Diabetes Mellitus and Diabetic Retinopathy Detection using Tongue Images

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Abstract. Diabetes Mellitus is a metabolic disorder caused by increasing blood sugar level. This includes invasive test to detect and diagnose. The image processing technology is introduced to diagnose through non-invasive method. Color, texture and geometry features are extracted. Color gamut is extracted to isolate the same kind of features. The color feature is represented from the extracted gamut. The feature based on distances, height, surface area, width are extracted. The SVM classifiers is used to differentiate the diabetes mellitus affected person and healthy person. Keywords: Diabetes, texture, NPDR.

1. Introduction

Diabetes is caused by insufficient insulin in the human body. The Type 1 diabetes mellitus is lacking of insulin because of lack in immunity system. The type 2 diabetes mellitus is the person with insulin and it is not supported to their body condition. The non invasive methods to detect diabetes play a major role in up-growing medical industry. The colour, texture and geometrical features are extracted. The colour features includes 12 gamut which represent the whole colour estimation of tongue images. 8 blocks from texture features determines the measurement of tongue feature and the sample gives the accuracy of 80.52% and 80.33% [1]. The colour and texture feature doesn’t determine the proper accuracy. The blood vessel is located by using sparse representation classifier with dictionary learning. T central line is located using SRC to detect the diabetes mellitus [2]. The correction algorithm like polynomial, ridge regression, SVM and NN mapping algorithm is measured. The performance is measured using CIE, LAB COLOUR spaces. It provides 95% colour difference for accurate detection of colours [3]. The common problem in diabetic retinopathy leads to blindness. So abnormalities in retina are measured to detect the DR. Multiscale correlation filtering and dynamic thersholding is developed to detect the diabetes retinopathy [4]. The diabetic retinopathy causes over blindness and it is detected by segmenting blood vessel. The blood vessels width, length is detected and compared. This produce a high efficient true positive rate and it is not sensitive. To overcome this situation the diameter and angles are measures to compare with segmented image and it is effective to separate the blood vessels [5]. The pathological details and different tongue parameter of patient cannot segment the tongue using tongue image processing. The BEDT and active contour model determines the shape and energy function of the tongue and it is automatically segment the tongue in efficient way [6][16]. The gradient vector and active contour is used in effective way to segment the
boundaries and 3D version of the active contour provides the efficient details of boundaries. The snakes in active contour model en route the detection of boundaries [7] [8]. Computer aided diagnosis is done using pathological feature. The colour determines the accurate features and it is inconstancy in light leads to affect in validation result. Support vector regression provides a colour calibration and provides proper acquisition technique [9]. The colour space provides the proper colour metrics and it extract proper feature. The probabilistic combined metric provides the performance that matched with tongue colour images [10][11]. The tongue decides the chronic condition with contradicting symptoms and signs. The different characteristics of tongue determine the different forms of diseases and diagnosis using non- invasive method [12]. The modern technology provides the automated tongue diagnosis, which is used to investigate the tongue characteristic to detect different kinds of diseases [13]. The classification using SVM ensures more accuracy than normal classifier [15][17]

2. Block Diagram
The images are collected from database. The image consists of noise, which is removed by using various filters. The bi-elliptical deformable contour algorithm is used to segment the non-proliferative affected region.

![Diagram](image)

**Figure 1.** Proposed Methodology.

3. BEDT Segmentation
The Segmentation using BEDT includes energy function minimization. The energy function is measured based on edge map, gray and colour level. The External Energy force field is given in Equation 1.

\[
P(x, y) = -h(x, y)
\]
The scale spaces measured are at different level, so the external force field for BEDT and BEDC are different. In BEDT the boundaries are located approximately from starting point which is far away from the true edges and it is too noisy. BEDT and BEDC leads to varying in methodology. The BEDT emphasis leads to cover the larger area and laplacian of gaussian filter is used to remove the noise and to cover the larger area. BEDC is used to filter the resultant contour formed by BEDC by small distance with true boundary. The input tongue image used for simulation is shown in figure 2. It is diabetes mellitus and diabetic non-proliferative affected patient’s image. The output of segmented image by using Bielliptical Deformable Contour (BEDC) algorithm is shown in figure 3.

![Figure 2. Input image](image)

The output of segmented image for determining the diabetes mellitus and diabetic non-proliferative is obtained using segmentation algorithms. The segmentation include region growing, edge based segmentation the output of the segmentation result of proposed method is compared against result of other segmentation algorithms. It is clearly observed that the diabetes mellitus and diabetic non-proliferative affected area is clearly detected by proposed method.

![Figure 3. Tongue Image Segmentation](image)

4. **Featureextraction**

The colour feature and colour gamut’s similarities are measured and healthy tongue colour gamut is classified. Healthy tongue color feature output is shown in the Fig 4. DM tongue image with 12 colour vector is classified as R. Color feature of diabetes affected tongue output is shown in the Fig 5.
The color feature extraction for both healthy and DM tongue samples is shown in Table 1&2.

Table 1. Color feature output for Healthy tongue image.

| samples  | cyan | Red   | Blue  | Purple  | Dark Red | Light Red | Light Purple | Light Blue | Black | Gray | White | Yellow |
|----------|------|-------|-------|---------|----------|-----------|--------------|------------|-------|------|-------|--------|
| Healthy  | 0.149| 34.263| 0.003 | 0       | 10.700   | 31.2151   | 0            | 0          | 0     | 11.0112 | 3.0402 | 9.6177 |
|          | 0.201| 33.662| 0.005 | 0       | 9.8001   | 31.3484   | 0            | 0          | 0     | 10.8451 | 2.0212 | 8.9512 |
|          | 0.187| 34.231| 0.007 | 0       | 9.9254   | 30.2587   | 0            | 0          | 0     | 11.9632 | 3.2142 | 8.4662 |
|          | 0.222| 34.321| 0.012 | 0       | 10.845   | 31.8521   | 0            | 0          | 0     | 11.2502 | 3.4123 | 9.4123 |

Figure 4. Healthy tongue color feature output

Figure 5. DM tongue color feature output
Table 2. Color feature output for DM tongue image

| Samples | cyan  | Red   | Blue  | Purple | Dark Red | Light Red | Light Purple | Light Blue | Black | Gray  | White | Yellow |
|---------|-------|-------|-------|--------|----------|-----------|--------------|------------|-------|-------|-------|--------|
| DM 0.125| 31.28 | 0.063 | 0     | 18.46  | 20.26    | 0.0881    | 0.0414       | 0          | 24.292| 1.810 | 3.548 |
| 0.212   | 30.85 | 0.084 | 0     | 18.32  | 20.74    | 0.0951    | 0.0231       | 0          | 23.841| 1.456 | 2.987 |
| 0.123   | 31.48 | 0.105 | 0     | 17.21  | 19.32    | 0.0845    | 0.0741       | 0          | 24.123| 0.987 | 3.456 |
| 0.178   | 31.74 | 0.041 | 0     | 18.98  | 20.47    | 0.08451   | 0.0512       | 0          | 24.147| 1.951 | 3.657 |

5. Texture Extraction Output

To represent the texture 64 X 64 block size was chosen to cover the dimension in different way. The 2D Gabor filter is used for extract the texture features. Texture extraction output for both healthy and DM tongue samples are shown in the fig 6 and fig 7.

![Figure 6](image)

**Figure 6.** Healthy tongue texture blocks with its texture value

![Figure 7](image)

**Figure 7.** Healthy tongue textures with its texture Value

6. SVM Classifiers

The features are extracted and it is given as input to the classifier. The colour and texture features are measured using 50 input images. Support vector machine is performed by training of 40 images and 10 images are goes for testing. The classification is also done by using K-Nearest Neighbour and it doesn’t lead to accuracy. The classification output of SVM classifier for DM tongue and healthy tongue is shown in Figure 8&9. The DM score is displayed as 88.28% while healthy score is 11.71% for diabetes affected person is shown in Figure 8.
Figure 8. SVMClassifier output for DM

Figure 9. SVMClassifier output for Healthy
7. Conclusion
The detection of diabetes mellitus by using non invasive method is efficient and easy way. The BENDT segmentation is used to segment the tongue image and various feature is used to differentiate the images. The efficient classifiers is used to classify the images. In future various algorithm for segmentation and classification will be used to improve the algorithm efficiency. The algorithm will be raised to automatic segmentation and classification in future process.

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