

Detection of Exudates in Retinal Images using Support Vector Machine

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Abstract - Diabetic retinopathy (DR) is a micro vascular complication of long-term diabetes and it is the major cause of visual impairment because of changes in blood vessels of the retina. The presence of exudates is one of the primitive signs of DR and the detection of these exudates in the first step in automated screening for DR. Hence, exudates detection becomes a significant diagnostic task, in which digital retinal imaging plays a vital role. Exudates are yellow white lesions with relatively distinct margins.

This paper presents detection of exudates in retinal images using Support Vector Machine (SVM). The input retinal image is pre-processed using median filter and Adaptive histogram equalization technique. The pre-processed image is segmented using K-means clustering algorithm. Exudates are normally detected by their high gray level variations and we have used Support Vector Machine to perform this task. The performance of the algorithm has been prospectively tested by using DIARETDB1 database.

Keywords—Diabetic Retinopathy, Exudates, GLCM, K-means clustering, Support Vector Machine.

1. INTRODUCTION

Diabetic Retinopathy is the common retinal complication associated with diabetes. It is a major cause of blindness in both middle and advanced age groups. DR is not painful and hence visual loss is often symptom, when treatment becomes less effective. If it is diagnosed at an early and still asymptomatic stage, laser photocoagulation is one of the effective treatments which prevent visual loss from macular oedema. The International Diabetes Federation reports that over 50 million people in India have this disease and it is growing rapidly. Therefore regular screening is the most efficient way of reducing the vision loss. Before the development of computer aided diagnostic tool various methods have been introduced. Retinal image analysis – concepts, application and potential [1] by N. Patton et al. in 2006, they have used matched filter, morphological

processing and neural network, it is unclear from current studies whether the detection of retinal micro vascular changes has additional predictive value. Automated system was proposed by Abramoff et al. [2] in the year 2008, in which set of optimally adjusted morphological operators were used and thresholding operation was applied. In the year 2010 the author named M. Cree et al. published paper on automated screening of Diabetic Retinopathy [3] in which non – mydriatic digital color fundus cameras were used to capture color images of the retina and these retinal images are examined to detect the presence of exudates. In the year 2012 Yazid et al. [4] have applied an inverse surface thresholding technique for the automated detection of exudates from color fundus images. In the same year Harangi [5] have identified the regions containing exudates in retinal images by using grey scale morphology and then active contour based method was used to extract the precise borders of the candidates. In this paper, we review the suitable tool and method for segmenting high resolution retinal images. The proposed method involve K-means clustering algorithm based segmentation and classification using SVM.

2. BLOCK DIAGRAM

Detection of exudates in the retinal images by using Support Vector Machine (SVM) involves the following blocks as mentioned in Figure 1. The input retinal image from the database is fed to the pre-processing block to remove the noise and to enhance the contrast of the image then the next step is image segmentation, in which the image is segmented into five clusters. Next the features of the optic disc is extracted and based on SVM classification the result is displayed whether the given retinal image contains exudates or not. In feature extraction Grey Level Co-Occurrence Matrix (GLCM) is used to extract both GLCM and statistical parameters. The GLCM parameters are namely Energy,

Homogeneity, Contrast, Correlation and statistical parameters are Mean and Standard deviation.

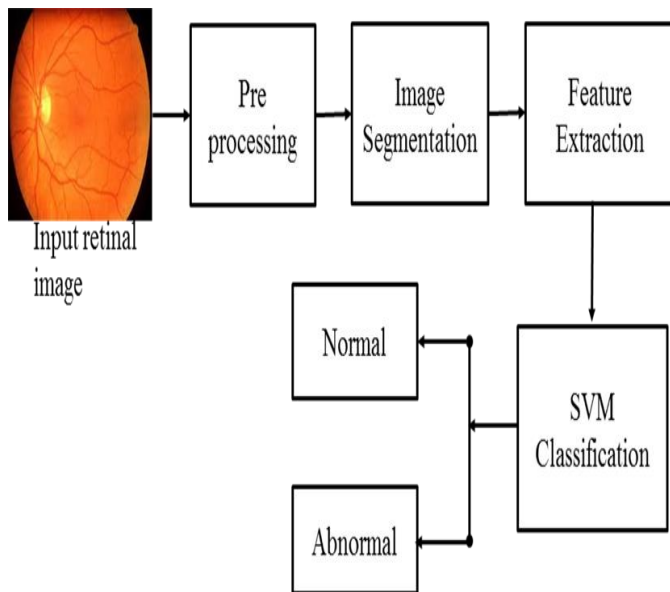


Figure 1: Block Diagram to detect exudates in retinal images

1. Input Retinal Image

The retinal images used to test and evaluate the performance of our system were taken from DR database DIARETDB1. The DIARETDB1 database consists of 89 high quality color fundus images. A fundus camera system (retinal microscope) is usually used for capturing retinal images. Retinal image contains essential diagnostic information which assists in determining whether the retina is healthy or unhealthy.

2. Preprocessing

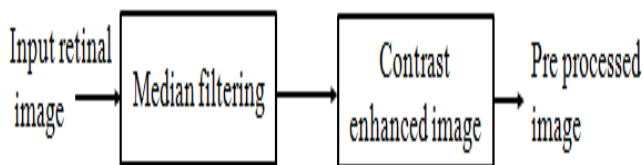


Figure 2: Preprocessing Steps

The main objective of image preprocessing is to remove noise and to enhance the contrast of the input image. It consisting of mainly two blocks Median filtering and Contrast enhanced image as shown in Figure 2.

2.1 Median Filter

The median filter is a nonlinear digital filtering technique, often used to remove noise. It only removes noise and preserves the edges [6]. In order to uniformly distribute the intensity throughout the image, the I-component of HSI color space is extracted and filtered out through a 2D median filter. Normally, instead of replacing the pixel value with the mean of neighboring pixel values, median filter replaces it with the median of those values. That is, the values from the surrounding neighborhood are first sorted numerical order, and then the value of the pixel in input is replaced with the middle (median) pixel value.

2.2 Contrast enhancement image

The retinal images captured by using fundus cameras might be of low contrast and with non-uniform illumination & their contrast must be enhanced before using them for exudates detection. Adaptive Histogram Equalization method is used for contrast enhancement.

3. Segmentation

Image segmentation is the process of partitioning of an image into meaningful regions. The K-mean algorithm can be used to segment the image into clusters. The K-means is a simple algorithm for segmenting or classifying images into k different clusters based on feature, attribute or intensity value [7, 8]. Unlike local thresholding, which can only group into two main classes while K-mean Algorithm can group into k different classes and that is part of the reason why we chosen as segmentation method for this work.

Algorithm

1. Give the no of cluster value as k.
2. Randomly choose the k cluster centers.
3. Calculate mean or center of the cluster.
4. Calculate the distance b/w each pixel to each cluster center.
5. If the distance is nearer to the center then move to that cluster.
6. Otherwise move to next cluster.
7. Re-estimate the center.
8. Repeat the process until the center doesn't move.

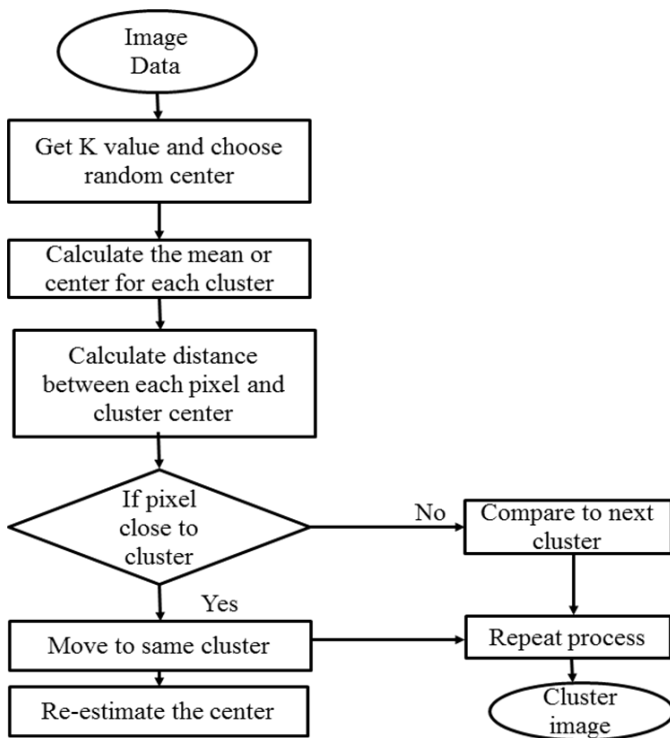


Figure 3: Flowchart for Segmentation.

4. Feature Extraction

Feature extraction techniques are applied to get features that will be useful in classifying and recognition of images [9]. An input retinal image after segmentation has to be classified into exudates or normal based on number of features which are extracted using Gray Level Co-occurrence Matrix (GLCM) and Stastical features.

4.1 Gray Level Co-Occurrence Matrix (GLCM)

GLCM Create gray-level co-occurrence matrix from image, GLCM is a tabulation of how often different combination of pixel brightness values occur in a pixel pair in an image. Each element (a, b) in GLCM specifies the number of times that the pixel with value 'a' occurred horizontally adjacent to a pixel with value 'b'. Graycomatrix calculates the GLCM from a scaled version of the image. By default, if it is a binary image, scales the image to two grey-levels. If it is an intensity image, graycomatrix scales the image to eight gray-levels. GLCMs can derive several parameters from them using the graycoprops function.

Contrast: Contrast is a measure of the intensity contrast between a pixel and its neighbor over the whole image. Contrast is given by:

$$\sum_{i,j} |i - j|^2 P(i, j) \quad (1)$$

Energy: Energy returns the sum of squared elements in the GLCM. Energy is 1 for a constant image.

Energy is given by:

$$\sum_{i,j} P(i, j)^2 \quad (2)$$

Homogeneity: Homogeneity returns a value that measures the closeness of the distribution of elements in the GLCM diagonal. Homogeneity is given by:

$$\sum_{i,j} \frac{P(i,j)}{1+|i-j|} \quad (3)$$

Correlation: correlation returns a measure of how correlated a pixel is to its neighbor over the whole image.

Correlation is given by:

$$\sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j} \quad (4)$$

4.2 Stastical Features

Mean: Mean is an average or mean value of array. If A is a matrix, then mean (A) returns a row vector containing the mean of each column.

The mean is defined as

$$\mu = \frac{1}{N} \sum_{i=1}^N A_i \quad (5)$$

Standard deviation: The standard deviation is the square root of the variance. If A is a matrix whose columns are random variables and whose rows are observations, then S is a row vector containing the standard deviations corresponding to each column.

The standard deviation is defined as

$$S = \sqrt{\frac{1}{N-1} \sum_{i=1}^N |A_i - \mu|^2} \quad (6)$$

Where μ is the mean of A:

$$\mu = \frac{1}{N} \sum_{i=1}^N A_i$$

5. Support vector machine

“Support Vector Machine” (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problem [10]. Support vector machine (SVM) is a supervised learning model with an associated learning

algorithm that can analyse data and recognize patterns which are then used for regression analysis and classification. If we take a set of training examples, where each is marked as belonging to one of two defined categories, an SVM training algorithm will build up a model that will assign new examples to one or the other category, making it non-probabilistic binary linear classifier.

It has two advantages: Firstly, it has the ability to generate non-linear decision boundaries using those methods which are designed for linear classifiers. Secondly, use of kernel functions will allow the user to apply classifier to the data that have no defined fixed-dimensional vector space representation.

In the below Figure. 4 training stage consists of training image set, SVM and a trained model. In the training image set color retinal images will be provided to SVM for training. By using polynomial kernel SVM does feature extraction of images and it builds up a trained model.

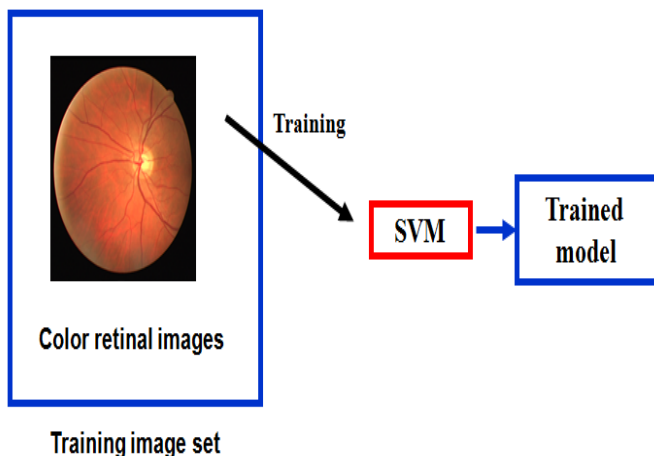


Figure 4: Training Stage

Figure. 5 shows the classification of retinal image using SVM. In the above Figure 4, retinal image is segmented using k-means algorithm. In the segmented output fifth cluster is chosen and fed to the SVM trained model. SVM trained model compares the features of the test image with the stored values and gives the output as normal or exudates.

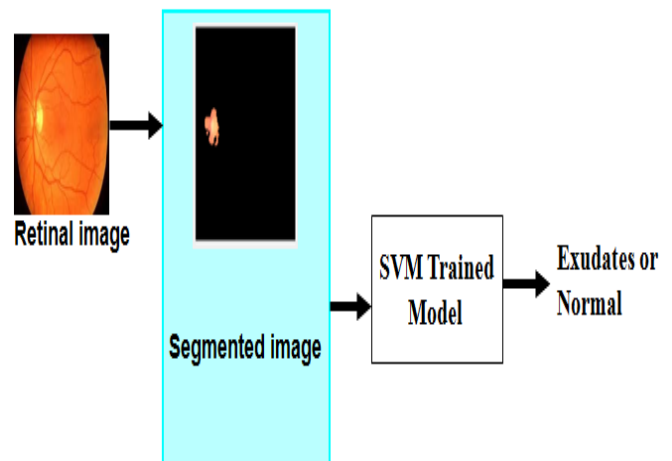


Figure 5: Classification of retinal image

3. RESULTS AND DISCUSSION

In this area, we have proposed a method to automatically detect exudates from images taken from diabetic patients with non-dilated pupils. The work is based on the K-means clustering segmentation and SVM technique. Six input features are extracted, based on the characteristics of exudates, namely Mean, Standard deviation, Energy, Homogeneity, Contrast and Correlation.

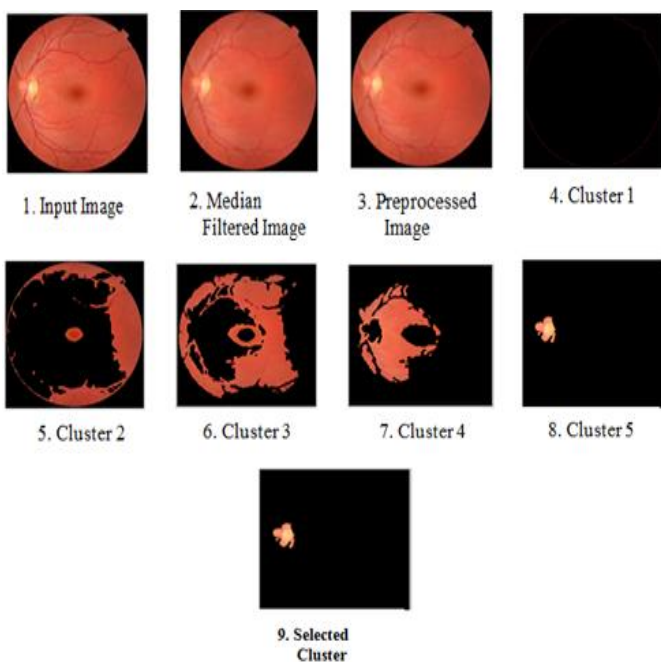
Table - 1: Performance Evaluation for existing system

| Parameters | Image Type | |
|--------------------|------------|----------|
| | Normal | Exudates |
| Mean | 88.0724 | 57.7392 |
| Standard Deviation | 74.3694 | 32.7949 |
| Energy | 0.31922 | 0.45077 |
| Homogeneity | 0.97783 | 0.98514 |
| Contrast | 0.045719 | 0.030515 |
| Correlation | 0.99536 | 0.98112 |
| Accuracy | 99.8186 | 99.908 |
| Precision | 99.5552 | 80.8993 |
| Sensitivity | 100 | 100 |
| Specificity | 99.6946 | 99.9076 |

Table – 2: Comparison of proposed Stastical measures with existing system

| Models | Sensitivi ty | Specificali ty | Accurac y | Precisi on |
|------------------------------------|-----------------|-------------------|--------------|---------------|
| Probabilistic Neural network (PNN) | 91 | 87 | 89.6 | - |
| Color Histogram (Thresholding) | 99 | 98 | 98.9 | - |
| Support Vector Machine (SVM) | 100 | 99.80 | 99.86 | 90.22 |

Initially the retinal image is made on to preprocessing (median filter and contrast enhancement) method. Then the preprocessed retinal image is converted to l^*a^*b color space. The color component of the image is extracted. It is then applied to the K-means clustering algorithm, which results in five clusters. Since Optic Disc and Exudates are homogenous in color, cluster containing Optic Disc is selected for feature extraction. Based on the feature extracted using GLCM, the SVM is trained for normal and abnormal images. Finally, image is classified as exudates are normal using SVM.



4. CONCLUSION

An efficient algorithm for the detection and segmentation of the exudates from the retinal images, which plays an important role in the diagnosis of DR, has been presented in this paper. In this work, a novel technique is presented, which automatically detects the exudates from the DR patients. This system will be incredibly useful in developing countries, where the availability of ophthalmologists is inadequate to treat more DR patients, thereby significantly reducing their work load. Ophthalmologists can make use of the system as a preliminary diagnosis tool in their DR screening procedure, which helps them to diagnose the symptom more accurately and quickly. Optic Disc has been distinguished utilizing the K-means segmentation algorithm from the fundus picture input. GLCM and Stastical feature have been extracted.

Exudates are only lipo protein spillages in diabetic retinopathy. Adaptive Histogram Equalization is utilized to improve the low difference computerized fundus picture. The contrast improved picture is divided utilizing K-means grouping, which is one of the least difficult unsupervised learning calculations for picture division. The diabetic retinopathy pictures were gathered from publically accessible DIRETDB1 site. To classify the segmented picture into exudates and normal, and arrangement of components in light of composition and shading or removed utilizing Gray Level Co-Occurrence matrix (GLCM). The chosen elements are grouped into exudates and normal utilizing Support Vector Machine (SVM) classifier. The results obtained while evaluating our system proves itself that computer-based retinal image analysis is the most powerful tool to detect exudates and diagnose DR easily in the early stages. The results obtained while evaluating our system proves itself that computer-based retinal image analysis is the most powerful tool to detect exudates and diagnose DR easily in the early stages.

5. FUTURE WORK

In medical image processing, automatic diagnosis of DR from digital fundus images has been a dynamic research for a long time. Because of the expanding predominance of diabetes mellitus, demand for diabetic retinopathy screening stages is steeply expanding. Early location and treatment of DR are essential public health intercessions that can incredibly diminish the probability of vision loss. In addition to this exudates detection, inclusion of retinal blood vessel segmentation can facilitate ophthalmologists to make earlier decisions on laser treatment. As the existing systems are

quite slow in operation, a real time implementation of screening system can provide the better performance. For such implementation on real time platform DSPs or FPGAs can be preferred as it can provide the advanced results for the detection of Diabetic Retinopathy. Such screening systems for the detection of different stages of diabetic retinopathy mainly benefit affected patients from rural areas who are mostly unaware of the presence of the diabetic retinopathy.

REFERENCES

- [1] Patton, N., Aslam, T.M., MacGillivray, T., et al.: "Retinal image analysis: concepts, applications and potential", *prog. Retin. Eye res.*, 2006, 25, (1), pp. 99-127.
- [2] Abramoff, M.D., Niemeijer, M., Suttorp- Schulten, M.S.A., Viergever, M.A., Russel, S.R., Ginneken, B.: "Evaluation of a system for automatic detection of diabetic retinopathy from color fundus photographs in a large population of patients with diabetes", *diabetes care*, 2008, 31, (2), pp. 193-198.
- [3] Niemeijer, M., Ginneken, B.V., Cree, M.J., et al.: "Retinopathy online challenge: automatic detection of microaneurysms in digital color fundus photographs", *IEEE Trans. Med. Imagine*, 2010, 29, (1), pp. 185-195.
- [4] Yazid, H., Arof, H., Isa, H.M.: "Automated identification of exudates and optic disc based on inverse surface thresholding", *J. Med. Syst.*, 2012, 36, pp. 1997-2004.
- [5] Harangi, B., Lazar, I., Hajdu, A.: "Automatic exudate detection using active contour model and region wise classification". *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, 2012, pp. 5951-5954.
- [6] Kwame Osei Boateng, Benjamin Weyori Asubam., and David Sanka Laar., "Improving the Effectiveness of the Median Filter", ISSN 0974-2166 Volume 5, Number1 (2012), pp. 85-97.
- [7] Thomas Walter and Jean-Claude Klein "Segmentation of color fundus image of the human; Detection of the optic disk and the vascular tree using morphological techniques"; LNCS Vol. 2199 p. 282-287, Springer-Verlag October 9-11, 2001.
- [8] Ricci.E, Perfetti, R., "Retinal Blood vessel segmentation using Line operators and Support Vector Classification" *IEEE Transactions on medical imaging*, vol. 28, no. 5, pp. 775-785, March 2009.
- [9] Huiqili, Chutatape. O., "Automated feature extraction in color retinal images by a model based approach", *IEEE Transactions on Bio-Medical Engineering*, Vol. 51, No. 2, pp. 246-254, February 2004.
- [10] Durgesh K. Srivastava, and L. Bhambhu, "Data Classification Using Support Vector Machine," *Journal of Theoretical and Applied Information Technology*, vol. 12, no.1, 2009.