ADVANCED RETINAL DISEASE SCREENING THROUGH LOCAL BINARY PATTERNS

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ABSTRACT

When sugar level (glucose) in the blood fails to regulate the insulin properly in human body, diabetic is occurred. The effect of diabetic on eye causes diabetic retinopathy. Diabetic Retinopathy is one of the complicated diabetes which can cause blindness. It is metabolic and the disordered patients perceive no symptoms until the disease is at late stage. So early detection and proper treatment has to be ensured. To serve this purpose, various automated systems have been designed). A key feature to recognize Diabetic Retinopathy is to detect Microaneurysm in the fundus of the eye. This work investigates discrimination capabilities in the texture of fundus images to differentiate between pathological and healthy images. For this purpose, the performance of Local Binary Patterns (LBP) as a texture descriptor for retinal images has been explored.The goal is to distinguish between diabetic retinopathy (DR) and normal fundus images analyzing the texture of the retina background and avoiding a previous lesion segmentation stage. We propose preprocessing technique such as Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the contrast of the input image and we use candidate extractors such as Circular Hough Transform to improve the red lesion detection. Finally the output image was classified as Normal and Diabetic retinopathy (DR). These results suggest that the method presented in this paper is a robust algorithm for describing retina texture and can be useful in a diagnosis aid system for retinal disease screening.

INTRODUCTION

Retinal microcirculation offers a unique non-invasive way to study the early manifestation of several diseases affecting the human circulatory system. Changes in retinal vascular geometrical patterns such as width, tortuosity, branching angle, junction exponents and fractal dimension have been investigated as candidate biomarkers in various ocular, systemic and neurodegenerative diseases . Data from long- term population-based studies have demonstrated a consistent link between the retinal microvascular changes with incident clinical stroke , hypertension , arteriosclerosis , dementia and other cerebral small vessel diseases [9]. For instance, the narrowing of arteries and widening of veins is a significant indicator of the progression of diabetic retinopathy. Visual surveillance in machine understanding has been investigated worldwide during last few decades. Human motion detection & tracking from video imagery is one of the most active research fields. The social interests in movement detection and tracking of people have enormously increase in recent years with numerous applications like human computer interface, surveillance, security and many others. Moving object detection and tracking is a challenging computer vision task consisting of two closely associated video analysis processes. The first one, object detection, involves locating an image object in the frames of a video sequence, while object tracking performs the monitoring of the video object temporal and spatial changes during sequence, including its presence, shape, size, position. Computers have become very important in our daily lives.

They perform repetitive, data intensive & computational tasks, more accurately and efficiently than humans. It is very natural to try to extend their capabilities to carry out more intelligent tasks for example analysis of visual scenes or speech, logical inference and reasoning – in brief the high-level tasks that we humans perform subconsciously hundreds of times every day with so much ease that we do not usually even realize that we are performing them. Privacy remains one of the ethically crucial issues of the information age [16] and it will remain like this forever because of the human nature. We desire the safety and the privacy of our life, but our actions and behaviours are defined by our own interests, which sometimes can be achieved only by violating other humans safety or/and privacy. To guard ones safety, thousands of surveillance cameras were installed all over the world. Human operators are processing the information collected by the cameras inefficiently and slowly. One possible solution for this issue is to build an automatic system, which would fulfil the human operator's job better and faster. This problem is difficult. First, the number of people has to be determined, and then their location needs tobe estimated. Detecting people and estimating their location is challenging task as peoples move randomly, they wear different clothes and appear in different gestures. This work is a research on object tracking and how it can be applied to surveillance footage.

Surveillance networks are typically monitored by one or more people, looking at several monitors displaying the camera feeds. Each person may potentially be responsible for monitoring hundreds of cameras, making it very difficult for the human operator to effectively detect events as they happen. During the last few decades there are attempts by various researches to design better surveillance system. But, the problem such as illumination change, motion blur, complexity etc. still persist hence there is vast scope to implement optimal system. The evaluation of human motion in image sequences involves different tasks, such as acquisition, detection motion segmentation and target classification. Detecting and tracking people in scenes supervised by cameras is an important step in many application scenarios such as surveillance, urban planning or behavioural etc. The amount of data produced by camera feeds is so large that it is also vital to be performed with the greatest computational efficiency and often even real-time. Human motion segmentation and tracking can be completed in two or three dimensions depending on the difficulty of analysis, representations of the human body shape range from volumetric models to basic stick figures. Tracking depends on the correspondence of image characteristics between consecutive frames of video, taking into concern information such as colour, shape, position, and consistency. Boundary segmentation can be performed by comparing the contrast or/and colour of neighbouring pixels, looking particularly for rapid changes or discontinuities. However, motion segmentation & tracking is still an open and significant problem due to dynamic environmental conditions such as illumination changes, shadows, waving tree branches in the wind, etc. and difficulties with physical changes in the scene. However, several important challenges still exist.

Tracking objects in video sequences of surveillance camera is nowadays a demanding application . Tracking objects is much more challenging in video sequences to improve recognition and tracking performances. Surveillance is used for intelligence gathering , the prevention of crime, the protection of a process, person, group or object, or for the investigation of crime. Surveillance can achieve this by three means: by deterrence, by observation and by reconstruction. Surveillance can assist rebuilding of an incidence through the availability of footage for forensics experts, yet again helped by video analytics. Surveillance can also control personal security if surveillance resources are visible or if the consequences of surveillance can be felt. In order to determine whether surveillance technology is actually improving surveillance, the usefulness of surveillance must be expressed in terms of these higher purposes. With their wide range of styles and features, surveillance systems are common in most industries around the world. The number of tasks where object detection & tracking can be employed is huge. Among these tasks, only few of them are ready for real applications, many of them need further technological improvements and some of them have not been even thought yet. In the following list we give a general overview of the principal fields of application where object detection & tracking can be helpful.

LITERATURE SURVEY

This chapter gives an overview, of the various methods and techniques generally used for object detection & tracking. In spite of being a relatively new research area, a massive number of contributions related to surveillance system using motion analysis have been published in the last few years As mentioned in Chapter 1 it is a challenging problem with many potential applications. This chapter reviews the state of the art in automatic object detection and localisation, with particular attention to object detection & tracking. In particular, it is still beyond the current state-of-the-art to expect a very general tracker, which would be able to follow people accurately in any situation, regardless of the environment, light, people density and activity, etc. Tracking is the process of following an object of interest within a series of frames, from its initial appearance to its last. The type of object and its description within the system depends upon the application. During the time that it is present in the scene, it may be occluded (either partially or fully) by other objects of

interest or fixed obstacles within the scene. A tracking system should be able to predict the position of any occluded objects through the occlusion, ensuring that the object is not temporarily lost and only detected again when the object appears after the occlusion. The process can be extended to design an algorithm which can help to overcome occlusions. Object tracking systems are typically geared toward surveillance applications where it is desired to monitor people and or vehicles moving about an area. Systems such as these need to perform in real time, and be able to deal with real world environments and effect such as changes in lighting and spurious movement in the background (such as tress moving in the wind). Other surveillance applications include data mining applications, where the aim is to annotate video after the event. Target representation can be categorized into two major classes. One is for a collection of general objects, such as human bodies or faces, computer monitors, motorcycles, and so on. The other is for one precise target including a specific person, car, toy, building and so on. The targets can be images, concrete objects or even abstract

feature points. Motion detection & segmentation in video sequences aims at detecting regions that corresponds to mobile objects such as humans and vehicles. Detecting moving regions gives a centre of attention for later processes such as tracking and behaviour analysis since only these particular regions need be considered in the later processes. At present, many segmentation methods use either spatial or temporal information in the image sequence. Different conventional approaches for motion segmentation are outlined as follows. 1) Background subtraction: Background subtraction is a well-known method for motion detection & tracking, particularly under those conditions with a reasonably unmoving background (N. Prabhakar et al. 2012). It identifies moving regions in an image by computing the disparity between the present image and the reference background image in a pixel-by- pixel manner. Background subtraction is simple, but extremely sensitive to variations in vibrant scenes derived from irrelevant and illumination events etc. Therefore, it is enormously dependent on an excellent background model to lessen the control of these changes (I. Haritaoglu et al. 2000 , S. McKenna et al. 2000 & C. Stauffer et al. 1999) as part of environment modelling. (Toyama et al. 2012) propose the Wall flower algorithmic technique in which background subtraction and background maintenance are performed at three different levels: the basic pixel level, the middle region level, and the last frame level. Recently, some statistical methods to find modified regions from the background are stimulated by the basic background subtraction methods. The statistical approaches uses the features of an individual pixels or groups of pixels to construct more advanced background models, and the information of the backgrounds can be vigorously updated during processing. Each pixel in the current image can be classified into foreground pixel or background pixel by comparing the statistics of the current background model. This approach is becoming progressively more popular due to its robustness to shadow, changing of lighting conditions etc. (C.
Stauffer et al. 2010). It is also possible that a few elements of background might actually move, such as tress moving in a breeze, Shadow, Rain drops etc. An example of motion mask is shownin figure 2.2. Eigen background subtraction is proposed by Oliver et al. 2000. It presents an Eigen space model for moving object segmentation. In this technique, dimensionality of the sample images constructed from space is decreased with the help of Principal Component Analysis. It is proposed that the condensed space following PCA should signify only the static parts of the scene, residual moving targets, if an image is projected on this space.

Temporal differencing makes the use of pixel-wise differences in between two or three consecutive frames in a video sequence to find motion regions. Temporal differencing is generally adaptive to changing environments, but usually does not work well for extracting all the appropriate pixels, for an example there might be holes present within moving entities. As an example of temporal differencing algorithm, Lipton et al. 1998 detect moving objects in a real video streams using temporal differencing method. After the complete difference between the existing and the preceding image is obtained, a threshold formula is used to find the alteration. By using a connected component analysis, the segmented moving foreground fragments are grouped into the motion regions. An enhanced edition uses three image frames as an alternative to two frame differencing method. This technique is computationally less difficult and adaptive to vibrant modifications in the video frames. In temporal difference method, removal of changing pixel is fast and simple. Temporal difference may induce holes in foreground regions, and is more susceptible to the threshold value when finding the variations in difference of successive video frames. Temporal difference method requires a special supportive algorithm to detect the moving object which suddenly becomes stationary.

Optical-flow-based motion detection uses features of flow vectors of moving targets over time to identify moving pixels in a video sequence. For example, Meyer et al. 1998 calculate the displacement vector field to begin a contour based tracking algorithm, called active rays, for the extraction of articulated targets. The results are used for gait analysis. Optical flow based techniques can be used to recognize separately moving objects even in the presence of camera movement. However, most flow computation techniques are computationally difficult and very sensitive to errors, and therefore cannot be applied to video sequences in real time simulation without using specialized hardware. Further comprehensive description of optical flow can be found in a work of Barron’s 1994 . Of course, besides the fundamental methods described above, there are several other ways for motion detection & segmentation.

extended expectation maximization (EM) algorithm, Friedman et al. 1997 implement a mixed Gaussian classification mixed model for every pixel. This model categorizes the pixel values into separate three fixed distributions corresponding to shadow, foreground and background. It also updates mixed component involuntarily for every class according to the probability of membership. Thus, slowly moving objects are handled faultlessly, while shadows are eliminated much more effectively. Figure shows optical flow method output. R. T. Collins et al. 2000 has successfully developed a fusion system for motion segmentation by combining three-frame difference method with an adaptive background subtraction model. This hybrid algorithm is very fast and unexpectedly efficient for segmenting moving pixels in an image sequences. Also, E. Stringa 2000 proposes a new morphological technique for detecting motion in scenes. This algorithm acquires steady segmentation results yet in altering ecological conditions.

The model selected to characterize object appearance limits the type of motion or deformation changes it can undergo. For an example, if an object is defined as a point, then only a translational model can be used. In the view where a geometric shape representation like an ellipse is used for the object, parametric motion models like projective transformations or affine are appropriate. These representations can approximate the motion of stiff objects in the scene. For a nonrigid object, shape or contour is the most descriptive representation and both nonparametric and parametric models can be used to specify their motion. Figure 2.4 represents the object detection taxonomy presented by Alper Yilmaz et al. 2006 .

Local “parts”-based detectors are also widely used in object and human recognition systems Forsyth and Fleck 1997 , Ioffe and Forsyth 1999 , Schneiderman and Kanade 2004 , Ronfard et al. 2002, Ramanan and Forsyth 2003 , Sigal et al. 2003 . For example, Forsyth and Fleck [1997], Ioffe and Forsyth [1999, 2001] and Ramanan and Forsyth [2003] use precise human body segments (upper leg, torso, forearm, upper arm, lower leg, etc.) which are assumed to be well represented by cylinders. Parallel edge detectors are then used to detect the corresponding image segments, and body- geometry based detectors are generated by means of articulation constraints or graphical models to constrain the relative geometry of the limbs. 3D limb detectors have also been used, c. f. Sigal et al. [2003]. One problem with these approaches is that the assumption that limbs can be represented by parallel lines is rather simplistic and its scalability to real world examples is questionable. This may explain the lack of extensive testing on real world images in these works. Image edges and gradient filters have also been used for object detection. Active contour-based tracking algorithms track moving targets by representing their outlines as bounding contours and updating these contours dynamically in successive frames These algorithms aim at directly extracting shapes of subjects and provide more effective descriptions of the objects than region based algorithms. Paragios detect and track multiple moving objects in an image sequences using a geodesic active contour.

BLOCK DIAGRAM

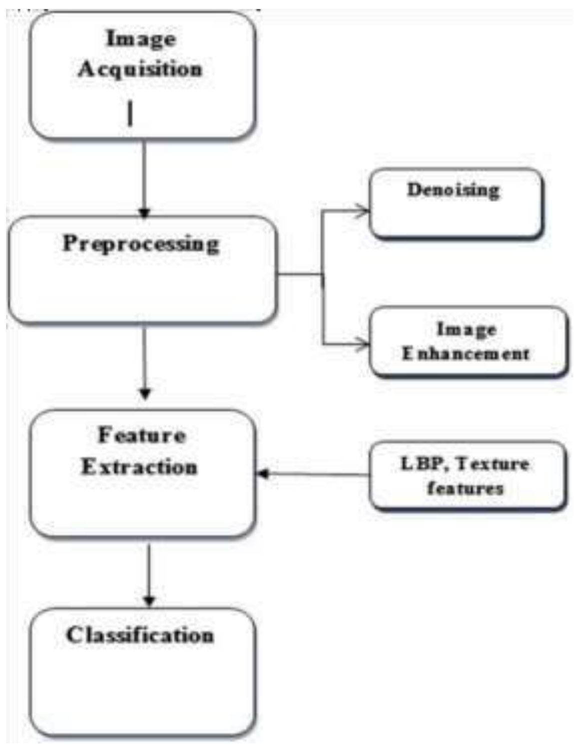

Figure 1: Block diagram of retinal disease screening through local binary patterns

PROPOSED SYSTEM RETINAL IMAGE

Retinal imaging takes a digital picture of the back of your eye. It shows the retina (where light and images hit), the optic disk (a spot on the retina that holds the optic nerve, which sends information to the brain), and blood vessels. This helps your optometrist or ophthalmologist find

objective function and a level set formulation scheme. Peterfreund explores a new active contour model based on a Kalman filter for tracking nonrigid moving objects such as people in spatio-velocity space. Isard et al. 1996 adopt stochastic differential equations to describe complex motion models, and merge this approach with deformable templates to cope with people tracking. D. Koller et al. 1994 Malik et al. 1997 have successfully applied active contour-based methods to vehicle tracking. certain diseases and check the health of your eyes. Doctors have long used a tool called an ophthalmoscope to look at the back of your eye. Retinal imaging allows doctors to get a much wider digital view of the retina. It doesn't replace a regular eye exam, but adds another layer of precision to it. Your doctor may recommend it if you have any the following diseases or conditions Diabetes: This disease can damage the blood vessels in your retina. Over time, it causes you to lose your sight if it is not controlled. Macular degeneration : The central part of your retina (the macula) starts to get worse with age. You may have blurry vision and find it harder to focus. If that happens, you may be considered legally blind even though you may still have peripheral vision. There are two kinds of macular degeneration: wet and dry.

Artery/Vein classification:

The morphological changes in retinal blood vessels indicate cardiovascular diseases and consequently those diseases lead to ocular complications such as hypertensive retinopathy. one of the significant clinical findings related to this ocular abnormality is alteration of width of vessel. the classification of retinal vessels into arteries and veins in eye fundus images is a relevant task for the automatic assessment of vascular changes. this paper presents an important approach to solve this problem by means of feature ranking strategies and multiple classifiers decision-combination scheme that is specifically adapted for artery /vein classification. for this, three databases are used with a local dataset of 44 images and two publically available databases, inspire- avr containing 40 images and vicavr containing 58 images. the local database also contains images with pathologically diseased structures. the performance of the proposed system is assessed by comparing the experimental results with the gold standard estimations as well as with the results of previous methodologies, achieving promising classification performance, with an over all accuracy of 90.45%, 93.90% and 87.82%, in retinal blood vessel separation for local, inspire-avr and vicavr dataset, respectively.

the prevalence of diabetes is expected to increase dramatically in coming years; already today it accounts for a major proportion of the health care budget in many countries. diabetic retinopathy (dr), a micro vascular complication very often seen in diabetes patients, is the most common cause of visual loss in working age population of developed countries today. since the possibility of slowing or even stopping the progress of this disease depends on the early detection of dr, an automatic analysis of fundus images would be of great help to the ophthalmologist due to the small size of the symptoms and the large number of patients. an important symptom for dr are abnormally wide veins leading to an unusually low ratio of the average diameter of arteries to veins (avr). there are also other diseases like high blood pressure or diseases of the pancreas with one symptom being an abnormal avr value. to determine it, a classification of vessels as arteries or veins is indispensable. as to our knowledge despite the importance there have only been two approaches to vessel classification yet. Therefore we propose an improved method. we compare two feature extraction methods and two classification methods based on support vector machines and neural networks. given a hand-segmentation of vessels our approach achieves 95.32% correctly classified vessel pixels. this value decreases by 10% on average, if the result of a segmentation algorithm is used as basis for the classification.

there are two types of vessels, arteries and veins. arteries are brighter, since they transport blood rich in oxygen to the organs of the body. the veins afterwards transport the blood, which is at a low oxygen level and thus darker, to the lungs and the liver. for many medical applications it would be of great benefit, if the vessels could be distinguished into arteries and veins, since there are many diseases with one symptom being an abnormal ratio of the size of arteries to veins. for example in diabetic patients the veins are abnormally wide, while diseases of the pancreas lead to narrowed arteries and high blood pressure results in thickened arteries. to detect these diseases the retina is routinely examined. as a basis for classification a good segmentation of blood vessels is of course needed (see [leandro2001]1 , [gang2002]2 or [hoover2000]3). there are mainly four different features that can be used to distinguish arteries from veins in general: • arteries are brighter in color than veins • arteries are thinner than neighboring veins • the central reflex (the light reflex of the inner parts of the vessels shown in figure 1) is wider in arteries and smaller in veins. • arteries and veins usually alternate near the optic disk before branching out; that means near the optic disk one artery is usually next to two veins and the other way roundto give an overall impression of the difficulty of this classification task, ten cropped veins and ten cropped arteries taken from four different retinal images can be seen in figure 4. the quality of the images, the background and the small size of the vessels and the subtleness of the features themselves make it very hard to distinguish between the two classes. these examples make clear that a classification method based only on local features will not be able to achieve good results. we combine these features in a learning based approach, which with the help of global meta-knowledge - is able to distinguish arteries from veins with a very high classification rate.

the significant limitations of the feature based approaches are two folds. first, due to the input image acquisition process, retinal images exhibit varying contrast and luminosity, often resulting in difficulty in distinguishing a/v segments of thin and peripheral vessels. second, the absence of vessel connectivity information leads to difficulty in precisely tracking a/v segments of branching and crossover points. to address these issues, graph-based approaches have gained increasing interest by incorporating the structural characteristics of the retinal vascular tree. these methods exploit the distinct nature of the underlying retinal vascular connectivity pattern, that the arteries and veins will cross each other, but never with themselves.

EXPERIMENTAL RESULTS

The proposed method consists of series of interlinked stages, where the performance of each stage depends on its previous stage output. Hence, to validate the robustness of our approach, we evaluate the performance at each stage starting from:

(i) identification of vessel subtrees - which is referred to as “DFS-search”;

(ii) A/V classification using only handcrafted features - which is referred to as “RF-only”; and

(iii) finally, subtree A/V labeling stage (which combines both the knowledge of graph search and hand-crafted features) - which is referred to as “DFS-search with RF”.

We also further investigate the relative importance of hand-crafted features using different feature selection techniques as well as various classifiers to examine the impact on final A/V labeling. The proposed three- stage refinement steps accurately predicts the A/V labeling from four different datasets, including images from fundus as well as SLO image modalities. It was shown how each of these steps contributes to yield a more accurate solution progressively. The experimental analysis also confirms this view, where it has been empirically shown, how each stage output improves upon the previous stage. We first evaluate the A/V separation at the output of DFSsearch by manually assigning A/V labels for individual vessel subtrees. We obtain an average Acc > 86% across all four datasets, while depending solely on the knowledge of graph search. This underscores the richness of metaheuristic approach - which efficiently exploits local as well as global vessel connectivity information to precisely track all the A/V segments from a given vascular network. A highest Acc of 0:921 is observed on INSPIRE-AVR dataset, while the lowest Acc of 0:861 is on the WIDE dataset. This is because the INSPIRE-AVR dataset consists of a fewer number of graph linking structures

- including the number of complex crossovers when compared to the WIDE dataset. We also observed a substantial improvement in mean Acc of 15% (AV- DRIVE), 15.6% (CT-DRIVE), 23.9%
(INSPIREAVR) and 12% (WIDE), when compared with DFS-search to the RF-only stage. The pixel level intensity-based features have shown to be vulnerable to varying image conditions such as resolution, contrast and illumination artefacts both within and across datasets. Finally, the combination of DFS-search with RF have shown a modest improvement in the Acc value of 5.1% (AV-
DRIVE), 2.3% (CT-DRIVE), 4.7%
(INSPIREAVR) and 4.1% (WIDE) from DFS-search to DFS-search with RF stage. This consistent improvement strongly indicates that the system is more accurate while relying on more complex knowledge of vessel connectivity as well as pixel-level feature information for classifying A/V.

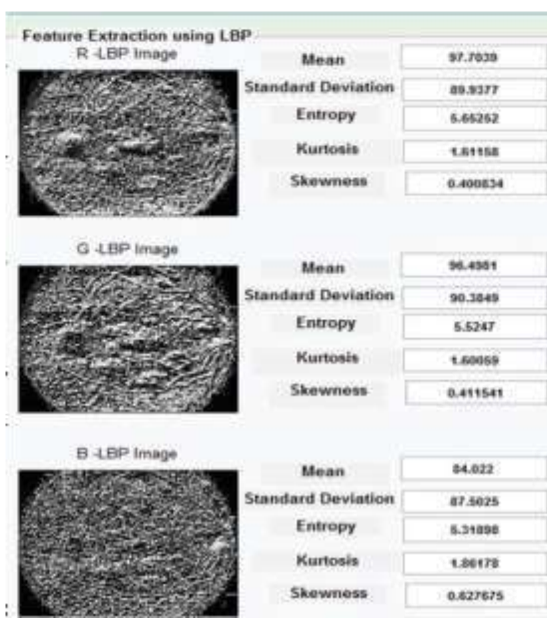

Figure 2: Feature extraction using LBP images of RGB component

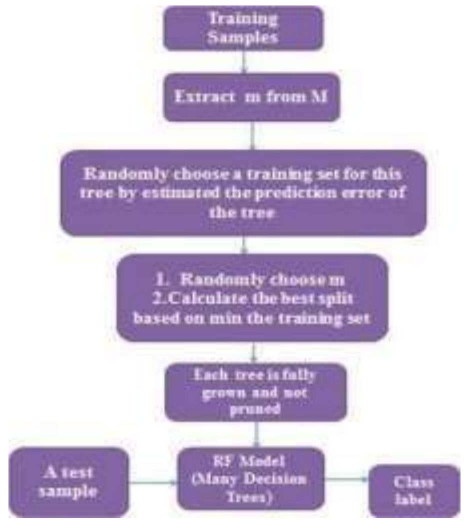

Figure 3: Random forest Algorithm steps

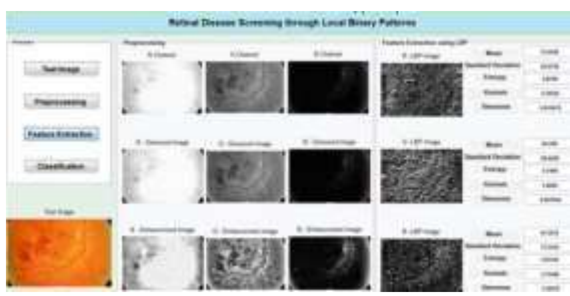

Figure 4: Process perform for detection of retinal disease using LPB technique

Figure 5: Final features and classification of test image

Class	Output	Mean	Standard deviation	Entropy	Kurtosis	Skewness
1	Disease eye	67.8718	79.7862	4.63267	2.5924	0.94667
0	Normal eye	47.9789	73.9333	3.87598	3.68930	1.43468

Table 1 Final average features of RGB channel

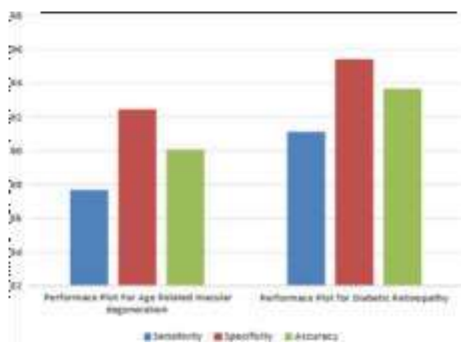

Figure 6: Performance plot for age related macular degeneration and diabetic retinopathy

The performance plot for age-related degeneration and diabetic retinopathy is as shown in Fig. 9. The graph represents the comparison between performance for age related degeneration and diabetic retinopathy. The blue shade shows the sensitivity, red shade shows the specificity, and green shade shows the accuracy.

CONCLUSION

An approach is made for DR diagnosis based on texture features on fundus images were introduced for differentiate healthy and pathological images. Compared with the other texture description the routine accuracy of the LBP is better in the screening of a retinal disease.The classification of different stages of a patient such as severe, moderate and mild helps the patients to the reduction of cost in diagnosis and results in a prevention of better healthIn the future work experiments with more images were carried out and tested by considering various phenomenon's such as exclusion of tessellated images and including the calculation of some more statistical parameters.

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