

# Detection of Diabetes Mellitus using Tongue images



Logeswaran T, Gowrishankar P, Surendar V, Tamilarasu P & Suresh M

**Abstract:** One of the major health problem faced by people around the world is diabetes mellitus. Tongue diagnosis (a non-invasive approach) is made to detect DM & NPDR in its early stages. It uses color, texture & geometry features for diagnosis. A color gamut of the tongue is confirmed with 12 colors describing the color characteristics of the tongue. To delineate the tongue texture attributes, texture feature values of various blocks are employed. There are 13 features extorted from dialect images includes measurements, areas, distance and ratios of the tongue and they are called as geometry characteristic features. Using these features, it is possible to differentiate non-proliferative diabetic retinopathy, diabetes mellitus & healthy human being using their tongue images.

**Keywords:** Color Gamut, Diabetes mellitus, Tongue Geometry, Tongue Image Tongue Texture.

## I. INTRODUCTION

It was estimated in 2013, over 382 million people throughout the world had diabetes, and it is predicted that this figure may twofold by the year 2025. This raise will happen in developing nations and will be because of increase in populace, unfortunate eating regimen, aging, stoutness, and inactive ways of life. By 2025, a large portion of the people with diabetes in developed nations will be aged 65 years or more whereas in the developing nations they will be aged 45 to 64 years. Two essential types of diabetes are Type1 and Type2:

Type 1 diabetes (named insulin- dependent) in which the pancreas neglects to create the insulin which is fundamental for endurance. Much of the time this sort happens in youngsters and teenagers however is being noted mostly in later life.

Type 2 diabetes (known as non-insulin- dependent) results from the body's incapability to respond and react appropriately to the activity of insulin made by the pancreas.

It is considerably more typical and liable for around 90% of all diabetes cases around the world.

It shows up most frequently in grown-ups however is being noted progressively in teenagers also. Prevention and treatment involve a physical exercise, a healthy diet, not using tobacco, and being a normal body weight. The people with this disease are instructed to maintain proper foot care and blood pressure, after the sufferer has moved out no less than 12 hours food, and need to take a test trial of the patient's blood control. Type 1 diabetes is treated using insulin injections. Medicines with or with no insulin are used for treatment of Type -2 Diabetes. Some oral medications and insulin can cause sugar. Weight in those with obesity is an effective measure in those with type 2 DM. Analysis using Fasting Plasma Glucose is the official technique adept by many medical experts to identify DM. Blood Glucose levels are determined by using FPG investigation (by penetrating their finger). Although this process is precise, it is considered insidious and somewhat aching (penetrating method). DR (Diabetic Retinopathy) is a very small complicatedness of diabetes mellitus specifically as regards 4.8% of the total 37 million persons with loss of sight around the globe, calculated by World Health Organization [1]. In its initial phase, referred to as non-proliferative diabetic retinopathy (NPDR), if this disease is detected, it can be treated to prevent further development and sight loss. A variety of imaging modalities like digital red-free photographs [2], angiography [3], [4], and digital color fundus imaging [5] – [10] is used to investigate the human retina to facilitate detection of DR and NPDR. Finding the salient characteristic features associated to DR along with but not limited to micro aneurysms, hemorrhages, retinal blood vessels, and outflow, forms the basic principle behind these techniques. Such modalities with various image can be considered as invaders, containing fluorescein interject into a vein for angiography or exposing the eye toward bright flashes. Hence, it necessitates developing a non-intrusive method but an authentic method to recognize NPDR as well as DM. At the outset, this paper takes account of the above mentioned issues and suggests a novel diagnostic method by means of a collection of tongue images which contains texture, color, and geometry features. The person tongue have various features so that it can be explored to diagnose ailment [11] – [25], using texture, color, and geometry feature being the most outstanding among all [11] – [25]. Conventionally, medical experts had analyzed these features [11] – [25]. On the other hand, uncertainty and prejudice are linked with their investigative results.

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Analysis of tongue images and quantitative feature extraction can be detailed. No papers have acknowledged the methods to identify DM or NPDR using these following features like geometry, tongue color, and texture characteristics. Domestic (in-house) device, which will take into account of color variation, are particularly designed to take images of tongue [26]. To locate the accent pixels, all the images were dissected [27]. without There are three sets of features namely geometry, texture, and color and they are extorted using the tongue accent pixels position. A database which contains healthy test data samples, DM trials including DM-sans and NPDR received from various hospitals are used to carry out investigations. The classification was performed between Healthy versus Diabetes mellitus.

II. BLOCK DIAGRAM

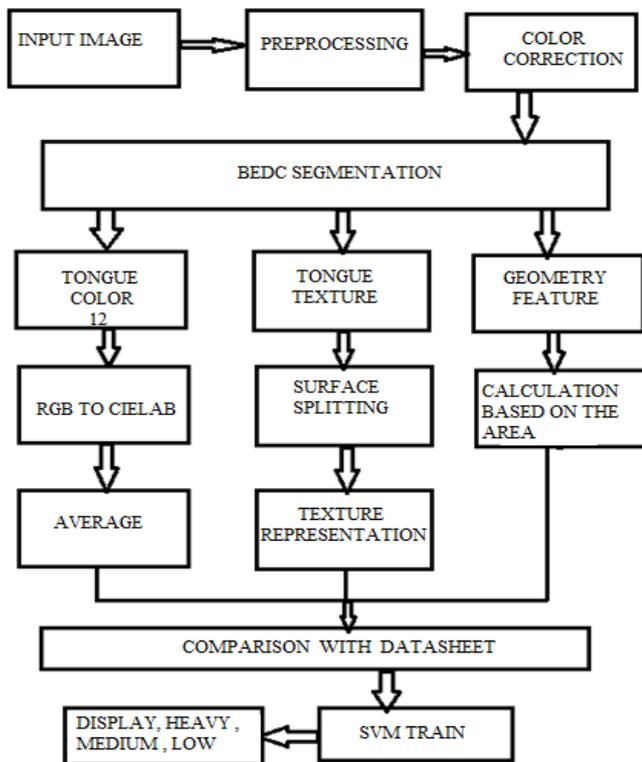


Fig. 1. General Block Diagram of Proposed Method

Fig. 1 indicates the steps in the proposed method. In this input images are collected from the benchmark, for those images preprocessing has to do, to remove noise and also to enhance the image, the filtering process is done after that using tongue features and bi-elliptical deformable contour algorithm is performed. Finally, the diabetes mellitus and non-proliferative affected region are segmented in an accurate manner.

III. CAPTURE DEVICE AND TONGUE IMAGE PREPROCESSING

With the concern of color variation, special domestic (in-house) devices are constructed for detaining tongue images. Segmentation is done on the images to identify their foreground pixels. Using the appropriate pixels positioned, three sets of features, namely texture, color, and geometry, were extorted from it.



Fig. 2. Tongue Image Capture Device

Fig. 2 represents the domestic (in-house) devised apparatus. It contains a 8-bit resolution camera (three chip CCD). With the purpose of producing uniform illumination, two fluorescent tubes were sited on the camera. CIE (Commission International de l’Eclairage) chose an angle of 45° across the incident and the emergent light. The person has to put down his/her chin over the chin rest and also he/she has to show his/her tongue to the camera for capturing the tongue picture. The images from these devices are in JPEG format and pixels range from 257x 189 to 443 x 355. Also they are color modified to get rid of the changes occurred due to illumination.

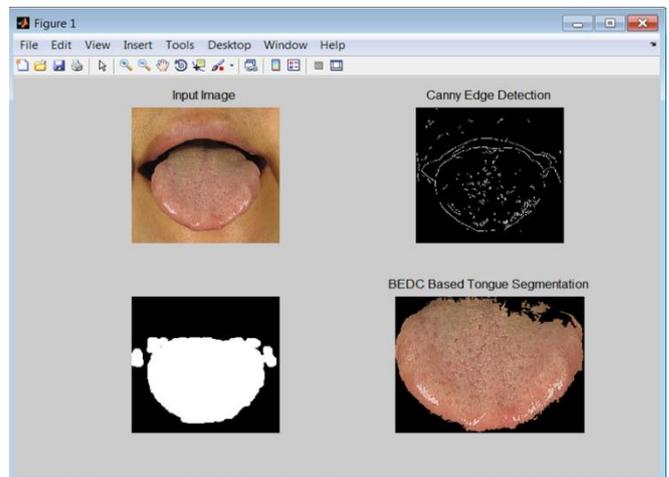


Fig. 3. Simulation output for BEDC segmentation

For analyzing the images, automatic segmentation is used [27]. It is realized by merging Bi-elliptical Deformable Contour (BEDC) and bi-elliptical deformable template (BEDT). In [27], by reducing the energy function of BEDT first and then BEDC, the segmented tongue is obtained. BEDT captures the entire shape features of the tongue, whereas by deforming BEDC, the basic information of the tongue can be matched. At the outset, a binary image is obtained. Tongue surface area and its boundaries represent the foreground pixels while area outside the tongue edges indicates the background pixels. The following section gives the various steps involved in the extraction of various features. The figure 3 shows the simulation output for BEDC segmentation.

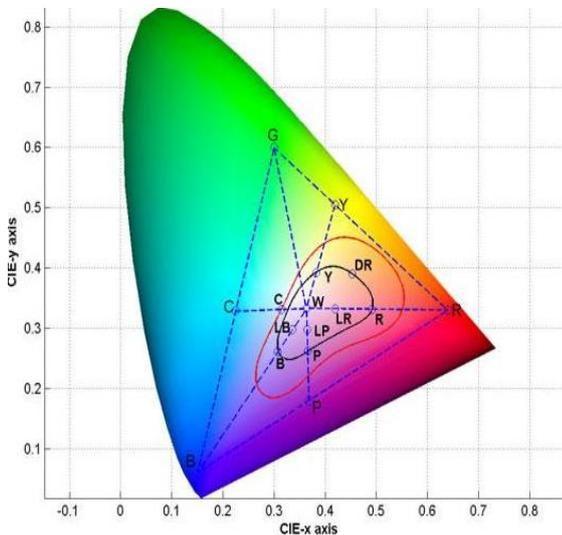
IV. TONGUE COLOR FEATURES

This part of the paper shows how color features are extorted from images of tongue.

From the summarization of tongue color gamut, and then all foreground pixel is contrasted and evaluated to twelve colors indicating the color gamut and allocate its nearby color.

**A. Tongue Color Gamut**

All desirable colors that become visible on the tongue surface are represented by the tongue color gamut and exist within the red boundary, as shown in Fig. 4.



**Fig. 4. Diagram showing CIE-XY chromaticity**

Surveys reveal that most of the points i.e. about 98% of it are present within the black boundaries. RGB color function is employed to exemplify the color gamut of the tongue with 12 colors. Yellow point represented by the letter Y is revealed by the RG line. Cyan point denoted by the letter C is shown on the GB line, and P (Purple) is noted on the line GB. The center point of the GBR color space is determined and it is assigned as W (White). After that, a straight line is drawn for each B (Blue), R (Red), Y, P and C point to W point. New additional color is utilized to represent the 12 colors, every time when these represented lines intercross the tongue color gamut. It mainly relates to C, B, R, Y, and P. LB (Light blue), LR (Light red) and LP (Light purple) indicates the centre points between the black boundaries to W. Since no preceding point fill up that region, DR (deep red) can be used. Additional information regarding the tongue color gamut is obtained.



**Fig. 5. Twelve Colors Representing the Tongue Color Gamut**

The tongue color gamut representing the 12 colors is extorted from fig. 4 and Fig. 5 represents the color square with its labels. In the same way, numerical values of CIELAB and RGB are shown in Table 1.

**Table 1 RGB and CIELAB values**

Color	[R G B]	[L A B]
C (Cyan)	[188 188 185]	[76.0693 -0.5580 1.3615]
R (Red)	[189 99 91]	[52.2540 34.8412 21.3002]
B (Blue)	[183 165 180]	[69.4695 9.5423 -5.4951]
P (Purple)	[226 142 214]	[69.4695 42.4732 -23.8880]
DR (Deep red)	[136 72 49]	[37.8424 24.5503 25.9396]
LR (Light red)	[227 150 147]	[69.4695 28.4947 13.3940]
LP (Light purple)	[225 173 207]	[76.0693 24.3246 -9.7749]
LB (Light blue)	[204 183 186]	[76.0693 7.8917 0.9885]
BK (Black)	[107 86 56]	[37.8424 3.9632 20.5874]
GY (Gray)	[163 146 143]	[61.6542 5.7160 3.7317]
W (White)	[200 167 160]	[70.9763 10.9843 8.2952]
Y (Yellow)	[166 129 93]	[56.3164 9.5539 24.4546]

**B. Color Features Extraction**

Initially, respective RGB values are extorted and transformed to LAB values. RGB function is shifted to XYZ function by making use of the following equation.

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

Convert CIEXYZ function to CIELAB function. CIEXYZ tristimulus values corresponding to white point reference value.

The values are obtained from the laboratory and they are evaluated with twelve colors of the tongue color gamut and closest color is chosen using distance (i.e., Euclidean distance) as a criteria and the respective color is allocated to it. Values of the foreground pixels for each color are estimated and then the values are added to get the net value. To find the proportion of the 12 colors, the total value obtained is divided by sum of pixels. Vector v represents the tongue color characteristic and it is given by

$$v = [O1, O2, O3, O4, O5, O6, O7, O8, O9, O10, O11, O12] \quad (2)$$

where Oi stand for the sequence of colors.

Vector indicating healthy tongue color feature and similar 12 color makeup with the majority of the pixel categorized as R. Output of the healthy tongue color features are shown in Fig. 6.

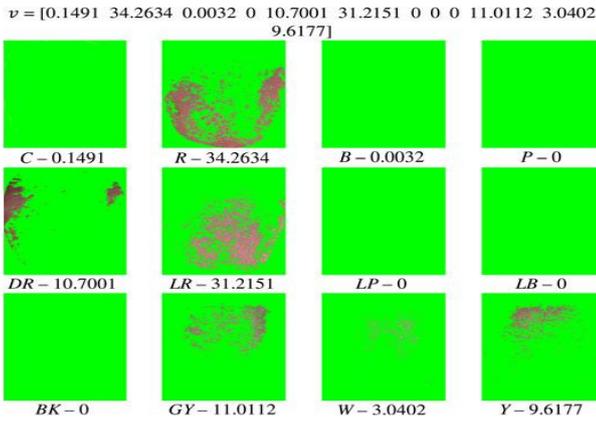


Fig. 6. Healthy Tongue Color Feature Output

DM tongue samples along with its vector indicating tongue color characteristic and similar 12 color composition with majority of the pixels categorized as R. DM tongue color feature output is shown in Fig. 7

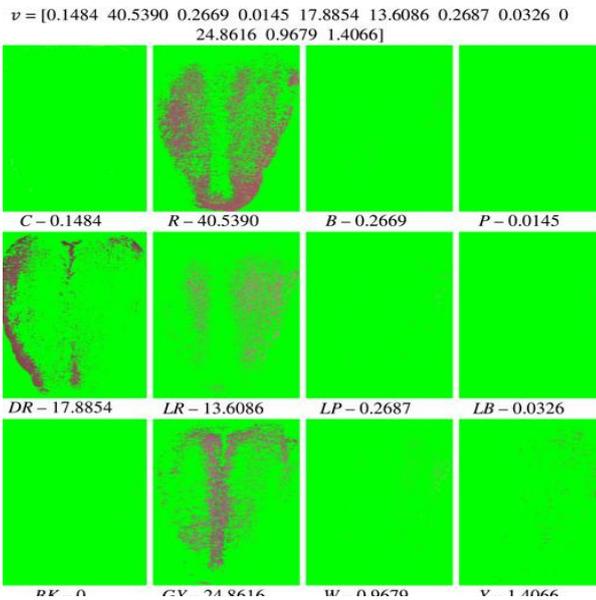


Fig. 7. DM Tongue Color Feature Output

Table 2 shows the color feature extraction for the healthy tongue samples, and Table 3 shows the color feature extraction for DM tongue samples.

Table 2 Color feature output for Healthy tongue images

Color	Feature Output of a Healthy image		
C	0.1491	0.1562	0.1423
R	34.2641	33.9854	33.6511
B	0.0032	0.0025	0.0036
P	0	0	0
DR	10.7001	10.9654	10.8045
LR	31.2154	32.9542	31.3694
LP	0	0	0
LBe	0	0	0
BK	0	0	0
GY	11.321	11.854	11.851
W	3.0456	3.2358	3.0214

Y	9.621	9.325	9.154
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Table 3 Color feature output for DM tongue images

Color	Feature Output of DM tongue Image		
C	0.1481	0.1456	0.1482
R	40.5390	40.6584	39.5941
B	0.2669	0.2564	0.2145
P	0.0142	0.0132	0.0093
DR	17.8854	17.2591	18.0321
LR	13.6068	12.8654	13.8462
LP	0.2684	0.2954	0.2485
LBe	0.0326	0.0321	0.0214
BK	0	0	0
GY	24.8645	25.3947	24.3584
W	0.9696	0.8654	0.8425
Y	1.4066	1.3651	1.4582

V. TONGUE TEXTURE FEATURES

This section presents the texture feature removal from the tongue images. In this paper, 20 blocks were chosen. Fig. 8 shows the texture of tongue images. There are 8 number of blocks with size 64 x 64 deliberately positioned on the tongue surface are utilized.

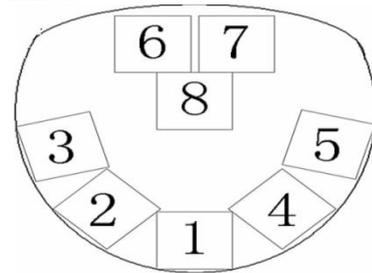


Fig. 8. Eight feature blocks position on the image of tongue

The different frequencies and orientations of Gabor filters may be helpful for extracting useful features from an image. For pattern analysis applications, the Gabor filter is widely used. In order to compute the texture value of all blocks, the 2D Gabor filter is widely used. Bigger size blocks occupy the region outside the tongue boundary and also partly cover the other blocks. Smaller size block prohibits the overlap but they do not expand the eight locations as effectively. Using a fragmented binary tongue picture, the blocks are computed. Subsequently, the boundaries of the tongue are created. The equal and alike parts are calculated commencing from the center and the eight blocks are located. Block numbered 1 is placed on the top, whereas blocks numbered 2 and 3 are placed on one side and blocks numbered 4 and 5 are placed on other side. Blocks numbered 6 and 7 are placed at the origin whereas Block numbered 8 is located at the middle.

Table 4 Healthy Texture Values

	Healthy Image		
Block 1	2.525	2.456	2.213
Block 2	1.671	1.789	1.987
Block 3	1.725	1.845	1.845
Block 4	2.246	2.145	1.751

Block 5	1.487	1.987	1.574
Block 6	1.987	1.785	1.423
Block 7	3.654	3.125	2.951
Block 8	3.458	3.321	3.756
Block 9	3.854	4.148	3.896
Block 10	4.852	3.984	4.741
Block 11	4.582	4.258	4.851
Block 12	4.789	4.369	4.962
Block 13	5.321	4.147	5.789
Block 14	5.851	5.741	5.845
Block 15	5.478	5.852	5.954
Block 16	6.154	5.963	6.746
Block 17	6.987	6.485	6.854
Block 18	7.123	6.987	7.256
Block 19	7.456	7.481	7.354
Block 20	7.489	7.451	7.351

Table 4 shows the output values of the texture features of the healthy images.

For image processing application, the most widely used linear filter is a Gabor filter. It is chosen to estimate the feature values of all block. It is represented by the relation as

$$B_k(A, B) = \exp\left(\frac{A^2 + \gamma^2 \cdot B^2}{-2\sigma^2}\right) \cos\left(2\pi \frac{A}{\tau}\right) \quad (3)$$

where  $A^1 = A \cdot \cos \theta + B \cdot \sin \theta$

$B^1 = -A \cdot \sin \theta + B \cdot \cos \theta$

$\sigma$  – Variance ,

$\tau$  – wavelength ,

$\gamma$  – Aspect ratio and

$\theta$  – orientation

By convolution, a response  $Z_k(a, b)$  is generated by the filter and it is given by

$$Z_k(a, b) = B_k(A, B) * tm(x, y) \quad (4)$$

where  $tm(x, y)$  represents the features of texture block and  $*$  correspond to convolution.

The output signals of every block are joined to get FZ<sub>i</sub> and its ultimate output response are calculated as shown below:

$$FZ_i(a, b) = \max(Z_1(a, b), Z_2(a, b), \dots, Z_n(a, b)) \quad (5)$$

By taking the average of all the pixel values of FZ<sub>i</sub>, the maximum value is found out.

$\sigma$  equals to 1 and 2 . The three orientation angle such as 45', 90' and 135' was chosen. Since in real conditions, the total addition of all the values of texture blocks among healthy and diabetes mellitus have the biggest difference.

Table 5 DM Texture Values

	DM Images		
Block 1	3.946	3.846	3.952
Block 2	2.036	2.136	2.048
Block 3	2.795	2.845	2.756
Block 4	3.714	3.756	3.698
Block 5	2.470	2.512	2.321
Block 6	1.484	1.642	1.524
Block 7	4.369	4.654	4.524
Block 8	3.784	3.842	3.954
Block 9	4.369	4.284	4.123
Block 10	4.987	4.951	4.524
Block 11	4.846	4.485	4.695
Block 12	5.789	5.621	5.145

Block 13	5.876	5.524	5.486
Block 14	5.984	5.954	5.985
Block 15	6.764	6.123	6.478
Block 16	6.823	6.456	6.952
Block 17	6.940	6.789	7.126
Block 18	7.789	7.752	7.456
Block 19	7.861	7.823	7.756
Block 20	7.987	7.934	7.994

Table 5 shows the output values of the texture features of the DM images.

## VI. TONGUE GEOMETRY FEATURES

This section describes 13 geometry features mainly extorted using tongue images.

**Width:** It is calculated taking into account the horizontal length in the x-axis. Length measured between tongue's utmost right border point ( $x_{max}$ ) and utmost left border point ( $x_{min}$ ):

$$\text{Width (W)} = x_{max} - x_{min} \quad (6)$$

**Length:** It is calculated with regards to the vertical length in the y-axis. Length measured between tongue's utmost bottom border point ( $y_{max}$ ) and its utmost top border point ( $y_{min}$ ). The Fig. 9 shows the length and width of the tongue.

$$\text{Length(l)} = Y_{max} - Y_{min} \quad (7)$$

**Length-width ratio:** It is calculated by dividing the length of the tongue by its width.

$$\text{Length-width} = l / w$$

**Smaller half-distance:** It is determined by dividing the distance of l or w by two, relying upon the little segment.

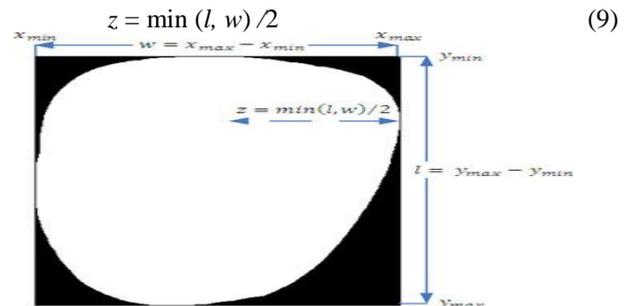


Fig. 9.Length and Width of the tongue

**Center distance:** It is the distance measured between y-axis midpoint and the midpoint of l ( $y_{cd}$ ).

$$Cd = [(max(y_{xmax}) + max(y_{xmin}))/2] - y_{cd} \quad (10)$$

**Center distance ratio:** It is calculated by dividing the center distance by length. Center distance and its ratio are as shown in Fig. 10.

$$cdr = cd / l \quad (11)$$

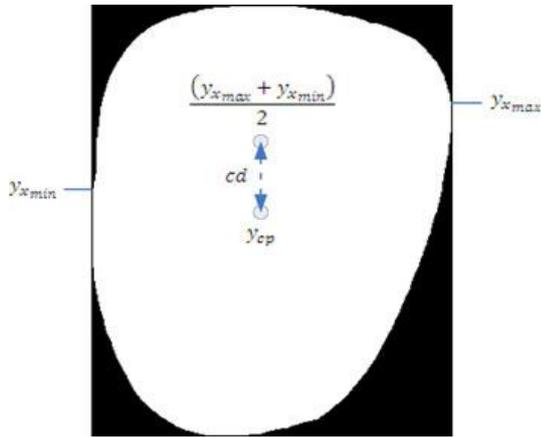


Fig. 10. Centre Distance and its Ratio of the Tongue

**Area:** Total count of tongue accent pixels represents the term area.

**Circle area:** Area inside the tongue accent with radius r is known as circle area.

$$\text{Circle area (ca)} = \pi * r^2 \tag{12}$$

**Circle Area (CA) ratio:** It is determined by dividing the circle area by area.

Figure 3.8 shows the area and circle area of the tongue.  
 $CA\ r = CA/a$  (13)

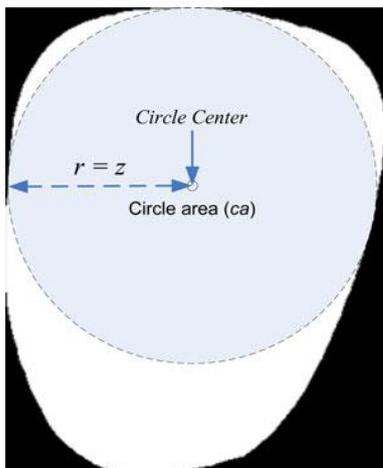


Fig. 11. Area and Circle of the Tongue

**Square Area:** It is the region or space of square described within the dialect accent via z.

$$\text{Square Area (SA)} = 4 * z^2 \tag{14}$$

**Square Area (SA) ratio:** Proportion between square area to area is said to be the square areas ratio. Square and its ratio are shown in Fig. 12.

$$\text{Square Area(SA) ratio} = SA / a \tag{15}$$

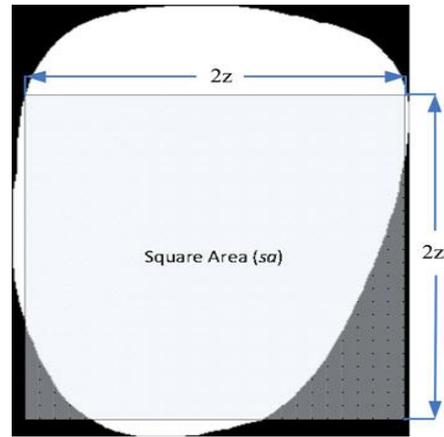


Fig. 12. Square and Its Ratio of the Tongue

**Triangle area:** Triangle territory is exemplified inside the tongue accent center. The dot marked at the right end of the triangle is represented as  $x_{max}$ . The point located at the left end is indicated as  $y_{min}$ , and the point corresponding to bottom end is symbolized as  $y_{max}$ .

Table 6 Geometry Features Values for the Healthy Images

	Healthy Image		
Width	321.81	320.46	321.96
Length	302.63	301.46	302.86
Length - width	0.9543	0.9873	0.9988
Small half distance	144.54	145.66	145.99
Centre distance	-49.63	-48.33	-48.23
Centre distance ratio	-0.1612	-0.1543	-0.1686
Area	76709.2	76728.7	77725.8
Circle area	66493.8	66487.8	65985.9
Circle area ratio	0.8634	0.9843	0.8655
Square area	84662.4	85754.7	86789.6
Square area ratio	0.8909	0.8952	0.8964
Triangle area	32092.2	32093.3	32084.4
Triangle area ratio	0.4213	0.5124	0.4324

Table 6 shows the geometry features for the healthy tongue images.

Table 7 Geometric Features values For the DM Images

	DM Image		
Width	335.81	340.62	344.41
Length	295.37	308.45	309.76
Length - width	0.8803	0.9542	0.9116
Small half distance	141.187	142.53	142.16
Centre distance	-66.79	-65.34	-64.75
Centre distance ratio	-0.2259	-0.2593	-0.2097
Area	82961.41	82546.9	83286.7
Circle area	64607.53	65845.7	68727.24
Circle area ratio	0.8233	0.8655	0.8165
Square area	87260.81	86874.6	87506.8
Square area ratio	0.8717	0.8655	0.8869

Triangle area	36077.44	36235.43	37959.17
Triangle area ratio	0.4723	0.4568	0.4634

Table 7 shows the geometry features for the DM tongue images.

**Triangle area ratio:** It is the proportion of ta to a. Triangle along with its ratio of the tongue is shown in Figure 3.10

$$tar = ta/a \tag{16}$$

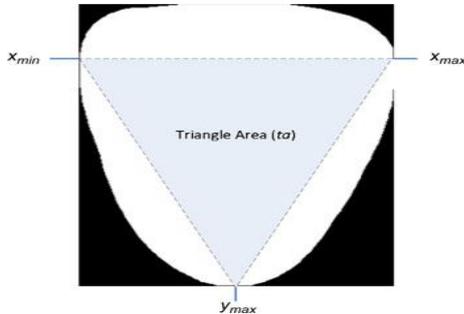


Fig. 13. Triangle and Its Ratio of the Tongue

### VII. CLASSIFIER OUTPUT

The arithmetical values are achieved on the tongue image dataset consist of 426 pictures separated as 130 Healthy and 290 DM. Healthy tests or trail are confirmed with a blood analysis and other assessment methods. On the off chance, if the output parameters obtained from these analysis lies within a particular range, they are considered as healthy person. In order to identify diabetes, analysis based on FPG is explored. The images are selected such that it can be used for developing and other half of the image is employed for testing. This process is repeated for five times. The *k*-nearest neighbor [30] and Support Vector Machine (SVM) [31] is utilized for classification purpose. The accuracy in use in order to measure the performance,

$$\text{Average Accuracy} = (\text{sensitivity} + \text{specificity}) / 2 \tag{17}$$

The final classification rate is obtained using the normal of every one of the five redundancies recorded. During the initial step, every entity (among the three sets or groups) was utilized to segregate Healthy against DM. Classifier output for the DM tongue sample is represented in the Fig.14. The sample or trial of the healthy tongue is given in Fig. 15.

```

Command Window
New to MATLAB? Watch this Video, see Examples, or read Getting Started.
Block - 4 value is 6.286
Block - 5 value is 6.220
Block - 6 value is 6.220
Block - 7 value is 6.075
Block - 8 value is 5.902
Block - 9 value is 5.781
Block - 10 value is 5.677
Block - 11 value is 5.677
Block - 12 value is 5.626
Block - 13 value is 5.547
Block - 14 value is 5.466
Block - 15 value is 5.363
Block - 16 value is 5.241
Block - 17 value is 5.199
Block - 18 value is 5.199
Block - 19 value is 5.169
Block - 20 value is 5.086

HEALTHY =

HEALTHY SCORE = 11.718750 Percentage

DM =

DM SCORE = 88.281250 Percentage
fx >>
    
```

Fig. 14. Classifier output for DM tongue image

```

Command Window
New to MATLAB? Watch this Video, see Examples, or read Getting Started.
Block - 9 value is 5.066
Block - 10 value is 4.963
Block - 11 value is 4.868
Block - 12 value is 4.782
Block - 13 value is 4.741
Block - 14 value is 4.699
Block - 15 value is 4.627
Block - 16 value is 4.588
Block - 17 value is 4.534
Block - 18 value is 4.488
Block - 19 value is 4.440
Block - 20 value is 4.389

HEALTHY =

HEALTHY SCORE = 75.781250 Percentage

DM =

DM SCORE = 24.218750 Percentage
fx >>
    
```

Fig. 15. Classifier output for Healthy tongue image

### VIII. CONCLUSION

A non-invasive approach was suggested in this paper to identify healthy / DM specimens using three sets of features taken from objects in the dialect. Three sets contains color, texture and geometry. A color gamut in the tongue was first used to indicate twelve colors for each image in the tongue. Twenty deliberately located blocks were consequently removed on the tongue and their texture quality was estimated. At last, thirteen geometry features were extorted from tongue images using the features such as distances, measurements, areas and their ratios. Utilizing 130 safe and healthy images and with 296 DM pictures, numerical measurements are carried out. By relating each feature independently to separate Healthy / DM images, the maximum accuracy attained by adopting SVM is 66.26 percent. On the other hand, using SFS along with the SVM, it was revealed that nine features (with elements present in all three sets) created the best possible result; the average 80.52 percent accuracy was achieved. Considering NPDR-sorting peoples, the optimum 80.33 percent result was achieved by means of five features. In the five features, three of the feature is from color whereas one feature from texture and other one feature from geometry. This sets the basis for possible novel ways of detecting DM while offering a new means of identifying NPDR without using retina images or investigations.

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