A NON-INVASIVE APPROACH TO DETECT DIABETES MELLITUS AND DIABETIC RETINOPATHY USING GRADIENT VECTOR FLOW

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ABSTRACT: Diabetes is a chronic disease and a major public health challenge worldwide. Due to lack of awareness among the people on eating habits, diabetic patient counts have been increased steadily in our country. This motivates researchers to develop a medical system which can screen a large number of people for life-threatening disease such as cardiovascular disease, the retinal disorder in diabetic patients. Tongue has played a prominent role in the diagnosis and the subsequent treatment of diseases. Tongue segmentation using Bi-Elliptical Deformable Contour (BEDC) does not process fake edges and also provides poor results. Hence this paper proposes Gradient Vector Flow (GVF) snake technique to extract the region as it encourages convergence in boundary concavities and also provides better results in detecting diabetes mellitus compared to BEDC. Moreover the hybrid classifier using Minimum Distance, Bayes Classifier and Support Vector Machine have been proposed and developed in this research work and gives promising results. The results are evaluated using performance evaluation metrics, Sensitivity and Specificity and gains an accuracy of 85.5% compared to BEDC which has an accuracy of 60%.

Index Terms--Bi-Elliptical Deformable Contour (BEDC), Diabetes Mellitus (DM), Feature Extraction, Gradient Vector Flow (GVF) snake technique, Hybrid Classifier.

I. INTRODUCTION

Diabetes mellitus is one of the most serious health challenges in both developing and developed countries. Diabetes is due to either the pancreas not producing enough insulin, or the cells of the body not responding properly to the insulin produced. Diabetes mellitus (DM), also known as simply diabetes, is a group of metabolic disorder in which blood sugar levels is high over a prolonged period. This high blood sugar results in the symptoms of frequent urination, increased thirst, and increased hunger. Disease that results in autoimmune destruction of insulin-producing beta cells of the pancreas is diabetes mellitus type-I. Metabolic disorder that is characterized by high blood glucose in the context of insulin fighting and relative insulin deficiency is diabetes mellitus type-II.

A fasting plasma glucose (FPG) test is the standard method practiced by many medical professionals to diagnose DM. It is performed after the patient has gone at least 12 hours without food, and requires taking a sample of the patient’s blood (by piercing their finger) in order to analyze its blood glucose levels. Even though this method is accurate, it can be considered invasive, and slightly painful. During the past several years, certain achievements have been made in tongue image and diagnostic classification technologies. Moreover tongue diagnosis is considered to be the most promising direction in the 21st century: no pain and no injury.

Tongue image analysis, especially its chromatic features provides plenty of valuable diagnostic information to reveal the disorder or even pathological changes of internal organs. Tongue images were captured using a specially designed in-house device taking color correction into consideration. Segmentation, feature extraction and classification techniques are used to detect diabetes mellitus from tongue image. Gradient Vector Flow has been used to segment tongue image alone. Then color, texture and geometry features are extracted from tongue image. Moreover hybrid classifier of minimum distance, bayes classifier and support vector machine is used to classify whether the tongue image is healthy or diabetes.

This paper is organized as follows: Related works are discussed in Section 2 and Section 3 describes the process of diabetes detection using Gradient Vector Flow (GVF) Snake Technique. Section 4 analyses the results based on the evaluation metrics. Finally, Section 5 concludes the work.

II. LITERATURE REVIEW

Diabetes mellitus have been detected using segmentation, feature extraction and classification. Particularly, there have been a considerable number of efforts that rely on segmentation to detect diabetes mellitus. It is beneficial to evaluate and examine the existing systems for better understanding of detecting diabetes mellitus. Hence, recent approaches and methodologies in the area of detecting diabetes mellitus have been discussed. Bob Zhang et al. [2014] proposed to detect Diabetes Mellitus and Non-proliferative Diabetic Retinopathy using support vector machine classifier. The Bi-Elliptical Deformable Contour is used to segment the tongue image. The color, texture and geometry features are extracted from the tongue foreground image and classified using support vector machine classifier.

Wangmeng Zuo et al. [2004] proposed automated tongue segmentation by merging polar edge detector and active contour model. First a polar edge detector was proposed to extract the edge of the tongue body efficiently. A local adaptive edge bi-threshold technique is proposed. Finally an initialization and active contour models are suggested to segment the tongue body from the tongue image.

Wenshu Li et al. [2009] proposed a novel method for tongue contour extraction based on improved level set method. First, the contour of tongue was initialized in the HSV color space and a technique which improves the contrast between tongue and other parts of the tongue image is presented. An improved level set method takes tongue contour shape constraint represented by energy function between the evolving curve and parametric shape model. This method gives accurate result.

Mehdivatankhah et al. [2014] described fully automated classification magnetic resonance images of the human brain that can detect the healthy or sick person. Features are extracted from MRI images using wavelet transform. PCA is used to reduce computational cost and computational complexity. A hybrid approach comprises of SVM and Cuckoo is used to classify whether the person is healthy or not.

Mahfuzah Mustafa et al. [2014] proposed Gradient Vector Flow snake technique to detect cancerous cells in breast tissues. Gaussian Low Pass Filter is used for pre-processing the mammography image to remove unwanted noise. GVF is used for segmentation to detect particular cancer region in breast tissue. Finally, the Snake algorithm converges toward the cancerous region.

Xingzheng Wang et al. [2013] proposed a mathematically described tongue color space for diagnostic feature extraction and also defined three characteristics of tongue color. Tongue color gamut used to predict the range of colors. They propose color gamut descriptor using one-class SVM algorithm and they describe about color distribution of different tongue features for validating effectiveness.

This section has reviewed the various research works and algorithms related to diabetes mellitus detection. The overall literature survey says that various methods and classification techniques are applied for classifying tongue images into healthy or diabetes. The BEDC does not work properly on the actual tongue boundary because for each image, initial curve is defined manually and then extra region has to be included in the interface. Hence the tongue segmentation using GVF Snake technique is used because it encourages convergence in boundary concavities which leads to better diagnosis.

III. METHODOLOGY

GVF Snake technique and Hybrid classifier algorithm is used to detect diabetes mellitus. Overall architecture of the system is shown in Fig 1.

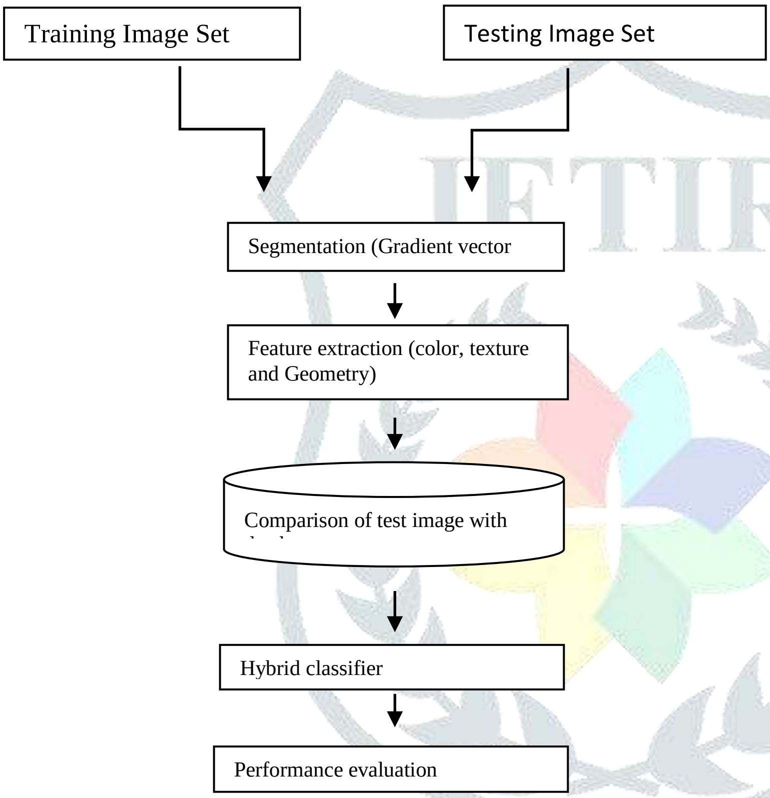

Fig.1 Overall architecture of the system

Initially tongue images are taken from Bio -Med Chinese medicine repository where the tongue images are captured using the following tongue capture device.

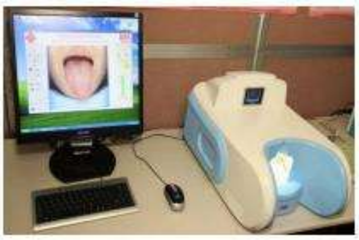

Fig.2 Tongue Capture Device

The proposed work consists of three phases in detecting diabetes mellitus.

- Segmentation using GVF
- Feature Extraction
- Classification using hybrid classifier

3.1 Segmentation using GVF

GVF snake is an extension of the well-known method or active contours. The difference between traditional snakes and GVF snakes consists of boundary concavities. The original snake v is a two dimensional dynamic contour defined parametrically as $v(s) = [x(s), y(s)]$, where $s \in [0, 1]$ that minimizes the energy function:

$$E = \int_{0}^{1} (E_{int}(v(s)) + E_{image}(v(s)) + E_{con}(v(s))ds$$

E_{int}

Where denotes the energy of the contour due to bending, the E_{image} represents the energy due to the

intensity of the image and E_{con} is a constraint energy established by a high-level process or the user. The typical definitions for all the energy functions can be found.
Image gradient allows calculating in a specified direction.

- Sable operator calculates gradient by convolving filter mask with matrix consisting of image pixels.
- Gradient width represents distance (in pixels) between two points, the intensity difference which defines the gradient value.
- The number of iteration is performed by GVF calculation.
- Smoothing parameter is the regularization parameter governing the tradeoffs between the first and the second integral term.
- Smoothing parameters should be set according to the amount of noise present in the image.
- Time length is calculated for each it eration.

GVF Snake technique is proposed to play a major role of segmenting the tongue image. GVF Snake technique diffusion of the gradient vectors of a gray level or binary edge map derived from the edge. Using several dimensional images, it can be shown that GVF has a large capture and is able to move deformable model into boundary concavities. Input image is shown in Fig.3 and segmented image using GVF Snake in Fig.4.

Fig. 3 Input Image

Fig. 4 segmented image using GVF Snake

3.2 Feature Extraction

Color, texture and geometry features are extracted from foreground tongue image. Color feature extraction is used to extract the range of color using tongue color gamut. In the case of texture feature, 2-D Log Gabor filter is used to divide the tongue into eight blocks. Geometry features based on measurements, distances, areas, and their ratios are calculated using the mathematical formula.

3.2.1 Color Feature

The Tongue Color Gamut is a process of extracting the range of colors. The tongue color gamut represents all possible colors that appear on the tongue surface and exists within the red boundary shown in Fig. 5 (CIE-xy chromaticity diagram).

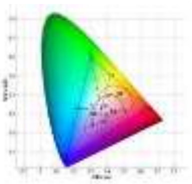

Fig. 5 CIE-x axis chromaticity diagram

Further investigation revealed that 98% of the points lie inside the black boundary. To represent the tongue color gamut using 12 colors, the RGB color space is employed and plotted in Fig.5. On the RG line a point Y (Yellow) is marked. Between RB a point P (Purple) is marked and C (Cyan) is marked connecting GB. The center of the RGB color space is calculated and designated as W (White), the first of the 12 colors. Then, for each R (Red), B (Blue), Y, P, and C point, a straight line is drawn to W. every time these lines overlap the tongue color gamut, a new color is added to represent the 12 colors. This accounts for R, Y, C, B, and P. LR (Light red), LP (Light purple), and LB (Light blue) are midpoints connecting lines from the black boundary to W, while DR (Deep red) is selected as no previous point occupies that area. More details about the tongue color gamut can be found. GY (Gray) and BK (Black) are not shown in Fig.5 since both belong to gray scale.

3.2.2 Texture Feature

The texture values of eight blocks strategically located on the tongue surface, with the extra mean of all eight blocks are used to characterize the nine tongue texture features. Texture feature extraction from tongue is shown in Fig. 6.

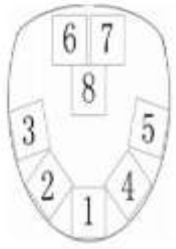

Fig. 6 Location of the eight texture blocks on the tongue

Larger blocks would cover areas outside the tongue boundary, and overlap more with other blocks. Smaller block sizes would prevent overlapping, but may not cover the eight areas as efficiently. The blocks are calculated automatically by locating the center of the tongue using a segmented binary tongue foreground image. Following this, the edges of the tongue are established and equal parts are measured from its center to position the eight blocks. 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. Then to compute the entire tongue block, the 2D Log Gabor Filter is applied.

$$G(f,\theta) = \exp\left(\frac{(-\left(\log\left(\frac{f}{f_0}\right)\right)^2}{2\left(\log\left(\frac{\sigma_f}{f_0}\right)\right)^2}\right)\exp\left(\frac{-(\theta-\theta_0)^2}{2\theta_\sigma^2}\right)$$

where,

f_0 − the center frequency

θ_σ − the width for the frequency

θ_0 − the center orientation

σ_θ − the width parameter of the orientation

The Tongue Log Gabor Filter is the process of extracting the blocks. To represent the texture of tongue images, eight blocks located on the tongue surface.

3.2.3 Geometry Features

Width: The width feature 'w' is measured as the horizontal distance beside the x-axis from a tongue's

furthest right edge poin (x_{max}) to its furthest left edge point (x_{min})

$w = x_{max} - x_{min}$

Length: The length feature 'l' is measured as the vertical distance along the y-axis as of a tongue's furthest bottom edge (y_{max}) point to its furthest top edge point (y_{min})

$$l = y_{max} = y_{min}$$

Length–Width Ratio: The length–width ratio $'lw'$ is the ratio of a tongue's length to its width

$$lw = l/w$$

Smaller half-distance: Smaller half-distance 'z' is the half distance of l or w depending on which segment is shorter

$$Z = \min(l,w)/2$$

Center distance: The center distance (cd) is distance from $w'^s y$-axis center point to the center point of $l(Yc\alpha)$

$$cd = \frac{(\max(y_{x_{max}}) + \max(y_{x_{min}}))}{2} - y_{cp}$$

$$y_{cp} = (y_{max} + y_{min})/2$$

Center distance ratio: Center distance ratio (cdr) is ratio of cd to l:

$$cdr = \frac{cd}{l}$$

Area: The area (a) of a tongue is defined as the number of tongue foreground pixels.

Circle area: Circle area (ca) is the area of a circle within the tongue foreground using minor half-distance z,

$$ca = \pi r^2$$

$$sar = sa/a$$

where r = z

Circle area ratio: Circle area ratio (car) is the ratio of ca to a

$$car = \frac{ca}{a}$$

Square area: Square area (sa) is the area of a square defined within the tongue foreground using smaller half-distance z:

$$sa = 4z^2$$

Square area ratio: Square area ratio (sar) is the ratio of sa to a:

$$sar = sa/a$$

Triangle area: Triangle area (ta) is the area of a triangle defined within the tongue foreground. The right point of

the triangle is x_{max}, the left point is x_{min} and the bottom is y_{max}.

Triangle area ratio: Triangle area ratio (tar) is the ratio of ta to a:

$$tar = \frac{ta}{a}$$

3.3 Classification using hybrid classifier

Combining the class predictions from multiple classifiers, known as hybrid classifier is one of the standard and most important technique for improving classification accuracy in machine learning.

Hybrid classifier to improve the efficiency of the Support Vector Machine, Minimum Distance and Bayes Classifier algorithm has been employed.

3.3.1 Bayes Classification

The Bayes Classifier is a classification technique. It is together of all the hypotheses in the hypothesis space. On average, no other hybrid can outperform it. Each hypothesis is given a vote proportional to the possibility that the training dataset would be sampled from a system if that hypothesis were true.

To facilitate training data of finite size, the vote of each hypothesis is also multiplied by the prior probability of that hypothesis. The Bayes Classifier can be expressed with the following equation:

$$y = \underset{c_j \in C}{\operatorname{argmax}} \sum_{h_i \in H} P(c_j|h_i)P(T|h_i)P(h_i)$$

where ci is the predict class, C is the set of all possible classes, H is the hypothesis space, P refers to a probability, and T is the training data. There are several reasons why the Bayes Classifier cannot be sensibly implemented:

1. Most interesting hypothesis spaces are too large to iterate over, as required by the argmax.

2. Many hypotheses yield only a predicted class, rather than a probability for each class as required by the term $P(c_j|h_i)$.

Computing an unbiased estimate of the probability of the training set given a hypothesis P(T | h_i) is non-trivial.

3.3.2 Minimum Distance Classifier

The minimum distance classifier is used to classify unknown image data to classes which lessen the distance between the image data and the class in multi-feature space. The distance is defined as an indicator of similarity so that the minimum distance is identical to the maximum similarity. The Distance formula is,

$$d_{x,m} = \sqrt{x^2 - m^2}$$

Each pixel is assigned to a class of minimum distance. Distance measure uses Euclidean distance from pixel to cluster mean where x is the pixel and m is mean value.

3.3.3 Support Vector Machine (SVM)

Support Vector Machines (SVMs) are the supervised learning methods used for classification. The Support Vector Machine constructs a set of hyper planes in high-dimensional space which is shown in Fig. 7. The goal of SVM is to find the optimal extrication hyper-plane which maximizes the margin of the training data. The main advantages of SVM are as follows:

- Works well with clear margin of separation
- Effective in high dimensional spaces
- Memory efficient

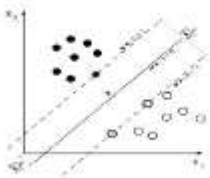

Fig. 7 Support Vector Machine

3.3.4 Hybrid Classifier

In the proposed system, three classifiers namely Bayes classifier, minimum distance classifier and support vector machine are combined to form a hybrid classifier. The class predictions of above mentioned classifiers are combined to improve the classification accuracy of the proposed technique.

- Bayes classifier is used to calculate the posterior probability for each class. The class with the highest posterior probability is the outcome of prediction.
- Minimum distance classifier identifies the class based on the image features and predicts how close the features are to the particular class.

In proposed work three classifiers are used individually to predict class where the feature belongs to. If the two classifiers declare that the taken image feature belongs to healthy class hence the taken image is healthy. If all the classifiers declare a feature to an unhealthy class the hybrid classifier results shows the taken image is unhealthy and hence confirms the diabetes.

Instead of concluding the class predictions based on one single classifier, the proposed work improves identification of healthy and diabetes mellitus images based on the predictions of three classifiers.

VI. RESULTS AND DISCUSSION

Based on the exiting work given in Section 2 and on the proposed work in Section 3, the results are discussed in this section through experimental analysis.

4.1 Experimental Analysis

The Process of existing and proposed work contains the following steps:

Step 1: Dataset is taken from Bio-Med Central in Chinese Medicine Repository.

Step 2: In existing work tongue images are segmented using Bi-Elliptical Deformable Contour (BEDC). It also separates foreground pixels from the background image. Diabetes mellitus affected patient image is taken as input. Fig. 8 shows the segmented image using BEDC technique.

Fig. 8 BEDC Segmented Image

Step3: After segmentation the features color, texture and geometry are extracted. Then the feature values are calculated by using mean and standard deviation. The mean colors, texture and geometry of DM and Healthy are displayed in Table 4.1, Table 4.2 and Table 4.3 along with their standard deviation.

Table 4.1 Color Features for Diabetes Mellitus and Healthy Images (BEDC)

COLORS	C	R	B	P	DR	LR	LP	LB	BK	GY	W	Y	MEAN	STD
DM	0.0451	0.0065	0	0	0	0.758	0	0.1755	0.4899	0	0.205	0.0001	0.9999	0.147
H	0	0.0006	0	0	0	0.4966	0.0296	0.0296	0.2778	0	0.1932	0	0.08334	0.1591

Table 4.2 Texture Features for Diabetes Mellitus and Healthy Images (BEDC)

BLOCKS	B-1	B-2	B-3	B-4	B-5	B-6	B-7	B-8	MEAN	STD
DM	6.598	5.997	5.811	5.570	5.346	5.215	5.112	5.002	5.5813	0.5351
H	8.097	7.296	6.934	6.627	6.289	6.148	6.057	5.927	6.6718	0.7411

Table 4.3 Geometry Features for Diabetes Mellitus and Healthy Images (BEDC)

FEATURES	DM	HEALTHY
Width	110	252
Length	161	251
Length with ratio	1.4636	0.996
Smaller half-distance	55	125.5
Center distance	80.5	125.5
Center distance ratio	0.5	0.5
Area	9033	45682

Circle area	20300	49500
Circle area ratio	2.2526	1.0826
Square area	48400	252004
Square area ratio	5.3581	5.5165
Triangle area	8855	23766
Triangle area ratio	0.9803	0.6923
Mean	66692	29198
Std	13941	69498

Now the extracted features are given as input for classification using Support Vector Machine. The features are compared with the trained features and the result is produced. After that the result is classified as healthy (or) DM using SVM.

Fig.9 Result of tongue analysis

Step 4: In proposed work, the images are segmented through segmentation process using Gradient Vector Flow (GVF). GVF segments the whole tongue image from the given input. The original tongue image used for segmentation is shown in Fig.10 and the GVF Snake segmented image is shown in Fig.11.

Fig. 10 The original image Fig.11GVF Snake segmented image

Step 5: The features color, texture and geometry are extracted from segmented tongue image. Then the feature values are calculated by using mean and standard deviation. The mean colors, texture and geometry of DM and Healthy are displayed in Table 4.4, Table 4.5 and Table 4.6 along with their standard deviation.

Table 4.4 Color Features for Diabetes Mellitus and Healthy Images (GVF)

COLORS	C	R	B	P	DR	LR	LP	LB	BK	GY	W	Y	MEAN	STD
DM	0.0094	0.1358	0	0	0.1171	0.3112	0	0.0499	0.2311	0.0001	0.0755	0.0698	0.9999	0.147
H	0	0.0006	0	0	0	0.4966	0.0296	0.0296	0.2778	0	0.1932	0	0.08334	0.1591

Table 4.5 Texture Features for Diabetes Mellitus and Healthy Images (GVF)

BLOCKS	B-1	B-2	B-3	B-4	B-5	B-6	B-7	B-8	MEAN	STD
DM	1.926	1.859	1.798	1.769	1.739	1.710	1.671	1.635	1.7633	0.0965
H	8.097	7.296	6.934	6.627	6.289	6.148	6.057	5.927	6.6718	0.7411

Table 4.6 Geometry features for Diabetes Mellitus and Healthy Images (GVF)

FEATURES	DM	HEALTHY
Width	302	252
Length	271	251
Length with ratio	0.8974	0.996
Smaller half-distance	135.5	125.5
Center distance	135.5	125.5
Center distance ratio	0.5	0.5
Area	62932	45682
Circle area	57700	49500
Circle area ratio	0.9161	1.0826
Square area	293764	252004
Square area ratio	4.668	5.5165
Triangle area	40921	23766
Triangle area ratio	.06502	0.6923
Mean	35089	29198
Std	81268	69498

The hybrid classifier (Minimum distance, Bayes classifier and Support Vector Machine) is used to classify whether the image is healthy or diabetes mellitus. The proposed work improves identification of healthy and diabetes mellitus images based on the predictions of three classifiers.

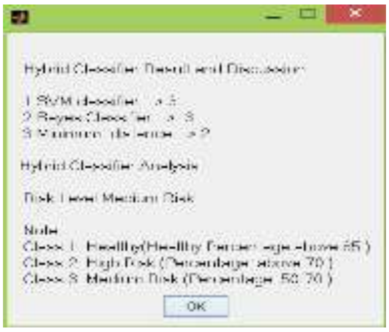

Fig.12 Result of hybrid classifier

Step 6: The classification is done for both existing and proposed data set which is trained and tested.
Step 7: Finally Sensitivity and Specificity values are calculated to compute the accuracy.

4.2 Performance Evaluation

The various assessment metrics are used to calculate and analyze our proposed technique Gradient Vector Flow to detect diabetes mellitus using tongue features. The metric values like Sensitivity (SE), Specificity (SP) and Average accuracy (AC) are used to evaluate the performance of the hybrid classifier. The formulas are given in the Table 4.7. Sensitivity is a portion of positive cases that are well detected by the test and the specificity is proportion of the negative cases that are well detected by the test. Classification accuracy depends on the number of samples correctly classified.

Table 4.7 Evaluation Measures

Measures	Formula
Sensitivity	SE=TP/(TP+FN)
Specificity	SP=TN/(TN+FP)
Average Accuracy	(SE+SP)/2

Confusion matrix is evaluated to make decision that can be made by classifier. We consider a confusion matrix illustrated in Table 4.8.
where,

- TP (True Positive) represents the number of diabetes mellitus correctly classified,
- FN (False Negative) refers to the number of healthy misclassified as diabetes mellitus,
- FP (False Positive) expresses the number of diabetes mellitus misclassified as healthy

TN (True Negative) is the number of healthy correctly classified.

Table 4.8 Confusion matrix

TYPES		PREDICTED	
		Healthy	DM
True	Healthy	TP	FP
	DM	FN	TN

4.3 Result Analysis

The table 4.9 describes the comparison of detecting diabetes mellitus in existing and proposed system. The table contains Sensitivity, Specificity and Accuracy of the existing and proposed system.

Table 4.9 Result Analysis of BEDC and GVF Snake

Images	Methods	Sensitivity	Specificity	Accuracy
10Hea 10 DM	BEDC	46%	73%	60%
	GVF	89%	82%	85.5%

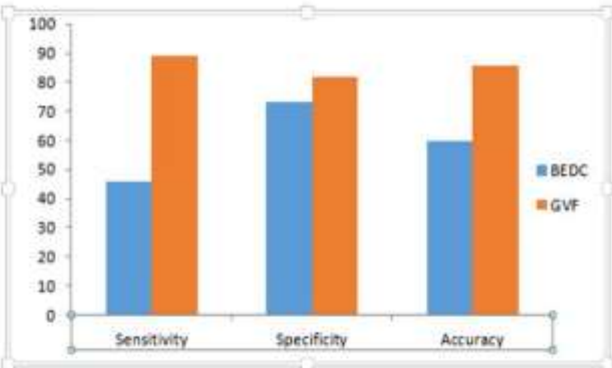

Fig. 13 Graphical Analysis of BEDC and GVF Snake

he Fig. 13, Graphical Analysis of BEDC and GVF Snake Technique are plotted based on the Table 4.9. In the X-axis the existing and the proposed algorithms (Sensitivity, Specificity and Accuracy) are plotted and in the Y- axis the values are plotted. The Evaluation metrics has attained the results like 46%, 73% and 60% in the existing BEDC algorithm. The proposed system GVF Snake Technique algorithm has increased the better result using evaluation metrics are 89%, 82% and 85.5% respectively.

V. CONCLUSION

The main objective in carrying out this project is to detect the diabetes mellitus from the tongue images. In this research diabetes mellitus is detected using advanced phases of image processing such as Gradient vector flow algorithm, Feature extraction(color, texture and geometry) and Hybrid classifier(support vector machine, bayes classifier and minimum distance classifier) which select the images in partly. The research work will have impact on the future work and it is an ongoing activity that never ends.

This research work can be enhanced in the future with the following scopes:

- Neural network, Neural fuzzy can be used as suitable classifiers for the process of classification to get more accurate results.
- Feature extraction can also be performed using wavelet transform techniques.

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