Development of Algorithm for Dual Stage Classification to Estimate Severity Level of Diabetic Retinopathy in Retinal Images using Soft Computing Techniques

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Abstract: Diabetic Retinopathy is a general origin of sight-threatening complication to which the condition occurring in persons with diabetes and which makes progressive damage to the retina. Retina is a back of eye with the light sensitive lining. The severity of this Diabetic Retinopathy in retina has four stages. The identification of the severity level of Diabetic Retinopathy in retina is a critical task. In order to make ease this task, a severity analysis method is proposed in this paper. The proposed method contains the 5 stages – (1) Pre-processing phase (2) Segmentation Phase (3) Feature Extraction Phase (4) Classification Phase I and (5) Classification Phase II. The retinal images are subjected to pre-processing phase for removing the noises from the image and make clear visible image of retina. Then the optic disks and the blood vessels in the retina are segmented using Modified Region Growing method and morphological operations, respectively. Before analyzing the severity in retinal images, it is necessary to classify the images into normal and abnormal images using Neural Network classifier. For this classification of images, the features mean, variance, entropy and area are extracted from the segmented optic disk of retinal images and also the features mean, variance, entropy, area, diameter and number of regions are extracted from the segmented blood vessels of retinal images. From the abnormal images, the severity of Diabetic Retinopathy can be evaluated by using SVM classifier based on area and intensity level of Hard Exudates and Hemorrhages. These techniques are implemented on publicly available database such as STARE and on real datasets using MATLAB 7.12. The performance of our proposed method is analyzed by Sensitivity, Specificity and Accuracy. From the results, it is proved that our work outperforms other works by providing very much better accuracy by classifying the severity level in Diabetic Retinopathy.

Keywords: Diabetic Retinopathy, Modified Region Growing, Morphological Operations, Neural Network, Support Vector Machine.

1. Introduction

Retina is a light-sensitive tissue lining the inner surface of the eye. It acts like the film in a camera. Images come through the eye's lens and are focused on the retina. The retina then converts these images to electric signals and sends them via the optic nerve to the brain [1]. Retinal elements of the two eyes that share a common subjective visual direction are called corresponding retinal points. All other retinal elements are non-corresponding or disparate with respect to a given retinal element in the fellow eye for a particular visual direction. Retinal Correspondence can be of two types: 1) Normal Retinal Correspondence, 2) Abnormal Retinal

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Correspondence. Retinal correspondence is called normal when both the fovea have a common visual direction and the retinal elements nasal to the fovea in one eye corresponds to the retinal elements temporal to the fovea in the other eye. Retinal correspondence is abnormal when the fovea of one eye has a common visual direction with an extra foveae area in the other eye. This is generally seen if the angle of squint is small and the extra foveae point is close to the fovea.

Optic disc (OD) is a bright disk area and all major blood vessels and nerves originate from it. With its high fractal dimension of blood vessel, optic disc can be easily differentiated from other bright regions such as hard exudates and artifacts [2]. The location of the optic disc is important in retinal image analysis, to locate anatomical components in retinal images, for vessel tracking, as a reference length for measuring distances in retinal images, and for registering changes within the optic disc region due to Disease [3]. Optic disc detection is required as a prerequisite for the subsequent stages in many methods applied for identification of the pathological structures in retinal images. For example, in blood vessel tracking approaches the position of vessels in the neighborhood of optic disc is used as seeds for vessel tracking [4]. The process of automatically detecting/localizing the OD aims only to correctly detect the centroid (center point) of the OD. On the other hand, disc boundary detection aims to correctly segment the OD by detecting the boundary between the retina and the nerve head [5]. Some of the methods Active contour model (ACM), fuzzy c-mean (FCM) clustering and artificial neural network (ANN) used for the segmentation of the optic disc regions. The results of these methods were evaluated using new databases that included images captured by different camera systems [6].

Retinal vessels are extracted by vessel tracing, the optic disc is located on the basis of the vessel network, the extracted arteries and veins are discriminated by the feature characterizing the central reflex, and the Arteriolar-to-venular diameter ratio [AVR] is estimated using vessels with greater diameters [7]. The capillary vessels are normally not visible in color fundus photographs but due to the local increase in size, micro aneurysms appear as small dots between the visible retinal vasculature [8]. Vessel tracking methods used to obtain the vasculature structure along with vessel diameters and branching points. Tracking consists of following vessel center lines guided by local information; usually trying to find the path which best matches a vessel profile model [9]. Using the Retina vessel analyzer, the retinal vein diameter auto-regulatory response to acute IOP elevation was diminished in patients with primary open-angle glaucoma. It was founded that auto-regulatory response to flicker- induced vasodilatation of retinal veins was significantly diminished in patients with glaucoma [10]. Retinal vein occlusion is the most common retinal vascular occlusion. Traditional angiographic techniques can be used to identify, monitor, and treat the potentially visually debilitating sequelae of retinal vein occlusion, such as neo-vascularization and macular edema [11]. Eyes with central retinal vein occlusion develop widespread peripheral vascular obliteration in regions that are difficult to image with conventional fundus cameras. These non-perfused areas may have important implications for visual function [12].

Dye dilution is a technique that involves tracing fluorescent dyes flowing in the retinal vessel by monitoring the fluorescence intensity. However, the dye injection is not comfortable for patients. Al-though laser Doppler velocimetry (LDV) can measure the volumetric flow rate of the retinal vessel [2, 13]. Automatic segmentation of the vessel tree from color retinal images has received much attention recently given its important role in image registration and in disease identification such as in diabetic retinopathy and hypertension [1]. There are different kinds of abnormal lesions caused by diabetic retinopathy in a diabetic's eye such as microaneurysm, hard exudates, soft exudates and hemorrhages that affect the normal vision [14]. Knowledge of how the size and intensity difference of hard exudates vary according to the degree of overexposure and underexposure is used to identify the often missed hard exudates in overexposed and underexposed retinal images [15]. The pixel values of hemorrhages are lower than those of other regions [16]. The presence of micro aneurysms in the eye is one of the early signs of diabetic retinopathy, which is one of the leading causes of vision loss. Approximately 3 million are thought to suffer from diabetic retinopathy (DR). This

disease can be prevented from causing blindness if it is treated at an early stage [17]. Digital photography of the retina is widely used for screening of patients suffering from sight threatening diseases such as Diabetic retinopathy and Glaucoma. The timely diagnosis and referral for management of these diseases can prevent 98% of severe visual loss [4]. Moreover, automated approaches will be much more precise and consistent in phenol typing of retinal diseases such as Age-related macular degeneration [18].

By using the biological or behavioral characteristics, biometric technology can automatically identify every individual. A number of biometric traits have been developed and are used to authenticate the person's identity. The idea is to use the special characteristics of a person to identify him. By using special characteristics we mean the using the features such as face, iris, fingerprint, signature, retina etc. Our work is also helpful to recognize a person with his/her retinal biometric data. Retinal biometrics involves the scanning of retina and analyzing the layer of blood vessels at the back of the eye. Retinal scanning involves using a low-intensity light source and an optical coupler and can read the patterns at a great level of accuracy. Thus, we can use our work in research field and medical field also with wide range of applications. The remaining parts of this paper are organized as follows: Section 2 review a lot of recent research works for the diabetic retinopathy detection and analysis in retina. Our research on retinal images of its segmentation phase and dual stage classification phase with severity analysis is explained in Section 3. The results part of our implementation of retinal images with discussions are given in Section 4 and finally our work is summed up with the conclusion part in Section 5.

2. Review of Recent Researches

A lot of works have been proposed by researchers for the Diabetic Retinopathy (DR) detection with segmentation and classification of its severity analysis in retina. A brief review of some of the recent researches is presented here.

A study on different stages of diabetic retinopathy was presented by Wong Li Yun *et al.* [19]. They were analyzed 124 retinal photographs. As a result, four groups were identified, viz., normal retina, moderate non-proliferative diabetic retinopathy, severe non-proliferative diabetic retinopathy and proliferative diabetic retinopathy. Classification of the four eye diseases was achieved using a three-layer feed forward neural network. The features were extracted from the raw images using the image processing techniques and fed to the classifier for classification. They have demonstrated a sensitivity of more than 90% for the classifier with the specificity of 100%.

Chisako Muramatsu *et al.* [20] have compared three different methods that employed active contour model (ACM), fuzzy c-mean (FCM) clustering and artificial neural network (ANN) for the segmentation of the optic disc regions. The results of these methods were evaluated using new databases that included the images captured by different camera systems. The average measures of overlap between the disc regions determined by an ophthalmologist and by using the ACM (0.88 and 0.87 for two test datasets) and ANN (0.88 and 0.89) methods were slightly higher than that by using FCM (0.86 and 0.86) method. These results on the unknown datasets were comparable with those of the reconstitution test; this indicates the generalizability of these methods.

A paper on automated method for segmentation of blood vessels in retinal images was presented by M.M. Fraz *et al.*[21]. A unique combination of techniques for vessel centerlines detection and morphological bit plane slicing was presented to extract the blood vessel tree from the retinal images. The center lines were extracted by using the first order derivative of a Gaussian filter in four orientations and then evaluation of derivative signs and average derivative values were performed. Mathematical morphology has emerged as a proficient technique for quantifying the blood vessels in the retina. The shape and orientation map of blood vessels was obtained by applying a multi-directional morphological top-hat operator with a linear structuring element followed by bit plane slicing of the vessel enhanced grayscale image. The center lines were

combined with these maps to obtain the segmented vessel tree. The methodology was tested on three publicly available databases DRIVE, STARE and MESSIDOR. The results demonstrate that the performance of the proposed algorithm was comparable with state of the art techniques in terms of accuracy, sensitivity and specificity.

Cemal Köse *et al* [22] developed an alternative simple approach to detect DR. The method was built on the inverse segmentation method, which suggested before detecting Age Related Macular Degeneration (ARMDs). The inverse method was proposed by them to exploit the homogeneity of healthy areas rather than dealing with varying structure of unhealthy areas for segmenting bright lesions (hard exudates and cotton wool spots). On the other hand, the background image, dividing the retinal image into high and low intensity areas, was exploited in segmentation of hard exudates and cotton wool spots, and micro aneurysms and hemorrhages (HEMs), separately. Therefore, a complete segmentation system was developed for segmenting DR, including hard exudates, cotton wool spots, MAs, and HEMs. This application was able to measure total changes across the whole retinal image. To make a comparison with other methods, a Naïve Bayes method was applied for segmentation of DR.

Hung-Kuei Hsiao *et al* [23] proposed a method of automatic identification of the optic disc in retinal images, based on the illumination-correction operator and the SGVF snake algorithm. The proposed illumination correction operator generates significant contrast between the optic disc and background, which directly solves the problem of non-uniform illumination through the image. This method takes advantage of the optic disc in the retina to extract the features of intensity distribution. These features are used to train the Bayesian classifier to classify the disc boundary into the correct contour point cluster or the vessel interference contour point cluster. The contour points are then updated into the correct disc edge locations after each GVF snake deformation. The experimental result also shows that 91% disc boundaries are correctly segmented by the SGVF snake algorithm out of 60 images.

Abnormal retinal image classification system is highly essential in the field of ophthalmology. Classification is a type of pattern recognition system which categorizes the different types of diseases. The effects of the eye abnormalities are mostly gradual in nature which shows the necessity for an accurate abnormality identification system. Most of the ophthalmologists depend on the visual interpretation for the identification of the types of diseases. But, inaccurate diagnosis will change the course of treatment planning which leads to fatal results. Hence, there is a requirement for a bias free automated system which yields highly accurate results. Besides being accurate, the system should be effective in terms of convergence rate which is highly essential for real time applications. Automating the classification process is a challenging task. Besides being automated, the technique should be accurate and robust. Several computer assisted methods have been proposed for the classification and quantification of brain tumors. Vector fields based pathology identification technique in retinal images yields superior results only if the abnormality is highly visible. The drawback of Contrast enhancement based abnormality detection system in retinal images is the over estimation of the contrast in the image. Though these techniques are highly impressive, they fail to incorporate the intelligence techniques which have proved to be much better than the image processing techniques. Artificial intelligence techniques generally yield highly accurate results and it includes neural networks, fuzzy theory, etc. These artificial intelligence based techniques are highly efficient in terms of accuracy. But, the major drawback of these techniques is the convergence rate. Since most of the techniques are iterative in nature, they are computationally slow. Another reason for the inferior convergence rate is the large number of feature set used for the training process. Such issues motivate us to make our research on retinal image segmentation and classification with its severity analysis in the field of image processing.

3. Proposed Work for Retinal Image Classification

Retinal classification techniques are highly important in the field of ophthalmology. One of the diabetic diseases that form in eyes is called as Diabetic Retinopathy, which occurs when the

blood vessels in retinal gets change. According to the severity of Diabetic Retinopathy only, treatment can be taken in hospitals. For this severity analysis of Diabetic Retinopathy, we propose a dual stage classification process is preferred in this paper. Retinal images are collected from various databases and then the process of our proposed work is done on the retinal images by getting the results of severity analysis. The phases in our work are given below and also the whole process is illustrated in figure 1.

(1) Pre-processing Phase
(2) Segmentation Phase
(3) Feature Extraction Phase
(4) Classification Phase I
(5) Classification Phase II

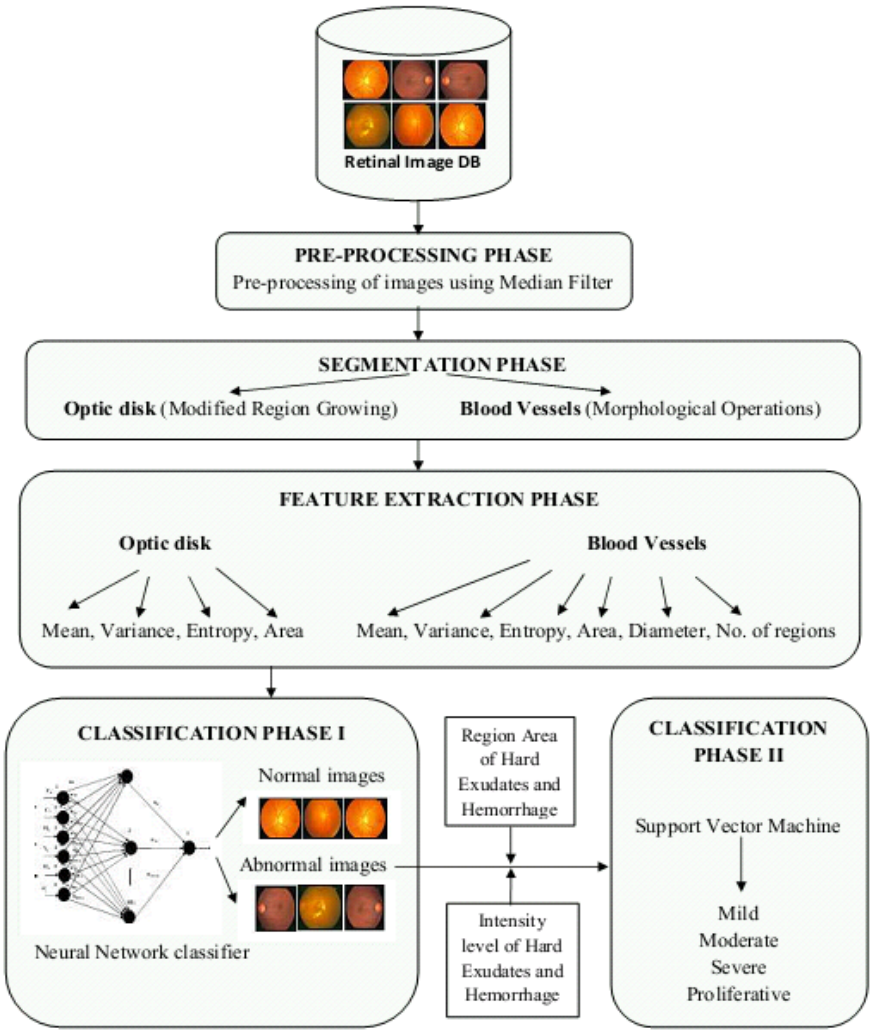


Figure 1. Process used in our proposed method

A. Pre-Processing Phase

In the initial stage, the images must be pre-processed. With the intention of removing the unwanted portions in the image such as noise, blur, reflections, the pre-processing is occurred. The pre-processing stages are given in figure 2.

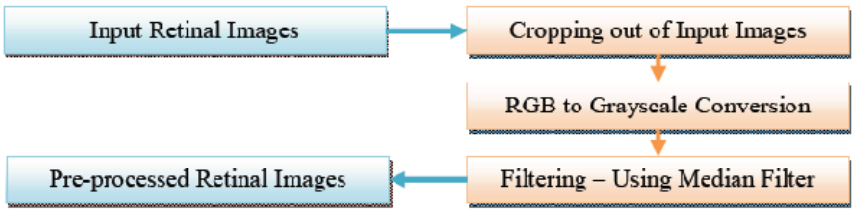


Figure 2. Pre-processing of retinal images

Initially, the retinal images are separately cropped out to get only the region of interest part followed by changing the image size. Then this image is converted into gray scale image, because the input images are in the RGB format. Then the filtering operations are applied on the grayscale retinal images. One of the non-linear smoothing methods used in our work is Median filter. The idea of Median Filter is to eliminate the blurring of edges and to reduce the noises by substituting the current point in the input image by the median of the brightness in its neighborhood. The process of substitution is represented as follows,

$$\boldsymbol{I(m,n) = Median[x(m-k,n-l) \in w]} \quad (1)$$

In eqn. (1), $\boldsymbol{w}$ represents the window around the pixels $\boldsymbol{m,n}$. Hence the given input images of the retinal images are efficiently pre-processed and the obtained preprocessed images are represented as $\boldsymbol{I_R}$.

B. Segmentation Phase - Optic Disk And Blood Vessel Segmentation In Retinal Images

After pre-processing the retinal images, the next step is to segment optic disks and blood vessels from the retinal images. The segmentation of optic disk is carried out by modified region growing algorithm and the blood vessels are segmented using morphological operations.

B.1. Segmentation of optic disk using Modified Region Growing (MRG) method

The pre-processed image I_R is given as the input to the segmentation process. Region growing method is a popular technique for image segmentation which involves seed point selection. In the segmentation process, the neighboring pixels are compared with the initial seed points to check based on some conditions, whether the neighboring pixels can added to the region or not. Seed point selection is important task in the segmentation. But, this normal Region Growing method selects the seed points by setting the intensity threshold, which has drawbacks of noise or variation in intensity that leads to over-segmentation or holes. Moreover, the shadings of real images may not be differentiated by this method. To overcome these difficulties, the intensity and orientation thresholds from the pre-processed images have been considered, modifying the region growing method to utilize those features in the selection of seed points. The process of MRG method is given in steps which are shown below:

Step 1: Calculate the gradient of the image for both x axis $\left(\boldsymbol{I_{Rx}}\right)$ and y axis $\left(\boldsymbol{I_{Ry}}\right)$.

Step 2: Form the gradient vector $\boldsymbol{GV}$ by combining the gradient values using the following eqn. (2),

$$\boldsymbol{GV} = \frac{1}{1 + \left(\boldsymbol{I_{Rx}}^2 + \boldsymbol{I_{Ry}}^2\right)} \quad (2)$$

Step 3: Change the gradient vector values that are usually in radians into degrees to get the values of orientation.

Step 4: Segregate the image into grids $\boldsymbol{G_i}$.

Step 5: Set intensity threshold (T_{IN}) and orientation threshold (T_{OR}).

Step 6: For every grid G_i, continue the following processes in step 7 until the number of grids reached total number of grids for an image.

Step 7:

Step 7.1: Find the histogram h of each pixel in G_i.

Step 7.2: Determine the most frequent histogram of the G_i th grid and denote it as F_h.

Step 7.3: Prefer any pixel, according to F_h and assign that pixel as seed point which has the intensity IN_p and Orientation OR_p.

Step 7.4: Consider the neighboring pixel having the intensity IN_n and orientation OR_n.

Step 7.5: Find the intensity and orientation difference of those pixels p and n.

(i.e.) $$D_{IN} = \left\| IN_p - IN_n \right\| \quad (3)$$

and $$D_{OR} = \left\| IN_p - IN_n \right\| \quad (4)$$

Step 7.6: If $D_{IN} \le T_{IN}$ && $D_{OR} \le T_{OR}$, then add the corresponding pixel to the region and the region is grown, else move to step 7(h).

Step 7.7: Check whether all pixels are added to the region. If true go to step 6 otherwise go to step 7(h).

Step 7.8: Re-estimate the region and find the new seed points and do the process from step 7.1

Step 8: Stop the whole process.

Using this Modified Region Growing process, optic disks are segmented from the pre-processed retinal images.

B.2. Segmentation of blood vessels using morphological operations

Blood vessel segmentation is carried out for early diagnosis of disease. The morphological alterations of the retinal blood vessels in retinal images are significant displays for finding the severity of lesions and hence, correct and accurate segmentation of blood vessel is of vital importance. The pre-processed retinal images I_R in gray scale format are given to the segmentation process which is then subjected to binary conversion followed by morphological operation and thinning.

- *Binary Conversion*

In this process, the original pre-processed image I_R in gray scale format is converted to binary image which has only two possible values for every pixel in the whole image denoted as 0 (black) and 1 (white). The pixel is assigned black or white based on the intensity values and setting a threshold accordingly. Now, the image is in binary format with only black and white colors for each pixel.

- *Morphological operation*

Morphology is a broad set of image processing operations that process images based on shapes and in morphological operations, structuring element is applied to an input image, creating an output image of the same size. Here, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. In our work, morphological operations are used to detect the blood vessels. The two primary morphological operations normally used are named as Erosion and Dilation. Erosion is typically applied to binary images and the basic effect of the operator on a binary image is to erode away the boundaries of regions of foreground pixels (*i.e.* white pixels, typically). Thus areas of foreground pixels shrink in size, and holes within those areas become larger making

easier for region separation. Once eroding is done, the small areas below a set threshold are removed and the remaining pixels are taken.

- *Thinning*

The thinning algorithm is applied to the existing areas to obtain the blood vessel segmentation. Thinning algorithm iteratively delete pixels inside the shape to shrink it without shortening it or breaking it apart. Thinning process decreases the thickness of every pattern vessels into a single pixel width and then to remove the redundant pixels of pattern vessels until all blood vessels are into a single pixel width. The location of the centre black pixel is found at every continuation of the curve. The redundant pixels in every small 3x3 window of image are marked for every scan. More number of scans is occurred and then finally all those pixels that are marked down in these scans are eliminated. Now the resultant images after applying thinning algorithm are in single pixel width with no discontinuities, which segments the retinal blood vessels effectively.

Thus, from the pre-processed retinal images, the optic disks and blood vessels are segmented using modified region growing method and morphological operations, respectively.

C. Feature Extraction Phase

From the segmented optic disks and blood vessels of retinal images, the features are extracted for the further classification of these images into normal and abnormal. After the segmentation process, the images are again converted into their original RGB format, for the extraction of features. Mean, variance, entropy, area are the features extracted from the segmented optic disk images and from the segmented blood vessel images, the features mean, variance, entropy, area, diameter and number of regions are extracted. And also, only the features mean, variance and entropy are extracted for each R, G, B components (R-Red, G-Green and B-Blue), separately in both the segmented optic disk and blood vessel images.

C.1. Extracting Features from Segmented Optic Disk of Retinal Images

From the segmented optic disk of retinal images, the features Mean, Variance, Entropy and Area are extracted. Pixel values in these images are represented as p_i and the features such as mean, variance and entropy are calculated for these pixels in the image. Features are calculated by using the following equations,

Mean
$$M_k = \frac{1}{n}\sum_{i=1}^{n} p_i \tag{5}$$

Variance
$$V_k = \left(\frac{1}{n}\left(\sum_{i=1}^{n}(p_i - M_k)^2\right)\right) \tag{6}$$

Entropy
$$E_k = -\sum_{i} p_i \log_2 p_i \tag{7}$$

In these eqns. (5) to (7), k represents R or G or B components, separately in the RGB format image. Mean, Variance and Entropy are calculated for each RGB components of the images, separately.

Area: Area (A) is a quantity that says the size of a 2-D surface or shape in the plane. In our work, area of the image can be found out by finding the total number of pixels in the region. Suppose N number of pixels is presented in the segmented region and then the area (A) is calculated as N.

Thus, totally 10 features are extracted from the segmented optic disks of retinal images and the features are represented as $\{M_k, V_k, E_k, A\}$.

C.2. Extracting features from segmented blood vessels of retinal images

From the segmented blood vessel images of retinal images, the features Mean, Variance, Entropy, Area, Diameter and Number of regions are extracted. Here, the features Mean, Variance, Entropy and Area are extracted as in the above *section C.1*. The features Diameter and Number of regions are extracted as follows.

Diameter **(*D*)** *:* Diameter of an image is calculated by using the following eqn. (8),

$$D = \sqrt{\frac{4 \times A}{\pi}} \tag{8}$$

In eqn. (8), A denotes the area of the image.

Number of regions **(*R*)** : From the segmented blood vessel retinal images, we are be able to find regions. The number of segmented regions in these segmented images is also considered as one of the features for our process.

Thus, totally 12 features are extracted from the segmented blood vessels of retinal images and the features are represented as $\{M_k', V_k', E_k', A', D, R\}$. Hence, totally 22 features, 10 features from optic disk segmented image and 12 features from blood vessel segmented image are extracted for the further classification process.

D. Classification Phase *I - Classification Of Retinal Images Using Neural Network Classifier*

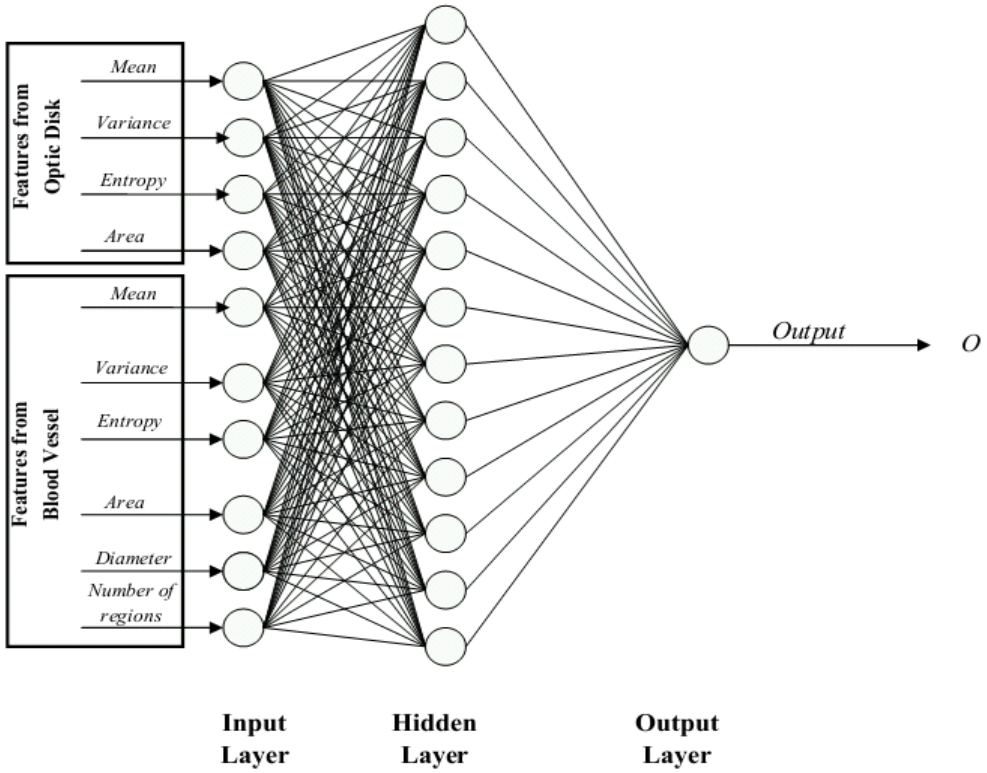


Figure. 3: Structure of FFBNN classifier for the proposed work

One of the classification methods utilizing Feed Forward Back Propagation Neural Network classifier (FFBNN) is used for classifying the retinal images. Neural network is a three-layer standard classifier with I_n input nodes, HU_{an} hidden nodes and O_n output nodes. It is examined that if the two hidden layers are used then one hidden layer is to associate every pair in one important unit and second is regarded as to be the real hidden layer after classifying

the input data in the first hidden layer. For our proposed work, the input layers are the twenty two extracted features from the Retinal image $\{M_k, V_k, E_k, A, M_k', V_k', E_k', A', D, R\}$, HU_a Hidden Units (20 hidden nodes are set for our work based on the classification accuracy) and one output unit, O. The structure of the FFBNN classifier is shown in figure 3.

D.1. NN Function Steps

Set weights for every neuron's except the neurons in the input layer.

Generate the neural network with the extracted features $\{M_k, V_k, E_k, A, M_k', V_k', E_k', A', D, R\}$ as the input units, HU_a Hidden units and whether the given input image is normal or abnormal O as the output unit.

The calculation of Bias function for the input layer is,

$$X = \beta + \sum_{n'=0}^{HU_a - 1} w_{(n')} M_k(n') + w_{(n')} V_k(n') + w_{(n')} E_k(n') + ... + w_{(n')} R(n') \quad (9)$$

The activation function for the output layer is calculated as

$$Active(X) = \frac{1}{1+e^{-X}} \quad (10)$$

Identify the learning error using equation (11).

$$LE = \frac{1}{HU_a} \sum_{n'=0}^{N_a - 1} Y_{n'} - Z_{n'} \quad (11)$$

where, LE - learning rate of FFBNN.

$Y_{n'}$ - Desired outputs.

$Z_{n'}$ - Actual outputs.

D.2. Learning Algorithm – Back Propagation Algorithm used for minimizing the error

In Feed Forward Neural Network, Back Propagation Algorithm is used as the Learning Algorithm. Back Propagation Algorithm is a supervised learning technique and moreover it is an overview of delta rule. To produce the training set, it wants a dataset of the required output for various inputs. Generally, Back Propagation Algorithm is helpful for Feed-Forward Networks. This learning algorithm needs that the activation function used by the neurons be differentiable.

Back propagation Algorithm Steps for FFBNN

1. The weights for the neurons of hidden layer and the output layer are assigned by randomly choosing the weight. But the input layer has the constant weight.
2. The Bias function and the activation function are calculated using Eqn. (9) and (10) for the FFBNN.
3. The Back Propagation Error is found for each node and then the weights are updated as follows,

$$w_{(n')} = w_{(n')} + \Delta w_{(n')} \quad (12)$$

4. The weight $\Delta w_{(n')}$ is changed as given below.

$$\Delta w_{(n')} = \delta . X_{(n')} . E^{(BP)} \quad (13)$$

where, δ - Learning Rate, which normally ranges from 0.2 to 0.5.

$E^{(BP)}$ - BP Error.

5. The process is repeated using (2) and (3) steps, until the BP error gets minimized. i.e. $E^{(BP)} < 0.1$.
6. If the minimum value is obtained, then the FFBNN is well trained for performing the testing phase.

Accordingly, FFBNN classifier is well trained and the Retinal Images are tested using the given input features. The classification of images is carried out which categorizes the entire Retinal images into normal and abnormal images from the output generated from both the classifiers.

E. CLASSFICATION PHASE II - Severity Analysis in Retinal Images

After the classification results of FFBNN, the whole retinal images are classified into normal and abnormal. In our work, we consider only the abnormal images for the analysis of Diabetic Retinopathy severity. The image abnormality is defined in terms of Diabetic Retinopathy (DR). The severity of the DR such as mild, moderate, severe and proliferative is identified by using multiclass Support Vector Machine (SVM) method.

E.1. Classification using Support Vector Machine

SVMs are related to the simplified linear classifier's family. SVMs are also viewed as a unique case of Tikhonov regularization. A strange property is that they minimize the practical classification error and boost the geometric margin at the same time. Therefore, they are named as maximum margin classifiers. The equation given below is the SVMs' objective function, which may recognizes the support vector for the classification,

$$OF = \sum_{i} \omega_i * K(SV_i, PR) + b_i \tag{14}$$

where, ω_i = **weight**

K = **kernel function**

SV_i = **support vectors**

PR = **vectors for classification**

b_i = **bias**

The above eqn. (14) is the objective function that operates an optimization method to find the support vectors, weights and bias for classifying the vector PR, where K is a kernel function. In case of a linear kernel, K is a dot product. In our work, PR vector is used for training process that discovers the severity level of Diabetic Retinopathy and classified according to the level. This vector uses the region area and intensity level of Hard Exudates and Hemorrhage in the abnormal retinal images. Based on this area and intensity level, we can set threshold for each mild, moderate, severe and proliferate and according to the threshold values, the severity of DR in every retinal image is classified as mild, moderate, severe and proliferate retinal images.

Support Vector Machine contains error and the following error minimization function is used for the minimization of this error that is given as follows,

$$\arg\min PC \sum_{x=0}^{n_s^{'}-1} \nu_x + 0.5\lambda^T . \lambda \tag{15}$$

with the following constraints,

$$CL_x(\lambda^T K(\hat{PR}_x) + c) \geq 1 - \nu_x \tag{16}$$

and

$$\nu_x \geq 0 \tag{17}$$

In Eqn. (15), $\boldsymbol{PC}$ is the penalty constant, ν is a parameter that handles the image and λ is a matrix of coefficients. In the constraints given in Eqns. (16) and (17), $\boldsymbol{CL}_x$ is the class label of the x^{th} image, c is a constant and K is the kernel that transforms the input image to the feature space. Hence, by minimizing the error function, the SVM gain knowledge of the training images $\hat{\boldsymbol{PR}}_x$ well and so that it can classify the vector that is similar to the training set.

Once the errors minimized to a minimum value and hence we obtain the classification of the retinal images into mild, moderate, severe and proliferative stages of Diabetic Retinopathy.

4. Results and Discussions

Our Proposed dual stage classification based diabetic retinopathy severity works in the platform MATLAB. For our work, we use various retinal images with both of the normal retinal images and abnormal retinal images.

A. Dataset Description

In our paper, the required retinal images for our proposed work are carried out using the databases STARE and Real datasets. We cannot get the images properly from only one database for our work. In order to work out the images for our proposed work, we make an STARE and REAL database with the collection of images from both these databases. The detailed description of the dataset images is given below.

STARE Database: - Nearly 400 raw retinal images were stored in the STARE database. With the help of TopCon TRV-50 fundus camera with 35 degree field of view, the retinal images were digitized slides. For making a 605x700 pixel image with 24 bits per pixel, the slides were digitized. A specialist was carefully labeled all the images by his hand for developing ground truth vessel segmentation.

Real Database: - For our convenient in our work, we have collected the diabetic retinal images based on the severity from Bejan Singh Eye Hospital - Nagercoil, India. The images were captured with fundus camera and digitized with a laser film scanner (ZE ISS Stratus OCT, Model 3000).

By using the both above collection of images, our S&R database is made. Among these collection of images, in the first classification phase (i.e., normal & abnormal classification) totally 59 images (17 normal and 42 abnormal images) are taken for training process and 10 images (5 normal and 5 abnormal images) are used for testing process. In the second

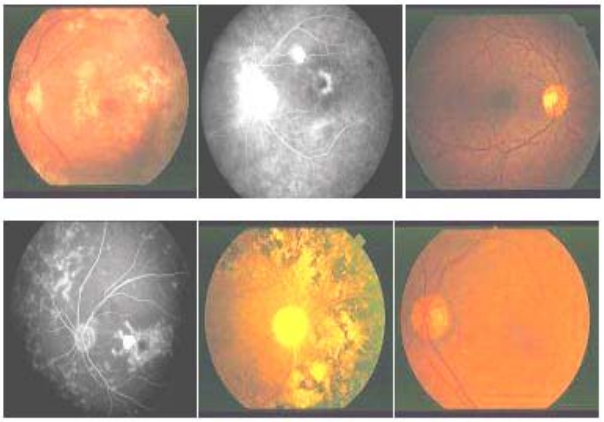


Figure 4. Sample diabetic retinal images from our S&R database

classification phase, totally 6 abnormal images are taken for training process and 11 images (10 abnormal images + 1 normal image) are used for testing process. The following Figure4 shows the sample collection of diabetic retinal images from our S&R database.

B. Experimental Results

Initially, the retinal images from S&R database are taken for our work and then these images are subjected to pre-processing step using median filter as explained in the *Section 3.A.* The retinal images that get pre-processed are shown in the following figure 5.

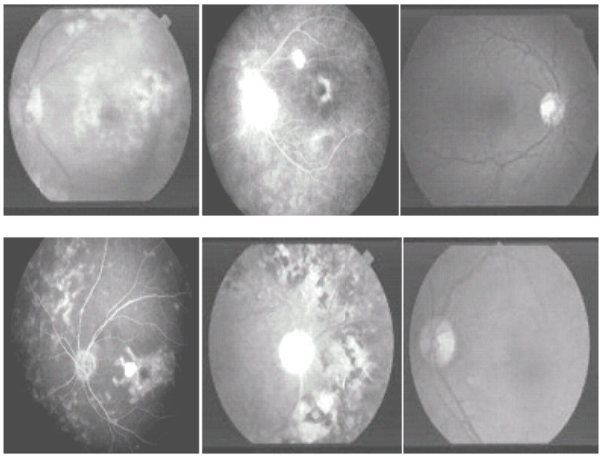


Figure 5. Pre-processed retinal images

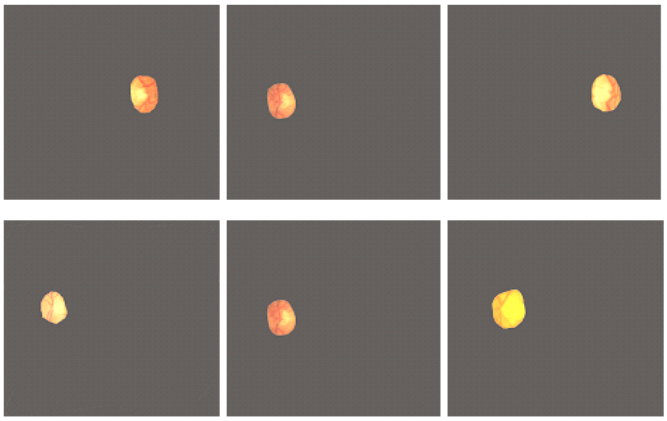


Figure 6. Segmented optic disks from pre-processed retinal images

After getting pre-processed, the images are segmented with the parts optic disks and blood vessels. The optic disks from the pre-processed retinal images are segmented using Modified Region Growing method. The methods to segment the retinal images, optic disks are given in the *Section 3.B.1* and the results of the optic disks segmentation from retinal images are shown in the figure 6.

The blood vessels are segmented from the pre-processed retinal images using simple Morphological operations. The blood vessel segmentation method is explained in the *Section 3.B.2* in detail. The segmented blood vessels are shown in the following figure 7.

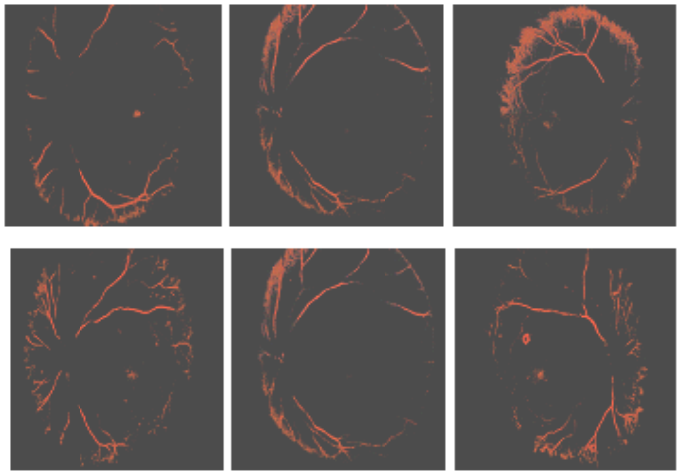


Figure 7. Segmented blood vessels from pre-processed retinal images

After the segmentation of the optic disks and blood vessels, the features are extracted from the segmented optic disks and blood vessels, separately. From the segmented optic disks retinal images, the features mean, variance, entropy and area are calculated and from the segmented blood vessels retinal images, the features mean, variance, entropy, area, diameter and number of regions. The feature extraction process is explained in detail in the *Section 3.C*. After the extraction of features from the segmented images, the normal and abnormal images are classified using Feed Forward Back Propagation Neural Network classifier (FFBNN), which is explained in *Section 3.D*. The classified images are given in the following figure 8.

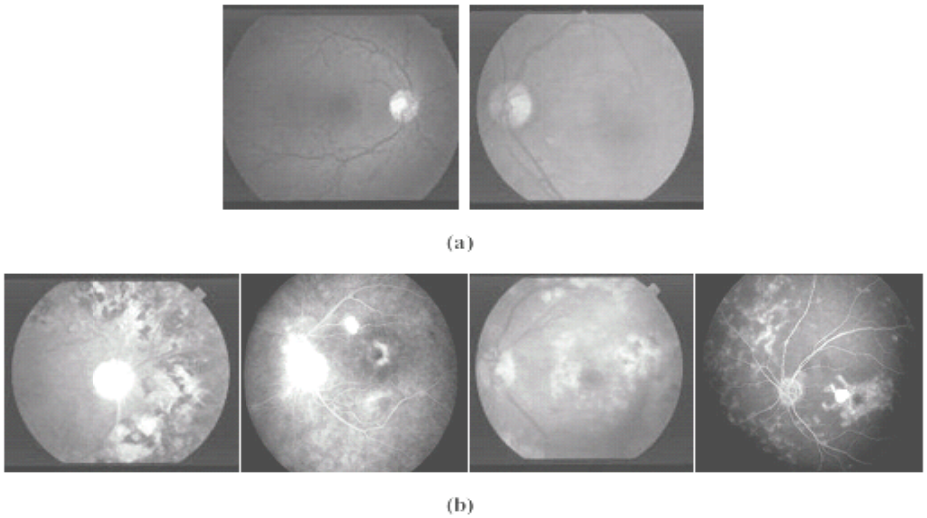
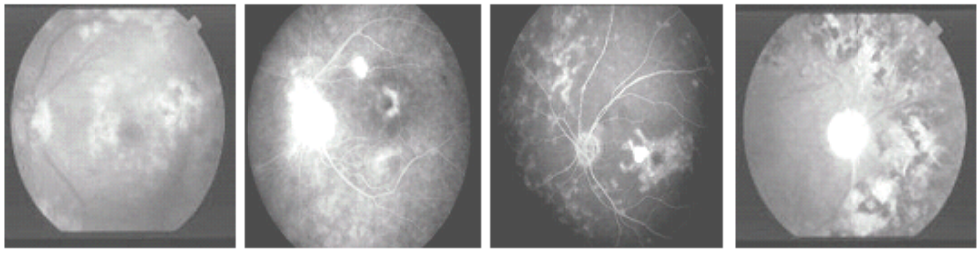


Figure 8. FFBNN Classification results of retinal images: (a) Normal Images (b) Abnormal images

After the classification of normal and abnormal diabetic retinopathy images, the abnormal images are classified using Support Vector Machine (SVM). The results of this classification classified the images that are in mild, moderate, severe and proliferative images. The classification process of abnormal images based on the diabetic retinopathy severity is explained in the *section 3.D*. The abnormal image's classification using SVM based on the diabetic retinopathy severity is shown in the following figure 9.



(a) (b) (c) (d)

Figure 9. SVM Classification results of abnormal images based on diabetic retinopathy severity- (a) Mild (b) Moderate (c) Severe and (d) Proliferate

C. Performance Evaluation of our proposed work with various evaluation metrics

We need various assessment metric values to be calculated in order to analyze our proposed technique for the efficient retinal image segmentation, normal-abnormal classification and severity based classification. The metric values are found based on True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) with the option of segmentation and grading. The usefulness of our proposed work is analyzed by five metrics namely False Positive Rate (FPR), False Negative Rate (FNR), Sensitivity, Specificity and Accuracy. The demonstration of these assessment metrics are specified in equations.

C.1. Evaluation Results of retinal image segmentation

From the retinal images, the optic disks and the blood vessels are segmented using Modified Region Growing method and simple morphological operations, respectively. The subsequent table 1 proves how the positive and negative values are described for the retinal image segmentation of optic disks and blood vessels.

Table 1. Description of TP, TN, FP and FN values

DESCRIPTION	Segmented as optic disks part	Segmented as non-optic disks part
Actually optic disks part	TP	FN
Actually non-optic disks part	FP	TN

False Positive Rate (FPR)

The percentage of cases where an image was segmented to optic disks part, but in fact it did not.

$$FPR = \frac{FP}{FP + TN} \tag{18}$$

False Negative Rate (FNR)

The percentage of cases where an image was segmented to non-optic disks part, but in fact it did.

$$FNR = \frac{FN}{FN + TP} \tag{19}$$

Sensitivity

The measure of the sensitivity is the proportion of actual positives which are properly recognized. It relates to the capacity of test to recognize positive results.

$$Sensitivity = \frac{Number\ of\ true\ positives}{Number\ of\ true\ positives + Number\ of\ false\ negatives} \times 100 \tag{20}$$

Specificity
The measure of the specificity is the proportion of negatives which are properly recognized. It relates to the capacity of test to recognize negative results.

$$\textbf{\textit{Specificity}} = \frac{\textbf{\textit{Number of true negatives}}}{\textbf{\textit{Number of true negatives}} + \textbf{\textit{Number of false positives}}} \times 100 \quad (21)$$

Accuracy
The weighted percentage of optic disks and non-optic disks parts in images is correctly segmented by the measurement accuracy. It is represented as,

$$\textbf{\textit{Accuracy}} = \frac{\textbf{\textit{TP}} + \textbf{\textit{TN}}}{\textbf{\textit{TP}} + \textbf{\textit{FP}} + \textbf{\textit{TN}} + \textbf{\textit{FN}}} \times 100 \quad (22)$$

Similarly, the segmentation effectiveness for the blood vessels in retina also analyzed using the eqns. (18) – (22). For examining the segmentation usefulness our proposed technique is assessed with these above explained assessment metrics False Positive Rate, False Negative Rate, Sensitivity, Specificity and Accuracy. The metrics values are estimated for the segmentation of optic disks and blood vessels from the pre-processed retinal images, which are specified below in table 2.

Table 2. Segmentation results in retinal images – (a) optic disks (b) blood vessels

Images	TP	TN	FP	FN	FPR	FNR	Sensitivity (in %)	Specificity (in %)	Accuracy (in %)
Img-1	22699	239434	111	2879	0.00046	0.112	88.744	99.953	98.872
Img-2	44787	207357	0	3938	0	0.080	91.917	100	98.462
Img-3	5438	255045	1661	859	0.0064	0.136	75.464	99.352	99.041
Img-4	7238	225464	53	1768	0.00023	0.196	80.368	99.976	99.223

(a)

Images	TP	TN	FP	FN	FPR	FNR	Sensitivity (in %)	Specificity (in %)	Accuracy (in %)
Img-1	1208	252820	816	61	0.003	0.048	95.193	99.678	99.655
Img-2	5436	244045	2551	765	0.0156	0.123	87.663	98.965	98.688
Img-3	7337	205464	45	1866	0.000218	0.202	79.724	99.978	99.109
Img-4	73618	188526	0	2882	0	0.037	96.232	100	98.912

(b)

The above table 2 shows the results of segmented optic disks and blood vessels, which is also illustrated in graphical representation

From table 2, we can understand the effectiveness of our proposed segmentation methodologies. For the optic disk segmentation, we use modified region growing method. Here table 2a, 4 of the images are taken into our consideration and in which, the FPR and FNR

provides only lower values. This leads to make the segmentation accuracy with higher values. The sensitivity values are 88.74%, 91.917%, 75.464% and 80.368%, for the 4 images, respectively with small values of FP. And also, the specificity values are very high (above 99%) for all the 4 images with lower FN values. Moreover, our proposed method provides very good optic disks segmentation accuracy of 98.899% value on average. Likewise, the blood vessel segmentation results are also provides very good accuracy of 99.09% on average. Blood vessel segmentation in these 4 images is also offered higher sensitivity (above 79%) and specificity (above 98%) values with lower FPR and FNR values. However, the Modified Region Growing and morphological methods facilitates good results for optic disks and blood vessels segmentation.

C.2. Evaluation results of normal-abnormal image Classification

The classification effectiveness for the normal and abnormal retinal images are also computed by the evaluation metrics FPR, FNR, Sensitivity, Specificity and Accuracy using the same equations as described above in (18) – (22). The description of TP, TN, FP and FN are given in the following table 3.

Table 3. Description of TP, TN, FP and FN for the normal-abnormal image classification

DESCRIPTION	Classified as Normal image	Classified as Abnormal image
Actually Normal image	TP	FN
Actually Abnormal image	FP	TN

The evaluation metrics are computed based on the above table 3 and the eqns. (18)-(22). The results of the normal-abnormal image classification are given in the following table 4. The graph results for this normal-abnormal retinal image classification in table 4.

The results of table 4 shows that the classification effectiveness of normal and abnormal retinal images with the help of extracted features. Totally, 10 images are given for the normal – abnormal retinal image classification and in which, among 5 normal images only 1 image is wrongly classified as abnormal and also, the 5 abnormal images are correctly classified as abnormal. So, the accuracy results reached 90% value with 80% of specificity and 100% of sensitivity values. Thus, we can understand that our proposed work gives very good normal – abnormal retinal image classification accuracy results by extracting the features of retinal images effectively.

Table 4. Normal-Abnormal image classification results

Evaluation metrics	Results
TP	4
TN	5
FP	0
FN	1
FPR	0
FNR	0.2
Sensitivity (in %)	80
Specificity (in %)	100
Accuracy (in %)	90

C.3. Evaluation results of abnormal image severity based Classification

The abnormal retinal images can be also classified into mild, moderate, severe and proliferative by means of the severity level of diabetic retinopathy. The classification effectiveness for the severity level of retinal images are also computed by the evaluation metrics FPR, FNR, Sensitivity, Specificity and Accuracy using the same equations as expressed above in (18) – (22). The description of TP, TN, FP and FN are given in the following table 5.

Table 5. Description of TP, TN, FP and FN for the normal-abnormal image classification

DESCRIPTION	Classified as Mild image	Classified as Non-Mild image
Actually Mild image	TP	FN
Actually Non-Mild image	FP	TN

Table 6. Diabetic Retinopathy severity based abnormal image classification results

Severity stages	TP	TN	FP	FN	FPR	FNR	Sensitivity (in %)	Specificity (in %)	Accuracy (in %)
Mild	5	5	1	0	0.166	0	100	83.333	90.909
Moderate	1	10	0	0	0	0	100	100	100
Severe	1	9	0	1	0	0.5	50	100	90.909
Proliferative	2	9	0	0	0	0	100	100	100

The confusion matrix for the 10 abnormal images is given in the following table 7.

Similarly, the TP, TN, FP, FN descriptions for the other three severity stages moderate, severe and proliferative are described as in table 5. The evaluation metrics are computed based on the above table 3 and the eqns. (18)-(22). Only the abnormal images are used in the severity classification. So, the obtained 6 abnormal images from the normal-abnormal classification phase are used for training purpose and 11 images (10 abnormal images + 1 normal image) are used for testing purpose. For checking out the efficiency of our proposed work, we have added one normal image with the 10 abnormal images in the testing phase. The results of the normal-abnormal image classification are given in the following table 6.

Table 7. Confusion matrix for 10 abnormal images

Images taken	Mild	Moderate	Severe	Proliferative
Mild	5	-	-	-
Moderate	-	1	-	-
Severe	1	-	1	-
Proliferative	-	-	-	2

The graph results for this abnormal retinal image classification in table 6

The results of table 6 shows that the severity analysis values from the abnormal retinal image classification. Totally, 11 images are taken for our work and which are given to the SVM classifier. Among these 11 images, one of the image is normal image. The severity stages

moderate and proliferative provide accurate classification results with 100% values of sensitivity, specificity and accuracy and 0 values for the False Positive and False Negative rates. But, in the classification of mild stage, among 5 mild images, 5 of the mild images are correctly classified as mild image and one of the non-mild images is also incorrectly classified as mild, which resulted in 0.166% of False Positive Rate with 100% of sensitivity value, 83.33% of specificity value and 90.909% of Accuracy value. And also, in the classification of severe stage image, among 2 non-severe stage retinal images, one of the images is incorrectly classified as severe stage image and where also, the classification accuracy is 90.909% with 0.5 of FNR, 50% of sensitivity and 100% of specificity values. From the results of mild and severe stage classification, we can observe that if any one of the images is classified as wrong class means, nearly 10% of accuracy is reduced. In our work, the severity stage classification results give 95.4545% of accuracy on average. Thus, we can prove that SVM facilitates very good classification results.

D. Comparative Analysis of our proposed work with existing works

Our proposed work is compared with various existing works, in order to prove that our proposed work is better one among all the existing methods.

D.1. Segmentation Comparison Results

Table 8. Segmentation comparison results

Methods	Average Sensitivity (in %)	Average Specificity (in %)	Average Accuracy (in %)
Proposed (MRG)	84.123	99.8207	98.899
Region Growing method	83.54	98.43	98.15

The segmentation result of our proposed work for segmenting the optic disks is obtained by using Modified Region Growing (MRG) algorithm. This MRG segmentation result is compared with the existing Region Growing Algorithm and the results of these two methods are given below in table 8.

The existing Region Growing method for the optic disks segmentation is taken for comparison. In our work, we modify the existing Region Growing algorithm in order to improve the segmentation accuracy results. Proposed MRG segmentation results in 98.899% of average accuracy with 84.123% of average sensitivity and 99.821% of average specificity values. But the existing Region Growing segmentation provides only 98.15% of average accuracy, which is 0.749% lower than our proposed Modified Region Growing method. And, 83.54% of average sensitivity and 98.43% of average specificity results are obtained by the segmentation results of existing Region Growing method and which is lower than our proposed modified Region Growing method. The reason behind getting lower accuracy in existing Region Growing method is noise or variation in intensity and which leads to over-segmentation or holes. Our observation from table 8 states that our proposed optic disks segmentation with Modified Region Growing outperforms the existing Region Growing method of optic disks segmentation.

D.2. Classification Comparison Results

Our proposed work with SVM based severity in retinal image classification gets very good accuracy results and which is also compared with the existing classifiers for prove that our proposed work is better. We compare our proposed work (SVM classifier) with other two existing classifiers Neural Network (NN) and Artificial Neuro-Fuzzy Inference System (ANFIS). NN provides 77.65% of accuracy for the mild and severe stage classification and also 85.7% of accuracy for the stages moderate and proliferative retinal images. These accuracy

values of NN is very low in compared with the ANFIS classifier, in which, 86.5% of accuracy is gained for the mild and severe stages and 91% of accuracy is obtained for the moderate and proliferative stages of diabetic retinopathy images. Even though, the ANFIS classifier acquires better classification results than the NN classifier, SVM classifier used in our proposed work facilitates very accurate classification of severity stages in abnormal retinal images. From these implementation results of performance analysis of our proposed work and the comparison results, we can say that our proposed work is excellent one for the effective segmentation of blood vessels and classification of abnormal retinopathy images based on its severity stage.

Table 9. Comparison Results of Classification

Severity stages	**Classification Accuracy (in %)**		
	NN	**ANFIS**	**Proposed (SVM)**
Mild	77.65	86.5	90.909
Moderate	85.7	91	100
Severe	77.65	86.5	90.909
Proliferative	85.7	91	100

5. Conclusion

Our proposed severity analysis of diabetic retinopathy by dual stage classification with neural network and support vector machine was implemented in the platform MATLAB of version 7.12. The segmentation and dual stage classification results were analyzed based on FPR, FNR, Sensitivity, Specificity and Accuracy. Our proposed work has provided 98.899% of optic disks segmentation accuracy on average and 99.09% of blood vessels segmentation accuracy on average by using MRG and morphological operations, respectively. The classification of normal and abnormal retinal images using Neural Network has gained 90% of accuracy. The second classification results based on the abnormal retinal image severity stage has achieved 90.909% of classification accuracy for mild and severe stage images and 100% accurate classification for moderate and proliferative stages. It was not only enough to prove that our proposed work is good for segmentation and dual stage classification. For proving that our proposed is only better, we have compared our proposed MRG segmentation in optic disks with the existing Region Growing method and which resulted in 0.749% higher values of MRG segmentation accuracy than the existing one. Moreover, the severity based classification with SVM was also compared with existing NN and ANFIS classifiers. We conclude that our proposed work outperforms other existing methods and provides effective segmentation and classification results for the retinal images.

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