Annotation and Retrieval of Retinal Images using Support Vector Machine with Active Learning

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***Abstract*—In the medical field, many images are acquired using different modalities like X-ray, Computed Tomography and Magnetic Resonance Imaging. Organizing these images and retrieving them is a critical task. In this paper, a novel retinal image retrieval and automatic annotation of ten different retinal diseases is presented and is comprised of three steps namely, feature extraction, automatic annotation and retrieval of similar images. In feature extraction, visual features like texture, color and shape were derived from the images and stored in a database. The retinal images are affected by various diseases and have to be identified easily and quickly for better treatment. For automatic annotation, we have considered ten different retinal diseases and annotated the retinal image with its corresponding disease using Support Vector Machine (SVM) with Active Learning (AL) and discriminative based automatic image annotation. In retrieval of images, Bray Curtis distance measure was used to retrieve the similar images by comparing the feature values of images stored in the database. Our proposed system has achieved a precision of 82% and specificity of 96.3%.**

***Keywords*—Content-Based Image Retrieval; Active Learning; Support Vector Machine; Image annotation.**

I. INTRODUCTION

Image retrieval means finding similar images from a large image archive with the help of some key attributes and the features inherently contained in the image. The image retrieval can be sub divided into two types: text based image retrieval and content based image retrieval. Humans manually annotate the image using text and then classification and retrieval of images was executed based on the footnoted textual description[1]. Moreover, it is also tedious, expensive, content sensitive and incomplete [2].

In Content Based Image Retrieval (CBIR), images are indexed and retrieved using the extracted visual content features like shape, texture and color. Many descriptors have been designed to describe the features like color, texture and shape [3] but they have many restrictions when used for broad image categories. Research efforts have shown that there is a significance gap between the low level visual features and the semantic concept of images interrupted by humans [4]. This can be regarded as image classification with a large number of classes based on the size of the vocabulary. Works following these efforts have included different classification approaches [5,6].

Image retrieval can be made easy by adopting Automatic Image Annotation (AIA) in which the system automatically assigns the description or keywords to a digital image [7]. This AIA can be made easy and effective by using active learning technique for machine learning. AL gives the advantage of reducing the annotating cost by querying the labels at informative points.

In this paper we focus on the novel methodology to automatically annotate the disease present in the retinal images using SVM active learning and retrieve the similar images using Bray Curtis distance measure. The retina of the eye is affected by various diseases like Retinal artery occlusion, cotton wool spots, hyperemia, etc. We have analyzed the texture properties of each disease using the different extracted features namely shape, inertia, kurtosis, etc. Discriminative based annotation method was used for labeling the retinal image with the corresponding disease to which it is affected.

The rest of the paper is organized as follows. Section II describes the related work that has been carried out in image retrieval and annotation. Section III elaborates our proposed system architecture and methodology. Section IV describes the architecture of SVM using Active Learning (AL) and implementation of our proposed work. Section V designates the results and discussion and section VI analysis the performance of our methodology and concluded in Section VII.

II. LITERATURE SURVEY

The content based image retrieval system's application in the field of medical imaging and sufficient information and knowledge about the use of CBIR in real time was discussed in[8]. In[9] content based medical image retrieval was done through unsupervised feature selection using "Customized –Queries Approach" (CQA). They have adopted two steps. First being the feature selection for classification to differentiate the query image to one of the given diseased group and second recognition of distinct characteristic similarity. This approach however has a limitation; it only retrieved the image only from one major group at a time and not the images from the adjacent most probable group. The retrieval of images can be achieved by integrating the color, shape and the texture.

In another approach the image retrieval was done using the color and texture information of the image and the image is divided into sub blocks. The color of every sub blocks is taken out by evaluating the HSV color space. This approach focuses only on the colored image and it does not prefer any particular medical domain and the HSV color space is a letdown in this approach. Since in medical fields, the absolute color and the grey features are used more [10].

The image retrieval using the texture based symbolic feature for medical image, is an approach which makes

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use of the CISMeF health catalogue-capacity to create queries by providing the keywords associated with the image. This approach was based on the use of texture and high order statistical movements and this could be further enhanced by adding the features and classifiers to modify the results obtained [11].

The performance of the content based image retrieval can be improved by the computer vision techniques to retrieve the image and locate the images from the database. The retrieval of images can be considered as multiclass image classification with a large number of classes depending on the vocabulary size[12,13].

A CBIR system [14] based on automated image annotations was implemented using the texture details from the images got from statistical co-occurrence matrix method by correlating the semantic gap between low-level visual features and high-level semantic concepts. Euclidean distance measure was used for similarity measurement and the images were indexed using hash function.

Different distance metrics have been compared for efficient image retrieval using the quantized histogram statistical texture features in the DCT domain[15] and they achieved an average precision value to be 80 for the Euclidean distance metric They have also analyzed the precision rate for each distance measure [16].

Semantically enhanced information extraction model was discussed in [17] and the semantic intensity (SI) of each object in the image was calculated and then enhance the tagged concept with the assistance of lexical and conceptual knowledge bases .i.e. Word Net and Concept Net. Redundant and unusual words are then filtered out by various techniques but redundancy level is high.

The authors in [18] surveyed on the latent space and generative approaches for automatic image annotation to build the semantic gap. AIA method based on Multi-instance Learning was proposed in [19]. and assigns a conceptual annotation to bags by learning from training bags.

Each work discussed here has its own advantage. From the above literature study we could infer that precision rate was high in many retrieval systems with considerable training time. Our experiment results demonstrate that we could retrieve similar retinal images with automatic labeling in few seconds as we have used active learning along with the SVM classifier.

III. Automatic Annotation of Retinal Images using SVM with Active Learning

In this work, we have retrieved the similar retinal images and labelled them with the name of disease it is being affected. For this work, features from the images were extracted and stored in a database for comparison of its values against the incoming input image features values. The similarity retrieval was carried out using Bray Curtis distance measure. Implementing the discriminative model of annotation using Active Learning based Support Vector Machine (AL-SVM) for labeling of the retinal disease associated with the retinal image was carried out as a last step.

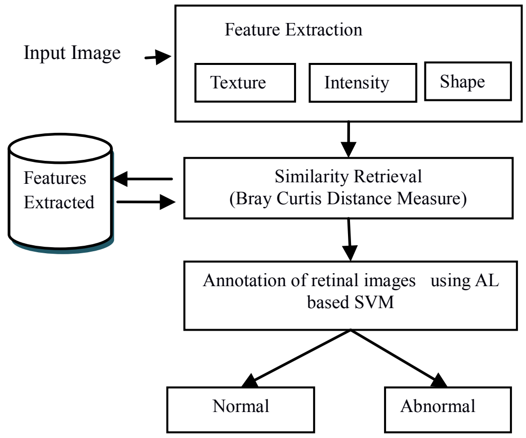

Fig. 1 Block Diagram of Proposed Work

3.1 Feature Extraction

The features like texture, shape and intensity of the images were used for annotation. These features were extracted from the entire image and grouped it as the global feature vector. Then the image was segmented into several regions or blocks. From each block, texture, shape and intensity of the image was extracted and they were considered as the local feature vector. Once the global and the local features were extracted, the image was resized to obtain the pixel information as feature vector. These three features extracted from the images were combined to form one large vector. The dimensionality of the feature vector was reduced using Principal Component Analysis. Then a combined feature vector for Texture and Intensity was constructed. 53 dimensional feature (16 texture +37 edges) vectors was obtained from the entire image by applying gray level co-occurrence matrix for texture extraction and edge histogram for shape feature extraction and pixel vector of size 225 was obtained. All these features were combined to make up a feature vector of size 490 [20]. The features were used to classify the image and the result was stored as 2D trans cons matrix also called as 2D transition matrix. Following are the features considered for our work.

3.1.1 Shape Features

The shape features are based on the shape boundary information by which we can retrieve the objects of similar shapes even though it is affected by noise. It's also known as shape descriptors and should be able to effectively find the similar shapes from the database even after the objects are rotated, translated, flipped, scaled, etc. The shape features which we have extracted are explained below.

Area

It is the total number of pixels that occupy the internal shape of the object.

Perimeter

It is the total number of pixels that define the perimeter of the contour

Circularity ratio

Circularity ratio represents the ratio of the area of a shape to the shape's perimeter square and is defined as

$$circularity\ \ ratio = \frac{Area\ of\ the\ shape}{(Shape's\ \ perimeter)^2} \tag{1}$$

Convexity

Convexity is defined as the ratio of perimeters of the convex hull over that of the original contour

3.1.2 Texture Features

Mean

$$m = \sum_{b=0}^{L-1} xp(x) \qquad (2)$$

where x represents the image and $p(x)$ denotes the probability.

$p(x)$ is defined by the following equation.

$$p(x) = \frac{N(x)}{M} \qquad (3)$$

$N(x)$ represents the total number of pixels having the gray value x. M denotes the total number of pixels in an image.

Standard Deviation

$$\sigma = \left[\sum_{x=0}^{L-1} (x-m)^2 p(x) \right]^{\frac{1}{2}} \qquad (4)$$

Variance

Measures how far a set of numbers is widening out and is distinguished as the probability distributions and is given by:

$$\sum_{i,j} (i-m)^2 P(i,j) \qquad (5)$$

Where, $P(i,j)$

represents the pixel value of an image.

Skeweness

Gives the measure of the unequal probability distribution of the real valued random variable. The skewness with zero value is an indication of equal distribution of intensity values on both sides of the mean and is given by the equation,

$$S = \frac{1}{\sigma^3} \sum_{x=0}^{L-1} (x-m)^3 p(x) \qquad (6)$$

Kurtosis

Quantifies the shape of the probability distribution of a real value random variable and is used to calculate the peak of the distribution of intensity values about the mean value.

$$K = \frac{1}{\sigma^4} \sum_{x=0}^{L-1} (x-m)^4 p(x) - 3 \qquad (7)$$

Energy

Energy describes the measure of information and is helpful in image segmentation.

$$E = \sum_{x=0}^{L-1} [p(x)]^2 \qquad (8)$$

Inertia

It is a momentum based feature which helps to find the shape of the irregular object.

$$Inertia = \sum_{i,j=0}^{n} (i-j)^2 C(i,j) \qquad (9)$$

where C (i, j) is the pixel of the image and (i, j) is the value of the mask.

Covariance

Covariance helps in quantifying the changes of the two random variables. If the covariance value is positive, it symbolizes similar behavior. If the covariance is negative, it symbolizes the opposite behavior.

$$Cov(x,y) = 1N \sum (x_i - \bar{x})(y_i - \bar{y}) \qquad (10)$$

where N is the number of attributes.

3.2 Retrieval and Annotation

In this phase, the features of the input image such as texture, intensity were extracted from the input image. The extracted features were compared with the database which consists of the features of multiple images. The distance and similarity measures [21] were calculated using Bray-Curtis Distance. The images with lowest distance and more similarity matrix are retrieved from the database and are given by the following equation.

$$d_{BC}(x,y) = \sum_{i=1}^{d} \frac{|xi - yi|}{xi + yi} \qquad (11)$$

where x and y are 2D feature vectors of database image and query image.

IV. Implementation of SVM based Active Learning for Annotation of Retinal Images

4.1 Materials Used

Two hundred retinal images containing normal images and abnormal images with ten different eye diseases like retinal artery occlusion, vitelliform macular dystrophy, retinal vein occlusion, crao, hyperemia, conjunctivitis, cotton wool spots, muscular edema, purtscher retinopathy and malignant hypertension were considered for evaluation. The image database was created by extracting shape, intensity and texture features of the image. All the values were stored in a database using Matlab.

4.2 SVM Architecture

The support vendor machine (SVM) methodology comes from the applications of statistical learning theory of separating hyperplanes to the binary classifications problems [22]. The fundamental idea of SVM is to adjust appreciative functions so that it makes optimal use of the separability information of the extremity cases. The set of cases belongs to one of two classes, training a linear SVM consist in searching for the hyperplane that leaves the largest number of cases of the same class on the same side, while maximizing the distance of both classes from the hyperplane [23]. A separable hyperplane is defined by a normal and a bias, which will satisfy the inequalities.

$$y_i(W.X_i + b) \geq 1 \forall i \in (1,2....,N) \qquad (9)$$

where $x_i \in R^d$ is a case for the training set $(i = 1,2,.....N)$, d being the dimension of the input space and $y_i \in (-1,+1)$ is the proportionate gathering. Among the detached hyperplanes, SVM approach selects the one for which the distance is closest case is maximal. $1/|W|$ With such a distance, finding an optimum hyperplane is equivalent in minimizing $|W|^2$ under the constraints from the equation. The support vectors are the hyperplane closest to the hyperplane, while $2/|W|$ is the quality for the margin.

4.3 Annotation using SVM Active Learning

Active Learning (AL) is an effective machine learning method used to solve unlabeled classification problems. Its basic function is to select the most valuable samples, label them by experts and add them to the training set iteratively.

In this process we have applied AL in SVM [27] for annotating the retinal disease. The classifier generates one concept or one keyword for every iteration based on the sub images of the retinal image. Finally these are combined to form one annotation. The radial based kernel function was used in SVM classifiers. There are two parameter involved with the radical basis kernel function: one parameter controls the tradeoff between margin maximization and error minimization, the second parameter was used to shape the kernel. The procedure for SVM Active Learning is illustrated in the Fig. 2.

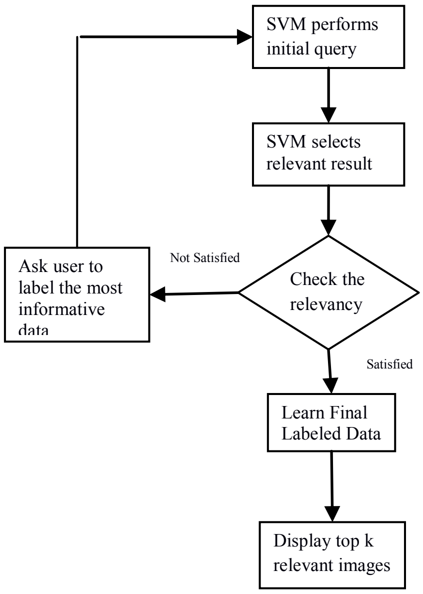

Fig. 2 Methodology for SVM Active Learning

V. RESULTS AND DISCUSSIONS

5.1 About the Database

The database consists of 200 retinal images which includes 20 normal images and 180 abnormal images. The abnormal images can be identified as anyone of the retinal disease like retinal artery occlusion, vitelliform macular dystrophy, retinal vein occlusion, crao, hyperemia, conjunctivitis, cotton wool spots, muscular edema, purtscher retinopathy and malignant hypertension. All the 200 images were considered for evaluation.

5.2 Results of Feature Extraction

The shape, texture and intensity features were extracted for every image and is stored in a database for comparison with the values of the input image. The following table shows the few values extracted for certain images stored in the database.

TABLE I. FEATURE VALUES OF SUBSET OF IMAGES IN DATABASE

Images	Mean	Standard Deviation	Kurtosis	Correlation
Image 1	0.7845	0.8163	0.7865	0.6823
Image 2	0.8176	0.9234	0.8324	0.7945
Image 3	0.7867	0.8087	0.7856	0.98432
Image 4	0.8321	0.8912	0.8134	0.7996
Image 5	0.8532	0.9245	0.8623	0.8034

5.3 Results of Retrieval and Annotation of Retinal Images

The following figure shows the result of annotation with Active Learning. The retinal images are annotated with the retinal disease present in it.

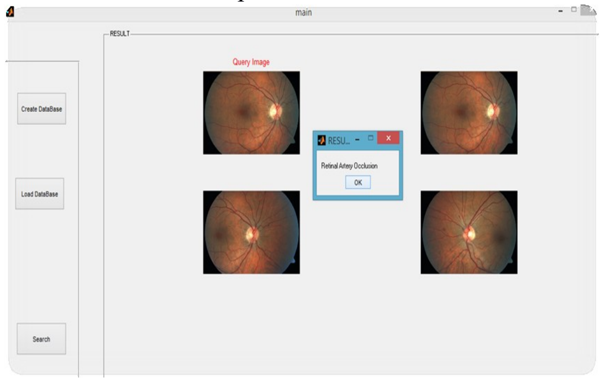

Fig. 3 Retrieval and Annotation of Retinal Images

The retrieval process was carried out using Bray Curtis distance Measure. This distance measure was found to retrieve with more accuracy when compared with the other distance measures. The following figure shows the comparison of different distance measures with its similarity retrieval accuracy.

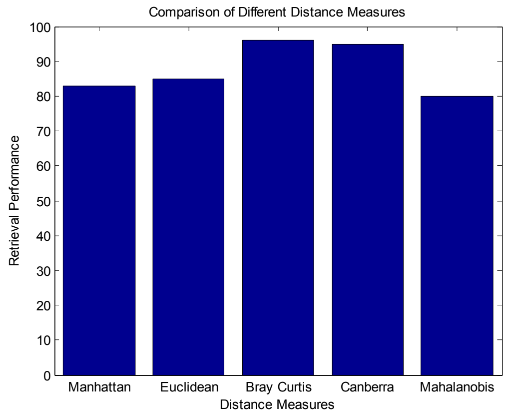

Fig. 4 Comparison of different Distance Measures

VI. PERFORMANCE EVALUATION

The performance of our method can be analyzed using the confusion matrix, ROC curve, Training and Testing time, Sensitivity and Specificity. The classification results were shown as a confusion matrix and precision, recall and specificity of each disease is given in the Table I. The average classification rate is 83.4%.

6.1 Confusion Matrix

Confusion Matrix can be used to assess the performance of the classifier on a set of test [28]. A confusion matrix is an n-by-n matrix showing the actual classifications based on the quantity of correct and incorrect prediction and n represents the number of classes from the dataset with each row representing the number of samples in actual class and column being the number of samples in predicted class. From the confusion matrix in Fig. 5, we can calculate Sensitivity, Precision and Specificity using the formulae given below:

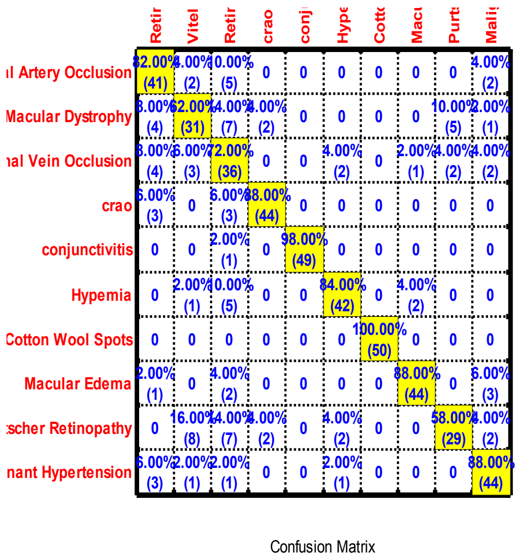

Fig. 5 Confusion Matrix

From the confusion matrix in Figure 5, we can calculate Sensitivity, Precision and Specificity [29] using the formulae given below:

$$Sensitivity = Recall = \frac{tp}{(tp + fn)} \tag{12}$$

$$Specificty = \frac{tn}{tn + fp} \tag{13}$$

$$Precision = \frac{tp}{tp + fp} \tag{14}$$

where tp, tn, fp are true positive, true negative and false positive and the values for each disease is given in the Table II. An image is considered as a true positive if the image is really abnormal and is also classified as abnormal by the algorithm. Similarly, a true negative refers to negative pixels correctly labeled as negative. A false positive means that the retinal image is actually normal, but the procedure classified it as abnormal whereas false negative indicates the procedure which classified the retinal image as correct but is actually incorrect. From this table we can find that the specificity rate is high for annotating all the diseases. The average precision, recall and specificity rate is 82%, 85.6% and 96.3%.

TABLE II EVALUATION METRICS

Retinal Disease	Precision%	Recall%	Specificity%
Retinal Artery Occlusion	73	91	94.7
Macular Dystrophy	63.3	68.5	93.1
Retinal Vein Occlusion	50	72	90.5
Crao	91.1	88	97.8
Conjunctivitis	100	98	99.7
Hyperemia	89.3	93.3	97.7
Cotton Wool spots	100	100	100
Macular Edema	93.6	88	98
Purtscher Retinopathy	80.5	68.9	94.0
Malignant Hypertension	81.4	88	96.4

6.2 Training and Testing Time

Also as we have used active learning for labeling the retinal images, the training time taken is less when compared without using Active Learning and is shown below

TABLE III COMPARISON OF TRAINING TIME

Method	Training Time (Sec)
Labeling without Active Learning	1.45
Labeling with Active Learning	0.67

VII. CONCLUSION

This paper has presented a novel approach for automatic image annotation using AL. Here we have considered retinal images with different diseases for evaluating our methodology. We have developed a system architecture which reckons feature extraction, multi level classification, quantifiers, two dimensional matrix creation and retrieval of image. All the retinal image features were stored in a database in the matrix format. The image that has to be annotated used those feature values for comparison. The aggregation of the textual and visual abstraction improves the retrieval results. The images which were similar are retrieved using Bray Curtis distance measure and the images that were similar were retrieved. The textual description of the visual image along with the description was implemented.

In our work we have considered only retinal images and in future the proposed methodology can be used for the retrieval and the analysis of various medical images. With SVM we have obtained the specificity of 96.3%and precision of 82%. We can try some new ways of automatically determining the unlabeled samples and the result of feature classification can be improved by using recently evolved classifiers like Extreme Learning Machine and Complex Valued Neural Classifier and using different active learning mechanisms. By using this we can improve the training time and classification accuracy.

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