A Framework for Medical Image Retrieval Using Local Tetra Patterns

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Abstract— **In medical field, the digital images used for diagnostics and therapy are produced in ever increasing quantities. So there is necessity of feature extraction and classification of medical images for easy and efficient retrieval. In this paper, a framework based on Local Tetra Pattern and Fourier Descriptor for content based image retrieval from medical databases is proposed. The proposed approach formulates the relationship between the reference or centre pixel and its neighbours, considering the vertical and horizontal directions calculated using the first-order derivatives. The texture feature of an image is of prime concern; the images filtered by this feature are more appropriate ones as a response to the query image. In this research work, the association of Euclidean Distance(ED) with local tetra pattern is also explored. The proposed framework is successfully tested on standard Messidor dataset of 1200 Retinal images which are annotated with Retinopathy and Macular Edema grades. A tool SS-SVM is applied on binary patterns for endoscopy, dental, skull and retinal images for classification, which results in better classification of images for various dataset, thus improving classifiers.**

Keywords: **Content Based Image Retrieval (CBIR), Local Tetra Pattern (LTrPs), Euclidean Distance (ED), Fourier Descriptor (FD), Small Scale-Support Vector Machine (SS-SVM).**

I. INTRODUCTION

Database of more than thousands of images has to be managed in large hospitals every year, making the database management an extremely annoying and uncouth task [1]. These images need to be indexed, classified and searched for easy retrieval [3]. To accomplish this task, a technique called CBIR has been extensively used to describe the process of retrieving desired images from a large scale medical database on the basis of features (such as colour, texture and shape) that can be extracted from the images themselves [6-7].There exist three basic levels of feature extraction; namely - global, local and pixel. The simplest of all visual image features are based on the pixel values of the image without any deviation. Images are first scaled to a common size and then compared with database images. Local features are extracted from small sub images which are derived from the original image. The global feature can be extracted to describe the whole image in an average fashion. The low-level features extracted from images and their local patches constitute the colour, texture, and shape [9].Texture is an important and extensively used feature in the human visual system for recognition and interpretation [4].

The Local Tetra Pattern is a stepping stone in the field of texture classification and retrieval. LTrP builds the association between the referenced pixel and its neighbours by computing the gray-level difference [19] .The Fourier Transform is an effective and important tool which is used to disintegrate an image into its sine and cosine components. This transformation represents the image in the Fourier or frequency domain, while the input image is the spatial domain equivalent. Fourier transform has advantage that frequency-domain feature are commonly less sensitive to noise then spatial domain ones [17].

In this paper, a framework for retrieval of medical images from a given database after due indexing and classification using LTrP is presented. The LTrP considers the direction of pixels calculated by horizontal and vertical derivative for encoding the images. Moreover, the fourier transform is used for feature extraction of query image and database images. The rest of the paper is organized as follows: Section II investigate the related work about image retrieval strategies and models. Section III outlines the major role highlighting the main contribution of Local Tetra patterns. In Section IV, the detailed description of proposed framework is presented. Section V comprises the experimental results along with their discussions. Finally, Section VI concludes the paper.

II. RELATED WORK

Müller *et al*. [6] provides a comprehensive and broad review of CBIR systems for medical applications. The Image Retrieval for Medical applications (IRMA) project [7][8] describes CBIR methods for medical images using intensity distribution and texture measure. The main characteristics of this project are its support to allow the retrieval of similar images from heterogeneous databases. Ojala et al. [10] presents a simple and efficient multiresolution method to gray-scale and rotation invariant texture classification based on local binary patterns and nonparametric discrimination of sample and prototype distributions. Laio et al [11] proposed an approach, in which features are robust to image rotation, less sensitive to histogram equalization and noise. It comprises of two sets of features: dominant local binary patterns (DLBP) in a texture image and the supplementary features extracted by using the circularly symmetric Gabor filter responses. A combined completed LBP (CLBP) scheme [12] is developed for texture classification in which a local region is represented by its centre pixel and a local difference sign-magnitude transform (LDSMT). Ahonen et al. [13] reported a novel and efficient facial image representation based on local binary pattern (LBP) texture features. The LBP technique [5] has been widely used in numerous applications due to its finest texture descriptor performance. It has proven to be highly discriminative and its key advantages, mainly, its invariance to monotonic gray-level changes and computational efficiency, make it suitable for demanding image analysis task. Zhang *et al.* proposed local derivative patterns (LDPs) for face recognition, in which LDP templates extract high-order local information by encoding various distinctive spatial relationships contained in a given local region[14]. Author et al. [15] proposed a novel approach for face representation and recognition by examining the information jointly in image space, scale and orientation domains. Information collected from different domains is explored and examined to give a efficient face representation for recognition. The main challenge is that the use of LBP, LDP and their extended techniques are not so much reliable under the unconstrained lighting conditions. To accomplish this challenge the local ternary pattern (LTP) [16] has been introduced for image recognition under different lighting conditions. LTP eliminates most of the effects of changing illumination and presents a local texture descriptor which is unique and less sensitive to noise in uniform region.

III. EXISTING MODEL

A. LBP

The idea of using LBP for face description is motivated by the fact that face description is motivated by the fact that faces can be seen as a composition of micro patterns which are well described by such operator [5]. The procedure of Face recognition using LBP consists of using the texture descriptor to build several local descriptions of the face and combining them in to a global description. The value of LBP operator is calculated by comparing the grey value of centre pixel with its neighbours as shown in Fig. 1 and is based on

$$LBP_{P,R} = \sum_{p=1}^{P} 2^{(p-1)} \times f_1(g_p - g_c) \qquad (1)$$

$$f(x) = \begin{cases} 1, & x \geq 1 \\ 0, & else \end{cases} \qquad (2)$$

where g_c is the gray value of the centre pixel, g_p is the gray value of its neighbors, P is the number of neighbors, and R is the radius of the neighbourhood. Fig. 1 illustrates that each neighbouring pixel of a centre pixel is assigned with binary label, which can be either “0” or “1”. The basic version of LBP works in 3 × 3 pixel block of an image.

2	2	4	17	29
6	4	45	3	12
10	1	5	2	6
4	7	9	8	25
2	1	1	2	3

8	4	2
16		1
32	64	128

8	4	2
16		1
32	64	128

	228	

Fig. 1. Calculation of LBP

B. LTP

In LTP the gray-levels in a zone of width $\pm t$ around g_c are quantized zero, above this are quantized to 1 and below it to -1 as shown in Fig. 2. So, the indicator $f(x)$ is replaced with a 3-valued function and the binary LBP code is replaced by a ternary LTP code.

$$\hat{f}(x) = \left. \begin{cases} +1, & x \geq g_c + t \\ 0, & |x - g_c| < t \\ -1, & x \leq g_c - t \end{cases} \right|_{x=g_p} \tag{3}$$

Here, t is a user-specified threshold and LTP codes are more resistant to noise, but no longer strictly invariant to gray-level transformations.

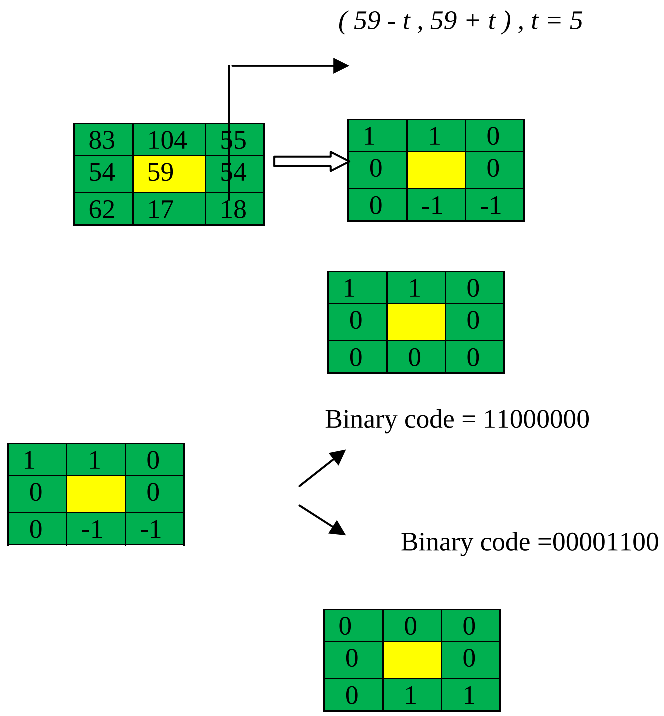

Fig. 2. Calculation of LTP

C. LDP

In LBP, the binary result of the first-order derivative is encoded among local neighbours by using a simple threshold function, which is unable to extract more detailed information from database in response to query image. Zhang et. al. [18] in their research work, considered the LBP as the non directional first-order local pattern operator, extended it to higher orders (nth-order) called LDP and applied it for face recognition. The LDP encodes the higher-order derivative information providing more detailed discriminative features which the first-order local pattern (LBP) cannot obtain from an image. Given an image $I(Z)$, the first-order derivative along 0^o , 45^o , 90^o and 135^o directions are denoted as $I'_{\alpha}(Z)$ where α = 0^o , 45^o , 90^o and 135^o.Let Z_0 be a point in $I(Z)$, and Z_i , $i = 1,\ldots\ldots,8$ be the neighbouring point around Z_0. The four first-order derivatives at $Z = Z_0$ can be written as:

$$I'_{0^0}(Z_0) = I(Z_0) - I(Z_4)$$

$$I'_{45^0}(Z_0) = I(Z_0) - I(Z_3)$$

$$I'_{90^0}(Z_0) = I(Z_0) - I(Z_2)$$

$$I'_{135^0}(Z_0) = I(Z_0) - I(Z_1) \tag{4}$$

Working in same manner, the ordered directional LDP can be calculated.

D. Local Tetra Pattern (LTrP)

Murala et. al. [19] adopted the LBP, LDP and LTP to define LTrPs. Local tetra pattern technique encodes the relationship between the centre pixel and its neighbors, based on the directions that are calculated using the first-order derivatives in vertical and horizontal directions. The LTrP describes the spatial structure of the local texture using the direction of the center gray pixel. In this method the first order derivative at center pixel g_c can be defined as

$$I'_{0^0}(g_c) = I(g_h) - I(g_c) \tag{5}$$

$$I'_{90^0}(g_c) = I(g_v) - I(g_c) \tag{6}$$

where g_h and g_v is the horizontal and vertical neighbours of g_c respectively and direction of centre pixel can be calculated as:

$$I^1_{Dir.}(g_c) = \begin{cases} 1, & I^1_{0^0}(g_c) \geq 0 \; and \; I^1_{90^0}(g_c) \geq 0 \\ 2, & I^1_{0^0}(g_c) < 0 \; and \; I^1_{90^0}(g_c) \geq 0 \\ 3, & I^1_{0^0}(g_c) < 0 \; and \; I^1_{90^0}(g_c) < 0 \\ 4, & I^1_{0^0}(g_c) \geq 0 \; and \; I^1_{90^0}(g_c) < 0 \end{cases} \tag{7}$$

From equation (7), it is obvious that image is converted in to four values i.e. 1, 2, 3, 4 and these four values can be treated as four directions. Next step is to calculate the second order derivative ($LTrP^2$) and from it an 8-bit tetra pattern is obtained for each center pixel. Then, this tetra pattern is divided in to four parts based on the direction of center pixel. Finally, the tetra patterns for each direction are converted to three binary patterns. So, if the direction of centre pixel is 1 then twelve (4 × 3) binary patterns are generated for four directions. LTrP method used 13th binary pattern (LP) which can be calculated by using the magnitudes of horizontal and vertical first-order derivatives:

$$M_{I^1(g_p)} = \sqrt{(I^1_{0^0}(g_p))^2 + (I^1_{90^0}(g_p))^2} \tag{8}$$

$$LP = \sum_{p=1}^{P} 2^{(p-1)} \times f_1(M_{I^1(g_p)} - M_{I^1(g_c)})\Big|_{P=8} \tag{9}$$

After identifying the 13 bit binary pattern, their histogram is calculated and query image is compared with the images of given database. During comparison process, the N best images similar to query image are selected. The experimental results confirmed that LTrP outperforms LBP, LDT and LTP in terms of retrieval and is able to extract more detailed information from the image.

IV. PROPOSED SYSTEM

The complete architecture of proposed model is shown in Figure 3. Initially, the query image is loaded and converted into grayscale image. As the dataset may be of different size, the image is resized. After resizing, the first-order derivative in both horizontal and vertical axis is applied and direction of every pixel is calculated. Based on the direction of the centre pixel the patterns are divided into four parts. The tetra patterns are calculated and separated into three binary patterns on which the Fourier descriptor is applied. The magnitude of centre pixels is calculated. Then binary patterns from the magnitude are constructed and Fourier descriptor is also applied on them. The features extracted from initial binary patterns as well as from binary patterns generated through magnitude are combined to form the feature vector. The query and database image is compared using Euclidean distance technique for similarity measurement. Finally, the best matched images are retrieved from the medical image database in response to the query image.

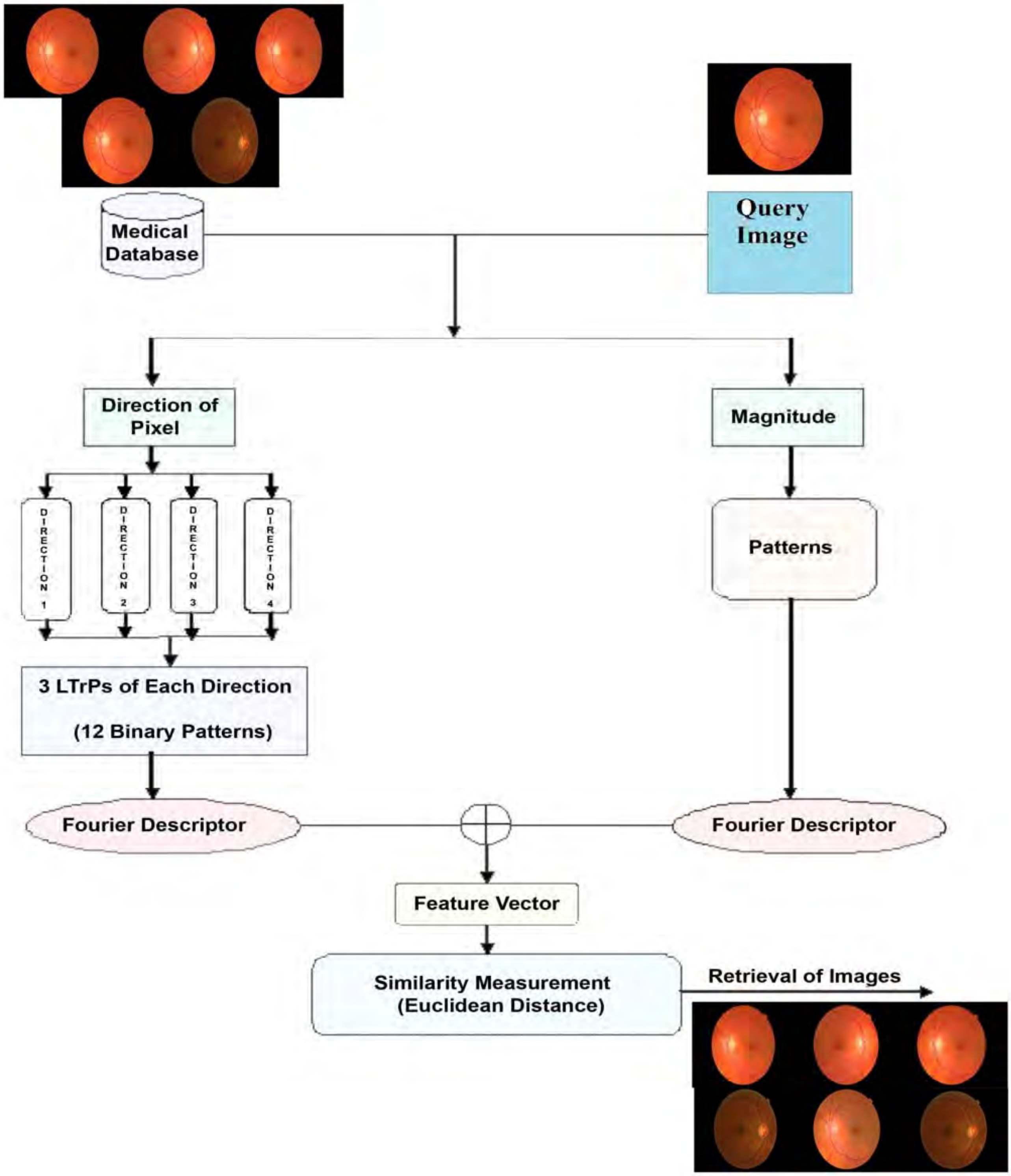

Fig. 3. Architecture of Proposed System

A. Fourier Descriptor

Fourier transform is used to generate the feature vectors based on the mean values of real and imaginary parts of complex numbers of polar coordinates in the frequency domain. Fourier Descriptors (shape based) can be used as a dominant feature for boundaries and object representation [20]. Consider a M point digital boundary; starting from an arbitrary point (x_0, y_0) then $(x_1, y_1),\ldots,(x_{M-1}, y_{M-1})$ can be generated. These coordinates can be represented in a complex form as:

$$q(m) = x(m) + y(m) \qquad m = 0,1,2\ldots M-1$$

The Discrete Fourier Transform (DFT) of $q(m)$ gives:

$$b(k) = \frac{1}{M}\sum_{m=0}^{M-1} q(m)\, e^{-j2\pi k\, m/M} \qquad k = 0,1,2\ldots M-1$$

The complex coefficients $b(k)$ are called Fourier descriptors of the boundary.

B. Similarity Comparison

Distance metric is the main tool for retrieving similar images from large medical databases. In proposed system, Euclidean distance [21] and Canberra distance [23] are used for the purpose of similarity comparison.

$$\mathrm{ED} = \sqrt{\sum_{i=1}^{\mathrm{N}} (\mathrm{fq(i)} - \mathrm{fdb(i)})^2}$$

Where $f_q(i)$ stands for i^{th} query image feature and $f_{db}(i)$ for corresponding feature vector database. Here N refers to number of images in database.

$$\text{Canberra Distance(CD)} = \frac{\sum_i \left|u_i - v_i\right|}{\sum_i \left|u_i\right| + \left|v_i\right|}$$ **,** where u and v are both n-dimensional vectors.

V. EXPERIMENTAL RESULTS

In this section, the experiments that have been carried out to test the efficiency and effectiveness of proposed framework is presented. The functional code is implemented using MATLAB R2011b on an Intel Core 2 duo, 2 GHz window based laptop. The performance of the proposed system is tested on standard Messidor dataset [24]of 1200 Retinal images.

A. Performance Parameters

Precision and Recall (P-R): The images are retrieved and measured against P-R [22] as:

$$\mathrm{P} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}}, \ \mathrm{R} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in the database}}$$

where P is the ratio to measure accuracy and R is used to measure robustness.

B. Scenario 1: Fig. 4 and Fig. 5 illustrate the performance gain of the proposed system based on LTrP along with FD/ED, over existing system [19] in terms of retrieval accuracy.

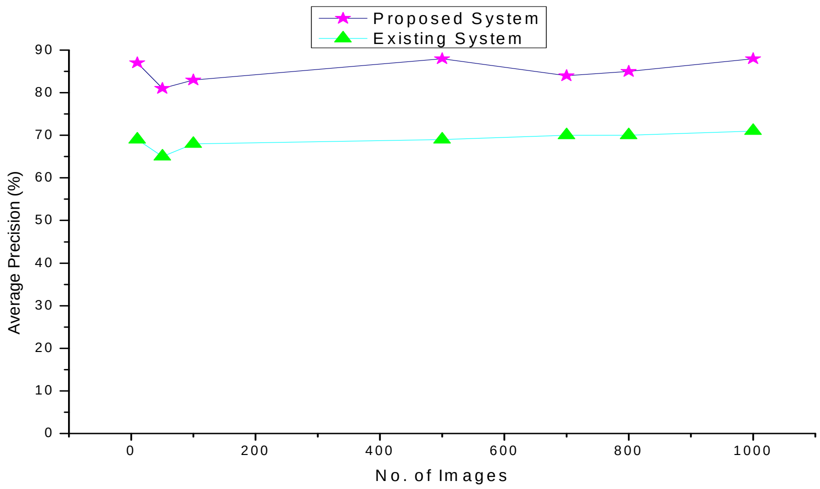

Fig. 4 Average Precision (%) against No. of Retinal Images under Scenario 1

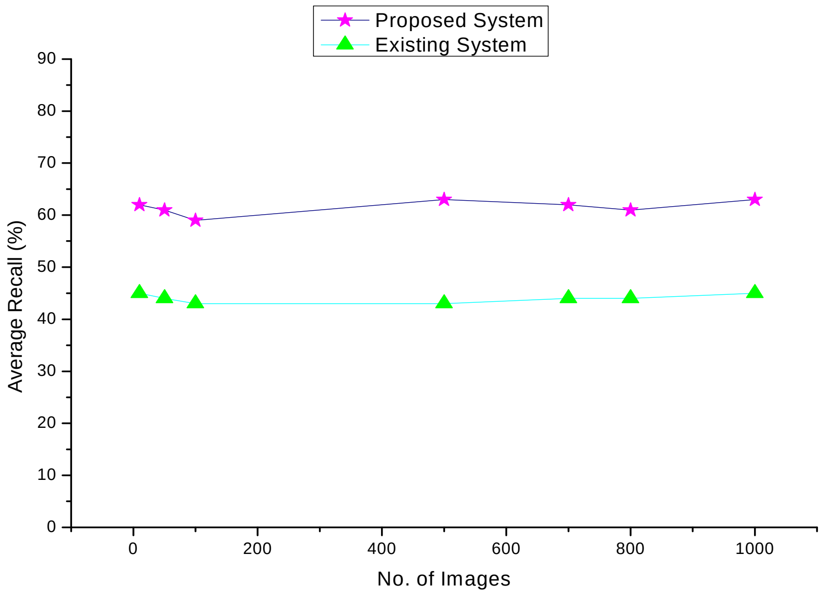

Fig. 5 Average Recall (%) against No. of Retinal Images under Scenario 1

C. Scenario 2: Fig. 6 and Fig. 7 illustrate the performance gain of the proposed system based on LTrP along with FD/CD, over existing system [19] in terms of retrieval accuracy.

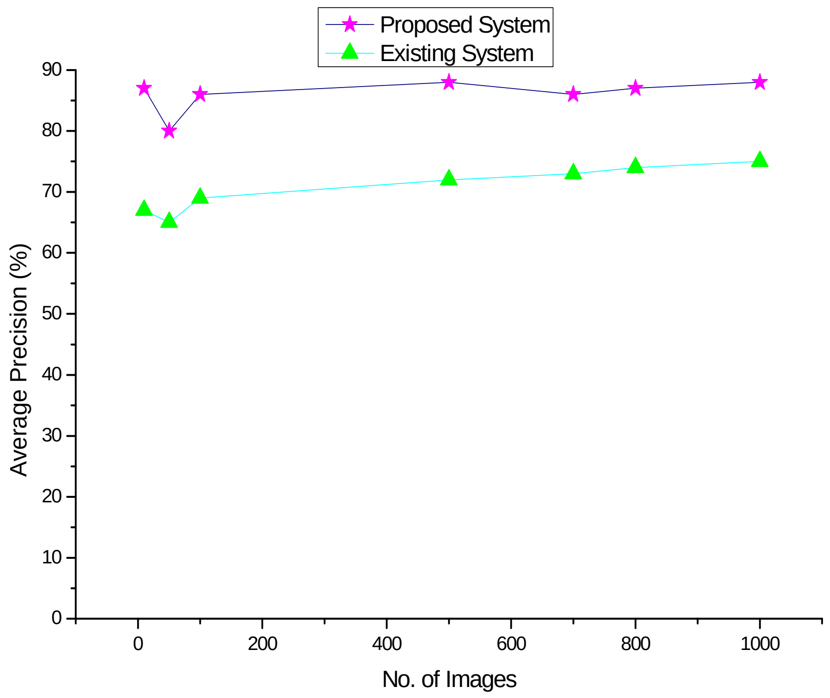

Fig. 6 Average Precision (%) against No. of Retinal Images under Scenario 2

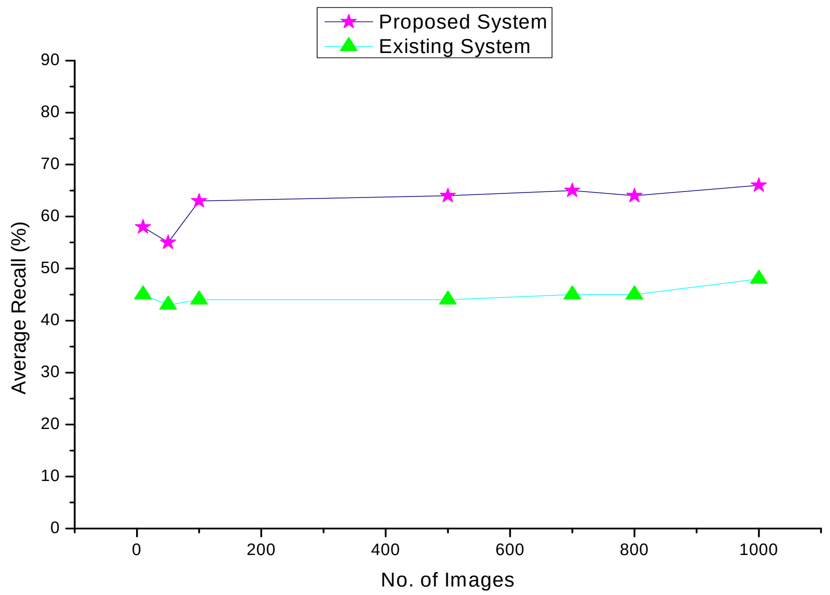

Fig. 7 Average Recall (%) against No. of Retinal Images under Scenario 2

The results obtained after successful implementation of the proposed system can be seen through output screens of the developed system for any query image (represented by Fig. 8) in Fig. 9 and Fig. 10.

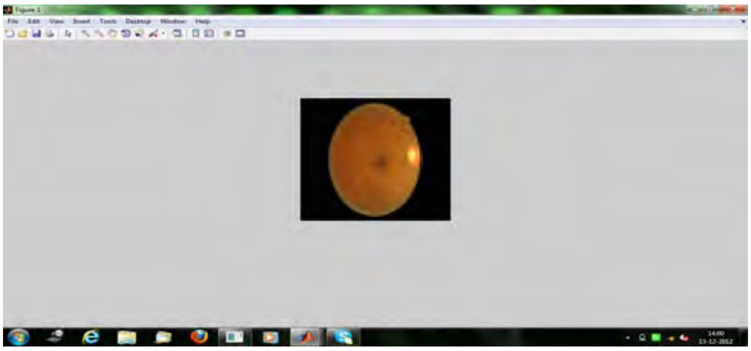

Fig. 8. Query Image for Retinal Images Dataset

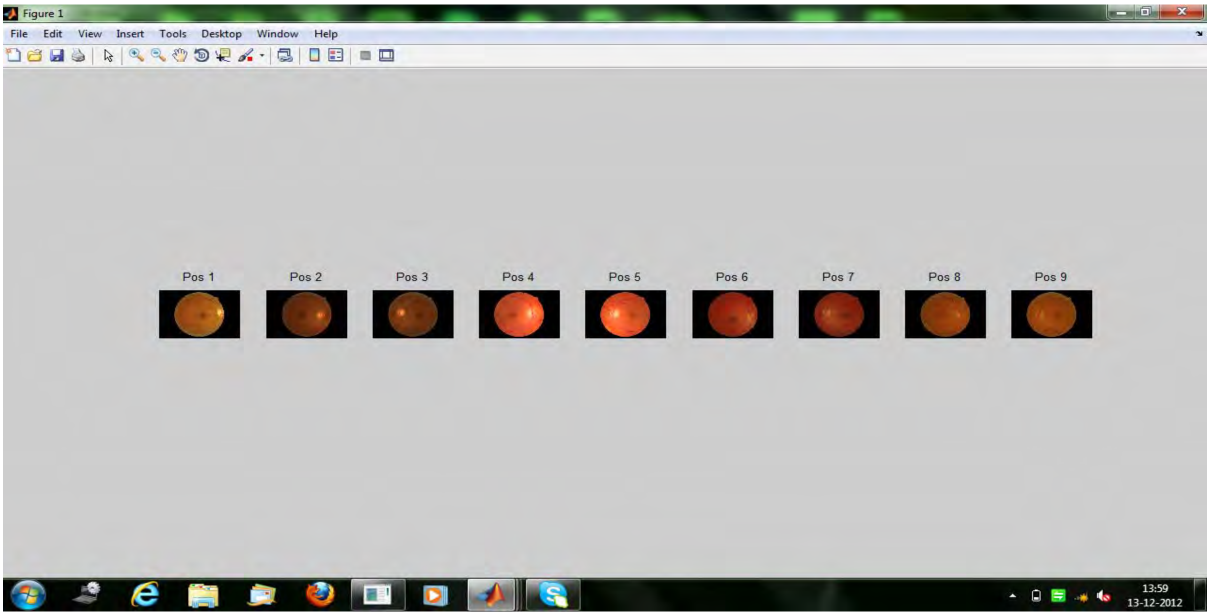

Fig. 9. Retrieved Images from Retinal images Dataset for the Query using FD/ED

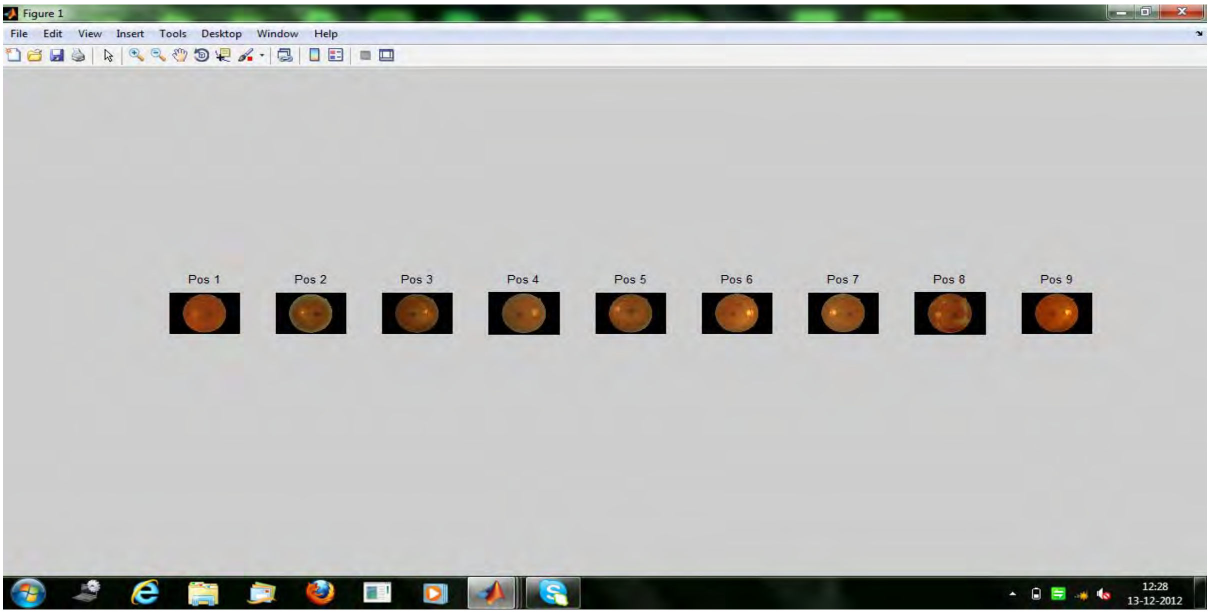

Fig. 10. Retrieved Images from Retinal images Dataset for the Query using FD/ED

VI. CONCLUSION

In this paper, a content based image retrieval system for medical images based on various techniques for feature extraction and similarity measurement is presented. In addition to this, the merits of local tetra pattern technique is also incorporated. The experiment is performed on Messidor dataset of 1200 retinal images and results confirm the efficiency of proposed enhanced medical image retrieval system. The results also highlight that the local tetra patterns provides superior performance when used with FD/CD rather than FD/ED. The SS-SVM applied on binary patterns of datasets images for classification of medical images which results in improved average accuracy from 77%,74%,68% and 70% to 81%, 78%, 74% and 88% for endoscopy, dental, skull and retinal images dataset.

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