A Cross Layer Approach for Feature Extraction with Accurate Detection through Blood Vessel Segmentation in Automatic Diabetic Retinopathy

Naluguru Udaya Kumar and Ramashri Tirumala

ABSTRACT

Diabetic Retinopathy (DR) is an eye abnormality in which the human retina is affected because of increasing amount of insulin in blood. The former identification and analysis of DR is vital to prevent the vision of diabetes patients. An automatic retinal image is rising as a significant testing tool for early recognition of eye diseases. The earlier indication of DR which seems on the surface of the retina is micro-aneurysms, hemorrhages and exudates. In this paper, a cross layer approach for feature extraction with higher accurate detection on retinal lesions is presented. Automatic diabetic retinopathy is used for identifying and detecting the difference between the normal and abnormal stages in retinal images of diabetic patients. The proposed methods made are up of three major stages such as preprocessing, feature extraction and classification. In this approach, preprocessing is performed to eliminate the imperfection of the input retina images such as difficult exudates and then extracts the blood vessel, texture, optic disc and entropies from the retina images. By statistically feature for Neutral Network (NN), Decision Tree (DT) and Support Vector Machine (SVM) to choose the efficient classifier by using Genetic Algorithm (GA) and Bacterial Foraging Algorithm (BFA) and hence this cross layer approach of GA an BFA is used to enhance the accuracy of hybrid classifier. Thus the stimulated results demonstrated about the classifier accuracy, sensitivity and specificity of the proposed hybrid classifier in NN is efficient than the existing methodologies.

INTRODUCTION

Digital photography of the retina is generally utilized for testing the patients enduring from retinal lesions such as Diabetic Retinopathy (DR) and glaucoma (Osareh, A., et al., 2013). Diabetic Retinopathy (DR) is one of the leading causes for blindness and vision defects in developed countries. A development in the growth populations leads to the physical inactivity and obesity as the major causes for diabetes (Usher, D., et al., 2014). The worldwide predominance of diabetes is anticipated to grow from 2.8% in 2000 to 4.4% of the worldwide population by 2030 (Sinthanayothin, C., et al., 2005). Diabetes Retinopathy (DR) is silent retinal lesions in which most of the patients are unaware of such disease; most of the patients remain unidentified by this disease (Welfer, D., et al., 2010). There are two types of diabetic retinopathy 1) Proliferative Diabetic Retinopathy (PDR) 2) Background or Non Proliferative Diabetic Retinopathy (NPDR). These two types of diabetes rely upon the vicinity of clinical features (micro-aneurysms, hemorrhages, hard exudates, cotton wool spots or venous circles) on the retina (Sathya, P.D. and R. Kayalvizhi, 2011). The automatic identification of Gentle DR, Moderate DR, Extreme DR and PDR stages of eyes were utilized for the bi-spectral constant features of higher-request spectra procedures are proposed (Usher, D., et al., 2004). Further, the same authors suggested morphological features of fundus images for DR grading (Aibinu, A.M., et al., 2007). In recent years, because of the constant increase in the number of diabetic patients, new tools and techniques had been developed to help in screening and evaluating the stages of DR are formulated (Gonzalez, R.C. and W.R. Woods, 2002). The above examined approach are primarily helpful in examination of the particular
features on the retina, however don’t offer a comprehensive framework for the automated identification of various stages of DR. The algorithms so far formulated were unable to identify an early phase of retinopathy (NPDR) precisely. Thus, the proposed framework for cross layer technique for feature extraction in the classification of DR retinal images by using automated detection in blood vessel, hard exudates, texture, optic disc and entropies features identifies the stages of the pathogenesis of the retinal damage (Ram, K., et al., 2011). In the proposed framework, the stages of the NPDR and PDR retinal pictures via naturally identifying the blood vessel, hard exudates, composition and entropy features has been identified.

**Literature Review:**

An image investigation framework for the automated determination of DR was produced (Osareh, A., et al., 2009). The methodology improved by their work did not have the capacity to recognize huge varieties in the features of the unusual retinal images. Algorithm for the PC based detection of micro-aneurysms was enhanced (Frounchi, K., et al., 2011), yet work did not give any trust on the computer detection of stages in DR and as well as it lack in usage of huge data base. In recent years numerous analysts proposed framework for the automatic detection of features for DR to support the automated diagnosis (Aibinu, A.M., et al., 2008; Acharya, U.R., et al., 2011). K. Ram (Mendonca, A.M. and A. Campilho, 2006) had exhibited a technique on successive clutter rejection in which the features based framework was equated which communicated genuine MAs while refusing false classes of clutter. G. Quellec (Osareh, A., et al., 2009) illustrated about wavelet transform based matching utilizing a Gaussian format was proposed. Hence, the strategy was examined on 120 fundus images. Some automated diagnostic frameworks for DR conceived Hemorrhage and Micro-aneurysm (HMA) as a typical class (Sinthanayothin, C., et al., 2007). They had utilized only 30 fundus images for the categorization of HMA and EXs. A comparable study was carried out in (Usher, D., et al., 2004) by utilizing retinal pictures from 1273 patients.


The segmentation approach had automatically determined the proper number of regions. On the other hand, the representative gray levels of regions were also determined and then a partitioning of the given image was done. The segmentation results were more continued and smoother than dynamic thresholding. CHNN methods, k-means and fuzzy c-means. Jegatha R et al. (Cristianini, N. and J. Shawe-Taylor, 2000) illustrated about retinal blood vessel segmentation utilizing gray-level and moment invariants-based features, the categorization evaluation had pointed that the best ideal classifier for recognizing vascular pixels was a NN classifier with 10 concealed units.

Marwan D. Saleh et al. (Chong, E.K. and S.H. Zak, 2013) introduced an automated blood vessel segmentation algorithm using histogram equalization and automatic threshold selection. The segmentation techniques in which exploits the effective preprocessing procedures, for example, the differentiation upgrade and thresholding offered an automated segmentation methodology for retinal veins. To assess the execution of the algorithm, an examination was led on 40 pictures gathered from DRIVE database. The outcomes demonstrated that the proposed algorithm executed effectively than the existing algorithm especially in terms of accuracy. Moreover, the proposed algorithm was direct and simple to actualize, ideally equipped for quick transforming applications.

The rest of the paper is organized as: section II that deals with literature survey of existing methods and its demerits, section III gives the detailed explanation about the proposed methods, preprocessing, segmentation, feature extraction and classification of the disease. It also deals with the neural network (NN) by using a cross layer approach of GA and BFA in the proposed method. Section IV elaborates about the performance evaluation of the stimulation results and finally section V discuss about the conclusion of the paper.

**Proposed Cross Layer Approach For Feature Extraction:**

The main objective of the proposed method is to precisely identify the presence of retinal lesions in fundus images as an early indication of some lesions that may cause blindness. DR is a dynamic disease and its identification at an early stage is very essential for saving patient’s eye vision and hence the methodology needs normal screening. The algorithm so far developed was still unable to identify an early symptom of Diabetic Retinopathy (DR) precisely. An automated screening framework for DR can assistant in decreasing the possibilities of total blindness because of DR along with lowering the work function on ophthalmologists. A PC assistant diagnostic system for testing for DR must able to distinguish an ordinary retina and a retina with possible DR. Therefore, it must grade the
influenced retina into the various classifications of DR. This proposed methodology shows a cross layer approach for categorize the retina lesions present in the retina images, which is then used to grade the influenced retina as indicated by the different classes of NPDR. The proposed framework is sub divided into three stages: preprocessing, feature extraction and classification of diseases, the retinal images examination for the identification of predictable retina lesion and the categorization of the areas into various diseases. The primary stage executes the background estimation and extracts the blood vessel and optic disc, texture and hard exudates to facilitate further steps. The second stage utilized the filter bank to extract all conceivable area of retina lesions and presents each area by the feature extraction methods. Thus the final stage of this proposed method is used to categorize the retinal lesion and detect the disease by using the hybrid classifier.

Thus the proposed framework for automated categorization of normal, NPDR, PDR retinal via consequently recognize the blood vessel, hard exudates, texture and entropy feature. A cross layer approach for feature extraction in the blood vessel, texture, optic disc and entropies from the retina images were used to enhance the accuracy in detection of retinal lesions. Fig.4 illustrated about a Block Diagram of the cross layer approach for feature extraction in the proposed method. These features were fed to the decision tree C4.5, SVM and Artificial Neural Network (NN) classifiers to be chosen as the best classifier.

![Fig. 1: Block Diagram of the Cross layer approach for Feature Extraction](image)

**Pre-processing:**
In proposed preprocessing algorithm, classifying the background utilizes mean and variance based approach and it also takes out the noise from images utilizing HSV method. The proposed work for the background separation utilized in the framework is established in (Ion, A.L., 2009). Gabor wavelets are utilized because of their directional upgrade capacities. Multilayered thresholding assists the huge vessels along with thin capillaries vessels. At first, the images are preprocessed for noise elimination utilizing median filter. The contrast upgrade procedure is elaborated and adopted to the green segment of the images. This strategy is depending upon the Gabor wavelet and multilayered thresholding methodology. The optic disc is focalized utilizing an averaging filtering and determining the circular area with the maximum intensity values. This result in the image of dark areas and thus the subtraction of two values provides the contrast developed image.

This method gives the mathematically expression in the Eq. (1)

\[ I_{ou} = I_{a} + \gamma_{TH}(I_{a} - \Phi_{TH}) \]  

(1)
Where, $I_{out}$, $I_w$, $\gamma_{in}(I_w)$, $\Phi_{in}$ are the input image (green component), output image, the results of proposed methods respectively. The proposed methods for blood vessel segmentation and optic disc focalized are given in Diabetic Retinopathy DR.

Fig. 2: Pre-Processing Stages (a) Original retina (b) Illumination Corrected area (C) Filtered retina image

**Segmentation:**
A morphologically enlarged cover is utilized to remove the thin high intensity peripheral area of the retina which may give false positives on utilization of the exudates segmentation algorithm. The accompanying steps are followed to segment the exudates and optic disc: An absolute threshold of 0.35 is utilized in order to receive the binary exudates images from the retina.

(i). The exudates images are increased utilizing an optic disc of radius 6, so that some nearby regions are additionally incorporated. This is needed for the restored step.

(ii). A marker images is generated by overlaying the dilated exudates areas on the real images.

(iii). The marker images are restored utilizing the real images as the mask (Frounchi, K., et al., 2011).

(iv). The contrast between the real image and the restored image is received.

(v). The distinction image is threshold at an absolute threshold of 0.1 to receive the segmented exudates area

After employing the proposed methodology on a mixture of images and detected by utilizing an absolute threshold at step (i) and (vi) is enough to segment the exudates, because the images are similar (band restricted) in utilizing preprocessing. Further, the exudates zone is processed. It is the total of aggregate number of pixels assigned as the major aspect of exudates.

**Blood vessel segmentation:**
After preprocessing by utilizing the 2D Gabor matched channel technique for blood vessel segmentation. The retinal vessel is a tube like structure whose cross segment can be scientifically related to a Gabor reaction. It has utilized a truncated 2D Gabor response channel to make an arrangement of 12 layouts, each being characterized at an interval of 15 degrees. This is capable to provide the vessels with various orientations (Mendonca, A.M. and A. Campilho, 2006). The Gabor response channel is given by

$$G(x, y) = \exp\left(\frac{2\pi^2}{\sigma^2} \cos\left(\frac{2\pi x}{\lambda}\right)\right)$$  \hspace{1cm} (2)

and thus where $x_i = y_i = x \cos \theta + y \sin \theta$ and $\sigma = \sigma_i = \sigma$. Finally it becomes,

$$G(x, y) = \exp\left(\frac{2\pi^2}{\sigma^2} \cos\left(\frac{2\pi x}{\lambda}\right)\right)$$  \hspace{1cm} (3)

A window size of 15x15 is utilized to give an exact result with lower computation load. Since the images contain vessels of fluctuating width, it has utilized two estimations value of $\sigma$, a lower measure for lower vessels and a bigger measure for the bigger vessel. The multi threshold are noted in this methodology in (Mabrouk, M.S., et al., 2006) is utilized for blood vessel multi-threshold since it can be adjusted to the Gabor channel. Since, every convolution results (from each and every direction) most intense pixels presenting to vessels in that particular direction. Thus by choosing the greatest pixel values for all the selected orientation which forms the vessel maps (Chaudhuri, D. and A. Samal, 2007). Therefore, the blood vessel area is equated. It is the entirety of aggregate number of pixels assigned as a component of blood vessels.
Fig. 3: Output of the blood vessel segmentation (a) normal retina image; (b) NPDR retina images; and (c) PDR retina image.

Bifurcation identification:

These are the points at which the blood vessel classifies into secondary and tertiary vessels. Since blood vessel lowered with the onset of DR, the quantity of nodal points is an index of DR seriousness. So as to detect the nodal points, the vessel-segmentation image is morphologically diminished to structure the vessel skeleton (Fig. 4 c) from which the integration of any pixel can be identified. Therefore, the quantity of nodal points present is equated. In this proposed method have carried out the Modified Hybrid Number (MHN) technique utilizes a 6×5 window with 18 encompassing pixels (See Fig. 2) to the focal pixel in distinguishing bifurcation and hybrid point (Passino, K.M., 2012). The criteria for the hybrid point is marginally altered HP\textsuperscript{≥}4 and hybrid point can be computed utilizing Eq. (4), with P19 = P1

\[
H_{pn} = \frac{1}{4} \sum_{n=1}^{5} |P_n - P_{n+1}|
\]  

The utilization of Modified Hybrid Points (MHP) technique, hybrid points which altered to bifurcation points are very simply identified

Fig. 4: (a) segmented blood vessel using proposed algorithm; (b) segmented bifurcation point using MCN; (c) segmented bifurcation point superimposed on original image.

Modified Hybrid Points for bifurcation detection is shown in fig. 5.

<table>
<thead>
<tr>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
</tr>
</thead>
<tbody>
<tr>
<td>P18</td>
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<td>P17</td>
<td>HP</td>
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<td>P16</td>
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<td>P15</td>
<td>P14</td>
<td>P13</td>
<td>P12</td>
<td>P11</td>
<td>P10</td>
</tr>
</tbody>
</table>

Fig. 5: Modified Hybrid Points

Feature extraction:

The configuration of this strategy is directed at the categorization of the images regions that control new vessels. These images regions have been depicted as controlling numerous vessel segments, which are closely spaced and displayed in numerous orientations. Prior to measurement of features, the blood vessel maps were simplified. This incorporated the straight vessel evacuation and the formation of vessel segments (single pixel in thickness). A sub window of size 151 x 151 pixels was produced in order to compute neighborhood features connected with the morphology of the vasculature. This sub window was filtered through the images and at every pixel position the accompanying features are demonstrated: number of vessel pixels, number of vessel segments, number of vessel density and vessel orientation. This same arrangement of features is measured from the blood vessel map from every the standard and changed technique to deliver different features set

Texture Extractions:

The optical thickness of the pixels in the fundus image described as matrix quantized as numbers from 0 to 255 for every primary color (Red, Green and Blue), yields about a M×N×3 lattice of whole numbers. Based upon either ordinary or DR
condition, the image has different granular structures which are self-comparable form at distinctive scale termed “texture”. It denoted to the properties in admiration to the smoothness, roughness and consistency of any structure (Cristianini, N. and J. Shawe-Taylor, 2000).

**Local Binary Pattern (LBP):**

Local Binary Pattern (LBP) is defined as a robust, effective texture descriptor and was initially exhibited by Ojala et al. (Osareh, A., et al., 2009). It has been effectively employed to an extensive variety of diverse applications from texture segmentation (Chaudhuri, D. and A. Samal, 2007) to face expression detection (Cree, M.J., et al., 2005). The LBP feature vector have been influenced as described below. The LBP administrator labels the pixels of a images by thresholding the area (i.e. 4×4) of every pixel with the core esteem value and conceiving the outcome of this thresholding as a binary number. At the point when all the pixels have been labeled with the representing LBP codes, the histogram of the labels is equated and utilized as a texture descriptor. The histogram of the labeled retina images f(x,y) is utilized as a descriptor. Thus, it can characterize this histogram as given below:

\[ H_i = \sum_{x,y} I(f(x,y) = i) \text{ for } i = 0,1,2,\ldots,n-1 \]

where \( n \) is the number of various labels created by the LBP administrator, furthermore, \( I(A) = 1 \) when \( A \) is true, while \( I(A) = 0 \) when \( A \) is false. The LBP of focus pixel can be processed by summing up the weighted threshold values. Fig. 9 gives the original computation code in the LBP and also provides the LBP estimation of 218 for the retina images.

**Fig. 9: Computation of Original Local Binary Pattern code**

**Entropy:**

Entropy is the measure of vulnerability linked with randomness. In this proposed work, by conceiving three various types sorts entropy measures specifically Shannon, Renyi, and Kapur entropy (Mabrouk, M.S., et al., 2006). Considering f(x,y) is the ordinary or DR image which having \( N_i \) (i = 0,1,2,3,4,...,L - 1) distinct dark quality. The standardized histogram can be characterized for a specific locale of interest of size (M×N) is

\[ E_i = \frac{N_i}{M \times N} \]  

(7)

Shannon capacity is established on the idea that data derived from an event is reciprocally associated to its possibility of occurrence. The Shannon entropy (Frounchi, K., et al., 2011) can be characterized as

\[ S = \sum_{i=0}^{L-1} E_i \log_2(E_i) \]  

(8)

In the same manner, Renyi and Kapur entropy measures are processed. These entropies have a higher element range than Shannon entropy more than a range of scattering conditions and therefore helpful in evaluating scatter density and normality. Renyi’s entropy has been referred as:

\[ R = \frac{1}{1-\alpha} \log \sum_{i=0}^{L-1} E_i^\alpha \]  

(9)

Where \( \alpha \), \( \alpha > 0 \) in this modeling and hence it conceived \( \alpha = 3 \). Kapur’s entropy has been referred as:

\[ K_{a,b} = \frac{1}{\beta-\alpha} \log \sum_{i=0}^{L-1} E_i^{a} \]  

(10)

Where, \( \alpha = \beta, \alpha > 0, \beta > 0 \) in this methods and hence by considering \( \alpha = 0.6 \) and \( \beta = 0.8 \)

**Statistical Evaluation:**

Prior order, it is very important to check whether a features or a group of features have the sharp ability among the labeled classes or not. In methodology, classical statistical inference gives demonstrates about the statistical test, which is utilized for contrasting more than two population means. This test utilizes the variation (variance)
inside the group and transform into variation. (i.e.
contrasts) between the group, taking into account
how numerous subjects there are in the group. In
case the noticed contrasts are high, it is conceived to
be efficient. The huge variation between the three
example means must lead to the dismissal of the null
hypothesis.

**Neural Network:**

The Neural Network is based upon the density
function estimators (Welfer, D., et al., 2010). NN is a
three-layer feed forward system made up of input
layer, structure layer and a summation layer as
indicated in (Ion, A.L., 2009). A radius basis
function and a Gaussian activation function have
been utilized for the structured nodes. In this NN
model is actualized utilizing radius basis function
(RBF) are given below:

\[ Q = f(x) = \exp[-\frac{|w - p|^2}{2\sigma^2}] \]

where \( \sigma \) is a smoothing parameter. The net
information to the radius basis transform function is
the vector distance between its weight vector \( w \) and
the input vector \( p \), multiplied by the bias \( b \). The RBF
has a greatest of 1 when its input is 0. As the vector
distance between of \( w \) and \( p \) minimizes, the results
increases. Therefore, radius basis neuron pretends as
an identifier, which generates 1 whenever the input \( p \)
is similar to its weight vector \( p \).

**Fig. 3: Neural Network Training the Statistical Dataset**

In this usage, it have utilized \( T = 104 \) data
training vector/target vector sets. Every target vector
has \( C = 3 \) components. One of these components is
one and the rest are zero. Accordingly, every input
vector is linked with one of \( C = 3 \) classes. The main
layer information weight \( w \) is situated to the
transpose of the network structured from the \( T \)
training sets. As the data features vector have \( I = 13 \)
inputs, the weight matrix is structured as dimension
given as \( 13 \times T \). When an input vector \( x \) is given as,
\( [W-X] \) is computed. \( [W-X] \) Represents how close the
information is to the vectors of the training set. The
training pattern is shown in fig. 3.

**Genetic algorithm:**

It utilizes three fundamental administrators,
selection/generation, cross over and mutation
(Gonzalez, R.C. and R.E. Woods, 2002). It considers
an approximate of variable and the matching solution
as initial resolutions. Any estimation of sigma has
been selected as the initial variable and the matching
fitness function which is the normal exactness over
the three folds of NN classifier is processed. In the
generation function, different cases (runs) of the
variable sigma are produced and a matching bit
string is produced. A cross over points is selected
and the bit function is partitioned into two sections.
Two parts of bit strings really belonged to various
strings are employed to finish cross over operation.
A certain rate of strings is connected with cross over
operation only and rest are left unaltered. Small
amount of function in mutation probability are
characterized and also given subsets of strings which
was selected from the cross over function. A given
bit position is selected for cross over function and the
matching bit is flipped. Again all new strings are
examined with the matching fitness function
capacity. The strings with grater fitness function
capacity are held and strings with less fitness
function capacity are rejected. This completes single
generation. The procedure is continued for so many
generations until it achieves the very higher fitness
function value within 95 iterations shown in fig. 4 of
the strings and hence it enhanced the system
efficiency.
Bacterial Foraging Algorithm:

In bacterial foraging algorithm presented by Passino (Soille, P., 2013), an arrangement of bacteria attempts to achieve an optimum features extraction by under following steps such as chemotaxis, swarming, generation, removal and dispersal these are various steps in this algorithm. Every bacterium generates an answer iteratively for an arrangement of optimal estimations of parameters. Steadily, all the bacteria organisms meet to the standard optimal threshold value. In the chemotaxis arrange, the bacteria organisms have choice to tumble or tumble followed by a run or swim in the segmentation. The development of bacteria is refined through swimming and tumbling. In swarming, every E. coli bacterium signals an alternate bacterium by means of attractants to swarm together. While in the removal process and dispersal stage, any bacterium is either killed or scattered from the set to a random area during the process. This stage mainly avoids the bacteria from achieving the local optimization. In the event that \( h \) speaks to the position of a bacterium and \( J(h) \) the estimation of the target capacity, then the conditions \( J(h) < 0 \), \( J(h) = 0 \), and \( J(h) > 0 \) demonstrates if the bacterium at area \( h \) is in supplement rich, neural network and toxic situations, respectively. The BFO algorithm is changed to discover the optimum thresholds suitable for identification of anatomical structures in the retina. The search space for bacteria made for detecting the optimal thresholds for segmentation of blood vessel in the retina images.

\[
\theta'(J+1,K,L) = \theta'(J,K,L)+C(i) = \frac{\Delta(i)}{\sqrt{\Delta(i)\Delta(i)}}
\]  

Proposed algorithm begins with the estimation of objective value using the equation target (2) for the initial bacterial populace inside the inner chemotaxis circle. Any \( I^\text{th} \) bacteria at the \( J^\text{th} \) chemotactic, \( K^\text{th} \) generation and where, \( L^\text{th} \) end stage is \( \theta(J,K,L) \) and its matching objective fitness function is given by \( J(i,I,J,K,L) \). The BFO calculation is utilized to detect the ideal retinal vessels in the fundus picture. The search space for bacteria made up of four optimal thresholds for segmentation of blood vessels in the retina images. Thus, bacterial foraging process with genetic algorithm provides a better fitness value (fig. 5) than normal genetic algorithm.

![Fitness Value for the Tested Data Set using Genetic Algorithm](image1)

![Fitness Value for the Tested Data Set using Genetic and BF Algorithm](image2)

Tabulations of the Proposed System: The proposed system performance is evaluated by using this parameter such as sensitivity, specificity and accuracy. Thus the sensitivity, specificity and accuracy formula are mentioned below:
Sensitivity = \( \frac{TP}{TP + FN} \)  
Specificity = \( \frac{TN}{TN + FP} \)  
Accuracy = \( \frac{TP + TN}{TP + TN + FP + FN} \)  

Where, TP represents True Positives: Retina Lesion areas which are exactly sorted out by the classifier. FP represents False Positives: Non-Retina lesion areas which are incorrectly sorted out as retina lesion area by the classifier. TN represents True Negatives: Non-Retina lesion areas which are exactly sorted out by the classifier. FN represents False Negatives: Retina Lesion areas which are incorrectly sorted out as non-retina lesion area by the classifier.

Table 1: Summary Statistics (Mean \( \pm \) Standard Derivation) of features used for normal, NPDR and PDR

<table>
<thead>
<tr>
<th>Features</th>
<th>Normal (Mean ( \pm ) SD)</th>
<th>NPDR (Mean ( \pm ) SD)</th>
<th>PDR (Mean ( \pm ) SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exudates area</td>
<td>0 ( \pm ) 0</td>
<td>1015.13 ( \pm ) 1051.326</td>
<td>3193.867 ( \pm ) 4903.35</td>
</tr>
<tr>
<td>Blood vessel area</td>
<td>36230.26 ( \pm ) 5151.323</td>
<td>33545.54 ( \pm ) 5494.929</td>
<td>35726.16 ( \pm ) 9806.93</td>
</tr>
<tr>
<td>Bifurcation point</td>
<td>304.4 ( \pm ) 53.263</td>
<td>308.6557 ( \pm ) 77.8039</td>
<td>373.5778 ( \pm ) 132.9823</td>
</tr>
<tr>
<td>LTE</td>
<td>(3.4 ( \pm ) 4.19)x10(^8)</td>
<td>(7.51 ( \pm ) 1.76)x10(^8)</td>
<td>(6.97 ( \pm ) 3.03)x10(^8)</td>
</tr>
<tr>
<td>Kapur entropy</td>
<td>7.2509 ( \pm ) 0.215</td>
<td>7.0467 ( \pm ) 0.22</td>
<td>2.8728 ( \pm ) 0.1157</td>
</tr>
<tr>
<td>Renyi entropy</td>
<td>4.9749 ( \pm ) 0.4026</td>
<td>4.7231 ( \pm ) 0.0946</td>
<td>3.4236 ( \pm ) 0.0953</td>
</tr>
</tbody>
</table>

Table 2: Efficiency of Proposed system

<table>
<thead>
<tr>
<th>Methods</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dara et al</td>
<td>88.5</td>
<td>98.7</td>
<td>-</td>
</tr>
<tr>
<td>Niemeijer et al</td>
<td>94.2</td>
<td>86.0</td>
<td>94.5</td>
</tr>
<tr>
<td>Walter et al</td>
<td>92.6</td>
<td>99.6</td>
<td>96.7</td>
</tr>
<tr>
<td>Proposed method</td>
<td>96.33</td>
<td>96.52</td>
<td>97.60</td>
</tr>
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</table>

Table 3: Comparison of best classifier with existing methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy</th>
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</thead>
<tbody>
<tr>
<td>Adaboost</td>
<td>92.36</td>
</tr>
<tr>
<td>Bagging</td>
<td>95.26</td>
</tr>
<tr>
<td>Proposed method</td>
<td>97.60</td>
</tr>
</tbody>
</table>

Conclusion:

In this paper, the proposed framework for the reliable grading of the retina images in the various phases of Diabetic Retinopathy (DR), Proliferative Diabetic Retinopathy (PDR) and Non-Proliferative Diabetic Retinopathy (NPDR) have been presented. In this proposed system, three stages of DR detection are subjected to preprocessing, segmentation, feature extraction and classification. The preprocessing stage extracts backgrounds pixels to empower the working on further stages on the foreground pixels only. The principle elements, such as, the exudates area, blood vessel and optic disc are extracted and the proposed system utilized a Gabor wavelet and multilayered thresholding based approach for blood vessel segmentation. It is also proposed to detect the phases of DR using bifurcation points of the blood vessel by using DR screening technique. During segmentation process from normal to PDR stages, there is alter in blood vessel, exudates, micro-aneurysms and hemorrhages leads to modification in pixel pattern and texture. These changes in pixels were captured by the following features such as LBP, entropies, exudates area and blood vessel area. Moreover, it represents each and every area by a cross layer approach of feature extraction and categorizes the retina images to Normal, NPDR, PDR classes, by proposing best classifier for the neutral network classifier which had performed was detected utilizing optimization methods such as Genetic Algorithm (GA) and Bacterial Foraging Algorithm (BFA). Thus, the stimulation results had displayed that the proposed system results are an average accuracy of 96.33%, sensitivity of 96.52% and Specificity of 97.60% respectively. Thus the proposed model had enhanced the overall performance and increases the efficiency of the system. Hence the proposed methods are significant than the existing methods and it can be utilized as an efficient diagnostic tool by the clinicians during the testing of retina images.

REFERENCES


