of the efficient ways of analysing textures.

$$C(R_i) = \frac{P(R_i)}{4\pi A(R_i)}$$

A multi-level local binary pattern operator is an extension of LBP is proposed for extracting texture feature from the images. In case of LMBP we take multiple levels into consideration so that we get accurate results and this in turn helps in identifying macro features. Octets are formed and their histograms are combined to frame the texture descriptor. LMBP operator is grey scale invariant. The operator is very simple since it depends on few operations within the neighborhood. Experimental results prove that the approach provides good discrimination between the textures the extension of the LBP, Here the range values the maximum, and the minimum values are taken in to consideration.

$$CDR = \frac{OC_{area}}{OD_{area}}$$

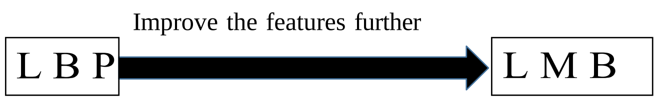

Fig. 5 : Block-diagrammatic approach for the flow chart of LMBP

The proposed system has the following steps that is firstly we take input image, then, we do pre-processing, segmentation and then the feature extraction. In the pre- processing stage we convert image to the grey scale and then the image is divided into many segments by using level segmentation, then the feature extraction is done by using the hybrid combination of LBP algorithm and LMBP algorithm. The figure 5 below shows the extracted cup and disc after applying the LMBP algorithm. The output from the LBP is given to the LMBP for more accurate results since ours is a hybrid method we take in the results from the previous method is given has an input to the next algorithm, i.e., to the LMBP to arrive at more sophisticated results.

9. Computation of CDR

Since the OD is generally elliptical in nature, the regions of the optic disc should be made circular so that the vertical & horizontal diameter when calculated could be used to compute the area. In this way, the biggest associated region, which is the circular optic disc's area can be computed using the minimization measure formula from the radii Ri as given by the eqn. as once the features (area, diameter) of the OD & the OC are obtained, the cup to disc ratio of the ROI considered in that particular fundus image is calculated using the relation given by the equation as ,

Finally, the output of the stage-I is given as input to the next stage-II which is discussed in the next research paper as per the Fig. 1 of the proposed overall block- diagram for glaucoma detection.

10. Simulation results

A program (.m code) along with subroutines & function calls is developed using the Matlab tool & the developed main program is run for different fundus images as the input & the results are observed for various cases of glaucoma, viz., normal case (case-1), moderate case (case-2) & severe case (case-3) for one particular set of images, say, image_1, image_2, image_3 …. Set 1. The exercise is repeated for another set of 2 groups set 2 & set 3, i.e., 6 images. To start with fundus images, viz., image_1.jpeg, image_2.jpeg & image_3.jpeg from the set 1 are given as inputs to the created hybrid algorithm one after other & the simulations results are observed to get the LBP & the LMBP outputs. Essentially, the investigation is completed for the remaining 51 pictures (27

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sets) which are available in the considered database In this paper, only one set of results is presented, say set-1 consisting of 3 images & the remaining are now shown here for the sake of convenience.

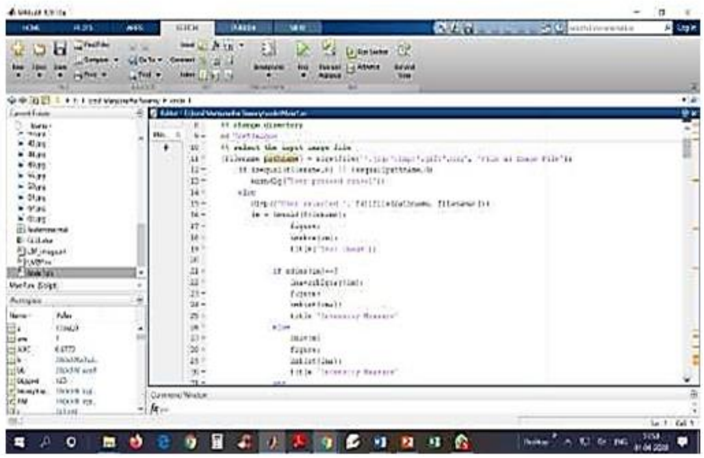

Fig. 6 : Matlab file showing the hybrid algorithm

Fig. 21 : The LBP image

Fig. 22 : The LMBP image

Set – 1 : image_3
Case 3 : Simulation results showing the severe glaucoma

Fig. 23 : Test sample

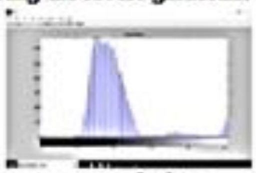

Fig. 24 : The histogram output

Fig. 25 : The disc image

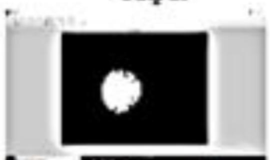

Fig. 26 : The cup image

Fig. 27 : The disc boundary

Fig. 28 : The extracted features

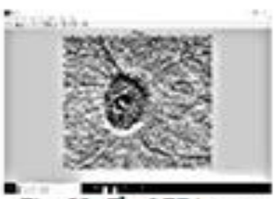

Fig. 29 : The LBP image

Fig. 30 : The LMBP image

Fig. 7 : test sample

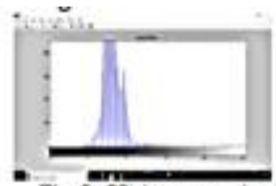

Fig. 8 : Histogram output

Fig. 9 : Disc image

Fig. 10 : Cup image

Fig. 11 : The boundary of the disc

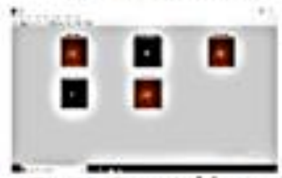

Fig. 12 : Extracted features

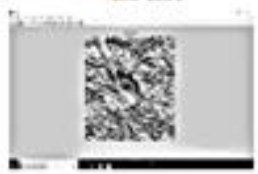

Fig. 13 : LBP image

Fig. 14 : The LMBP image

The following processes are to be carried out for one set of image from the database Set – 1 : image_1
Case 1 : Simulation results showing normal glaucoma

- Select the test sample (give input from the database)
- Histogram output : we get the intensity of the colours of the image
- We extract the disc image as we have to find the CDR ratio taking it as the ROI
- We extract the cup : in order to find the cup to disc ratio.
- The boundary of the disc
- All the parameters in single image
- LBP image : The grey scale image is shown in the figure below
- The LMBP image: the figure shows local multilevel binary pattern extracted image

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Set – 1 : image_2
Case 2 : Simulation results showing the moderate glaucoma

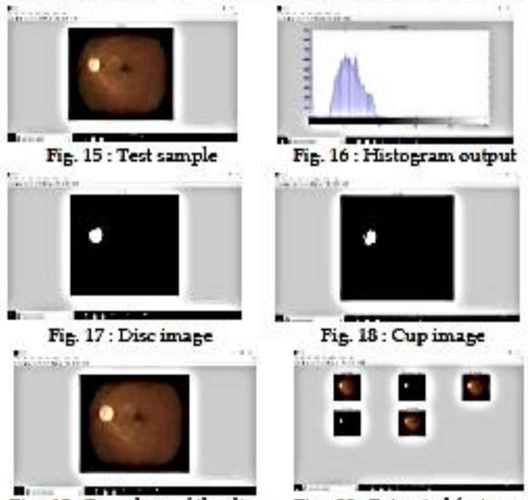

Fig. 15 : Test sample
Fig. 16 : Histogram output
Fig. 17 : Disc image
Fig. 18 : Cup image
Fig. 19 : Boundary of the disc
Fig. 20 : Extracted features

11. Conclusions

In this section, we present the concise result (outcome or the end-result), i.e., the simulation results w.r.t. the software implementation of the glaucoma detection work done. Research was carried out on the development of bio medical image processing algorithms w.r.t. the diagnosis & detection of the glaucomatic disease in human beings. To start with, an extensive background research was carried out on the chosen research topic. A number of reference text books, conference & journal research papers which covered the basic & fundamental concepts relating to the theoretical aspects, practical aspects, hospital aspects and w.r.t. the implementation point of view were collected and a brief study was carried out.

Codes were developed in Matlab for all the stage-I of the proposed block diagram shown in the Fig. 1 of our contributory work, the program was run & the results were observed for various cases healthy-normal (non- glaucomatic), unhealthy-moderate, severe (glaucomatic) cases. Only 3 case studies (normal, moderate & severe) were carried out of 60 images from the database for a particular set of images. Like this, another 2 sets of case studies was conducted. It has to be noted in this context that CDR concept was used for the glaucoma detection, actually the simulation results till the LBP & LMBP is shown here for the sake of convenience as this is the highlight of the paper. The Figs. 6-30 shows the effectiveness of the method proposed by us.

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