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AN IMPROVED FIREFLY ALGORITHM BASED DIABETES DETECTION APPROACH

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Abstract: - Objectives: The main aim of this work is to classify the Healthy/Diabetes samples with better accuracy.
Methods: An improved firefly algorithm is used for select optimal features which are extracted from tongue surface. Transductive Support vector machine is a class classification technique which is used for separate the diabetes from healthy samples.
Findings: The proposed method achieves high performance in terms of precision, recall, accuracy and F-measure.
Application/Improvements: The proposed system is done by using an improved firefly algorithm and TSVM classifier. The experimental results show that the proposed system achieves higher performance compared with existing system.
Keyword: Diabetes mellitus, Support vector machine, Non proliferative diabetic retinopathy and median filter.

INTRODUCTION

Diabetes mellitus (DM) is one of the growing diseases in India. It is a group of metabolic diseases in which there are high blood sugar levels over a prolonged period. DM occurs when the pancreas fails to secrete enough insulin, which slowly affecting the retina of the human eye [1]. It causes blindness. The frequent urination, increased thirst, and increased hunger are symptoms of high blood sugar. Diabetes mellitus DM is simply called as diabetes.

The Diabetes mellitus and its complications lead to diabetic retinopathy. The diabetic retinopathy categorized into two types [2]. They are non proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR) [3]. The NPDR is a starting stage of diabetic retinopathy [4]. It causes the minute blood vessels within the retina leak the blood or fluid. The PDR is a final stage of diabetic retinopathy, in which the minute blood vessels within the retina leak blood or fluid which leads to traction retinal detachments [5][6].

In [2011] Introduced an Automatic Microaneurysm Detection from Non-dilated Diabetic Retinopathy Retinal Images. Here the retinal images are taken of patients with non-dilated pupils. In order to remove noise and improve quality the noise removal, contrast enhancement and shade correction process are implemented. Then compute Exudate detection mechanism. The MA and vessels both are appear in a reddish color. To identify vessels, two intermediate images are generated. The first image is achieved by using a closing operator on shade corrected image for remove the details from the image. The second image is attained by filled-in small

black dots on shade corrected image [7]. Finally it detects the microaneurysm from diabetic retinopathy patient's non-dilated pupil digital images.

In [2012] introduced a new mechanism for detection for diabetic Retinopathy in Non-dilated RGB Retinal Fundus Images. The fundus image is taken as an input. In order to get better result and remove noises in the images, the preprocessing method such as background normalization, contrast enhancement and image binarization are used. Then features such as background normalization, contrast enhancement and image binarization are extracted for detect microaneurysm. Finally classification groups the eye images as either diseased or normal depending on the count of detected microaneurysm. Classification can be used to grade the DR into four stages as no DR, mild DR, moderate DR, and severe DR [8]. However it does not produced high accuracy.

2. MATERIALS AND METHODS

DIABETIC RETINOPATHY ANALYSIS USING MACHINE LEARNING

To detect and grade the severity of diabetic retinopathy automatically, this system introduced a three-stage algorithm. The patient retinal image is taken as an input. In order to eliminate the false photographic artifacts and illumination inconsistencies the preprocessing is applied on the image. The histogram equalization and contrast enhancement are applied on the image, the resulting image is represented as I_m. To enhance the sharpness and illumination of the image is important. By using Laplacian of Gaussian filter I_m is filtered, which is performed for extract the gradient variations (I_h). Then, to obtain enhanced images ($I_m - I_h$) is median filtered.

Stage 1: Image Segmentation

In Stage 1, minimum-intensity maximum-solidity (Min- IMaS) algorithm is used to detect the region which is lie on the intersection of the largest red region and the bright regions in the image. After the detection of intersecting bright regions, the region containing the OD is the bright region with minimum pixel intensity sum and maximum compactness (Sol) are described by following,

If, $R = \{R_1, R_2 ..... R_r\}$, $i \in \{1, 2, ...r\}$

$\wedge(R) = [i_1, i_2 : i_1 = \arg\min \text{Intensity}(Ri)$ ..... (1)

$i2 = \arg\max \text{Sol}(Ri)$

$$\text{ROD}(R) = \begin{cases} R_{i1} = R_{i2} & i_1 = i_2 \\ R_{OD}((R = R = R \backslash R_{i1})) & i_1 \neq i_2 \end{cases} \quad \text{.....(2)}$$

The region with minimum pixel intensity sum is eliminated when the region with minimum pixel intensity sum is not the same as the region with maximum solidity ($i_1 \neq i_2$). The above equation is again evaluated for the residual regions till convergence is attained. Once R_{OD} is detected, to find out the majority part of the blood vasculature (R_{vasc}) each image is gradient smoothened by median filtering and to get a shade corrected image ($Isc = I_M - I_{bg}$) subtracted from image I_m. These are pursued by thresholding and region growing. The region growing is corresponds to Rvasc , the largest regions were extracted. After the detection of OD and blood vessels it can be masked out as background region and foreground candidate regions (Rfore) which are denote the retinopathy lesions are detected.

Stage 2: Lesion Classification

The training dataset is utilized for getting optimal parameters for classification, and also testing data set is used to analyze their performance. Two hierarchical binary classification approach is used for perform lesion classification. In first level, the bright candidate regions (RBL) are classified as true bright lesions (RTBL, class 1) and non-bright lesions (RNBL, class 0), when the red candidate regions (RRL) are classified as true red lesions (RTRL, class 1) and non-red lesions (RNRL, class 0), respectively. In the second step, the true bright

lesions are reclassified as cotton wool spots ($\widehat{R_{CWS}}$, class 1) and hard exudates ($\hat{R}_{HE}$, class 0), when the true red lesions are classified as micro-aneurysms ($\widehat{R_{MA}}$, class 1) and hemorrhages ($\widehat{R_{HA}}$, class 0). In order to reduce the time, the feature selection is an important factor. Here, the 14 structure based features such as area, convex area, solidity, orientation etc and 16 features which are correspond to the mean, minimum, maximum and standard deviation of pixels within each object region in the green plane (Igreen), red plane (Ired), saturation plane (Isat) and intensity plane (Iinten) of the RGB to HSI converted image. The 14 structure based features are useful primarily for separating the non-lesion regions from the lesion candidates. For the red lesion classification, the non-lesion regions generally represent fine blood vessels and hence the non-lesions on an average have a smaller distance from the blood vessels than the red lesions. Also, the blood vessels are elongated structures, and hence for the non-lesion regions, the ratio of major axis to minor axis lengths is higher than the hemorrhages or micro-aneurysms. In next step of hierarchical bright lesion classification, hard exudates (HE) are compact bright regions with well defined boundaries as compared to the cotton-wool spots (CWS) that are larger in area, and less compact (low solidity). The remaining 48 features correspond to the mean and standard deviation of second-order derivative images corresponding to coefficients of the constant, first and second-order horizontal derivative and vertical derivative images ([1, I_x, I_Y, I_{xy}; I_{xx}, I_{yy}]) scaled in [0,1], using a Gaussian filter with zero mean and σ^2 = [1; 2; 4; 8]. These 48 features are useful for the second step of hierarchical classification. Next the Adaboost algorithm is invoked to generate feature w eights based on the linear discriminating performance of each feature, followed by feature ranking.

The AdaBoost is used for feature selection. At first initialize the weight of each feature then analyze the feature over certain iteration rounds. For each feature 'j', at iteration't', a linear classifier classifies sample xi as $h_{t;j}$ (xi), such that the classification outcome $h_{t;j}$ (xi) = 0 or 1. The misclassified sample has more weight than correctly classified samples. The final resulting classifier is a weighted linear combination of the linear classifiers in each iteration step. Then based on their weights the features are ranked in descending order.

The position of each object in the feature space is determined by the feature vector (x), and the class labels of the objects belonging to the training data set (y) are used to determine the class labels of objects belonging to the test data ($\widehat{y*}$) in the testing phase.

Initialize: $W_{1.i} = 1/N;\ t = 1 : T$

Define : $\forall_j$=1: F , $h_{t,j}(X_j) \in [0,1]$

$\epsilon_{t,j} = \sum_{i=1}^{N} w_{t,i} |h_{t,j}(X_i) - y_i|$

$h_t = \arg \min_j \epsilon_{t;j}$; $\epsilon_t = \min_j \epsilon_{t,j}$

Stop iterating if $\epsilon_t \geq 0$

Update : $W_{t+1,i} = \frac{W_{t,i} \exp(\alpha_t(er_i))}{Z_t}$

$\alpha_t = \frac{1}{2} \ln(\frac{1-\epsilon_t}{\epsilon_t})$: Zt = Normalizer

Finally: $\widehat{y*} = \{\begin{cases} 1 : \sum_{t=1}^{T} \alpha_t . h_t(X^*) \\ 0 : Otherwise \end{cases}\}$

Feature Weight: $S(j) = \frac{\sum_{t=1}^{T} \propto_{t,j}}{\sum_j^F \sum_{t=1}^{T} \propto_{t,j}}$

4. Stage 3: DR Severity Grading

After the detection of regions corresponding to the retinopathy lesions, the number of hemorrhages (HA), microaneurysms (MA), hard exudates (HE) and cotton-wool spots (CWS) are determined per image using SVM classifier. Thus, detection of bright lesions must incur less false positives. However, for red lesion detection, failure to detect lesions will result in false interpretation of the DR severity. Thus, it is imperative for any automated system to incur low false negatives for red lesion. An automated system produce incur low false negatives for red lesion classification.

Bright lesion classifier: It must incur low false positives, or high specificity.

Red lesion classifier: It must incur low false negatives, or high sensitivity.

DETECTING DIABETES MELLITUS AND NONPROLIFERATIVE DIABETIC RETINOPATHY USING TONGUE

The previous system introduced machine learning approach for detect severity of Diabetic retinopathy. However it only measured severity grade for diabetic retinopathy (DR). Diabetes mellitus (DM) and its complications leading to diabetic retinopathy (DR) are soon to become one of the 21st century's major health problems. To detect DM and NPDR by distinguishing Healthy/DM and NPDR/DM sans NPDR (DM without NPDR) samples using an array of tongue features consisting of color, texture, and geometry.

2.1. Tongue image capturing

The tongue image is captured by using image capture device. During the capturing process, the patients placed their chin on a chinrest. In order to eliminate the noise from image Preprocessing is used. To separate foreground pixels from its background the automatic segmentation is performed. The three groups of features such as color, texture, and geometry features are extracted from the tongue foreground image.

2.2 Color feature extraction

To represent the all possible colors in the tongue image tongue color gamut is used. From foreground pixel, the RGB values are extracted. Then it can be converted to CIELAB by transferring RBG to CIEXYZ.

2.3 Texture feature extraction

The eight blocks of size 64 × 64 strategically located on the tongue surface are utilized for represent the texture of tongue images. The huge blocks are cover areas outside the tongue boundary, and overlap more with others. The Smaller block sizes avoid the overlapping, but it does not cover the areas. The blocks are computed automatically by locating the center of the tongue. Based on this, edges of the tongue are recognized and equal parts are computed from its center to position the eight blocks. Block 1 is positioned at the tip; Blocks 2 and 3, and Blocks 4 and 5 are on either side; Blocks 6 and 7 are positioned at the root, and Block 8 located at the center.

The 2-D Gabor filter is used for compute the texture value of each block 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 combined to form FR_i , and its final response calculated by below,

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

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

Geometry feature extraction

In this process 13 geometry features are extracted from images. These are based on measurements, distances, areas, and their ratios.

Width: The width is defined as the difference between right edge point (x_{max}) to its furthest left edge point (x_{min}).

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

Length*:* The length *l* feature is computed as the vertical distance along the *y*-axis from a tongue's furthest bottom edge (y_{max}) point to its furthest top edge point (y_{min}):

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

Length–width ratio: It is the ratio of tongue's length to its width

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

Smaller half-distance (z): Smaller half-distance is defined as half distance of l or w.

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

Center distance (cd): it 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 (cdr): cdr is ratio of cd to l:

$$cdr = cd / l$$

Area: The number of tongue foreground pixels is defined as area.

Circle area (ca): It is defined as the area of a circle within the tongue foreground using smaller half-distance z, where r = z

$ca = \pi r^2$.

Circle area ratio: The ratio of ca to a is known as Circle area ratio.

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

Square area (sa) : Square area (sa) is the area of a square defined within the tongue foreground using smaller half-distance z

$$sa = 4z^2$$

Square area ratio (sar): The ratio of Square area to area is defined as Square area ratio.

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

Triangle area: Triangle area (ta) is the area of a triangle defined within the tongue foreground .The right point of the triangle is x_{max}, the left point is x_{min}, and the bottom is y_{max}.

Triangle area ratio:

The ratio of Triangle area to area is defined as triangle area ratio.

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

An efficient feature selection and classification approach

One of the metaheuristic algorithms is firefly algorithm (FA) which inspired by the flashing behaviour of another firefly. In this algorithm firefly will be attracted to a brighter firefly, and also if there is no brighter firefly, it will moves arbitrarily. Here modify this random movement of the brighter firefly by generating random directions in order to find out the best direction in which the brightness increases.

Algorithm

1. Compute a random solution set, $\{x_1, x_2. . . x_k\}$.

2. Generate intensity for each solution member, $\{I_1, I_2, . . . , I_k\}$.

3. Move each firefly *i* towards other brighter fireflies,

4. Select direction U

5. Brightest firefly movement described by

x :=x α U

// α - random step length

6. If direction does not exist among the randomly generated solution

7. Brightest firefly will stay in its current position

8. Else

9. Follow computed direction

10. Update the solution set.

11. Terminate if a termination criterion is fulfilled

12. Otherwise

13. go back to step 2.

Classification using TSVM classifier

Instead of support vector machine, Transductive SVMs is used for classification. TSVM is an iterative algorithm which is used for gradually search the optimal separating hyperplane in the feature space with a transductive process that integrates unlabeled samples in the training stage. This process increases the generalization capability of the classifier.

In this proposed system, TSVM classifier is used to classify Healthy/DM samples using three groups of feature include colour, texture and geometry features.

Results and discussion

In existing system, diabetes is detected by using retinal images. In proposed system, the Diabetes is detected by using tongue images. The experimental results show that the proposed system achieves high performance compared with existing system in terms of accuracy, precision, recall and f-measure.

1. 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,

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

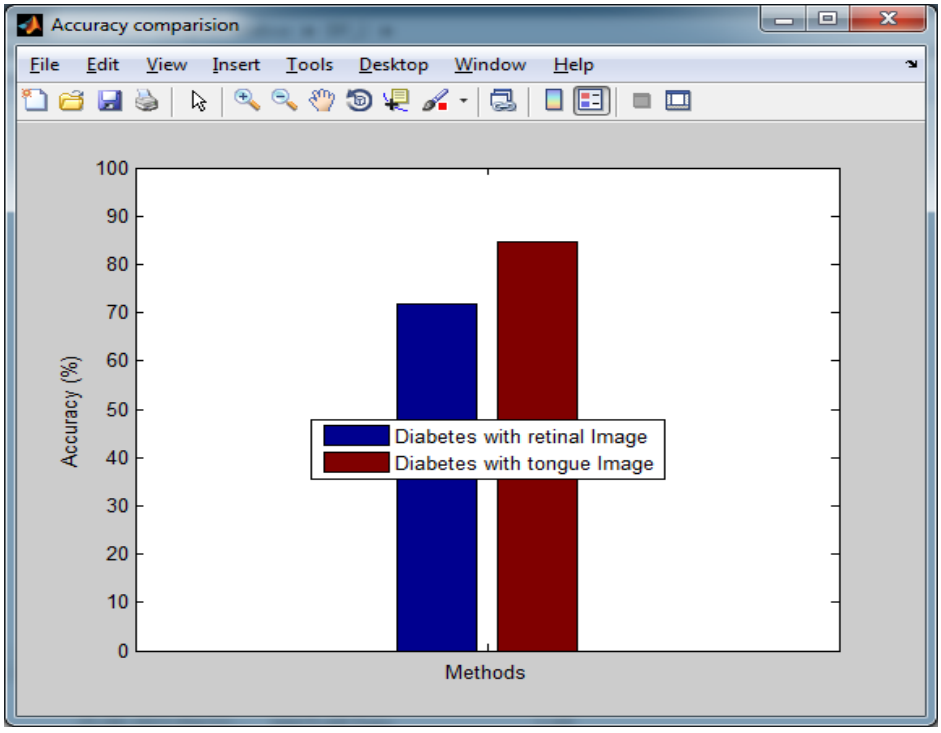


Figure 1. Accuracy comparison

In this graph, x axis will be the two approaches of diabetes detection and y axis will be accuracy in %. In existing system, diabetes is detected by using retinal images. In proposed system, the Diabetes is detected by using tongue images. From the graph see that, accuracy of the proposed system detecting diabetics using tongue image is better than existing one.

2. Precision

Precision value is determined based on the retrieval of information at true positive prediction, false positive. In healthcare data precision is determined the percentage of positive outcome returned that are relevant.

Precision =TP/ (TP+FP)

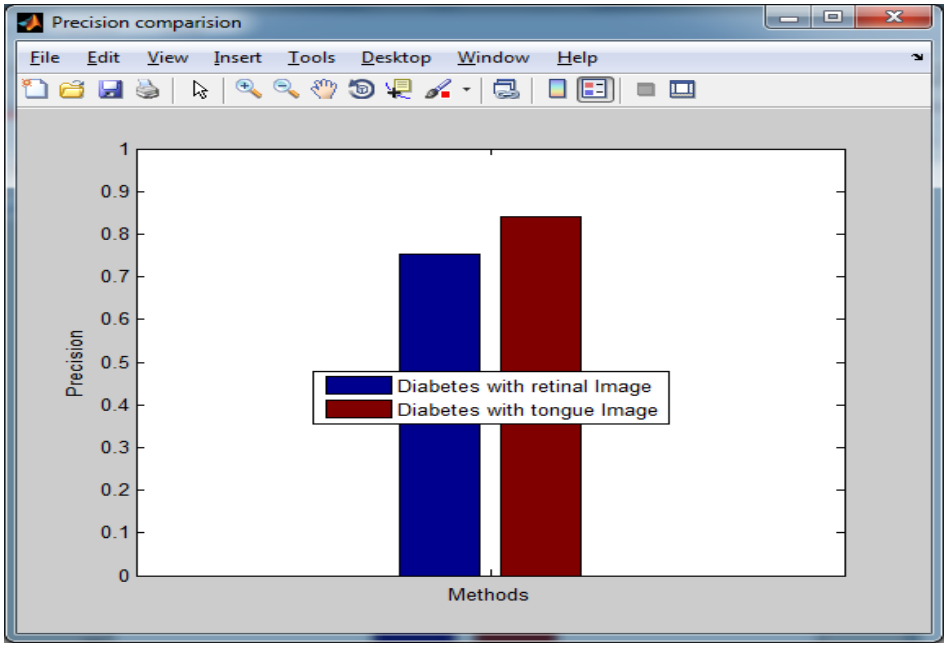


Figure 2. Precision comparison

In this graph, x axis will be the two approaches of diabetes detection and y axis will be precision. In existing system, diabetes is detected by using retinal images. In proposed system, the Diabetes is detected by using tongue images. From the graph see that, precision of the proposed system detecting diabetes using tongue image is better than existing one.

3. Recall

Recall value is determined based on the retrieval of information at true positive prediction, false negative. Recall in this context is also referred to as the True Positive Rate. In that process the fraction of relevant instances that are retrieved.

Recall =TP / (TP+FN)

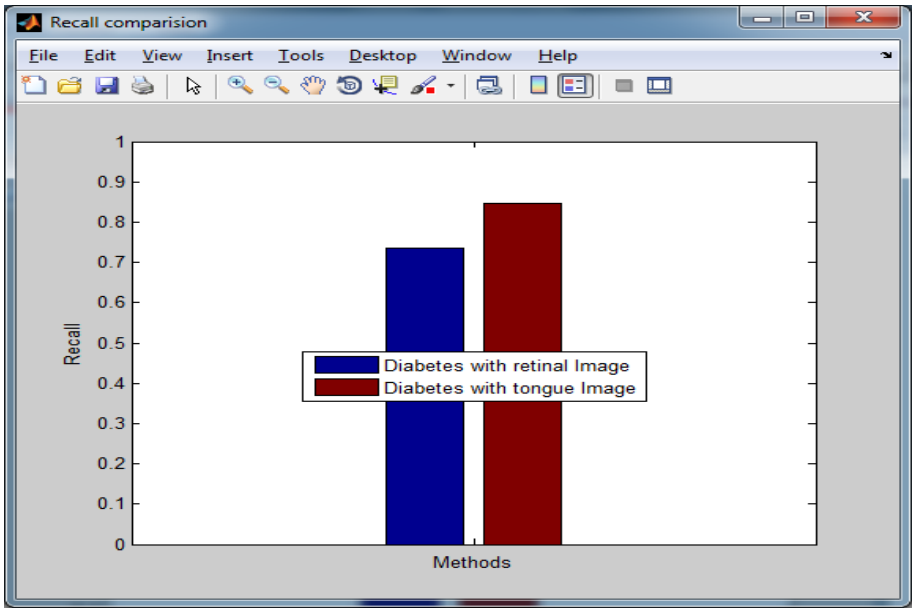


Figure 3. Recall comparison

In this graph, x axis will be the two approaches of diabetes detection and y axis will be recall. In existing system, diabetes is detected by using retinal images. In proposed system, the Diabetes is detected by using tongue images. From the graph see that, recall of the proposed system detecting diabetics using tongue image is better than existing one.

4. F measure

The F-measure of the system is defined as the weighted harmonic mean of its precision and recall, that is, F=1α1P+(1−α)1R, where the weight α ∈ [0,1]. The balanced F-measure, commonly denoted as F_1 or just F, equally weighs precision and recall, which means α = 1⁄2

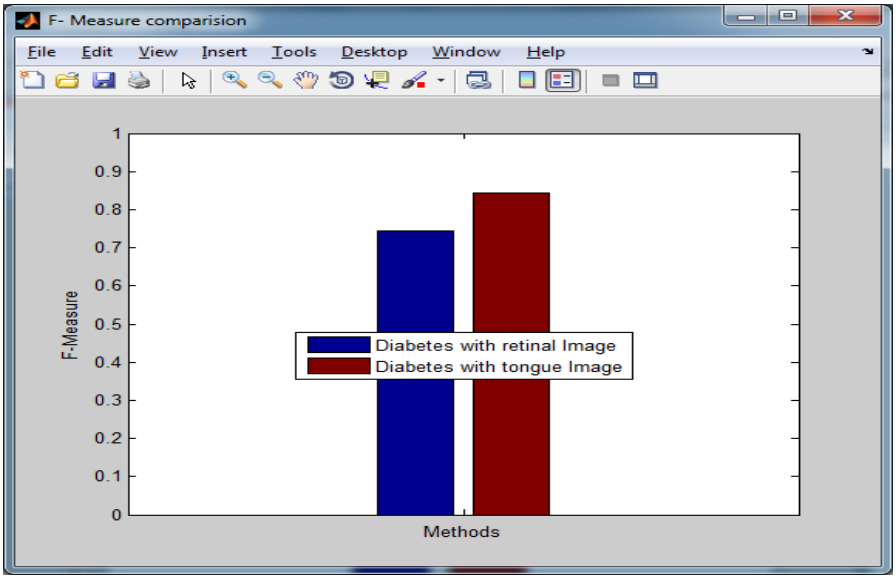
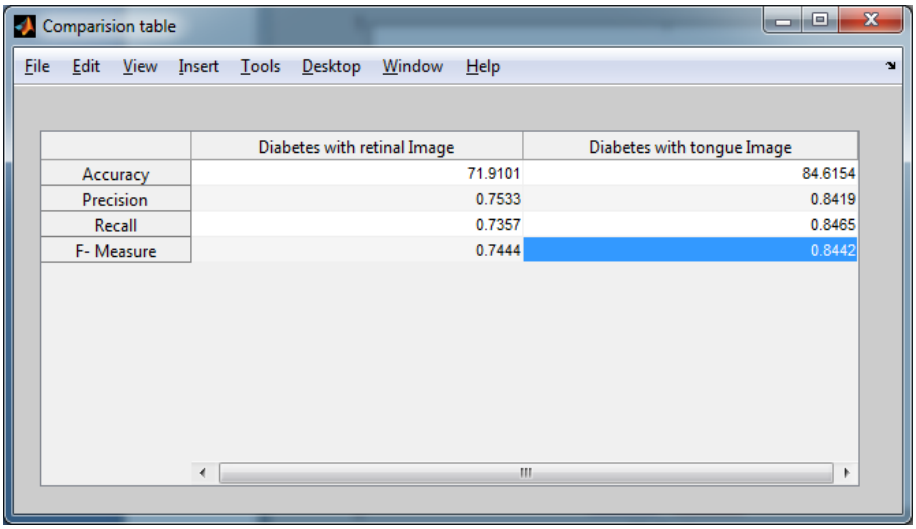


Figure 4. F-Measure comparison

In this graph, x axis will be the two approaches of diabetes detection and y axis will be F-Measure. In existing system, diabetes is detected by using retinal images. In proposed system, the Diabetes is detected by using tongue images. From the graph see that, F-Measure of the proposed system detecting diabetes using tongue image is better than existing one.

Comparison table



	Diabetes with retinal Image	Diabetes with tongue Image
Accuracy	71.9101	84.6154
Precision	0.7533	0.8419
Recall	0.7357	0.8465
F- Measure	0.7444	0.8442

The above comparison table shows that the proposed system (Diabetes is detected by using tongue images) is achieves higher performance compared with the existing system (diabetes is detected by using retinal images) in terms of accuracy, precision, recall and F-Measure.

Conclusion

The proposed system introduced an improved firefly algorithm based diabetes detection approach. The tongue images are taken from dataset. Then three groups of features namely color, texture, and geometry were extracted from the tongue foreground. In this system an improved firefly algorithm firefly algorithm is used for select optimal features by utilizing three type of features. After the feature selection the TSVM classifier used in this produces the more accurate information than the SVM classifier. The experimental results show that the proposed system achieves higher performance compared with the existing system in terms of accuracy, precision, recall and f-measure.

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