Diabetes Diagnostic Method based on Tongue Image Using SVM with Gabor Feature

E. Srividhya, A. Muthukumaravel

ABSTRACT--- Tongue diagnosis is an important diagnostic method for evaluating the condition of internal organ by looking at the image of tongue. However, due to its qualitative, subjective and experience-based nature, traditional tongue diagnosis has a very limited application in clinical medicine. Moreover, traditional tongue diagnosis is always concerned with the identification of syndromes rather than with the connection between tongue abnormal appearances and diseases. .In this paper, we present a novel computerized tongue inspection method aiming to address these problems. First, three kinds of features, shape, color and textural measures, are extracted from tongue images by using hough transform, edge detection and gabor filter. Latter on these quantifies features will be classify by using SVM Classifier. Tongue image segmentation is done by using color image segmentation and region of interest. The feature parameters like Area, Perimeter, Width, Length, Smaller half-distance, Circle Area and Square Area have been measured for each tongue in order to obtain the better classification result. Experimental results shows the effectiveness of proposed method. SVM classifier achieves 95 percentage Accuracy.

Keywords--- Tongue Image Segmentation, SVM Classifier, Hough Transform, Smaller Half-distance.

I. INTRODUCTION

Diabetes mellitus and its complication are of the major health problems in worldwide. World Health Organization (WHO) stated that by the year of 2030 diabetic will reach to 366 million. So alternative non-invasive method should be considered. This diabetes mellitus is of two types as DM1 and DM2.DM1 indicates the insulin needed for survival. This is B-cell destruction. The next type DM2 is the common one. To avoid this maintaining healthy lifestyle, exercising and eating well is must. If it is not maintained, its effect leads to diabetic retinopathy (DR). Thus results in micro vascular complication. If a person having 20 years of DM1, their survive results in DR major. In early stage diabetes was identified by invasive method (piercing blood) and its effect DR is identified by exposing eye to bright flash in case of angiography. So non-invasive method is needed.

Tongue diagnosis [1], [11] is one of the most important diagnostic methods, which is used to observe any abnormal changes in the tongue (also the body of the tongue or substance of the tongue) and the coating of the tongue in making diagnosis of disease [1]. The beauty of tongue diagnosis lies in its simplicity and immediacy: whenever there is a complex disorder full of contradictions, examination of the tongue instantly clarifies the main pathological process. Therefore, it is of great value in both clinic applications and self-diagnosis.

In its earliest stage known as Non-proliferative Diabetic Retinopathy (NPDR), the disease if detected can be treated to prevent further progression and sight loss. Various imaging modalities such as red-free [2], [3], angiography [3], [4], and color [5] -[10] fundus imaging are used to examine the human retina in order to detect DR and subsequently NPDR. These methods are based on the detection of relevant features related to DR, including but not limited to hemorrhages, micro aneurysms, various exudates.

II. RELATED WORK

Bob Zhang et.al [12] proposes a non-invasive method to detect DM and Non-proliferative Diabetic Retinopathy (NPDR)the initial stage of DR based on three groups of features extracted from tongue images. They include color, texture and geometry. Anon-invasive capture device with image correction first captures the tongue images. A tongue color gamut is established with 12colors representing the tongue color features. The texture values of 8 blocks strategically located on the tongue surface, with the additional mean of all 8 blocks is used to characterize the 9 tongue texture features.

Jianfeng Zhang et.al [13] develops a diagnostic method of diabetes based on standardized tongue image using support vector machine (SVM). Methods. Tongue images of 296 diabetic subjects and 531 no diabetic subjects were collected by the TDA-1 digital tongue instrument. Tongue body and tongue coating were separated by the division-merging method and chrominance-threshold method. With extracted color and texture features of the tongue image as input variables, the diagnostic model of diabetes with SVM was trained. After optimizing the combination of SVM kernel parameters and input variables, the influences of the combinations on the model were analyzed.

Ramachandran Sudarshan et.al [14] presents the newer classification for fissured tongue, its pattern, frequencies of pattern, associated symptoms, and coexisting systemic disorders. The association of fissured tongue with several systemic disorders has to be extensively studied in a larger population to validate its specific relation with systemic illness. Genetic preponderance of fissured tongue should also be extensively investigated.

Dan Meng et.al [15] proposes a novel feature extraction framework called constrained high dispersal neural

Revised Manuscript Received on February 14, 2019.

E. Srividhya Research Scholar, Bharath Institute of Higher Education and Research, Chennai, TN, India. (e-mail: srividhya.e@gmail.com)

Dr.A. Muthukumaravel Dean, Faculty of Arts & Science, Professor & Head, Department of MCA, Bharath Institute of Higher Education and Research, Chennai, TN, India. (e-mail: muthu14673@gmail.com)

networks (CHDNet) to extract unbiased features and reduce human labor for tongue diagnosis in TCM. Previous CNN models have mostly focused on learning convolutional filters and adapting weights between them, but these models have two major issues: redundancy and insufficient capability in handling unbalanced sample distribution. We introduce high dispersal and local response normalization operation to address the issue of redundancy.

Chuang-ChienChiu et al.[16] proposed computerized tongue examination system (CTES) based on computerized image analysis for the purpose of quantizing the tongue properties in traditional Chinese medical diagnosis. The CTES is helpful to provide the physicians a systematic and objective diagnostic standard for the tongue diagnosis in the clinical practice and research.

III. PROPOSED METHODOLOGY

To detect the DM and NPDR, the initial stage of DR based on three groups of features extracted from tongue images. The features are color, texture, and shape. Then median filter can be used for removal of noise from tongue image. For matching, divide the database into training and testing set. Then SVM is used for training and classification to determine whether the input image is diseased / healthy.

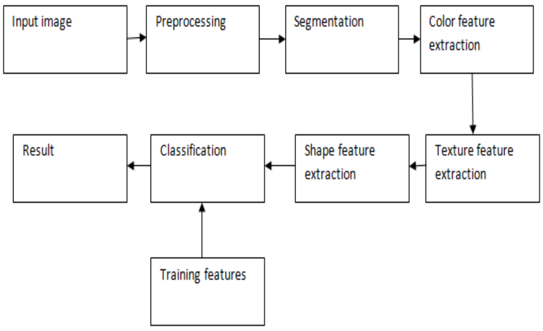

Fig. 1: Block diagram of proposed method

Explanation of blocks given in Fig 1

1.Input image is selected from tongue image database.

2.Preprocess the image to remove noise

3.For color features,

- 12 colors are extracted & converted to corresponding LAB values.
- The Euclidian distance is calculated
- Mean, average & standard deviation is calculated.

4.For texture features,

- The tongue image is divided in 8 blocks strategically located on tongue.
- Gabor filter is used for texture feature extraction of each block

5.For matching,

- Divide the database into training and testing set.
- SVM is used for training and classification
- Determine whether the input image is diseased/Healthy.

6.Result

IV. COLOR FEATURE EXTRACTION

RGB

RGB is an additive color system, based on trichromatic theory in which red, green, and blue light components are added together to produce a specific pigment. The RGB model encodes the intensity of red, green, and blue, respectively. (R_i,G_i,B_i) for each pixel is an unsigned integer between 0 and 255. Each RGB feature represents the normalized intensity value of the red, green, and blue component, respectively, of theith pixel in the image. We denote the normalized value of each component as. Thus,

$r_i = R_i/255$

$g_i = G_i/255$

$b_i = B_i/255$

All the remaining color-space model features described in our feature set derive their value from the RGB feature set.

V. XYZ

Brightness and chromaticity are two principal components of color that interact with human vision. XYZ are developed under CIE XYZ color space [16]. The XYZ values can be obtained by a linear transformation of the gamma corrected value of the RGB normalized color space { r_i, g_i, b_i}.

The gamma-corrected function is defined as

$$\gamma(t) = \begin{cases} \dfrac{t}{12.92}, & \text{if } t \le 0.04045, \\ \left(\dfrac{t+a}{1+a}\right)^{2.4}, & \text{otherwise,} \end{cases}$$

Where a=0.055 Thus, XYZ model consisting of components is given by

$$\begin{bmatrix} X_i \\ Y_i'' \\ Z_i \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} \gamma(r_i) \\ \gamma(g_i) \\ \gamma(b_i) \end{bmatrix}.$$

VI. L*A*B*

CIE L*a*b* color space is a nonlinear transformation of the CIE XYZ color space [17]. CIE L*a*b* try to imitate the logarithmic response of the human eye. The L * component is designed to match closely with human perception of lightness. The other two components describe the chroma.

The forward transformation of CIE XYZ color space to CIE L*a*b* is computed as follows:

$$L_i^* = 116\varphi\left(\frac{Y_i''}{\delta_2}\right) - 16,$$

$$A_i = 500\left[\varphi\left(\frac{X_i}{\delta_1}\right) - \varphi\left(\frac{Y_i''}{\delta_2}\right)\right],$$

$$B_i = 200\left[\varphi\left(\frac{Y_i''}{\delta_2}\right) - \varphi\left(\frac{Z_i}{\delta_3}\right)\right],$$

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Where,

$$\varphi(t) = \begin{cases} t^{1/3}, & \text{if } t > \left(\frac{6}{29}\right)^3, \\ \frac{1}{3}\left(\frac{29}{6}\right)^2 t + \frac{4}{29}, & \text{otherwise,} \end{cases}$$

VII. TEXTURE FEATURE EXTRACTION

Gabor filter is the implementation of the Gabor transform which is a short term Fourier transformation with Gaussian window for analysis in the spatial domain. This texture a can be characterized by the Gabor output obtained by 2D Gabor filtering. The two dimensional Gabor filter represents the texture information because of its spatial selectivity and orientation [17].

For obtaining the Gabor residuals u(x,y), convolution of an image I(x,y) is done with a two dimensional Gabor function g(x,y).

$$u(x,y) = \iint_{\delta} I(\alpha,\beta) g(x-\alpha, y-\beta) d\alpha d\beta$$

$$g_{\lambda,\theta,\varphi,\sigma,\gamma}(x,y) = \exp\left(-\frac{\left(x^2+\gamma^2 y^2\right)}{2\sigma^2}\right)\cos\left(2\pi\frac{x}{\lambda}+\varphi\right)$$

Where

$$x = a\cos\theta + b\sin\theta$$

$$y = -a\cos\theta + b\sin\theta$$

λ -- Wavelength of Gabor function cosine factor.

θ -- Orientation of Gabor function normal to the parallel stripes.

φ -- Phase offset of the of Gabor function cosine factor.

σ -- Standard deviation sigma of Gaussian factor.

γ -- Ellipticity of the Gaussian factor.

VIII. SHAPE FEATURE EXTRACTION

The Hough Transform (HT) has been recognized as a very powerful tool for the detection of parametric curves in images. It is implemented by a voting process that maps image edge points into manifolds in a properly defined parameter space. The Circular Hough Transform (CHT) is one of the modified versions of the HT. The purpose of using CHT is to find the circular patterns within an image scene. The CHT is used to transform a set of feature points in the image space into a set of accumulated votes in a parameter space. Then, for each feature point, votes are accumulated in an accumulator array for all parameter combinations. The array elements that contain the highest number of votes indicate the presence of the shape.

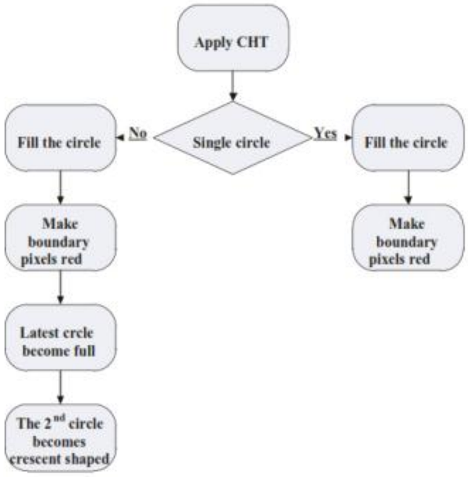

Fig. 2: Flow chart of hough transformation

IX. EDGE DETECTION

Canny Edge detection, it is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images, its aim was to discover the optimal edge detection algorithm.

The method can be summarized below:

1. The image is smoothed using a Gaussian filter with a specified standard deviation, to reduce noise.
2. The local gradient and edge direction are computed at each point using different operator.
3. Apply non-maximal or critical suppression to the gradient magnitude.
4. Apply threshold to the non-maximal suppression image.

X. CLASSIFICATION

SVM is a powerful method for building a classifier. It aims to create a decision boundary between two classes that enables the prediction of labels from one or more feature vectors . This decision boundary, known as the hyperplane, is orientated in such a way that it is as far as possible from the closest data points from each of the classes. These closest points are called support vectors.

Given a labeled training dataset:

$$(x_1, y_1), \ldots, (x_n, y_n), x_i \in R^d \text{ and } y_i \in (-1, +1)$$

where x_i is a feature vector representation and y_i the class label (negative or positive) of a training compound *i*.

The optimal hyperplane can then be defined as:

$$wx^T + b = 0$$

where *w* is the weight vector, *x* is the input feature vector, and *b* is the bias.

The w and b would satisfy the following inequalities for all elements of the training set:

$$wx_i^T + b \geq +1 \text{ if } y_i = 1$$

$$wx_i^T + b \leq -1 \text{ if } y_i = -1$$

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The objective of training an SVM model is to find the w and b so that the hyperplane separates the data and maximizes the margin $1 / \| w \|^2$.

Vectors x_i for which $|y_i|\ (wx_i^T + b) = 1$ will be termed support vector

XI. EXPERIMENTAL RESULTS

In this section, we evaluated the performance of our proposed system using the SVM classification model. We evaluated the performance of training the classifier models using the set of features extracted from the entire tongue image . Fig 3 shows the input image taken for processing. Fig 4 is the gray scale image which is obtained by converting RGB into Gray scale. Fig 5 is the histogram plot of input image. Fig 7 is the histogram plot of equalization and the corresponding equalized image showed in Fig 6.The segmented tongue image showed in Fig 8. Fig 9 to Fig 14 showed different colors of tongue. Fig 15 is a Magnitude response of Gabor filter and Real parts of gabor filter showed in Fig 16. Fig 17 shows the Edge detection result. The output result of Hough transformation showed in Fig 18.

The edge features and Hough features gives the best features as a input to a classifier to obtain the detection efficiency.

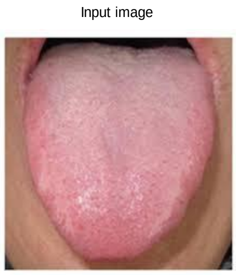

Fig. 3: Input image

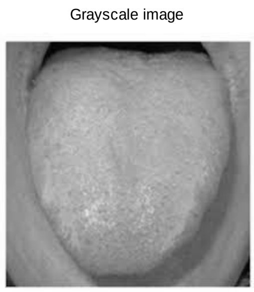

Fig. 4: Grayscale image

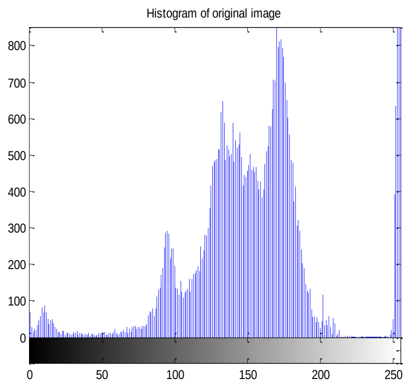

Fig. 5: Histogram of input image

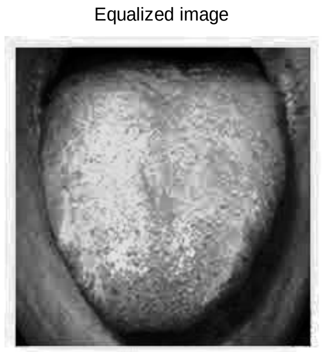

Fig. 6: Equalized image

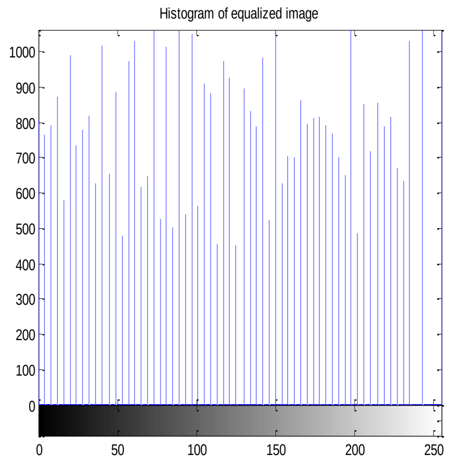

Fig. 7: Histogram of equalized image

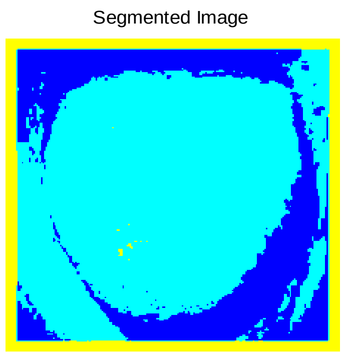

Fig. 8: Segmented Tongue

Fig. 9: Red plane

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Fig. 10: Green plane

Fig. 11: Blue plane

Fig. 12: Lightness

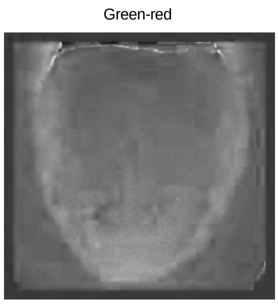

Fig. 13: Green-Red

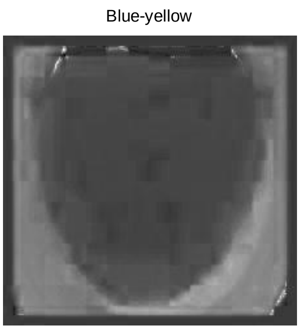

Fig. 14: Blue-Yellow

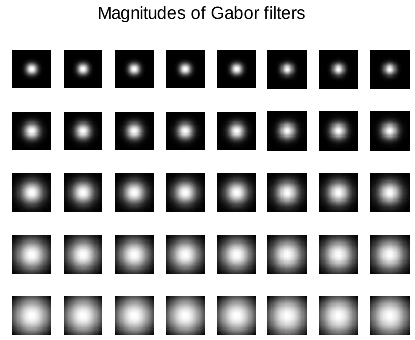

Fig. 15: Magnitude of Gabor Filter

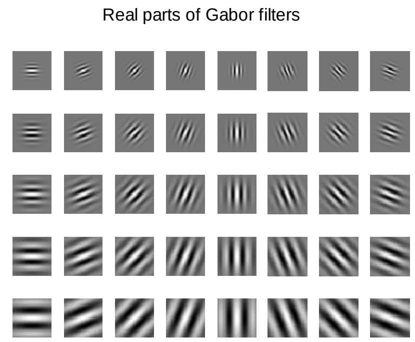

Fig. 16: Real parts of Gabor Filter

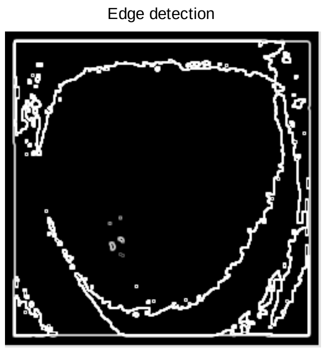

Fig. 17: Edge Detection

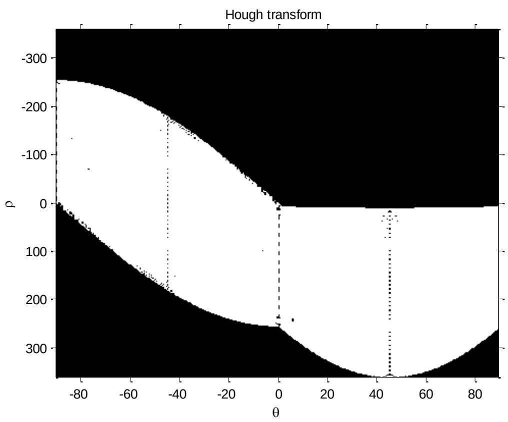

Fig. 18: Hough Transformation

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

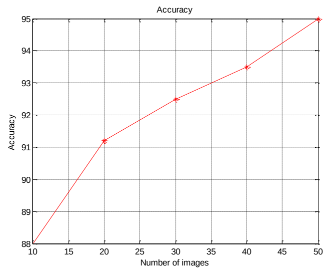

Fig. 19: Accuracy

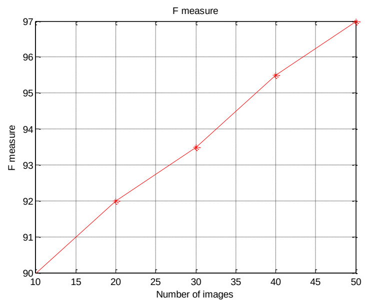

Fig. 20: F- measure

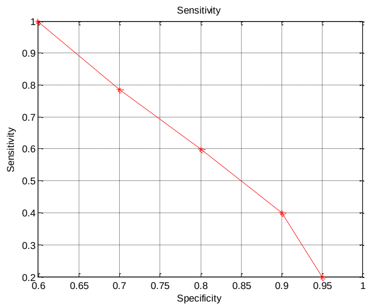

Fig. 21: Sensitivity Vs Specificity

XII. CONCLUSION

In this paper, tongue image is classified more accurately by using support vector machines. Results shows that classification accuracy of SVM is significantly improved by texture, shape and color features and preprocessing methodology. The characteristics of SVM helped to speed up the training and testing of tongue image. Experimental results proven that gist and color information is more essential than color and texture. The results proved that classification accuracy of hepatitis tongue image is 95%.

REFERENCES

1. B. Kirschbaum, “Atlas of Chinese TongueDiagnosis. Seattle”, WA: Eastland, 2000.
2. J.H. Hipwell, F. Strachan, J.A. Olson, K.C. McHardy, P.F. Sharp, andJ.V. Forrester, “Automated detect ion of microaneurysms in digitalred-free photographs: A diabetic ret inopathy screening tool,” *DiabetMed.*, vol. 7, pp. 588-594, 2000.
3. M.E. Martínez-Pérez, A. Hughes, S. Thom, A. Bharath, and K. Parker,“ Segment at ion of blood vessels from red-free and fluorescein ret inalimages,” *Medical Image Analysis*, vol. 11, pp. 47-61, 2007.
4. T. Spencer, J.A. Olson, K.C. McHardy, P.F. Sharp, and J.V. Forrester,“An image-processing strategy for the segmentation of microaneurysmsin fluorescein angiograms of the ocular fundus,” *Computers and Biomedical Research*, vol. 29, pp. 284-302, 1996.
5. M. Niemeijer, B. van Ginneken, J. Staal, M.S.A. Suttorp-Schulten, and M.D. Abramoff, “Automatic detect ion of red lesions in digital colorfundus photographs,” *IEEE Trans. on Medical Imaging*, vol. 24, pp.584-592, 2005.
6. M. Niemeijer, B. van Ginneken, M.J. Cree, A. Mizutani, G. Quellec, C.I.Sanchez, B. Zhang, R. Hornero, M. Lamard, C. Muramatsu, X. Wu, G.Cazuguel, J. You, A. Mayo, Q. Li, Y. Hatanaka, B. Cochener, C. Roux, F.Karray, M. Garcia, H. Fujita, and M.D. Abramoff, “Ret inopathyonlinechallenge: automat ic detect ion of microaneurysms in digital color fundusphotographs,” *IEEE Trans. on Medical Imaging*, vol. 29, pp. 185-195, 2010.
7. J.J. Staal, M.D. Abramoff, M. Niemeijer, M.A. Viergever, and B. vanGinneken, “Ridge based vessel segment ation in color images of the retina,” *IEEE Trans. on Medical Imaging*, vol. 23, pp. 501-509, 2004.
8. B. Zhang, F. Karray, Q. Li, and L. Zhang, “Sparse Representat ionClassifier for microaneurysm detection and retinal blood vesselextraction,” *Inf. Sci.*, vol. 200, pp. 78-90, 2012.
9. B. Zhang, X. Wu, J. You, Q. Li, and F. Karray, “Detection ofmicroaneurysms using multi-scale correlat ion coefficient s,” *PatternRecognition*, vol. 43, pp. 2237-2248, 2010.
10. B. Zhang, L. Zhang, L. Zhang, and F. Karray, “Retinal vessel extractionby matched filter with first-order derivative of Gaussian,” *Comp. in Bio.and Med.*, vol. 40, pp. 438-445, 2010.
11. G. Maciocia, “Tongue Diagnosis in Chinese Medicine. Seattle”, WA: Eastland, 1995.
12. Bob Zhang, B.V.K. Vijaya Kumar and David Zhang,” Detecting Diabetes Mellitus andNon-Proliferative Diabetic Retinopathy usingTongue Color, Texture, and Geometry Features”, Copyright (c) 2013 IEEE.
13. Jianfeng Zhang,1 Jiatuo Xu,1 Xiaojuan Hu,2 Qingguang Chen,3 Liping Tu,2 Jingbin Huang,1 and Ji Cui,” Diagnostic Method of Diabetes Based on Support Vector Machine and Tongue Images”, HindawiBioMed Research International Volume 2017, Article ID 7961494, 9 pages https://doi.org/10.1155/2017/7961494.
14. Ramachandran Sudarshan,1 G. Sree Vijayabala,2 Y. Samata,3 and A. Ravikiran3,” Newer Classification System for Fissured Tongue: An Epidemiological Approach”, Hindawi Publishing Corporation Journal of Tropical Medicine Volume 2015, Article ID 262079, 5 pages.
15. Dan Meng,1 Guitao Cao,1,2 Ye Duan,2 Minghua Zhu,1 Liping Tu,2,3Dong Xu,2 and Jiatuo Xu4,” Tongue Images Classification Based on Constrained High Dispersal Network”, Hindawi Evidence-Based Complementary and Alternative Medicine Volume 2017, Article ID 7452427, 12 pages https://doi.org/10.1155/2017/7452427.
16. “A novel approach based on computerized image analysis for traditional Chinese medical diagnosis of the tongue “,*Chuang-Chien Chiu Institute of Automatic Control Engineering, Feng Chia Uni6ersity, Taichung, Taiwan, ROC Received 18 August 1998; accepted 25 March 1999.*Computer Methods and Programs in Biomedicine 61 (2000) 77–89.
17. Song X, Liu F, Zhang Z, Yang C, Luo X, Chen L. 2D Gabor Filters-Based Steganalysis of Content-Adaptive JPEG Steganography, Springer Multimedia Tools and Applications. December 2016, pp.1-29.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication