

Detection of Diabetes mellitus using Tongue Color, Texture, And Shape Features

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ABSTRACT

Diabetes mellitus (DM) and its complications leading to diabetic retinopathy (DR) are soon to become one of the 21st century's major health problems. The main drawback is that there is lack of awareness of the people on eating habits. It is characterized by hyperglycemia. The persistent hyperglycemia of diabetes leads to damage malfunction and failure of different organs such as kidneys, eyes, nerves, blood vessels and heart. To combat this approaching epidemic, this paper proposes a noninvasive method to detect DM. Three groups of features extracted from tongue images. They include color, texture, and geometry [1]. A noninvasive capture device with image correction first captures the tongue images. A tongue color gamut is established with 12 colors representing the tongue color features. The texture values of eight blocks strategically located on the tongue surface, with the additional mean of all eight blocks are used to characterize the nine tongue texture features. Finally, 13 features extracted from tongue images based on measurements, distances, areas, and their ratios represent the geometry features. Applying a combination of the 34 features, the proposed method can separate Healthy/DM tongues.

Index Terms—Diabetes mellitus (DM) detection, tongue color features, tongue geometry features, tongue texture features, SVM, ANN.

INRODUCTION

WORLD Health Organization (WHO) has estimated that in 2000 there were 171 million people worldwide with diabetes mellitus (DM), and the number will increase to 366 million by 2030 making the disease among the leading causes of death, disabilities, and economic hardship in the world [2][3]. Two main types of DM exist, Type 1 DM and Type 2 DM. People with Type 1 DM fail to produce insulin, and therefore require injections of it. Type 2 DM is the most common type and can be categorized by insulin resistance. Currently, there is no cure for Type 1 DM or Type 2 DM. However, Type 2 DM can be managed by eating well, exercising, and maintaining a healthy lifestyle

Existing System:- Fasting plasma glucose (FPG) test is the standard method practiced by many medical professionals to diagnose DM. FPG test is performed after the patient has gone at least 12 h without food, and requires taking a sample of the patient's blood (by piercing their finger) in order to analyze its blood glucose levels. So Existing systems are Painful and More time taken consider for diabetic test. These imaging modalities themselves can be regarded as invasive, exposing the eye to bright flashes or having fluorescein

injected into a vein in the case of angiography. Therefore, there is a need to develop a noninvasive techniques to detect DM.

The human tongue contains numerous features that can used to diagnose disease, with color, texture, and geometry features being the most prominent' Traditionally, medical practitioners would examine these features based on years of experience. However, ambiguity and subjectivity are always associated with their diagnostic results. To remove these qualitative aspects, quantitative feature extraction and analysis from tongue images can be established[1]. To the best of our knowledge, there is no other published work to detect DM or NPDR using tongue color, texture, and geometry features. Section II describes the tongue image capture device, color correction, and tongue segmentation, while Section III discusses tongue color feature extraction. In Section IV, tongue texture feature extraction is given in detail, with tongue geometry feature extraction presented in Section V. Section VI describes the experimental results and discussion, followed by concluding remarks in Section VII.

2. CAPTURE DEVICE AND TONGUE IMAGE PREPROCESSING

The capture device, color correction of the tongue images, and tongue segmentation are given in this section. It shows the in-house designed device consisting of a three-chip CCD camera with 8 bit resolution, and two D65 fluorescent tubes placed symmetrically around the camera in order to produce a uniform illumination. The angle between the incident light and emergent light is 45° , recommended by Commission Internationale de l'Ecl. During image capture, patients placed their chin on a chinrest while showing their tongue to the camera. The images captured in JPEG format that ranged from 257×189 pixels to 443×355 pixels were color corrected to eliminate any variability in color images caused by changes of illumination and device dependence. airage (CIE). Each image was segmented in order to locate its foreground pixels. With the relevant pixels located, three groups of features namely color, texture, and geometry were extracted from the tongue foreground[3].

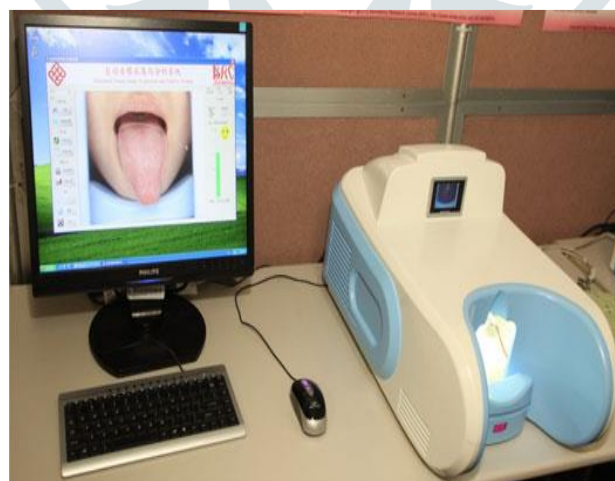


Fig. Tongue capture device

3. TONGUE COLOR FEATURES

The following section describes how color features are extracted from tongue images. The tongue color gamut is first summarized in Section III-A[2][3]. In Section III-B, every foreground tongue pixel is compared to 12 colors representing the tongue color gamut and assigned its nearest color. This forms the color features.

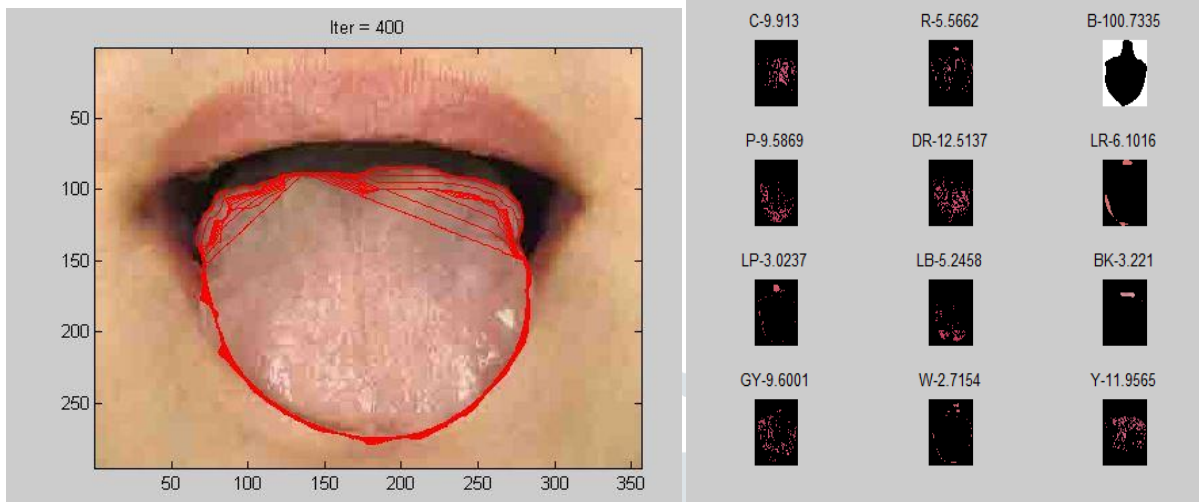


Fig. Image segmentation upto 400 Iteraion

Fig: tongue color gamut with its label on top.

COLOR FEATURE EXTRACTION

For the foreground pixels of a tongue image, corresponding RGB values are first extracted, and converted to CIELAB by transferring RGB to CIEXYZ using

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

IV. TONGUE TEXTURE FEATURES

Texture feature extraction from tongue images is presented in this section. To better represent the texture of tongue images, eight blocks of size 64 × 64 strategically located on the tongue surface are used. A block size of 64 × 64 was chosen

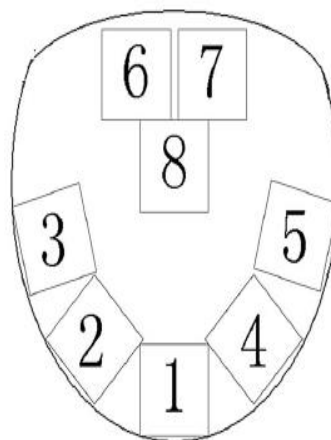
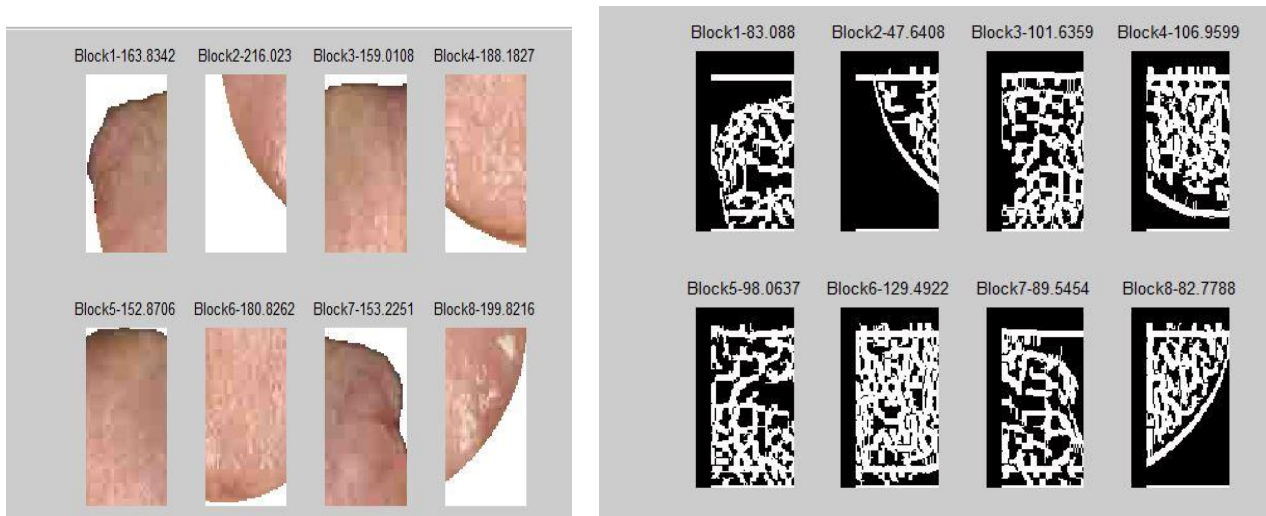


Fig: Location of the eight texture blocks on the tongue



Healthy texture blocks with its texture value

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. The Gabor filter is a linear filter used in image processing, and is commonly used in texture representation. To compute the texture value of each block, the 2-D Gabor filter is applied and defined as

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

V. TONGUE GEOMETRY FEATURES

Total 13 geometry features extracted from tongue images. These features are based on measurements, distances, areas, and their ratios[3].

	Healthy	DM
w	320.8077 (36.5289)	335.9189 (42.7073)
l	302.6231 (43.4015)	295.2703 (62.2306)
lw	0.9527 (0.1638)	0.8897 (0.2067)
z	144.5385 (16.6250)	141.1875 (25.1676)
cd	-49.6231 (29.2308)	-66.6926 (30.9031)
cdr	-0.1631 (0.0871)	-0.2249 (0.0900)
a	76709.14 (15525.3172)	76961.31 (21599.4127)
ca	66493.77 (15079.8031)	64607.43 (21983.2771)
car	0.8635 (0.0873)	0.8232 (0.1232)
sa	84662.52 (19200.1304)	82260.71 (27989.9621)
sar	0.8908 (0.0703)	0.871689 (0.0848)
ta	32092.11 (7336.0657)	36077.43 (10624.3571)
tar	0.4212 (0.0631)	0.4722 (0.0745)

Fig. The Geometry Features For Healthy and DM

HEALTHY VERSUS DM CLASSIFICATION

The numerical results were obtained on the tongue image database comprised of 426 images divided into 130 Healthy, and 296 DM. Healthy samples were verified through a blood test and other examinations[4]. If indicators from these tests fall within a certain range, they were deemed healthy. In the DM class, FPG test was used to diagnose diabetes. Half of the images were randomly selected for training, while the other half was used as testing. This process was repeated five times. Classification was performed using k-nearest neighbor (k-NN) (with $k = 1$) and a support vector machine (SVM), where the kernel function (linear) mapped the training data into kernel space[7]. To measure the performance, average accuracy was employed with the average of all five repetitions recorded as the final classification rate. Receiver operating characteristic (ROC) analysis was also performed on this classification.

K Value	Test Data1		Test Data 2	
	Accuracy	Error rate	Accuracy	Error rate
K=3	70%	30%	57%	43%
K=5	75%	25%	66%	34%

The average accuracy of this result is higher than the optimal combination from the three feature groups (80.23%), and contains fewer features. The mean of features, from the best overall grouping for Healthy and DM, and depicts three typical samples from Healthy and DM.

RESULTS AND DISCUSSION

All the images of the dataset are processed for the color feature, texture feature and geometry features. A typical image from each set is considered for comparison. Values for each feature is calculated for the typical image of each case. The accuracy obtained is 92.85%.

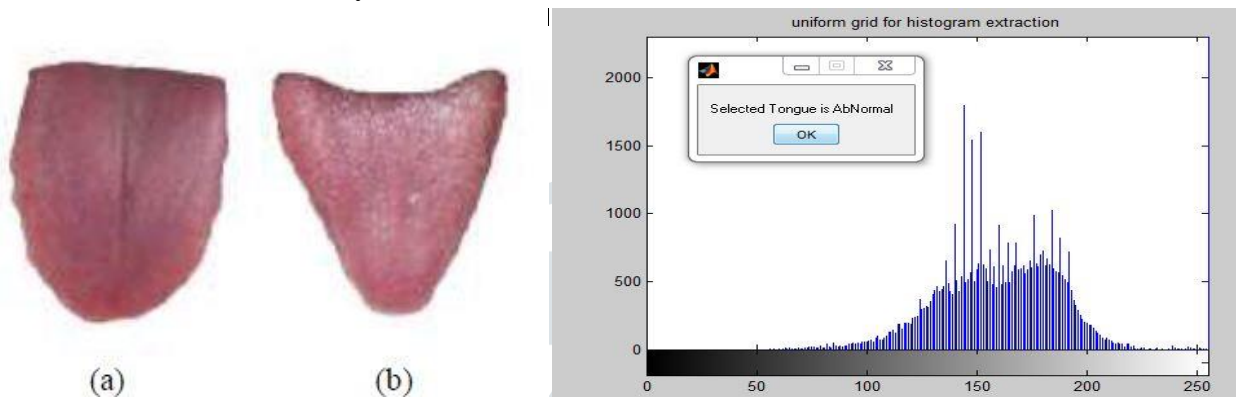


Fig. Typical images for (a) Healthy, (b) Diabetic

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