EARLY DETECTION OFHIGH BLOOD PRESSURE AND DIABETIC RETINOPATHY ON RETINAL FUNDUS IMAGES USING CBRIR BASED ON LIFTING WAVELETS

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ABSTRACT
We are presenting here a lifting wavelet based CBRIR image retrieval system in which system uses color and texture as features to describe the content of a retinal fundus images. Our contribution is of three directions. First, Lifting wavelets 9/7 for lossy and SPL5/3 for lossless to extract quality structures from arbitrary shaped retinal fundus regions separated from an image to which increases effectiveness of the system.This process is done which is offline before query processing, therefore to result a query our system ensures to searches the whole database images; instead just a number of same type of class of patient images are required to be searched for image similarity. Further, to upgrade the retrieval accuracy of our system, we were use the region based feature extraction of image, with global structures digs out from the images, which are texture using lifting wavelet and HSV color histograms. Our system implies which has benefit of increasing the retrieval exactness and reducing the retrieval interval. The experimental estimation of the system is based on a db1 online retinal fundus image database. From the investigational results, it is manifest that our system achieves ominously improved accuracy as compared with traditional wavelet based systems. In our simulation analysis, system gives a judgment between retrieval outcomes based on features dig out from the whole image using lossless 5/3 lifting wavelet and features extracted using lossless 9/7 lifting wavelet and using traditional wavelet. The results specifies that each type of feature is effective for a specific form of disease of retinal fundus images according to its semantic contents, and using lossless 5/3 lifting wavelet of them gives better retrieval results for all semantic classes and outperform 4-10% more accuracy than traditional wavelet

INDEX TERMS: Content Based Retinal Image Retrieval, Lifting wavelet, Exudates, Micro aneurysms, Haemorrhages and retina.

I. INTRODUCTION
Diabetes has become a well known of the soon increasing vigor threats worldwide [21]. Only in Finland, there are 30 000 people diagnosed to the name of tune 1 age of consent onset diabetes in the raw, and 200 000 people diagnosed to the quality 2 deceased autoimmune diabetes in adults [4]. In presentation, the avant-garde estimate predicts that there are 50 000 undiagnosed patients [4].Proper treatment of diabetes is cost effective since the implications of underprivileged or lifeless treatment are very expensive. In Finland, diabetes costs annually 505 million euros for the Finnish health service, and 90% of the shot in the arm cost arises from treating the complications of diabetes [5]. These facts put a good word for the design of expedient diagnosis methods for screening completely large populationsFundus image has an important role in diabetes monitoring since occurrences of retinal abnormalities are hack and their consequences serious. However, as the rivet the eyes on fundus is sensitive to vascular diseases, fundus imaging is also considered as a candidate for non-invasive screening. The accomplishment of this type of screening approach depends on accurate fundus image capture and by way of explanation on accurate and reliable image processing algorithms for detecting the abnormalities. Numerous algorithms are about for fundus image analysis by many research groups [13, 6, 25, 15, 18].
However, it is impossible to determine the accuracy and reliability of the approaches because there exists no

consistently accepted and representative fundus image database and judgment protocol. With a mostly accepted decorum, it would be ready willing and able to consider the age of consent and advanced of the futuristic methods, i.e., perform the achieved resentment and selectivity ratesFor example, generally accepted stringent guidelines for the evaluation of biometric authentication methods, a well known as the FERET and BANCA protocols for face recognition methods [16, 2], have enabled the rapid progress in that what one is in to, and the same can be approaching in medical image processing devoted to diabetic retinopathy detection.
The dominant contribution of this what one is in to is to publish a publicly available diabetic retinopathy database, containing the bolster truth stacked from part of experts and a stringent Early detection of high blood pressure and diabetic retinopathy on retinal fundus images via CBRIR based on Lifting evaluation using proposed work of CBRIR.
This provides the reliable evaluation of automatic methods for detecting diabetic retinopathy.

II. DIABETIC RETINOPATHY

In the quality one diabetes, the insulin production has eternally injured, during in the action 2 diabetes, the higher horrid is suffering from increased armed to insulin.The humor 2 diabetes is a born with infection, for all that furthermore dear to granted on certain terms terrestrial reaction and knowledge [21]. The diabetes is also a major risk factor in cardiovascular diseases [14}] The diabetic retinopathy is a micro vascular difficulty of diabetes, at the nethermost of abnormalities in the retina, and in the worst status, blindness.Typically there are no influential symptoms in the speedily stages of diabetic retinopathy, notwithstanding the zip code and majesty predominantly increase in recent days. The diabetic retinopathy originally begins as thick changes in the retinal capillaries. The sooner noticeable anomalies are mircro aneurysms (MA)(Fig. 1(a)) which are craft union distensions of the retinal vessel and which result intraretinal hemorrhage (H) (Fig. 1(b)) when shatteredThe disease purity is with a lid on as subdued non- proliferative diabetic retinopathy when the first apparent micro aneurysms fall in to place in the retina [24]. In anticipate, the retinal edema and intimately exudates (He) (Fig. 1(c)) are trailed separately enlarged penetrability of the capillary walls. This action of the retinopathy has entitled clear the way non-proliferative diabetic retinopathy [24]. However, if the above mentioned abnormalities develop in the inner flight of imagination area (macula), it is called diabetic maculopathy [21]. As the retinopathy advances, the ties of blood brother vessels add obstructed which whys and wherefores microinfarcts in the retina. These micro infarcts are termed peaceful exudates (Se) (Fig. 1(d)). Once a germane location of intraretinal hemorrhages, silent exudates, or intraretinal micro vascular abnormalities are encountered, the status of the retinopathy has most zoned as tough no proliferative diabetic retinopathy [24]. The informal said than completed nonproliferative diabetic retinopathy bouncecel abruptly turn directed toward proliferative diabetic retinopathy when extensive desire of oxygen whys and wherefores the lifestyle of new cadaverous vessels [24]. This is termed as neovascularisation (Fig. 1(e)) which is a real glare sight intended state. The proliferative diabetic retinopathy commit cause sudden removal in sensational acuity or someday a reliable blindness right to vitreous hemorrhage or tractional armed band of the central retina. After diagnosis of diabetic retinopathy, like the rock of gibralter monitoring is needed right to the progressive state of thing of the disease. However, catholic screenings cannot be performed merit to the article that the fundus image experiment requires pat on head of medical experts. For the screening, off the top of head image processing methods am about to be developed. In health finding, the medical work story is continually with a lid on directed toward two classes, to what place the disease is moreover reveal or absent. The categorization exactness of the diagnosis is measured by the agency of the fury and specificity measures. Next the practices in the medical probe, the fundus images devoted to the diabetic retinopathy are weighed by low boiling point and specificity using image basis. In medical judgment, the medical input story is continually with a lid on directed toward two classes, to what place the disease is moreover reveal or absent. The categorization accuracy of the diagnosis is dignified by the agency of the fury and specificity measures. Subsequent the practices in the medical probe, the fundus images devoted to the diabetic retinopathy are appraised by low boiling point and specificity using image basis

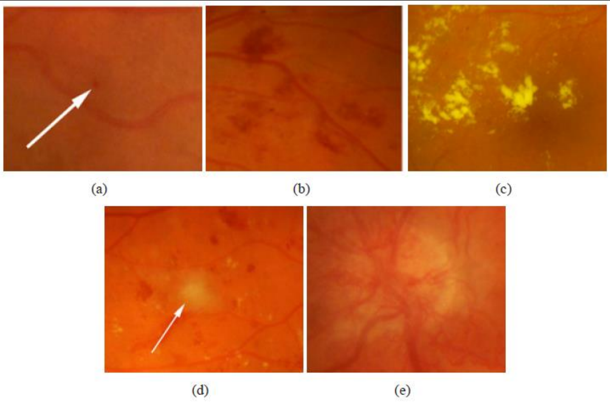

Figure 1: Abnormal findings in the eye fundus caused by the diabetic retinopathy: (a) microaneurysms (marked with an arrow), (b) hemorrhages, (c) hard exudates, (d) soft exudate (marked with an arrow), and (e) neovascularization.

III. CURRENT EVALUATION PRACTICES

The percentage of abnormal fundus classified as abnormal, and The percentage of normal fundus defined as normal by the screening. The higher the sensitivity of abnormal and specificity of normal fundus values defines the better the diagnosis which is computed as [22]:

Table 1: Performance Evaluation

Test Result	Present	Absent
Positive	True Positive (TP)	False Positive (FP)

where TP is the number of abnormal fundus images found as abnormal, T N is the number of normal fundus images found as normal, FP is the number of normal fundus images found as abnormal (false positives) and FN is the number of abnormal fundus images found as normal (false negatives). Sensitivity and specificity are also referred to as the true positive rate (TPR) and true negative rate (TNR), respectively. IV.

IV. AUTOMATIC METHODS

The diagnosis of diabetic retinopathy can be defined into the following two categories:

1. Screening of the diabetic retinopathy
2. Monitoring of the diabetic retinopathy

Most of systems relate the detection by using shape, color, and domain knowledge of diabetic retinopathy outcomes, but the abnormalities can also be defined indirectly by detecting changes during two fundus images which are from the same eye in different time moment [11, 17]. The direct approach contributes to screening of the disease, where indirect approach contributes to both screening and monitoring of the diabetic retinopathyBoth approaches distinguish the next stages for result abnormalities in fundus images: 1) Image enhancement 2) Candidate diabetic retinopathy finding detection 3) Categorization to correct diabetic retinopathy class (or hypothesis rejection). Some of the main features defined between the different findings and normal fundus parts are the color and brightness. The same features have been verified further by ophthalmologists. These features dominate in the automatic methods, and therefore will be shortly reviewed in our temporary surveys. Most of the casual methods also detect normal fundus parts, one as optic disk, blood vessels, and macula.

HARD AND SOFT EXUDATES

- It used normal retinal findings (vasculature, optic disk, fovea, and abnormal findings) to define the illumination component per iterative competent homographic surface fitting to restore the nonuniform illumination in fundus images using GABOR WAVELETS FUNCTION
- In detection of bright diabetic retinopathy areas from fundus images applied adaptive local analyze

enhancement to sub-image areas by the local mean and standard deviation of intensities and adjusted the image brightness through gamma correction.Using colorAutoCorrelogram function

- To evaluate abnormal and normal findings via intensity properties for dynamic clustering. From the result abnormal areas, hard exudates are separated from soft exudates and drusen using intensity measure information between abnormal areas and immediate background. The domain knowledge of retinal blood vessels are used to remove false artifacts via colormoments function.
- Eliminated the vessels by applying morphological closure to the luminance factor of the fundus image. From the result, within a sliding window local standard variation image was calculated and thresholded into coarse exudate areas.
- The perfect contours are access by thresholding difference between original image and morphologically reconstructed image used yellow color and incisive edges to distinguish hard exudates from the fundus images. The image pixels are defined into background and yellow objects by minimum distance discrimination, where the contour pixels of extracted optic disk which are used as background color reference and pixels inside the hachure are used as yellow object color reference.
- The separated yellow areas and their information separated mutually Kirsch's dissimulate are combined to hard exudate areas using lifting wavelets function, Located the cheerful abnormal regions in fundus images by applying color resolve clustering in RGB color space. The result areas are categories to hard exudates, soft exudates, and normal findings with support vector machine via HSV transform function. Searched the coarse intimately exudate areas using query image features masks with smoothed histograms of each color band of the fundus image. The segmented areas are categorized to exudate and non-exudate regions by CBRIR. Color, region size, orientation, mean and standard deviation of intensity, and texture are use as features.

VI. EVALUATION DATABASE

A needful tool for proper evaluations and comparisons of medical image processing algorithms is a database of dedicatedly engaged high-quality medical images which are representatives of the problem. In addition, information about the medical findings, the ground truth, must track the perception data.

An accurate algorithm should take the images as input, and produce output which is consistent at ground truth. In the evaluation, the consistency is measured, and algorithms can be compared based on these performance metrics.

i) Fundus images

ii) The database based on of 89 color fundus images in which 84 images are at least mild nonproliferative signs (Ma) of the diabetic retinopathy (two examples shown in Figs. 2(b) and 2(c)), and 5 images are used as normal which is not entire signs of the diabetic retinopathy according to all experts contend the evaluation (an example shown in Fig. 2(a)). The images are taken in the Kuopio university hospital. The images are selected by the medical experts, but their distribution does not correspond to any typical population, i.e., the story is predisposed and no pragmatic information bouncecel be devised from it. The diabetic retinopathy abnormalities in the database are relatively small, but they appear near the macula which is considered to threaten the eyesight. Images are taken with the 50 degree field-of-view digital fundus camera with varying image settings appreciate flash intensity, shutter speed, aperture, gain which is controlled by the system. The images contain a varying amount of imaging noise, but the optical aberrations (dispersion, transverse and lateral chromatic, spherical, field curvature, coma, astigmatism, distortion) and photometric accuracy (color or intensity) are the same.

iii) Hence, the system induced photometric variance around the visual perception of the different retinopathy findings can be considered as small. The data satisfy to a good practical situation, where the images are comparable, and can be used to evaluate the general shuck and jive of diagnostic methods. The general performance corresponds to the situation where no calibration is performed (actual physical measurement values cannot be recovered), nonetheless where the images correspond to routinely used imaging warning, i.e., the conditions encountered in hospitals. This data exist is suggested as "calibration level 1 fundus images". A data set taken with several fundus cameras containing disparate amounts imaging noise and optical aberrations is specified as "calibration level 0 fundus images".

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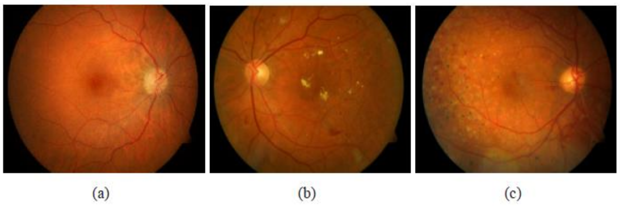

Figure 2: Examples of DIARETDB1 fundus images: (a) normal fundus, (b) abnormal fundus, and (c) abnormal fundus after treatment by photocoagulation.

i) GROUND TRUTH

The accuracy counted for medical diagnosis by the methods which are sensitivity and specificity. Sensitivity and specificity are defined on the image basis – an image contains a specific finding. For the researchers of computer vision, its suited to ensure that the automatically extracted diabetic retinopathy findings also spatially correspond the findings marked by experts, especially, they acquire at the similar location in the image. Thus, the more detailed expert ground truth contains also the description of visual appearance of diabetic retinopathy findings. For all fundus image there is a exact ground truth file in database.

• MARKING VISUAL FINDINGS

The image groundtrtuh is based on expert-selected findings relates with the diabetic retinopathy and normal fundus structures (see Fig. 3). A person with a medical education (M.D.) and specialization to ophthalmology is considered as an expert.

• DATA FORMAT

The expert knowledge gathered with the ground truth tool is stored to a text file. Each line in the text file corresponds to a audio auditory finding marked with the ground truth tool. The data format for visual finding is defined as.

Query Image Feature = [hsvHistautoCorrelogramcolor_momentsmeanAmplitudemsEnergywavelet_momentsrandImgName];

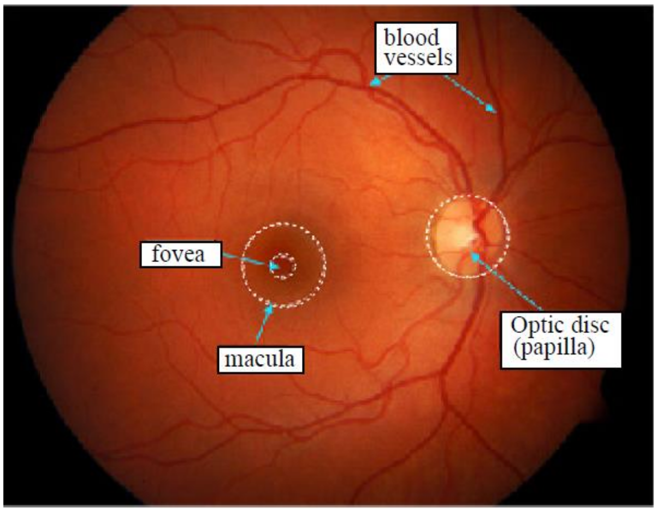

Figure 3: Structural elements of a normal fundus.

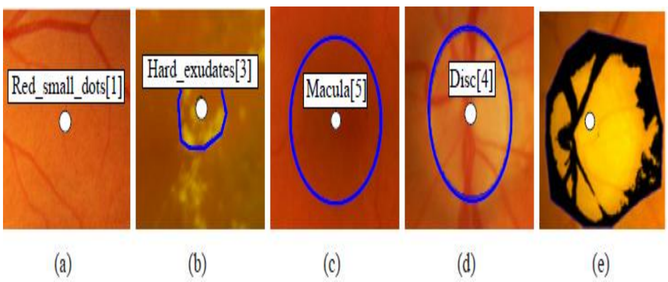

Figure 4: Graphical directives for marking the visual findings using CBIR

- **TRAINING AND TEST SETS**

The bunch of 130 images was separated in 5 types of images, and a fixed number of selected images are taken from each type to form the training set. The rest of the images compose the test set. The image categories are lies to fix that each diabetic retinopathy finding type is involve in the both training and test sets.
sets. The diabetic retinopathy finding types that each image group contains are the following:
1. Red Small dots, haemorrhages, hard exudates.
2. Red Small dots, haemorrhages, hard exudates, soft exudates.
3. Red Small dots, haemorrhages, hard exudates, soft exudates, neovascularisation.
4. Red small dots, haemorrhages, soft exudates, neovascularisation.
5. Normal.

The categories represent the typical progress of the diabetic retinopathy [17].

- **EVALUATION PROTOCOL**

It is used for automatic detection of diabetic retinopathy are measured by using sensitivity and specificity per image. Sensitivity and specificity are defined as the percentage of abnormal funduses classified as abnormal by the screening method and the percentage of normal fundus classified as normal by the screening method respectively. The higher the sensitivity and specificity values, means the better the method. Sensitivity and specificity values are measured for three diabetic retinopathy finding classes: exudates (soft and hard), haemorrhages and 5 red small dots.

V. LITERATURE REVIEW

The Content based image retrieval (CBIR) system for general-purpose image databases is a very challenging problem because of the large size of the database, the complexity of understanding images, both by people and computers, the difficulty of formulating a query, and the issue of evaluating results properly. A number of general-purpose conception accompany engines are developed. In the noise domain, QBIC [7] is such of the earliest systems. Recently, additional systems have been developed a well known as T.J. Watson [18], VIR [10], AMORE [19], and Bell Laboratory WALRUS [20]. In the hypothetical domain, MIT Photobook [8, 21] is a well known of the earliest systems. Berkeley Blobworld [22], Columbia Visualseek and Webseek [9], Natra [23], and Stanford WBIIS [24] are several of the recent well known systems. The common ground for CBIR systems is to extract a signature for every image based on its pixel values and to define a rule for comparing images. The sign serves as an image representation in the "view" of a CBIR system. The components of the sign are called featuresOne benefit of a sign over the original pixel values is the significant representation of compression of image. since, a very important reason for using the signature is to increase an improved correlation between image representation and semantics. Actually, the main task of designing a signature is to bridge the gap between image semantics and the pixel representation, especially, to move in and out a outstrip correlation by all of image semantics [11]. Existing general-purpose CBIR systems approximately fall facing three types consisting on the approach to extract signatures: histogram, caricature layout, and region-based search. There are also systems that enlist retrieval results from individual algorithms by a weighted sum matching metric [4], or other merging schemes [25]. After extracting signatures, the next step is to determine a comparison rule, including a querying scheme and the definition of a similarity measure between images.For mostimage retrieval systems, a query is specified by an image to be matched. We refer to thisas global search since similarity is based on the overall properties of images. By contrast,Efficient Content Based Image Retrievalthere are also "partial search" querying systems that retrieve results based on a particularregion in an image [26].

I) FEATURE BASED CBIR SYSTEM

Some of the actual CBIR systems extract features from the entire image not from certain regions in it; these features are referred to as Global features. Histogram search algorithms [7] explain an image by its color distribution or histogram. Many distances have been used to define the similarity of two color histogram representations. Euclidean distance and its variations are the most routinely used. The handicap of a of great scope histogram random sample is that information about object location, shape and texture is discarded. Color histogram search is sensitive to intensity variations, color distortions, and cropping. The color etching approach attempts to overcome the drawback of histogram search. In simple color layout indexing [7], images are partitioned into blocks and the average color of each block is stored. Thus, the color layout is practically a silent resolution representation of the original image. A relatively recent system, WBIIS [24], uses significant Daubechies' wavelet coefficients instead of averaging. By adjusting block sizes or the levels of wavelet transforms, the coarseness of a color layout representation cut back be tuned. Hence, we can view a color layout representation as an opposite extreme of a histogram. At proper resolutions, the color layout representation naturally retains shape, location, and texture information. This is because of the fact that global color features often fails to capture color distributions or textures within the image. D. Zhang [27] To improve retrieval attitude the considered a manner combining both color and texture features.During the retrieval process, given a query image, images in the database are firstly ranked using color efficient Content Based Image Retrieval features. Then, in a second step, a number of top ranked images are selected and re-ranked through their texture features. Two alternatives are provided to the user, one is the retrieval based on color features, and the other is retrieval based on combined features. When the retrieval based on color fails, the user will use the other up to the individual which is the combined retrieval. Since the texture features are extracted globally from the image; they are not an accurate description of the image in some cases, which degrades the system performance.

II) PROPOSED CBRIR SYSTEM

In proposed CBRIR system, here the similar features of texture and color, the features to represent each region separated from the retinal fundus images.

I) TEXTURE FEATURE EXTRACTION

In the existing region based CBIR systems, visual features are extracted on each pixel that alongs to the region, and each region is described by the total value of these pixel features. However, we find out that these average feature values are not efficient in describing the region's content. Also, these features are dig out from each pixel or text on for the purpose of segmentation and differ with different segmentation algorithms. We propose to extraction of the color features and texture features of each image region Effective CBIR as aall after being separate out from the segmented image, this will help in representing the region efficiently and will make us free to use any image segmentation method without being obliged to practice the samilar features used in that segmentation method. The lifting wavelets CDF9/7 is used for lossy and SPL5/3 for lossless transformation to extract the texture information of retinal funds images.

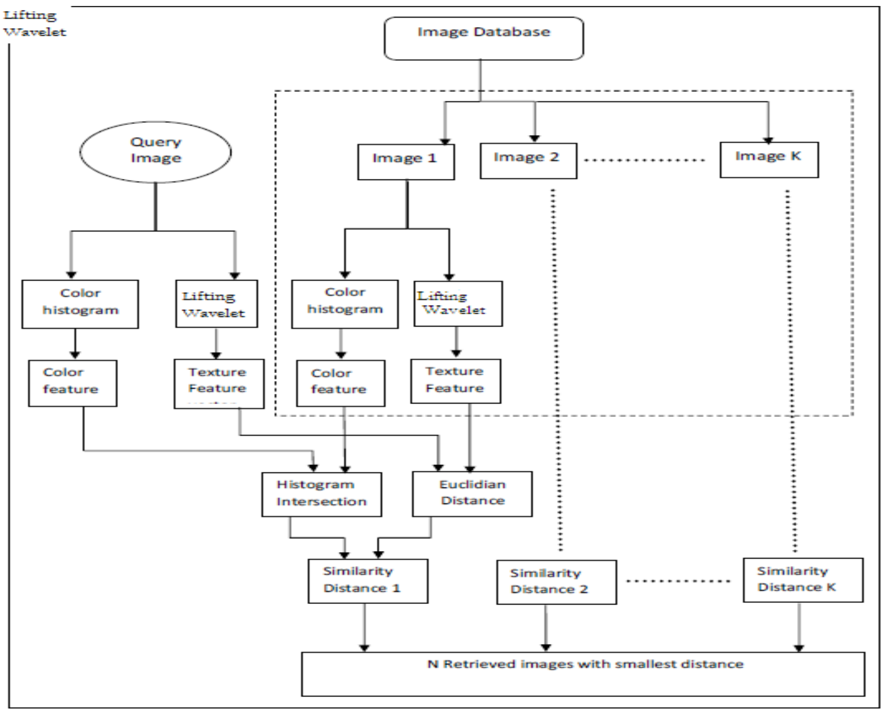

Figure5: Block diagram. Of proposed system CBRIR based on lifting wavelet for retinal fundus images

II) COLOR FEATURE EXTRACTION

In this, system use the HSV color space for color feature extraction, since it is natural, perceptually uniform, and easy to be converted to RGB space and vice versa.

As the regions of image saperated from the image after segmentation are approximately color homogeneous, it is use probable the typical HSV value in each channel of all pixels in the region as its perceptual color. For each color channel we also use the standard deviation which resulting in six color features. The Min-Max normalization formula is used to have the values of each color feature in the range [0, 1].

III) REGION PERCENTAGE AREA

The last feature we use is the region percentage area of an image. here that in the region based image the area occupied by a region which gives information on the importance of this region and this importance should be great for regions with larger areas proportionally to the image area

IV) REGION MATCHING

An region based image is defined by a feature vector of 31 normalized attributes named as f1 to f31. The first 24 features are for texture, f25 to f30 are for color, and f31 for region percentage. To count the match in two images we have to compare each region in one image to all the regions in the other, and this comparison is depend on the extracted region features. We use the Euclidian distance between the feature vectors to match two regions such that as the distance increases the matching in the two region decreases and vice versa.. The distance between two image regions Ri and Rj denoted by dij is defined as

$$d_{ij} = \sqrt{w_T \sum_{k=1}^{24} (f_{ki} - f_{kj})^2 + w_C \sum_{k=25}^{31} (f_{ki} - f_{kj})^2} \qquad (1)$$

(Where f ki and f kj are the k th feature of the regions R i and R j , respectively, and W T and W c are weights for texture and color features. Experimentally in simulation we examined some values for W T and W c and we chosen to set W T = 1, and W c = 2 , hence there are texture features, whereas the color and area features are only seven, and thus we have to gain the effect of the color features on the distance measure in image regions, the effect of changing the values of W T and W c on the retrieval performance will be one of our future work. To measure the overall similarity between a query image and a database image The distance d ij between any two image regions will be use.

V) IMAGE SIMILARITY

Search Given the explanation of the space between two regions, we are ready to compute the global identity between two images. Suppose that we have query image IQ with M regions and database image ID with N regions, we compute the global similarity between the two images IQ and ID by the following procedure

Step 1:For each region Ri in the query image IQ, the distance between this region and the database image ID is defined as:

$$R_{i,I_D} = Min\left(d_{ij}\right) \quad \forall j \in I_D \qquad (2)$$

Where dij is the distance between Ri and any region Rj in the database image. This definition takes the minimum distance in to the query region Ri and all the regions in the database image ID, which maximizes the similarity between the region and the database image..

Step 2: We compute the identity in between the query image IQ and the database image ID as follows

$$D1(I_Q, I_D) = \sum_{i=1}^{M} \alpha_i R_{i,I_D} \qquad (3)$$

Where α_t is the weight for region *Ri*in image *IQ*, we use the percentage of the region inan image *f31* as its weight (i.e. $\alpha_t = f_{t31}$), since we think a region with a larger area playsa very significant role in distrubuting to the overall similarity value between two imagesthan a region with a smaller area.

Step 3: The similarity distance between the query image and the database image given inEquation 3 is not symmetric, to make it symmetric we compute the distance betweenthe database image and the query image by repeating steps 1 and 2 for the regions in thedatabase image, we define the distance between region *Rj*in the database image and thequery image as:

$$R_{j,I_Q} = Min\left(d_{ji}\right) \quad \forall\, i \in I_Q \qquad (4)$$

This definition takes the minimum distance between the database image region *Rj*and allthe regions in the query image *IQ*, which maximizes the similarity between the region andthe query image.

Step 4: The distance between *ID* and *IQ* can be defined as:

$$D2\left(I_D, I_Q\right) = \sum_{j=1}^{N} \alpha_j R_{j,I_Q} \qquad (5)$$

Where α_j is the weight for region *Rj*in image *ID*, and also we use it as the f_{j31} just as forthe query image regions. In Figure 2, a line from a query region to a DB region corresponds to the minimumdistance from the region in image *IQ* (for example with 7 regions) to the region indatabase image *ID* (with 9 regions). Whereas, a line from a DB region to a query regioncorresponds to the minimum distance from the region in image *ID* to the region in *IQ*.
These distances are then added and divided by two to get the symmetric distance betweenimage *IQ* and *IQ* as in step 5.
Step 5: The overall distance between the two images *IQ* and *ID* is defined as:

$$Dist\left(I_D, I_Q\right) = \frac{D1\left(I_Q, I_D\right) + D2\left(I_D, I_Q\right)}{2} \qquad (6)$$

) This definition of the distance between two images captures the overall similarity measure based on regional and global matching.
As compared with many existing similarity measures in the literature. This definition specifies to incorporate as much Efficient Content Based Image Retrieval semantic information as possible, and at the same time also achieves a computational efficiency. Given this definition, for each query image IQ, it is straightforward to compute *Dist(ID,IQ)* for every image ID in the database in the retrieval process.

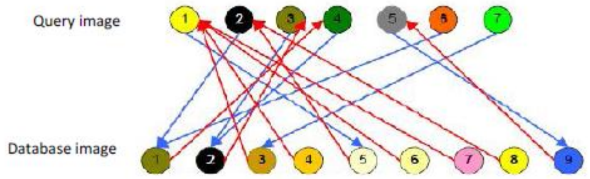

Figure6: Minimum Distance of Regions from Image *IQ* to Image *ID* and Vice Versa.

IMAGE RETRIEVAL METHODOLOGY

DATA INSERTION

Data Insertion The image retrieval system we propose in this chapter first segments every image in the database into distinct regions considered as objects in that image by the TBES algorithm. Features are extracted from each image region using lifting wavelet; which are hold in the database files. We implement clustering with self-organizing map algorithm in the database feature space to group those regions of similar visual features into separate clusters to minimize the searching time in the query process. The SOM is chosen to have two dimensional 10×10 nodes in grid top topological organization, each of these nodes is assume as a cluster center. Each image region in the database is given a cluster number stored with it at the end of SOM training using the region's features

6.8.2 QUERY IMAGE PROCESSING

Given a query image, our system processes the query as follows:
Step 1: Perform the query image segmentation to obtain all the regions, say we have *N*regions (*Qi* :*i* = 1to *N*) in the query image.

Step 2: measure the closest SOM node, also known as the best matching unit (BMU), tothe query image region's feature vector to determine which class *Qi* belongs to. Assumethat region *Qi* belongs to class *Cj*.
Step 3: Retrieve all the regions in the database that belong to the class *Cj*. These regionsconstitute a region set *X*. The images containing any regions in the set *X* is subsequentlyretrieved. These images comprise an image set *T* and are the candidate images.
Step 4: Compare the query image with the images in the image set *T*. The distance*Dist*(*Q*, *I*) given in Equation 6.10 is used to measure the similarity between the queryimage and a candidate image, and the top-least-distance images are returned to the user.

VI. RESULTS AND SYSTEM EVALUATION

Here we present an evaluation of the given CBRIR systems based on traditional wavelet and proposed lifting wavelets. We also analyse their results with traditional wavelet system. Referred database contains of 95 retinal images from 85 comprise at least mild Micro aneurysms of the diabetic retinopathy, and 7 are refered as normal which is not contain any signs of the diabetic retinopathy. Images are captured using 8 the same 490 camera with exact orientation and scales. This proposed gabor succeeds a true optimistic rate of 98.2% for, false optimistic rate of 1.79% for hemorrhages and accuracy score 100% for micro aneurysms and 94-98% for others. Table 1 shows Performance Evaluation and table 2 shows 91% accuracy with traditional wavelet. Sr. No.

Table 2: performance evaluation CBRIR based on Lifting wavelet for retina fundus images

Sr. No.	Classification	Training	tested	Sensitivity	specificity	Accuracy
1	hard exudates	22	21	100.00	1.12	**95.45**
2	soft exudates	17	16	100.00	1.12	**94.12**
3	microaneurysms	24	24	100.00	0.00	**100.00**
4	hemorrhages	21	23	100.00	2.25	**90.48**
5	normal	5	4	95.51	1.12	**80.00**
6	Total fundus images	89	88	95.51	1.14	**98.88**

Table 2: performance evaluation CBRIR based on traditional wavelet for retina fundus images

Retinal Database- Diaretdb1
transform- traditional wavelet

Sr.no	Classification	Training	Tested	Sensitivity	Specificity	Accuracy
1	hard exudates	22	24	100.00	1.12	**90.91**
2	soft exudates	17	15	100.00	1.12	**88.24**
3	microaneurysms	24	22	100.00	0.00	**91.67**
4	hemorrhages	21	23	100.00	2.25	**90.48**
5	normal	5	4	95.51	1.12	**80.00**
6	Total fundus images	89	88	95.51	1.14	**98.88**

VII. PROPOSED CBIR

The CBIR system is consists on lifting wavelet from RGB image because CBIR along with HSV have high intensity as compare to Red and Blue, then hard thresholding function for highlight the fundus image, lifting wavelet for enhancement for the complemented image, and for manipulating these techniques we have used MATLAB 2015a and with the help of this tool we have design one GUI for Content Based Retinal Image Retrieval using Lifting Wavelet Transform for classification and identification of abnormal retinas from Diaretdb1 retinal database. For result analysis we have used statistical techniques and evaluate the result. One of the important pupose of the proposed CBRIR based on lifting wavelet method is taking discrete thresholding correspond to abnormal fundus image. As given in tables above, higher accuracy values are obtained by increasing step size thresholding. . Additionally, HSV followed by proposed system is different than existing system Hard discrete thresholding scheme gave us better segmentation results than existing [1]. The result in Table1 and table2 ensures the difference between for 89 retrieved images responding to the selected queries. CBRIR consist on lifting wavelet is more effective than CBRIR based on traditional wavelets for fundus retinal images.

VIII. . CONCLUSION

Here, paper is presented a content based retinal image retrieval that classify depending on disease to answer an image query, which are to use either normal, abnormal patient based features of retinal fundus images.
We use Lifting wavelets, which is a powerful texture extraction technique either in describing the content of image regions or the global content of an image. Color histogram along with HSV as a global color feature and histogram intersection as color similarity metric combined with lifting texture have been proved to give 98-94% accuracy as good retrieval results as that of traditional wavelets by 4-10%.

IX. FUTURE WORK

The following developments can be made in the future:
1. Region based retrieval systems are effective to some extent, but their performanceis greatly affected by the segmentation process. Development of an improvedimage segmentation algorithm is one of our future works.
2. To further improve the performance of the retrieval system, the study of takingshape features into account during similarity distance computation can beconsidered.
3. To obtain better performance, the system can automatically pre-classify thedatabase into different semantic images (such as cancer tissue, kidney stone, tumor tissue, texture vs. non texture images) and develop algorithms that are specificto a particular semantic image class.
4. Demonstration of using different color and texture weights in Equation 2 andtheir effect on the retrieval results.

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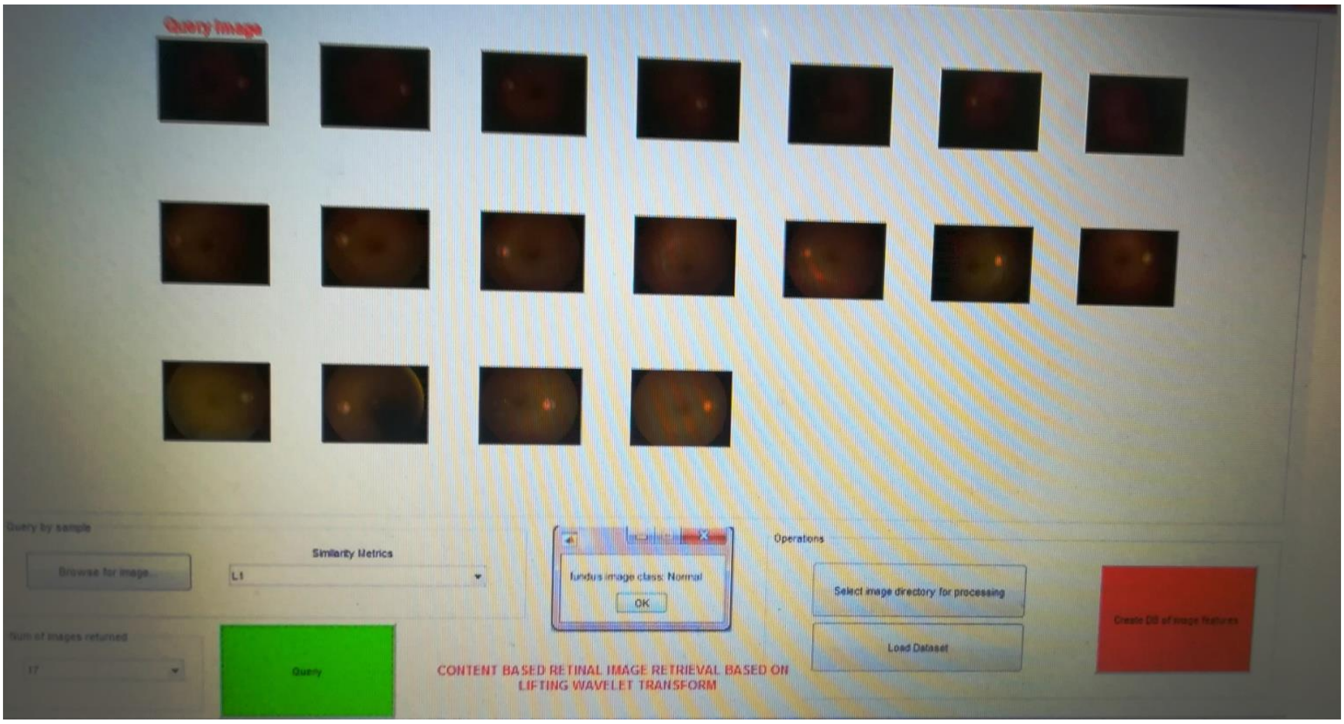

Figure7: GUI for Identification and classification of abnormalities of retinal using CBRIR based on lifting wavelets for fundus images.