Detection and Classification of Hard Exudates in Human Retinal Fundus Images Using Clustering and RVM Methods

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Abstract—Diabetic Retinopathy (DR) is a vascular disorder where the retina is damaged because fluid leaks from blood vessels into the retina. One of the primary lesions of diabetic retinopathy is exudates, which appear on retinal images as bright patches with various borders. In this work an image processing framework is presented to automatically detect and classify the presence of hard exudates in the human retinal fundus images. A total of 50 images have been used to detect the hard exudates from the Messidor database. Digital image processing methods help to extract the location and level of abnormalities in retinal fundus images. The contrast adaptive histogram equalization is used for preprocessing stage and Fuzzy C-Means (FCM) and K-means clustering algorithms are applied to segment the exudates in abnormal images. A set of features such as the standard deviation, mean, energy, entropy and homogeneity of the segmented regions are extracted and fed as inputs into relevance vector machine (RVM) classification to discriminate between the normal and pathological image. The proposed method achieved 91.95% accuracy for early detection of DR.

Index Terms—Hard Exudates, k-means clustering, Fuzzy c-means, relevance vector machine.

I. INTRODUCTION

Retina is the innermost coat at the back of the eye and light sensitive layer of tissue. It sends visual messages through the optic nerve. The retina serves as the film in a camera. When Light strike on the retina which initiates a cascade of electrical and chemical events that activate nerve impulses. These are sent to different visual centers of the brain through the fibers of the optic nerve. In the developed countries, the diabetic retinopathy is the most common cause of vision loss. According to the fact, diabetes is a rapidly growing disease among large part of the population. When the disease is detected in its early stages, laser photocoagulation can slow down the progression of DR. The retinal fundus of diabetic patients needs to be examined at least once a year, to ensure that treatment is received on time.

Digital image processing techniques help to extract the location and size or the level of abnormalities in retinal images. DR is the main cause of new cases of blindness among adults aged 20–74 years. During the first 20 years of the disease, approximately all patients with type 1 diabetes and greater than 60% of patients with type 2 diabetes have retinopathy. In the older-onset group, in which other eye diseases were common, due to DR one-third of the cases have blindness. It occurs when the increased glucose level in the blood damages the capillaries. As a result of this damage, the capillaries leak blood and fluid on the retina [14]. The visual effects of this leakage are features, such as hard exudates, microaneurysms, cotton wool spots or venous loops, hemorrhages, of DR [15].

Exudates are accumulations of lipid and protein in the retina. Typically they are bright, reflective, white or cream colored lesions. They indicate increased vessel permeability and a connected risk of retinal edema. They are a marker of fluid accumulation in the retina. When they present close to the macula center they form sight threatening lesions [2]. Most of the time they are seen together with microaneurysms.

The aim of the present work is to process digital color retinal images to automatically detect and classify hard exudates. Image segmentation is widely used in grouping, exploratory pattern-analysis, decision-making, and machine-learning situations for medical images. These algorithms are used to automate process of segmentation of the hard exudates in retinal fundus images. K-means algorithm follows a simple and easy way to classify a given document set through a certain number of clusters. The K-Means clustering method has low complexity [11]. Fuzzy clustering is more natural than hard clustering. It is used to highlight salient regions, extracts relevant features and finally classifies those regions using RVM classifier.

In this work, the abnormal retinal images are subjected to two clustering algorithms. K-Means and Fuzzy C-Means algorithms are used. Abnormalities are extracted using these algorithms. From the segmented regions, features are extracted and fed as input to the development of a supervised classification technique that is relevance vector machine. Better results are given as input to RVM classifier which is a convex quadratic program can provide probabilistic interpretation of the output of relevance vector machine, which can be developed for multi-class classification [21, 24, 25]. The idea of RVM is that the input data are mapped to a high-dimensional feature space by kernel function.

II. METHODOLOGY

A. Preprocessing

Contrast-Limited Adaptive Histogram Equalization (CLAHE) [15] was applied for contrast enhancement to improve the image quality. CLAHE operates on small regions
in the image. Each small region’s contrast is enhanced with histogram equalization. This image processing technique can improve the local contrast of the image and have a more uniform image so the edges of the exudates are enhanced.

**B. Segmentation**

Image segmentation is used to partition an image into meaningful regions. They were HE candidate regions that had to be classified afterwards. Segmentation was accomplished using the histogram properties of the second color component of the preprocessed image. The goal of segmentation is to simplify the representation of an image and provide meaningful information which is easier to analyze. This paper use two clustering based techniques that are K-means clustering and FCM clustering.

K-Means or Hard C-Means clustering is basically a partitioning method applied to analyze data and treats observations of the data as objects based on locations and distance between various input data points [11]. Figure 1 shows that the block diagram of hard exudates detection. Clusters can be chosen randomly, manually, or based on some conditions. Distance between the cluster centre and pixel is calculated by the absolute difference or squared between a cluster centre and pixel. The difference is normally based on intensity, pixel color, location, texture and, or a weighted combination of these factors. The initial set of clusters is important to the quality of the final result of the clustering method. The algorithm is extremely fast, a collective method is to run the obtainable.

Clustering Method is an iterative technique that is used to partition an image into clusters [16, 17]. The following method can be employed to find the cluster centers

1. Compute the intensity distribution (also called the histogram) of the intensities.
2. Initialize the centroids with k random intensities.
   \[ C(i) = \text{argmin}_{j} \| X(i) - \mu_j \|^2 \]  
3. Cluster the points from the centroid intensities based on distance of their intensities.
4. Calculate the new centroid for each of the clusters.

Where i iterates over all the intensities, k is a the number of clusters to be found, \( \mu_i \) are the centroid intensities and j iterates over all the centroids (1). The algorithm is very fast, a common method is to run the algorithm several times and return the best clustering found.

Fuzzy C-Means is a soft segmentation algorithm. It allows pixels belong to multiple clusters with varying degree of membership [18]. This technique preserves lot of information from the original image than other segmentation methods. K-means and the Fuzzy C-Means are two successful region-based approaches. FCM can be obtained from the k-means algorithm by a little modification [20].

The algorithm is an iterative clustering technique that produce an optimal c partition by minimizing the weighted within group sum of squared error objective function H

\[ H = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^q d^2(x_i, v_k) \]  

where \( X = \{x_1, x_2, \ldots, x_n\} \) is the data set in the p-dimensional vector space, \( n \) is the number of data items, \( c \) is the number of clusters with \( 2 \leq c < n \), cluster centre \( v_i \), \( u_{ik} \) is the degree of membership of \( x_i \) in the \( i \text{th} \) cluster, \( v_i \) is the prototype of the centre of cluster \( i \), \( q \) is a weighting exponent on each fuzzy membership and \( d^2(x_i, v_k) \) is a distance measure between object \( x_i \). A solution of the object function \( H \) (2) can be obtained through an iterative process [23]. The following steps can be employed to find the object function:

- Select a number of clusters
- Assign indiscriminately to each point coefficients
- Repeat until the algorithm has meet at a point
- Determine the centroid for all cluster
- Compute each point coefficients of being in the clusters

**C. Feature extraction**

From the segmented region, features are extracted. Extracted features consist of standard deviation, mean, energy, entropy and homogeneity. The features show distinct variation

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Fig 1. Block diagram of hard exudates detection

In a dataset, a desired number of clusters K and a set of k initial starting points, the desired number of distinct clusters and their centroids are found by the K-Means clustering algorithm. A centroid is the point whose co-ordinates are obtained by means of computing the average of each of the co-ordinates of the points of samples assigned to the clusters.
between normal and abnormal images and it is given as input to classifier.

D. Classification using relevance vector machine

A relevance vector machine (RVM) is a machine learning technique that uses Bayesian inference to obtain parsimonious solutions for regression and probabilistic classification. Relevance vector machine (RVM) can provide probabilistic interpretation of the output of relevance vector machine, which can be developed for multi-class classification. The idea of RVM is that the input data are mapped to a high-dimensional feature space by kernel function. Relevance vector machine starts with the input vector and their corresponding outputs. Given a set of data \( \{ x_i, y_i \}_{i=1}^n \) where \( x_i \) is the input vector and \( y_i \) is their corresponding outputs.

The output of RVM is described by:

\[
y(x) = \sum_{i=1}^{n} \omega_i k(x, x_i) + \omega_0
\]

(1)

Where \( \omega = [\omega_0, \omega_1, \ldots, \omega_n] \) represents the weight vector, \( k(x; x_i) \) represents the kernel function. In RVM, Gaussian kernel is used as the encountered kernel, which is expressed as followings:

\[
k(x, x_i) = \exp\left[-\frac{||x-x_i||^2}{2\sigma^2}\right]
\]

(2)

Where \( \sigma \) represents the width of Gaussian kernel. RVM produces probabilistic predictions and it can be applied to general functions and not only to kernel functions (2). The likelihood of the dataset can be expressed as followings:

\[
p(y|\omega, \sigma^2) = (2\pi\sigma^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma^2}||y-\rho||^2\right]
\]

(3)

Where \( \rho(x) = [1, k(x, x_1), k(x, x_2), \ldots, k(x, x_n)] \)

RVMs use expectation maximization (EM)-like learning method and are therefore at risk of local minima. An explicit prior probability distribution over the weights to improve the generalization ability of RVM model, which is expressed as followings:

\[
p(\omega|a) = \prod_{i=1}^{n} N(\omega_i|0, a_i^{-1})
\]

(4)

Relevance vector machine (RVM) is a machine learning technique that uses Bayesian interface to obtain parsimonious solutions for regression and classification. The RVM has an identical functional form to the support vector machine, but provides probabilistic classification (4). It is actually equivalent to a Gaussian process model with covariance function.

Where \( a \) represents a hyper-parameter vector. Thus, the classifier function of relevance vector machine can be expressed as followings:

\[
y(x) = \rho'(x)(\sum_{i=1}^{n} a_i \rho(x_i))
\]

(5)

RVM is a classification method that uses a Bayesian model to minimize classification errors without requiring a statistical model. By mapping data into a higher dimensional space, RVM (1) can use a hyperplanar boundary to separate data that might be poorly separated by a hyperplanar boundary in the original lower-dimensional space. RVM (5) finds a hyperplane that maximizes the distance between a sparse selection of examples of healthy and glaucomatous eyes that are difficult to classify. The internal parameters successively self-adjust against a pre-defined gold standard until the classification performance no longer improves.

The RVM classifier trained on optimized combinations of structural and functional parameters differentiated between glaucomatous and non-glaucomatous eyes better than the RVM trained on functional parameters alone and structural parameters alone. These results were obtained in a study designed to minimize classification bias. Backward elimination optimization identified a near-optimal smaller set of features that can be used to classify healthy and glaucomatous eyes. Advantage of the RVM classifier is its standard formulation as a probabilistic generalized linear model.

III. RESULTS AND DISCUSSION

Figure 2 shows the result obtained using k-means and fuzzy c-means clustering methods. The retinal images are segmented and each image is characterized by its corresponding segmented region. Extracted regions are discriminated as exudates or non-exudates. Figure 2(a) shows the grayscale of the input images. Figure 2 (b) shows the preprocessed input images.

This is accomplished by extracting a set of features for each region and then the regions are classified based on the generated feature vectors. Figure 2(c) shows the exudates detection of retinal fundus images using artificial intelligence technique based clustering segmentation. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When perform analysis of complex data one of the major problems stems from the number of variables involved. Figure 2(d) shows the segmentation of hard exudates using FCM clustering technique.
Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Statistical features for the hard exudates and their values have been determined and given in the table 1.

The mean is the average value which defines the general brightness of the image. The standard deviation is known as the square root of the variance and defines the contrast. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. The energy measures something about how gray levels are distributed. Homogeneity returns a value that measures the closeness of the distribution of elements in the gray level. Table 1 contains the feature extraction of normal and abnormal images using k means clustering. Table 2 contains the feature extraction of normal and abnormal images using fuzzy c-means clustering.

The difference between the feature extraction of normal and abnormal image values using FCM clustering are higher than the feature extraction of image values using K-means clustering. The quality of the end result of the clustering method depends on the initial set of clusters. The reasons for the popularity of k-means are ease and, speed of convergence, simplicity of implementation scalability and adaptability to sparse data.

Feature sets play one of the most important roles in a detection system. A best feature set should signify characteristic of a class that helps distinguish it from other classes.

### TABLE 1. FEATURE EXTRACTION OF NORMAL AND ABNORMAL IMAGES USING FCM

<table>
<thead>
<tr>
<th>Features</th>
<th>Normal image values</th>
<th>Abnormal image values</th>
<th>Differences</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entropy</td>
<td>0.010832</td>
<td>0.010367</td>
<td>0.000465</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.718685</td>
<td>0.725455</td>
<td>0.006787</td>
</tr>
<tr>
<td>Energy</td>
<td>0.992693</td>
<td>1</td>
<td>0.007307</td>
</tr>
<tr>
<td>Mean</td>
<td>0.004666</td>
<td>0.003956</td>
<td>0.000709</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.230728</td>
<td>0.341111</td>
<td>0.105382</td>
</tr>
</tbody>
</table>

### TABLE 2. FEATURE EXTRACTION OF NORMAL AND ABNORMAL IMAGES USING K-MEANS

<table>
<thead>
<tr>
<th>Features</th>
<th>Normal image values</th>
<th>Abnormal image values</th>
<th>Differences</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entropy</td>
<td>0.01247</td>
<td>0.012523</td>
<td>0.000053</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.72245</td>
<td>0.726656</td>
<td>0.004206</td>
</tr>
<tr>
<td>Energy</td>
<td>0.999469</td>
<td>1</td>
<td>0.000531</td>
</tr>
<tr>
<td>Mean</td>
<td>0.004732</td>
<td>0.004801</td>
<td>0.000078</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.279445</td>
<td>0.301971</td>
<td>0.022526</td>
</tr>
</tbody>
</table>

A patient was classified as abnormal if the presence of exudates is found else it is classified as normal. This relevance vector machine classifier has a sensitivity of 85.8%, specificity of 93% and accuracy of 91.95% from the calculation of true positive, false positive, true negative and false negative. Specificity was always high because the number of true negatives was much higher than the number of false positives. The positive predictive value was regarded as a more informative measure. The relevance vector machine classifier is not very sensitive to outliers in training data and easy to set parameters. It offers an experimental method for detecting variable intersections.
IV. CONCLUSION

In this work exudates are extracted and classified using two clustering techniques and RVM classifier. Results show that FCM produces close results to K-Means clustering but from the obtained results the FCM algorithm is better than K-Means algorithm. The relevance vector machine classifier produces good classification of abnormalities. Accuracy is found to be 91.95%. Hence this framework could be used to assist the ophthalmologist to grade the retinal diseases.

REFERENCES
