



Analysis of Retinal Fundus Images Exudates Using Texture Based RLBP

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ABSTRACT: Retinal images are used for diagnose eye diseases such as diabetic retinopathy, glaucoma and macular degeneration. Automatic diagnosis must be robust enough to establish the disease's existence and to classify it. The performance of automated methods strongly depends on the quality of the images. Factors such as operating personnel's level of experience, patient head or eye movement and blinking can significantly influence the quality of retinal fundus images. Photos of poor quality might lead to incorrect diagnosis of eye disease and the grading of its severity. Major factors that reduce image quality include uneven illumination, poor contrast, blurriness and poor visibility of important components such as the macula and optic disc. So in order to classify or detection of these diseases with more accuracy, retinal image need to be enhanced first. Existed literature did not carried out contrast improvements it takes LBP features of original images.

KEYWORDS:Exudates ,RLBP ,k-Nearest Neighbour , ANN , Feature Extraction.

I. INTRODUCTION

Around 300 BC, a Greek physician called Herophilus of Chalcedon was the anatomist who described the retina, but it was named by another physician called Rufos of Ephesus in 110 AD. It seemed to the early anatomists as a container which supports and contains the vitreous. In the second century AD, Galen defined many of the fundamental features of the anatomy and physiology of the eye. He noted structural similarities to the brain; however he was incapable to present further understanding on how the retina functions. The first scientist who suggested that the retina plays a vital role as the primary photoreceptor tissue was Johannes Kepler in the 17th century. In 1835, Treviranus performed the first extensive microscopic retinal researches by using alcohol fixation. With the modern scientific revolution, the subsequent development of electron microscopy, fluorescein angiography, trypsin digestion, and optical coherence tomography have enabled scientists to comprehend the cellular connections within the retina, ultra-structure, and retinal vasculature, and also correlate clinical and anatomical findings (Browning (2010)) [1]. Nowadays, fundus images are used as visual records which document the current ocular fundus of a patient. One fundus image is worth a thousand words in the ophthalmologist's notes. They allow the ophthalmologist to further study a patient's retina and identify retinal changes for more accurate diagnosis.

II. LITERATURE SURVEY

Mohamed Omar et. al. [2] applied a new LBP-based feature extraction technique for the classification. Based on experiments, the system has shown good ability for the detection of abnormalities associated with diabetic retinopathy. Exudates are signs of DR and are not easy to detect due to other normal retinal characteristics with similar features such as contrast, intensity levels, colour and shape. When digital fundus images are captured using cameras with uneven illumination the detection problem becomes even more difficult. However, it has been revealed that LBP texture features offer an efficient solution to overcome these issues.

Roberto Annunziata et. al. [3] presents a new unsupervised vessel segmentation approach. A novel inpainting filter, called neighborhood estimator before filling, is proposed to inpaint exudates in a way that nearby false positives are



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significantly reduced during vessel enhancement. Retinal vascular enhancement is achieved with a multiple-scale Hessian approach.

TraianCaramihaleet. al. [4]proposes a new method for the detection and evaluation of exudates in retinal images. In the learning phase they focus on selecting efficient features that can uniquely identify the exudates. In this process they develop a neural network for image processing. They then further extend and train the neural network to detect and evaluate the exudates. The efficiency of the proposed method is compared with other similar researches, improvements in accuracy being observed.

Qing Liu et. al. [5] presented a location-to-segmentation strategy to segment the exudates in retinal fundus images. It involves three stages. The first stage, i.e. pre-process stage, can provide the visualisation for the main anatomic structures such as the optic disk and the main vessels. In the second stage, the local structure of the exudates is described via CLBP. A random forest classifier is learned to locate the exudate candidates. In third stage, the local variance, exudate size prior and local contrast prior is used to segment the exudate regions from each patch. The proposed method detect sand quantifies the exudate regions, and further facilitates for the ophthalmologists in the diabetic retinopathy screening and diagnosis process. The experimental results on the public exudate detection data set show its superiority both at exudate-level evaluation and image-level evaluation compared to the state-of-the-art method.

III. SCOPE OF RESEARCH

The present research introduces a comparison among two classifiers for EXs detection. These are a K nearest neighbor and neural network classifier: multilayer perceptron (MLP) Hence, the aims of the present study were: (i) to develop an automatic method for the detection of EXs in retinal images, (ii) to compare the performance of two classifiers in this context, (iii) to assess the diagnostic potential of the proposed method in DR detection.

IV. PROPOSED WORK

The system module of the proposed system is shown in Fig 1. The input image is first enhanced by block based using mean and deviation properties from which patches has been obtained for both normal and exudate images. Next a set of features are extracted from each image patch to help discriminate between normal and exudate patches and used to build a Feature vector.



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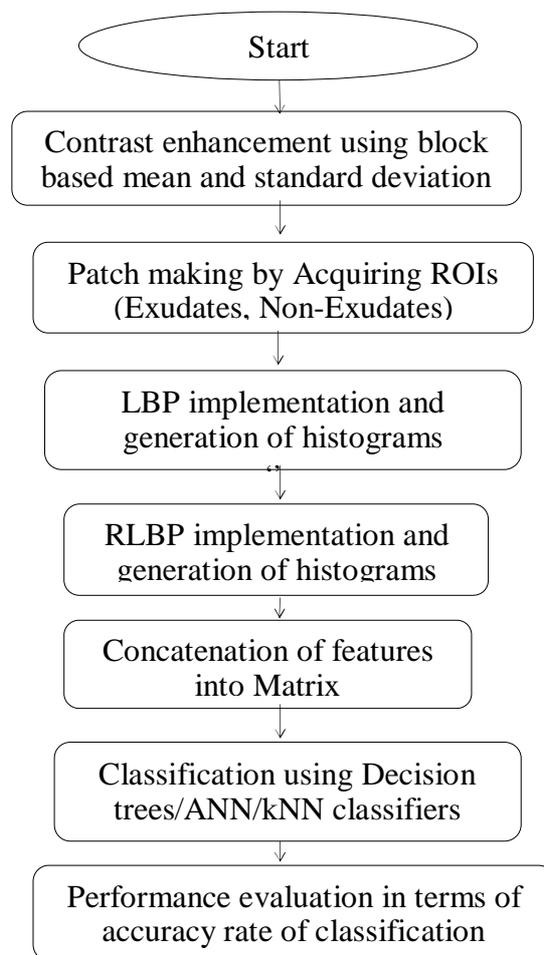


Fig 1: System Module

Given an image feature set, different classifiers are employed to classify the images into normal and exudate image. The steps used are explained above.

• **Image enhancement**

In order to have an effective estimation, we follow the strategy of [6]. Here, the image (green channel) is separated into a set of background and foreground (made up of retinal structures of interest) pixels first. Next, the degradation components are estimated from the background image. This strategy is motivated by the fact that the retinal structures can bias the luminosity component. For instance, the optic disk is a naturally high luminosity zone and the vessels (dark) are a low luminosity zone.

The background pixels are extracted from I using the local mean and standard deviation as follows:

1. For every point on the sampling grid compute the local mean μ and σ within a window of size $w \times w$.
2. Interpolate between the sampling points to obtain $\mu(x, y)$ and $\sigma(x, y)$ for all (x, y) .



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3. Compute the Mahalanobis distance $D(x, y)$ as follows.

$$D(x, y) = \left| \frac{I(x-y) - \mu(x, y)}{\sigma(x, y)} \right| \quad (4.3)$$

Given an image, a pixel is taken to belong to the background if $D(x, y) \leq t$ where t is a fixed threshold. The degradation components are estimated from the background image by computing the local mean and the standard deviation values at every point (x, y) , within a window of size $(w_0 \times w_0)$. The desired contrast component S_M is nothing but the standard deviation and the luminosity component is S_A . Finally, the true image $U(x, y)$ is obtained by applying the point transformation (equation 2) to each pixel of the image.

- **Patch Extraction**

A given image is divided into fixed number of square patches $P(r)$, with r denoting the location with reference to the image origin. Different patches are extracted from both normal images and images having exudates in them.

- **Patch Level Feature Extraction**

Features are derived on each patch $P(r)$ in the image. Since the objective is to retrieve pathologically similar (exudates/normal) images, derived features must discriminate between normal and exudates patches.

- **Local binary patterns for texture evaluation**

The Local Binary Pattern (LBP) operator is an operator that describes the surroundings of a pixel by generating a bit code from the binary derivatives of a pixel. The operator is usually applied to gray scale images and derivative of the intensities.

The LBP operator takes 3×3 surrounding of a pixel and

1. Generates a binary 1 if the neighbor is greater than or equal to the centre.
2. Generates a binary 0 if the neighbor is less than the centre.

The eight neighbours of the centre can then be represented by an 8-bit number.

- **Rotated Local Binary Pattern (RLBP)**

The problem of variations to rotations in LBP arises due to the fixed arrangement of weights. As the weights are aligned in a circular manner, the effect of image rotations can be countered by rotating the weights by the same angle while computing the descriptor. Since the angle of the rotation cannot be known, we propose an adaptive arrangement of weights based on the locally computed reference direction.

The proposed descriptor is computed by rotating the weights with respect to the Dominant Direction; hence, the descriptor is called Rotated Local Binary Pattern (RLBP). Since the dominant direction is taken as the reference in the circular neighbourhood, the weights are assigned with respect to it [7]. Thus, the RLBP operator is defined as



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$$RLBP_{R,P} = \sum_{p=0}^{P-1} s(g_p - g_c) \cdot 2^{\text{mod}(p-D,P)}$$

• Classifiers Testing

We have used three classifiers Artificial neural network, K-nearest neighbor and Decision trees. The classifiers have been trained by training data is now tested that how much they learn to identify an exudate image this is done by giving testing data to the classifiers. The outputs are calculated for all the images present in the testing data and compared with the tag values to evaluate the performance of each classifier respectively.

V. RESULTS

We use MATLAB software to verify the algorithm. MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. The information which is required for further processing on the retinal image may be degraded due to fluctuations of light or proper illumination problem, & the same image capture by camera is known as raw image. For further operations on this image, quality improvement of the same is necessary as hard and soft exudates need to be separated in intensity from the background; that's why preprocessing is essential stage in which mean and standard deviation based on blocks has been used to get the enhanced image. After that patches has been generated by using corresponding binary mask of the retinal images which gives the information regarding the content in the original image. High intensity mask shows the locations where the defected pixels has been found having exudates in them. Square patches have been extracted from whole dataset and feature extraction has been carried out using LBP and RLBP texture algorithms. After that classifiers has been used to classify the dataset into two categories i.e. normal and having exudates.

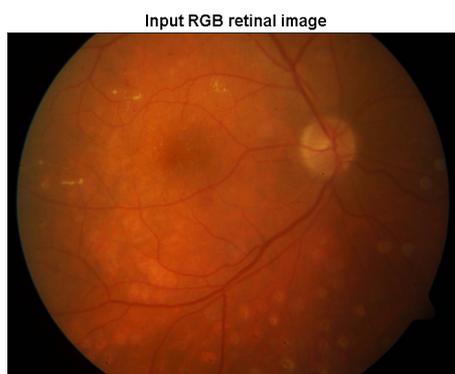


Fig 2: Input retinal RGB image



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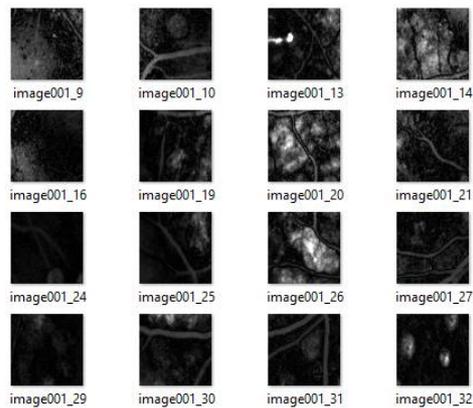


Fig3: Square patches extracted from preprocessed image

- **Classification Accuracy**

The classification accuracy is the extent to which the classifier is able to correctly classify the exemplars and is summarized in the form of confusion matrix to the test data. This is defined as the ratio of the number of correctly classified patterns (TP and TN) to the total number of patterns (species) classified.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Sensitivity**

The sensitivity of a classifier is the fraction of the Plant samples correctly classified as that specific species class. It is defined by equation below :

$$Se = \frac{TP}{TP + FN}$$

- **Specificity**

The specificity is the fraction of normal species correctly classified as normal class. It is also called selectivity.

$$Sp = \frac{TN}{TN + FP}$$

The results for the actual pixel location using ground truth images and that of resulted outputs has been described with above parameters.



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Table1 Results in tabular form using LBP feature extraction

Classifier	Parameters			
	Sensitivity	Specificity	Accuracy	F-factor
ANN Classifier	78.55823	76.50177	77.50678	77.34304
KNN classifier	87.61553	83.21555	85.36585	85.40541
Decision tree classifier	98.52126	96.81979	97.65131	97.61905

Table 2: Results in tabular form using RLBP feature extraction

Classifier	Parameters			
	Sensitivity	Specificity	Accuracy	F-factor
ANN Classifier	78.92791128	88.86925795	84.01084011	82.83220175
KNN classifier	87.6155268	83.2155477	85.36585366	85.40540541
Decision tree classifier	98.52125693	96.81978799	97.65130985	97.61904762

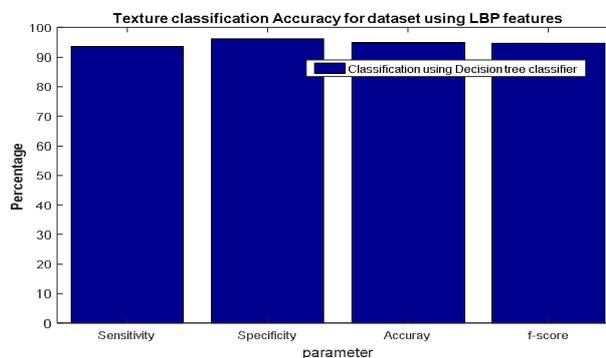


Fig4: Performance evaluation using Decision tree classifier for LBP features

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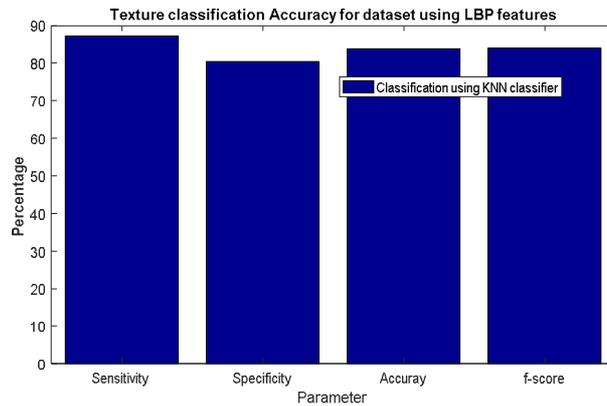


Fig 5: Performance evaluation using KNN classifier for LBP features

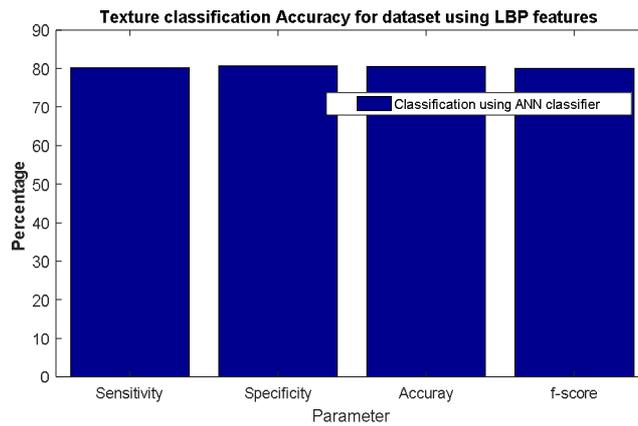


Fig 6: Performance evaluation using ANN classifier for LBP features

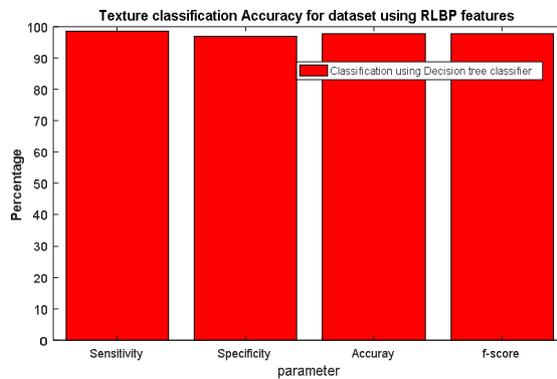


Fig 7: Performance evaluation using Decision tree classifier for RLBP features

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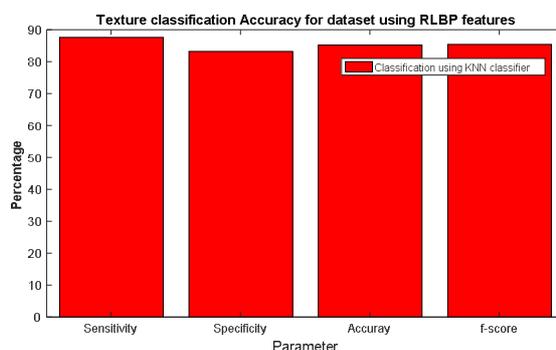


Fig 8: Performance evaluation using KNN for RLBP features

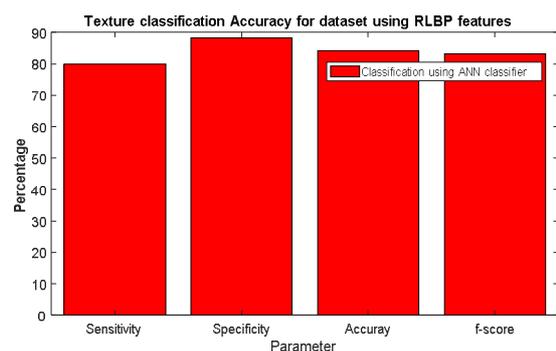


Fig9: Performance evaluation using ANN classifier for RLBP features

From the table and graphs above it has been found that there is more accuracy in classification using the proposed feature extraction algorithm. We have used rotated local binary pattern which considers the dominant direction while defining weights in center pixel evaluation. We have tested the LBP and RLBP features using three different classifiers i.e. KNN, ANN and decision tree in which all classifiers gives high accuracy when RLBP is used. Hence founds it better than LBP features.

VI. CONCLUSION

In this work, a new rotated LBP-based feature extraction technique has been applied for the classification. Based on experiments, the system has shown good ability for the detection of abnormalities associated with diabetic retinopathy. Exudates are signs of DR and are not easy to detect due to other normal retinal characteristics with similar features such as contrast, intensity levels, color and shape. When digital fundus images are captured using cameras with uneven illumination the detection problem becomes even more difficult. However, it has been revealed that RLBP texture features offer an efficient solution to overcome these issues. The problem of variations to rotations in LBP arises due to the fixed arrangement of weights. As the weights are aligned in a circular manner, the effect of image rotations can be countered by rotating the weights by the same angle while computing the descriptor. Since the angle of the rotation cannot be known, we propose an adaptive arrangement of weights based on the locally computed reference direction. The reference direction should be such that if an image undergoes a rotation, it should also undergo a rotation by the same angle. The best results were obtained with what we call, the Dominant Direction. The dataset has been tested using three different classifiers in which decision trees gives high accuracy rates as compared to KNN and ANN classifiers.



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