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Computer Aided Diagnosis (CAD) of Bright Lesion Detection in Fundus Images

[*]V. Ratna Bhargavi[1], Dr.V.Rajesh[2], P.Satyanarayana[3] ,Vadlani Dinesh[4], Alla Sasi Kanth[5], Mankina Sowmya[6], Naraharisetty Jaswanth[7]
[1]Research Scholar, [3] Assoc. Prof, [4,5,6,7] B. Tech Students
[2]Principal, Usha Rama College of Engineering, Telaprolu, Vijayawada, A.P-521109
[1, 3, 4, 5, 6, 7] K L University, Vaddeswaram, Guntur Dt., Andhra Pradesh 522502, India

Abstract

Diabetes mellitus will lead to vision loss that is the retina gets damaged. Often diabetic retinopathy has no early warning signs. For early detection and treatment the screening program will help a lot. Early symptoms of this disease are exudates, so early diagnosis and treatment at right time is very important to prevent blindness. In this paper our idea lies in the use of Block Variation of Local Correlation Coefficients (BVLC) and Block Difference of Inverse Probabilities (BDIP) texture features to characterize detected lesions using Active Contour technique (ACT). Then, Support Vector Machine (SVM) classifier is utilized to classify the detected lesions and the accuracy obtained is about 96.6%, Mathew correlation coefficient is about 0.972 and fisher score is about 0.9625.From these techniques we can reduce false positives for the detection of bright lesions in Fundus images.

Keywords: Bright Lesions; Block Variation of Local Correlation Coefficients (BVLC); Support Vector machine (SVM); false positives.

Introduction

Diabetic retinopathy is a complication of diabetes that affects the eyes. It is created by harm to the veins of the light-delicate tissue at the back of the eye (retina). Right away, diabetic retinopathy may cause no side effects or just gentle vision issues. In the long run, diabetic retinopathy can bring about visual deficiency [1].

The more extended a man has diabetes, and the less controlled his sugar is, the more probable he is to develop Diabetic retinopathy. Regardless of these threatening insights, research indicates that not less than 90% of these new cases could be lessened if there were legitimate and vigilant treatment and checking of the eyes. The more extended a man has diabetes, the higher his or her risks of increasing diabetic retinopathy [2]

At present, 40.9 million Indians are estimated to have diabetes. By 2025, this count would be around 69.9 million, and 85 million by 2030. Many people diabetes in India these days are being affected by diabetes as early as 25 years of age [3]. Increasing number of cases of diabetes is being seen in rural areas of India.

In this paper, we propose an alternative way to perform false positive reduction using moment features of the detected RoIs. Region of interest is detected with the help of the Active Contour Method [5]. Our idea is inspired by the recent work in which Block Variance of Local Correlation Coefficients (BVLC) features are applied successfully to the early detection of tumours in retina. Once the BVLC features are extracted, Support Vector Machine (SVM) is used as pattern classifier [4].

We experiment the proposed method on a dataset of about 500 RoIs that are detected from the Diabetic Retinopathy Database. The obtained results demonstrate the effectiveness and efficiency of our approach. To our knowledge, this is the first attempt to use BVLC features in the field of bright lesions detection in retinopathy [4].

Materials and Methods

Region of Interest detection using Active Contour Technique (ACT)

Before the feature extraction, the RoI is determined with the help of active contour technique (ACT) and the essential thought of ACT is to develop a bend under a few limitations to extract the desired object[5,6] and for acquiring the curve a standard Signed Pressure Force (SPF) function is used. This Function can more appropriately end the contours at feeble or obscured edges. The Region of Interests i.e., the exudated regions in abnormal Fundus image is detected using the above mentioned method (Fig.1). The radiologists have to focus their attention to these extracted regions. The steps of the procedure is explained in the below block diagram. Detected RoIs are marked as true positive RoIs (TP-RoIs) or false positive RoIs (FP-RoIs) based on the ground truth provided in the Diabetic Retinopathy Database. There are about 500 detected RoIs.

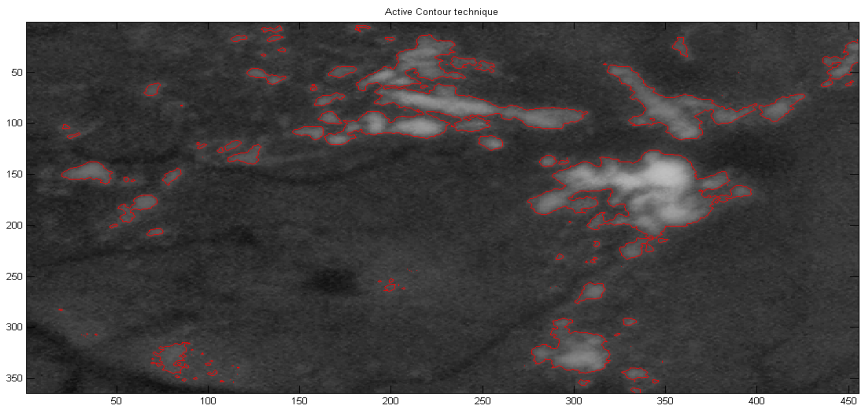
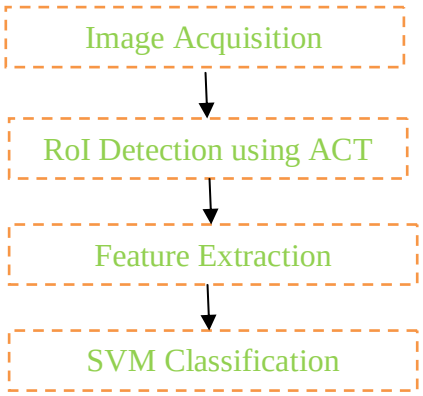


Figure 1: Active Contour Technique applied for abnormal Fundus image.

Block Diagram



Feature extraction

BVLC:

Each detected RoI is characterized by a set of features that is formed using BVLC features. The computation of BVLC starts from correlation coefficients in a local region, which are characterized in the following way:

$$\rho(g,h,c) = 1/(\sigma(g,h) * (\sigma(g,h) + c))X[\frac{1}{R(g,h)}X\sum(p,q)€(g,h)I(g,h) * (I(g,h) + c) - \mu(g,h) * \mu(g,h) + c)]$$

Where *c* signifies a shifting orientation and $\mu(g,h)$ and $\sigma(g,h)$are the mean and standard deviation in a local region *R (*g,h*)*, respectively. The terms $\mu(g,h) + c)$ and $\sigma(g,h) + c)$ are the mean and standard deviation in a local region shifted by *c* from *(*g,h*)*, respectively.

BVLC is then defined as

BVLC (g,h) =max [$\rho(g,h,c)$]-min [$\rho(g,h,c)$]

r €Ol r €Ol

where *Ol* signifies a set of orientations with *r* of distance *k*. For instance, *Ol* may be picked as *Ol*= {(l, 0), (0, l), (0, l), (l, 0)}. The value of BVLC is determined as the difference between the maximum and minimum values of the local correlation coefficients according to orientations [4]. The higher the level of roughness in the local region is, the bigger the value of BVLC.

BDIP:

The distinction of inverse probabilities (DIP) is an operator for separating sketch features that contain valleys and edges subject to nearby intensities. In the DIP, the proportion of pixel intensity in a picture window to the total of all pixel intensities in a window is considered as Likelihood. In this way, the name DIP implies the difference between the inverse of the probability for the center pixel in a window and that for the pixel of maximum intensity in the window. BDIP, which is one of the proposed texture features, is a block-based version of the DIP. It is characterized as the

difference between the number of pixels in a block and the ratio of the sum of pixel intensities in the block to the maximum in the block. That is

$$BDIP=M^2 - [\sum_{(g,h)\,€B} I(g,h) / \max_{(g,h)€B} I(g,h)]$$

Where I(g,h) denotes the intensity of a pixel(g,h) and B a block of size MxM. The larger the variation of intensities there is in a block, the higher the value of BDIP.

Classification by SVM

In this paper, Support Vector Machine (SVM) is utilized to classify the images into normal and anomalous. The images with lesions are anomalous and pictures without lesions are normal. The fundamental operation of binary SVM is by discovering the hyper-plane that best divides vectors from both classes in feature space in the meantime augmenting the separation from every class to the hyper plane. It incorporates both straight and nonlinear methods for this hyper plane creation [7]. In the event that the two classes are linearly separable, SVM processes the ideal dividing hyper-plane with the maximum margin by minimizing the objective function $\|w\|^2$ subject to:

$$(xi * w + b)\, yi \geq 1,$$

Since SVM is a linear classifier, it has it impediment when a non-linear classification is required. To overcome this Kernel functions can be utilized as a solution for nonlinear limits problems.SVM has 2 sets namely Training set and the Testing set and with the help of these it classifies the data into normal and abnormal images, making the SVM a non- probabilistic binary linear classifier. Given a set of training samples, each marked as belonging to one of two categories, a SVM training algorithm manufactures a model that allots new samples into one class or the other. A SVM model is a representation of the examples as points in space, mapped so that the samples of the different categories are divided by a clear gap that is as wide as could be allowed. New samples are then mapped into that same space and anticipated to belong to a category based on which side of the gap they fall on [7].

Results

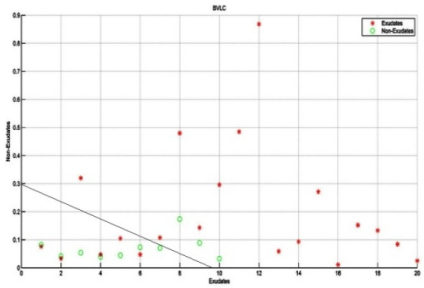


Figure 1: BVLC 2x2 feature values

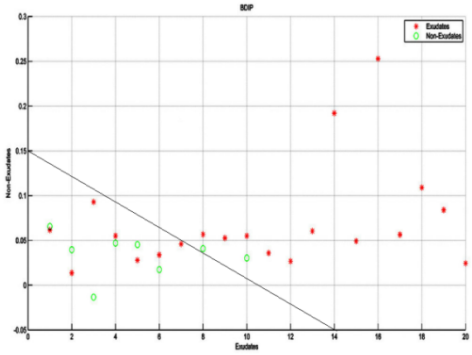


Figure 2: BDIP 2x2 feature values

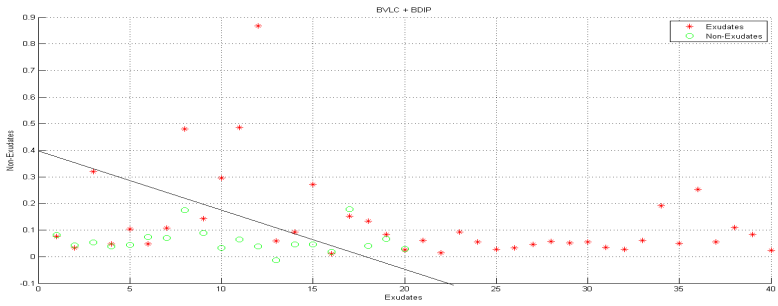


Figure 3: BVLC + BDIP 2x2 Feature Values

The accuracy value (ACC) to estimate the performance of classification process is given by

Specificity = TN / (TN + FP)

Sensitivity = TP / (TP + FN)

ACC = [(TP +TN) / (TP +FP +TN +FN)] x100%.

Where

True positive (TP): Sick individuals effectively diagnosed as sick

False positive (FP): Healthy individuals erroneously distinguished as sick

True negative (TN): Healthy individuals effectively recognized as healthy

False negative (FN): Sick individuals mistakenly distinguished as healthy

To improve the accuracy further, the feature values are normalised using the formula

$N_{xy} = F_{xy} – \min(F_{xy}) / \max(F_{xy})_{– \min(}F_{xy})$

Table 1: Sensitivity, Specificity and Accuracy values with various feature extraction techniques

Feature extraction technique	Sensitivity (%)	Specificity (%)	Accuracy (%)
BVLC	95.23	94.77	95.0
BDIP	95	90	93.33
BVLC + BDIP	95.23	100	96.66
BVLC + BDIP + Normalization	100	94.2	97.1

Previous work	Accuracy (%)
K. Deepak[25]	96
A. Rocha[26]	95.3
Ramon Pires [27]	93.4
Our Proposed Method	97.1

Conclusions

In this paper, we have approached an efficient technique to reduce false positives in abnormal Fundus images based on BVLC and BDIP features and SVM. Experiments have shown that normalized BVLC+ BDIP features are effective and efficient descriptors for bright lesions in Fundus images. In comparison with other descriptors, combining BVLC features with BDIP features also provide better and more constant results.

In the future, combining the above features with other efficient techniques will be investigated. Also better performing classifiers will be studied.

Acknowledgment

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Author Profile:

Vadlani.Dinesh was born in India, A.P, in 1993. He is pursuing his B.Tech in Electronics and Communication Engineering from K L University. He is getting his specialization in Networking. He is member of IETE. His interest in research includes Signal Processing and antennas. At present, he is engaged in Bio-medical Image analysis.

Alla Sasi Kanth was born in India, A.P, in 1993. He is pursuing his B.Tech in Electronics and Communication Engineering from K L University. He is getting his specialization in Signal Processing. He is member of IETE. His interest in research includes antennas and image processing.

Mankina Sowmya was born in India, A.P, in 1993. She is pursuing her B.Tech in Electronics and Communication Engineering from K L University. She is getting her specialization in Signal Processing. She is member of IETE. Her interest in research includes antennas.

Naraharisetty Jaswanth was born in India, A.P, in 1993. He is pursuing his B.Tech in Electronics and Communication Engineering from K L University. He is getting his specialization in Signal Processing. He is member of IETE. His interest in research includes antennas and Embedded Systems.