# Diabetes Diagnostic Method based on Tongue Image Using ANN & CNN Classifier

**E. Srividhya, A. Muthukumaravel**

***Abstract--- In this paper diagnosing diabetic using tongue image is classified based on the machine learning and deep learning concepts. For machine learning Artificial Neural Network (ANN) and for deep learning Convolution Neural Network (CNN) are used to classify the diabetic patients tongue. There is a strong relationship between the characteristics of tongue and human health diagnosis for any diseases. In this proposed method we are going to get the input image, preprocessing the image for noise reduction and segment the image with size, shape and color, then we have to classify whether that image is diabetic or healthy tongue image. If it is a diabetic image again we have to classify for Diabetic Mellitus types that istype 1 and type 2 based on the severity in the image. The proposed method is compared with SVM classifier for better accuracy. As the experiment results in 98% of accuracy in diagnosing the diabetic diseases.***

***Keywords: Tongue image classification, ANN classifier, CNN classifier, Machine learning techniques, Deep learning techniques.***

## I. INTRODUCTION

A tongue is an organ that reflects physiological and clinic pathological condition of one's body. Each part of the tongue is related to corresponding internal organs. [1] Especially, the visual information is used in tongue diagnosis. The color, the form, and the motion of a tongue, tongue substance, and tongue coating are main factors for the diagnosis. The geometrical shape also helps to diagnose one's health, whose method diagnoses the illness by observing the change of the tongue body such as thickness, size, cracks, and teeth-marks. The tongue coating, covered on a tongue like moss is the most important factor, depending on colour, degree of wetness, thickness, form, and distributed range to determine a patient's disease and body condition. It is classified by its color – white, yellow, grayish, black, mixed colour, and so on. Even if a tongue diagnosis is convenient and non-invasive, it has the problem of objectification and standardization. The change of the inspection circumstance like a light source affects the result a lot. Moreover, since the diagnosis relies on doctor's experience and knowledge, it is hard to get a standardized result. Recently, many researches are being carried out to solve these problems. [2]-[4]

In practice, evaluation results are influenced by several factors such as the medical practitioner's tactile sense, color sensitivity or viewing environment as well as their interpretation tendencies based on experience or other clinical information. In addition, clinical practices vary among physicians in different countries. Thus, a method to objectify tongue color diagnosis using optical methods under stable conditions is desirable [5], [6], [7]. A color quantification method that can differentiate colors reliably will advance the field of traditional medicine. Texture analysis describes the symptoms of diseases and so it is considered to be an important criterion in disease diagnosis. The roughness or bumpiness refers to difference in the intensity values, or gray levels. Inflammation lesions or ulceration and deterioration associated to body part pointed out by dark red in tongue. White designates stagnation of blood.

The color of the patient's tongue color provides information about his/her health status. For example [10], dark red color can indicate inflammation or ulceration, while a white tongue indicates cold attack, mucus deposits, or a weakness in the blood leading to such conditions as anemia [9]. Moreover, a yellow tongue points out a disorder of the liver and gallbladder, and blue or purple implies stagnation of blood circulation and a serious weakening of the part of the digestive system that corresponds to the area of the tongue where the colorappears. The coating on the tongue is discriminated by not only its presence but also its color. The color could be yellow, white, and other colors. However, the color in image is not the exact true color of the tongue. To properly identify the color of the tongue coating, we applied the specular component technique presented in our prior work on tongue detection and analysis [8]

## II. RELATED WORK

Xingzheng Wangaet al.[11] discussed Several important performance indicators, including illumination uniformity, system reproducibility and accuracy, are elaborately tested. Experimental results show that captured images are in high quality and keep stable when acquisitions are repeated.

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. A non-invasive 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 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.

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Tongue images of 296 diabetic subjects and 531 nondiabetic 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.

RamachandranSudarshan 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 relationwith 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 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-ChienChiuet 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.

Bo Pang a et al.[17] have been proposed Computerized tongue inspection method aim to identify and diagnosis the diseases earlier. First, two kinds of quantitative features, chromatic and textural measures, are extracted from tongue images.

## III. EXISTING METHOD

Support Vector Machines (SVMs) is a type of classifier that are a set of associated supervised learning methods used for classification. SVM will build a separating hyper plane in the space, one which maximizes the margin between the two data sets. To determine the margin, two parallel hyper planes are constructed, one on each side of the separating hyper plane, which are “pushed up against” the two data sets. In existing system, SVM has disadvantage for large features and characteristics of image makes the detection of disease difficult.

## IV. PROPOSED METHOD

In this method ANN based classification is implemented. The advantage of this is, it is easy to implement and convergence to minimum mean squared error solutions.

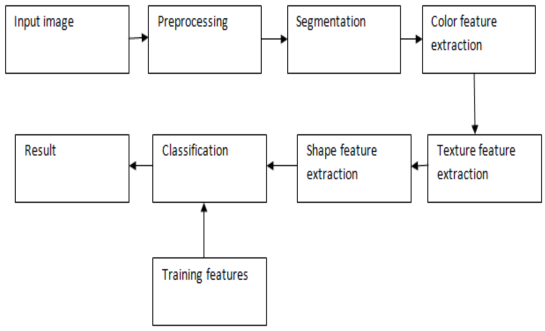


**Fig. 1: Block diagram of proposed method**

**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

*Artificial neural network*

The simple ANN is a three-layered architecture described as; the first layer is the input layer, a middle hidden layer and the output layer at last. It is massive, parallel and strongly connected network architecture. Back propagation network (BPN) algorithm is mostly used to train MLP. It uses a gradient descent approach to minimize the errors produced during training. The steps for training ANN are gave below:

1: Initialize the synaptic weights and biases with random values.

2: Load the training data. For the jth sample,

3: The net input at the hidden layer is calculated as

$$\mathrm{net}_h^j = \sum_{n=1}^{N} x_n w1_{h,n} + b1_h, \quad h = 1, \ldots, H$$

where w1h, n is the weight between input neuron ‘n’ and hidden neuron ‘h’, N and H are the sizes of input and hidden layers, respectively, and b1h is the bias value of hidden neuron ‘h’. Thehidden layer output is calculated as

$$O_h^j = \mathrm{sigmoid}(\mathrm{net}_h^j) = \frac{1}{1 + e^{(-\mathrm{net}_h^j)}}$$



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4: Calculation of net input using at output layer is done as

$$\text{net}_m^j = \sum_{h=1}^{H} O_h^j w2_{m,j} + b2_m, \quad m = 1, \ldots, M$$

where w2m, h is the weight between hidden neuron 'h' and output neuron 'm', b2m is the bias value of output neuron 'm'. M is the number of output nodes. The network output is calculated below

$$y_m^j = f(\text{net}_m^j)$$

5: The difference between the target output and network output gives the error value, which is calculated using the following equation:

$$E^j = \sum_{m=1}^{M} (T_m^j - y_m^j)^2$$

Where $T^j_m$ and $y^j_m$ are the target output and network output, respectively.

6. The weight and bias values are updated.

7. Repeat from steps 2 to 6, for all training data till the error is minimized, which indicates the completion of the training process.

## V. RESULTS AND DISCUSSION

We have implemented our proposed approach using MATLAB and the results showed that the approach produce better results in tongue segmentation and classification methods. Let us have a detailed look with the different tongue image samples. In classification three types of operations are performed. First the diabetic and non-diabetic persons are identified. If diabetic is confirmed then it will classify the person belongs to male or female category. If the person is female then if the disease stage is identified. If the stage is type 2then it is identified as severe, if it is type 1 then it is identified as medium.

In this section, we compared the performance of our proposed system using ANN classification model with SVM.

We evaluated the performance of training the classifier models using the set of features extracted from the entire tongue image. Fig 3shows 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**

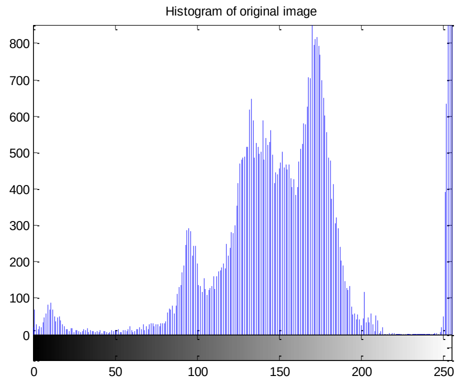


**Fig. 5: Histogram of input image**

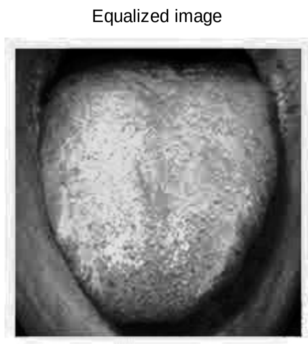


**Fig. 6: Equalized image**


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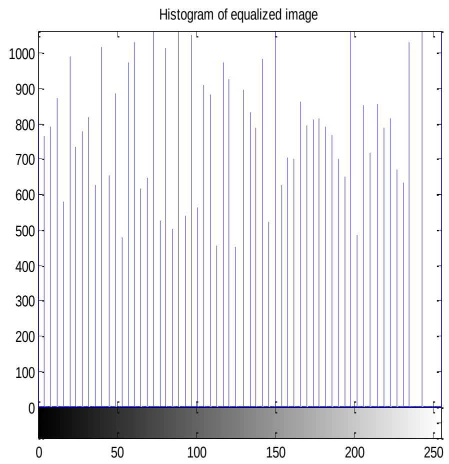


**Fig. 7: Histogram of equalized image**

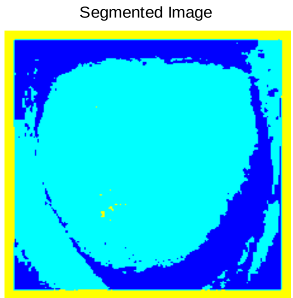


**Fig. 8: Segmented Tongue**

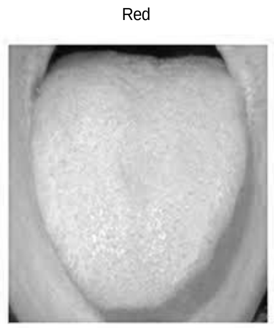


**Fig. 9: Red plane**


**Fig. 10: Green plane**


**Fig. 11: Blue plane**


**Fig. 12: Lightness**

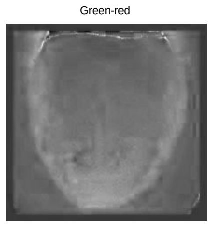


**Fig. 13: Green-Red**

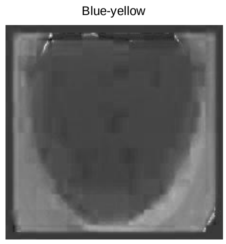


**Fig. 14: Blue-Yellow**

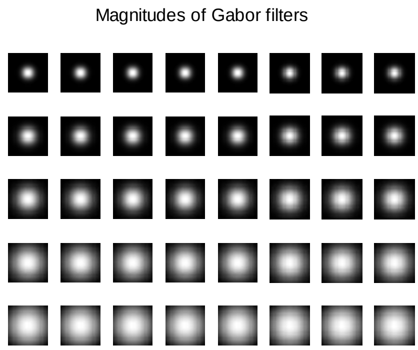


**Fig. 15: Magnitude of Gabor Filter**



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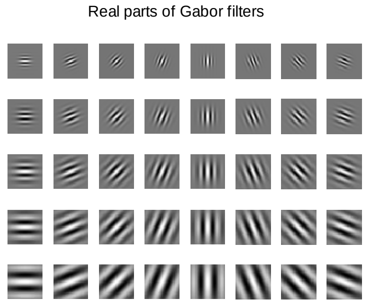


**Fig.16: Real parts of Gabor Filter**

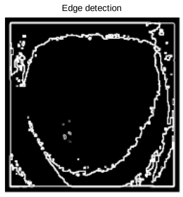


**Fig. 17: Edge Detection**

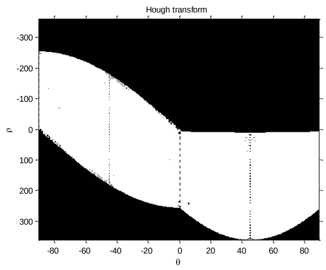


**Fig. 18: Hough Transformation**

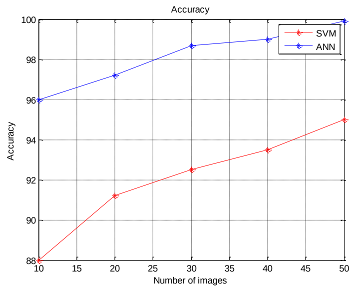


**Fig. 19: Accuracy comparison**

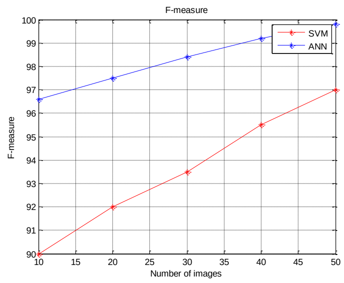


**Fig. 20: F-measure comparison**

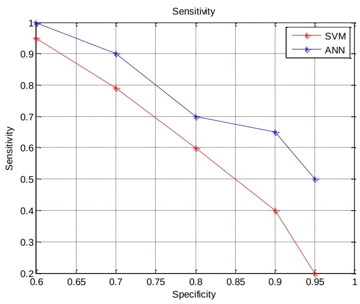


**Fig. 21: Sensitivity comparison**

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