A novel approach for analyzing diabetes mellitus and non proliferative diabetic retinopathy using tongue

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Abstract

Objectives: To find out the diabetes mellitus disease with better accuracy by comparing the tongue features of diseased persons with the tongue features of normal persons.
Methods: Median filter is used for remove the unwanted noise from tongue image. The proximal support vector machine is a classification technique which is used for separate the diabetes mellitus and non proliferative diabetic retinopathy samples from the healthy samples.
Findings: The proposed method achieves high performance in terms of precision, recall, accuracy and F-measure.
Application/Improvements: Median filter is used for preprocessing the tongue image and PSVM classifier used for classification which results in better accuracy than the SVM classifier.

Keyword: Diabetes mellitus, Support vector machine, Non proliferative diabetic retinopathy and median filter.

1. Introduction

The Diabetes mellitus and its complications lead to diabetic retinopathy (DR). DR is classified into two stages: non proliferative diabetic retinopathy and proliferative diabetic retinopathy. The starting stage of DR is known as non proliferative diabetic retinopathy [1][2]. Here, the minute blood vessels within the retina leak blood or fluid. The escaping fluid causes the retina to form deposits which is known as exudates. It may decrease the vision of eye. The final stage of diabetic retinopathy is called as proliferative DR. In this case, the blood vessels in the retina accept insufficient oxygen because of circulation problem. Here blood vessels bulge in order to keep sufficient oxygen level. These are very weak and lead to leakage which decreases the vision [3].
Diabetes mellitus (DM) categorized into three types [4]: Type 1 DM, Type 2 DM and Type3 DM.

1. Type 1 DM

It is known as "insulin-dependent diabetes mellitus" (IDDM) or "juvenile diabetes”. In this method the whole body is failed to generate insulin.

2. Type 2 DM

It is known as non insulin dependent diabetes mellitus (NIDDM) or "adult-onset diabetes. In this type of diabetes mellitus insulin acts as a resistance.

3. **Type 3 DM**

Gestational diabetes, when pregnant women without a previous diagnosis of diabetes, develop a high blood glucose level.

In [5] proposed Microaneurysm and DR detection in Fundus Retinal Images. Microaneurysm occurs when the retina degenerates. It is the first sign of DR**.** Early microaneurysm detection will reduce the blindness. Pre Processing the fundus image is the first step of Microaneurysm detection scheme. After that candidates are extracted by using Circular Hough-Transformation. Each and every candidate is classified based on colour and morphological features. At last neural network architecture is used for classification. Here the candidate features are classified as Microaneurysm or non Microaneurysm. However it only detects the DR. It does not differentiate the non proliferative DR with that of proliferative DR.

In [6] proposed an automatic method for analysis the severity of tongue fissures. Preprocessing is a first step after the tongue image extraction process. The tongue fissures are extracted by using wide line detector mechanism and compute the relative depth of tongue fissures. For every image area, the evaluation model for the severity of tongue fissures combines the area portion of fissure regions with the relative depth of each fissure region. This system produces well the performance of fissures extraction model. However, supervised learning does not consider for compute the severity of trained tongue images.

In [7] introduced an Automatic detection of Microaneurysm. Here the set of morphological operators are used for detect the microaneurysm on non-dilated pupil and low-contrast retinal images. Pre processing is an initial step for microaneurysm detection to improve the quality. An exudates and vessels may cause false discovery that is detected in second step. Vessels are removed from the image before detection of Microaneurysm. Finally, the Microaneurysm was detected on poor quality images. However it only detects the microaneurysm, it does not evaluate the severity of the disease.

In [8] proposed to detect DM and Non proliferative DR by using support vector machine classifier. The tongue image is captured by camera. The tongue color, texture and geometry features are extracted from the tongue foreground image. That can be classified by using support vector machine classifier. However, it does not suitable for large data set.

2. Materials and Methods

2.1. Tongue image capturing

Tongue image is captured by camera. The patients are located their chin on a chinrest while showing their tongue to the capturing device. The captured image ranged from 257 × 189 pixels to 443 × 355 pixels. There are in JPEG format. It remove the variability occurred by alteration of illumination.

2.2 Preprocessing process

The aim of the pre-processing is to increase the image quality to construct it ready to continuous processing by removing or reducing the unrelated parts or noise. Hence pre-processing is necessary for improve the quality. The mean filters used to increase the image quality for human spectators. In median filter, filter substitutes each pixel with the regular value of the intensities in the neighborhood. It normally decreases the variance, and simple to carry out. After that, automatic segmentation is applied for each image. It takes apart foreground pixels from its background. Here the binary image clearly shows tongue surface area and its edges from its outside tongue edge areas. The color, texture, and geometry features in tongue foreground image are extracted.

2.3. Color feature extraction

All possible colours are appeared on the image surface which is represented by tongue colour gamut. Here 12 colours are plotted to achieve best tongue color gamut. The 12 colors signifying the tongue color gamut which are extracted from tongue image. From the foreground pixels, the RGB values are first extracted, and transformed to CIELAB by transferring RBG to CIEXYZ.

2.4. Texture feature extraction

To achieve better representation the tongue image is separated into eight texture blocks. Each texture blocks have a size 64 × 64. The blocks are computed automatically for the center of the tongue using a segmented foreground image. The edges of the tongue foreground image are established. Block 1 is located at the tip; Blocks 2 and 3, and Blocks 4 and 5 are on either side; Blocks 6 and 7 are at the root, and Block 8 is at the center.

To compute the texture value of each block, the 2-D Gabor filter is applied and defined as

$$G_k(x,y) = exp\left(\frac{x'^2 + \gamma^2 . y'^2}{-2\sigma^2}\right) cos\left(2\pi \frac{x'}{\lambda}\right)$$

Where,

$x' = x \cdot \cos\theta + y \cdot \sin\theta$,

$y' = -x \cdot \sin\theta + y \cdot \cos\theta$,

σ = variance,

λ - Wavelength,

γ - Aspect ratio of the sinusoidal function,

θ - Orientation

Each filter is convolved with a texture block to produce a response *R_k (x, y):*

$$R_k(x,y) = G_k(x,y) * im(x,y)$$

Where.

$im(x,y)$ - Texture block

*- 2-D convolution

An answerable blocks are merged to form FR_i , and its final response computed below,

$$FR_i(x,y) = \max\big(R_1(x,y), R_2(x,y), \dots, R_n(x,y)\big)$$

This final response chose the maximum pixel intensities and it average the pixel values of FR_i for denote texture of a block.

2.5. Geometry feature extraction

In this work 13 geometry features are extracted which is depends on the length, distances and area of the tongue image.

Width: Tongue width features are computed horizontally from right edge point (x max) to its left edge point (x min)

$$W = x_{max} - x_{min}$$

Length: The length features are computed as vertically from bottom edge (y_{max}) point to its furthest top edge point (y_{min})

$$l = y_{max} - y_{min}$$

Length–width ratio: The ratio of length to width is called as length–width ratio

$$l_w = \frac{l}{w}$$

Smaller half-distance: It is defined as half distance of length or width.

$$z = \frac{min\ (l,w)}{2}$$

Center distance: The center distance (cd) is distance from w'^{s} ,y-axis center point to the center point of l (y_{cp})

$$cd = \frac{(\max(y_{xmax}) + \max(y_{xmin}))}{2} - y_{cp}$$

Where

$$y_{cp} = \frac{y_{max} + y_{min}}{2}$$

Center distance ratio: The ratio of tongue center distance to length is called as Center distance ratio.

$$cdr = \frac{cd}{l}$$

Area: The number of tongue foreground pixels is known as the area of the tongue

Circle area: circle area is denoted as the area of a circle within the tongue foreground

$$ca = \pi r^2$$

Where

r = z

Circle area ratio: The ratio of Circle area to area is known as Circle area ratio

$$car = \frac{ca}{a}$$

Square area: The area of a square within the tongue foreground is known as Square area

$$sa = 4z^2$$

Where

z -smaller half-distance

Square area ratio: The ratio of square area to area is called as Square area ratio

$$sar = \frac{sa}{a}$$

Triangle area: It is defined within the tongue foreground. Here

x_{max} − right point of the triangle
x_{min} − left point of the triangle
y_{max} - bottom point of the triangle

Triangle area ratio: It is defined as triangle area to area.

$$\text{tar} = \frac{\text{ta}}{\text{a}}$$

2.6. Classification using PSVM

Proximal Support Vector Machine is based on Support Vector Machine, it is simpler and faster than traditional Support Vector Machines algorithm, which is especially suitable for large amounts of data or image classification and operations.

Classification is computed between Healthy samples and DM in addition to NPDR versus DM-sans NPDR. Here proximal support vector machine classifier is used for classification process.

On assumption that there are N training samples, such as,(x_1, y_1) (x_2, y_2) …(x_N, y_N) among them , so the target function of Proximal Support Vector Machine can be denoted by

$$\text{Min}\, \frac{c}{2}\,||y||^2 + \frac{1}{2}\,(w^T w + r^2)$$

$$\text{Subject to : } L(Aw - er) + y = e$$

C represented as castigation factor, y denote the sample output, w figure the normal vector of the classification hyperplane, e denoted as units vector, g is the parameter which can ascertain the position of two dividing-line plane relating to the origin in Proximal Support Vector Machine; A represent the n×m dimensional training data set, each sample is corresponding to a listA_1.

By applying each feature individually to separate Healthy/DM, the highest average accuracy achieved via proximal Support Vector Machines.

Algorithm

Input: Training image

Output: Result analysis

1. Initialize N samples

// N is a training image samples

2. Capture the tongue images from data set
3. Compute preprocessing process by using median filter
4. Compute Colour feature extraction by using Gabor filter

$$G_k(x,y) = exp\left(\frac{x'^2 + \gamma^2 . y'^2}{-2\sigma^2}\right) cos\left(2\pi \frac{x'}{\lambda}\right)$$

// $x' = x \cdot \cos\theta + y \cdot \sin\theta$, $y' = -x \cdot \sin\theta + y \cdot \cos\theta$, σ is variance, λ is wavelength, γ is aspect ratio.

6. Compute Texture feature extraction
7. If sample is healthy
   High texture value
8. Else
   Low texture value
9. To extract 13 geometry features
10. Compute PSVM classifier for classification
11. The target function of Proximal Support Vector Machine is denoted by

$$\text{Min}\, \frac{c}{2}\,||y||^2 + \frac{1}{2}\,(w^T w + r^2)$$

// C is castigation factor, y express sample output, w figure the normal vector of the classification hyperplane, e is units vector, g is parameter.

12. The cost function is given as follows:

$$min_{\omega,b,\xi}\, J(\omega, b, \xi) = \frac{1}{2}\|[\omega, b]^T\|^2 + \frac{c}{2}\sum_{i=1}^{m}\|\xi_i\|^2$$

13. Samples result

3. Experimental results

The existing DM and non proliferative DR detection system uses support vector machine classifier for classification and proposed DM and NPDR detection system is used median filter for preprocessing and proximal support vector machine for classification. An experimental result shows that the proposed method achieves high performance in terms of precision, recall, F-measure and accuracy.

3.1. Precision

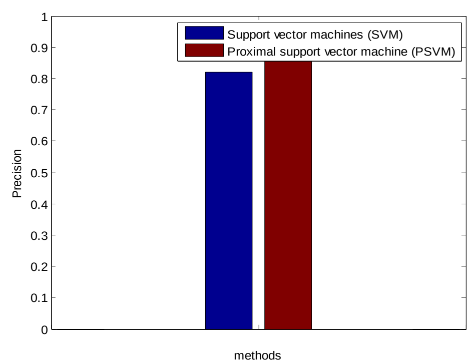
The Percentage of correct predicted results from the set of input is called as Precision. The proposed system is having better accuracy than the existing approach.

Precision value is calculated by using following equation

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Figure 1. represents the comparison of two methods which are detecting diabetics using svm and detecting diabetics using Psvm methods. In this graph, x axis will be the two approaches of diabetics detection and y axis will be precision .The proposed has high precision compare to another one.

Figure 1. Precision comparison



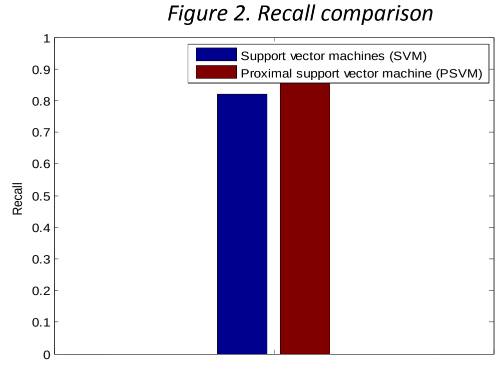
3.2. Recall

The recall or true positive rate (TP) is the proportion of positive cases that were correctly identified, as calculated using the equation:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{True Negative}}$$

In this graph, x axis will be the two approaches of diabetics detection and y axis will be recall. From this Figure 2, we can say that the recall of diabetics detection is increased, which will be the best one.

Figure 2. Recall comparison



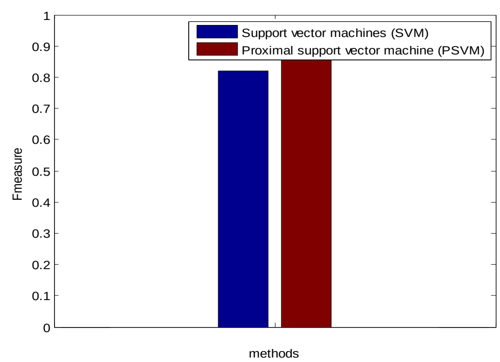
3.3. F measure

The F-measure of the system is defined as the weighted harmonic mean of its precision and recall, The balanced F-measure, commonly denoted as F_1 or just F, equally weighs precision and recall, which means α = 1⁄2. F-measure can be represented as

$$F = \frac{2PR}{P+R}$$

In this graph, x axis will be the two approaches of diabetics detection and y axis will be F measure. From this Figure 3, we can say that the F measure of diabetics detection is increased, which will be the best one.

Figure 3. F measure comparison



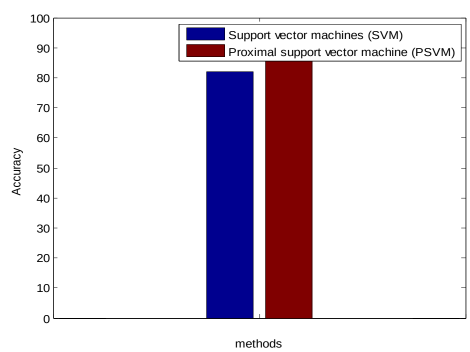
3.4. Accuracy

The Accuracy of the system is calculated with the values of the True Negative, True Positive, False Positive, False negative actual class and predicted class outcome it is defined as follows,

$$\text{Accuracy} = \frac{True\ positive + True\ negative}{True\ positive + True\ negative + False\ positve + False\ negative}$$

In this graph, x axis will be the two approaches of diabetics detection and y axis will be accuracy in %. From the Figure 4. See that, accuracy of the proposed system detecting diabetics using proximal svm is better than existing one.

Figure 4. Accuracy comparison



4. Conclusion

In this proposed system, proximal support vector machine approach to classify Healthy/DM and NPDR/DM samples using three groups of feature include colour, texture and geometry features. By applying each feature individually to separate Healthy/DM, the highest average accuracy achieved via proximal support vector machine. An experimental result shows that the proposed method achieves high performance in terms precision, recall, F-measure and accuracy.

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