

RETINAL DISEASE SCREENING USING CO-OCCURRENCE METHOD AND SVM

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Abstract---This work involves the detection of Diabetic Retinopathy (DR) and Age-Related Macular Degeneration (AMD) through Local Binary Patterns (LBP) and further experimentation using Gray-Level Co-Occurrence Matrix (GLCM). For this purpose, the performance of Gray level Co-occurrence Matrix (GLCM) as a texture descriptor for retinal images has been explored and compared with other descriptors such as GLCM filtering (GLCMF) and local phase quantization (LPQ). This leads to the determination of blood vessel features such as energy, contrast, correlation and homogeneity values. This technique uses SVM as a classifier to distinguish between true and false vessels. This method is suitable for diagnosis aid system for retinal disease screening and preparation of drugs.

Keywords---DR, AMD, Local Binary Patterns (LBP), Gray- level Co-occurrence Matrix (GLCM), Texture Descriptor, Blood vessel features, SVM, Medicinal preparation.

1.INTRODUCTION

The Human Eye is nearly a sphere, with an average diameter of approximately 20mm. Three membranes enclose the eye: The cornea and sclera outer cover, Choroid and Retina. Retina is the innermost membrane of the eye. It lines the entire posterior of the inner wall. Central portion of the retina is called Fovea. There are two classes of photoreceptors present in the retina: Cones and Rods. Cone vision is called photopic or bright-light vision. Rods are responsible for scotopic or dim light vision. Blind Spot is where the photoreceptors are absent at the spot from which the optic nerves emerges.

Blindness is nothing but improper vision. This is because the human eye loses the capability of perception. This generally occurs either due to Diabetes or Age- Related issues.

Two main diseases of visual impairment are Diabetic Retinopathy(DR) and Age-Related Macular Degeneration(AMD) [1]. DR affects up to 80 percent of people who have diabetes for 20 years or more. 90% of the disease could be reduced if there were proper treatment and monitoring of the eyes. The existence of diabetic retinopathy detected can be examining the retina for its individual features.

Screening of these diseases involve segmentation of lesions which results in heavy workload for the experts due to population increase and also economically inaccessible. Therefore, automatic screening is required. This is achieved by using Local Binary Patterns (LBP). This technique has been given a higher attention in recent years [2], [3]. This algorithm acts as a texture descriptor for retinal images. It distinguishes the affected and healthy images.

LBP texture operator can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis [4]-[6] and also in medical imaging [7]-[9]. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. It results in obtaining sensitivity and specificity values for DR and AMD detection [10]-[12].

Further, this paper adds the calculation of energy, contrast, correlation and homogeneity values using Gray- Level Co-occurrence Matrix (GLCM) method. The performance of Gray level Co-occurrence Matrix (GLCM) as a texture descriptor for retinal images has been explored. In the above mentioned methods, SVM is used as a classifier for data classification and regression [13]. These classifiers are effective in high dimensional space. Thus, it is memory efficient and versatile. It can be observed that the SVM based classification yields the vessel classification with greater accuracy.

Section II illustrates the proposed method in detail. This section gives us the idea about the GLCM method and the features obtained from it. Section III discusses on the results obtained and the applications of GLCM method.

Given below are the sample dataset images that are used as input image to distinguish between DR and AMD.



Fig 1. Dataset Images.

II. PROPOSED METHOD

As manual lesion segmentation is time consuming and might not be accurate, there is a need for the removal of lesion segmentation. Thus, the classification becomes simpler and robust. So, this section discusses about the GLCM algorithm which is mainly based on the texture analysis of fundus images and this system is evaluated on a large dataset containing 100 retinal images. It results in obtaining the features of blood vessels. Our algorithm has the advantage that it is applicable to all types of retinal images, healthy as well as abnormal compared to the approaches by other researchers.

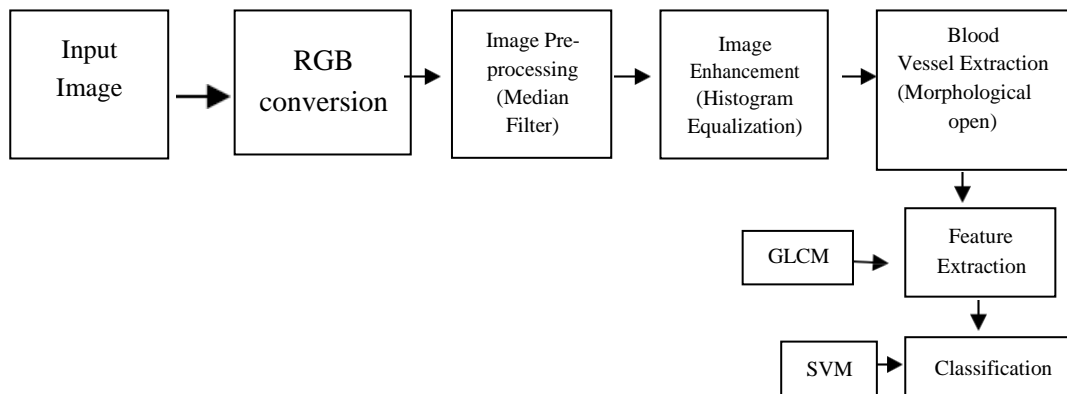


Fig 2. Block Diagram of proposed method.

A. RGB Conversion

In the RGB color model, each color appears in its primary spectral components of red, green and blue. This model is based on cartesian coordinate system. The color subspace of interest is the cube in which RGB primary values at three corners; the secondary colors cyan, magenta, and yellow are three other corners, black is at the origin; white is at the corner farthest from the origin. In this model, the gray scale (points of equal RGB values) extends from black to white along the line joining these two points. All the values of R, G and B are assumed to be in the range of [0,1].

Images represented in the RGB color model consist of three component images, one for each primary color. When fed into an RGB monitor, these three images combine on the screen to produce a composite color image, as explained. Acquiring the color image is basically the process shown in Figure 2 in reverse.

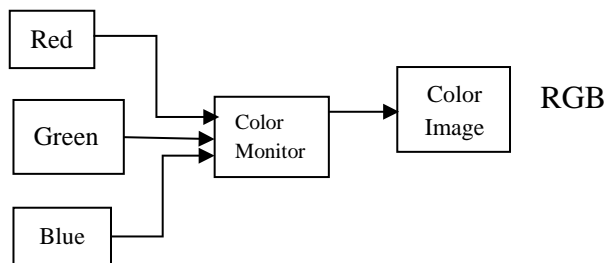


Fig 3. Generating the RGB color image.

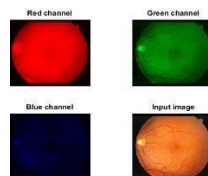


Fig 4. RGB Images.

B. Image Pre-processing

RGB conversion converts the input color image into grayscale intensity image. It eliminates the hue and saturation while retaining the luminance. Since the images under study are from different databases, the size of the images varies. To obtain comparable texture descriptors, the images should be resized to a particular size [14]-16]. Pre-processing includes noise removal and this denoising is done using Median Filter.

Median filter, the best-known order statistics filter, which as its name implies replacing the value of pixel by the median of the intensity values in the neighborhood of that pixel [17]. Median filters are quite popular because, for certain types of random noise, they provide excellent noise-reduction capabilities, with considerably less blurring than linear smoothing filters of similar size.

This type of filtering sets the value of the output pixel to the average of the pixel values in the neighbourhood around the corresponding input pixel. Median filters are very effective in the presence of both bipolar and unipolar impulse noise [18]. The median filter yields excellent results for images corrupted by this type of noise.

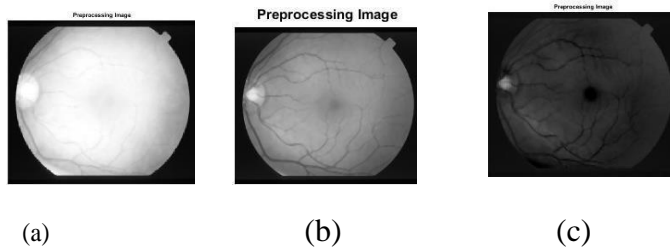


Fig 5. (a) Pre-processed red channel Image.
(b) Pre-processed green channel Image.
(c) Pre-processed blue channel Image.

C. Image Enhancement

The pre-processed image is then manipulated so that the resulting image is more suitable than the original image for a specific application. This manipulation is called as Image Enhancement. The term ‘Specific Application’ indicates that the method of enhancement varies with respect to the application. The idea behind enhancement techniques is to bring out details that are obscured or simple to highlight certain features of an image.

Histogram equalization is used as a technique to enhance the pre-processed image. It comes under spatial domain enhancement technique. Histogram is a plot that shows the number of pixels corresponding to each gray level value in the image. In histogram equalization, all the pixels in the image are taken into consideration which constitutes to global operation. Based on histogram components, images can be classified into dark, bright, low contrast and high contrast. Histogram equalization produces an output image that has a uniform histogram [19].

The main advantage of histogram equalization is that it is fully automatic i.e it is only based on information that can be directly extracted from the given image.

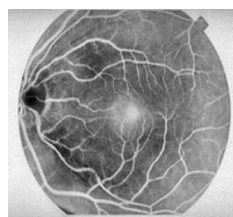


Fig 6. Histogram Equalized image.

D. Blood Vessel Extraction

Retinal vessel segmentation is an important division of automated retinal disease screening systems. The morphological variations of the retinal blood vessels correspond with the chances of cardiovascular and other related diseases. Retinal blood vessels have a significant role in the diagnosis and treatment of various retinal diseases such as diabetic

retinopathy, glaucoma, arteriosclerosis, and hypertension [20]. For this reason, retinal vasculature extraction is important in order to help specialists for the diagnosis and treatment of systematic diseases.

In this paper, a novel approach is developed to extract retinal blood vessel network. This algorithm comprises of four stages: (1) Pre-processing stage in order to prepare the datasets for segmentation; (2) an enhancement procedure including Gabor, Frangi, and Gauss filters obtained separately before a top-hat transform; (3) a hard and soft clustering stage which includes K-means and Fuzzy C- means (FCM) in order to get binary vessel map; and (4) a post-processing step which removes false segmented isolated regions.

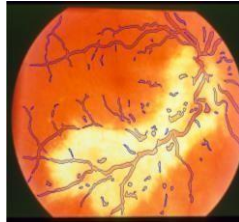


Fig 7. Vessel extraction.

E. GLCM Feature Extraction

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative, non-redundant, facilitating subsequent learning and generalization steps, in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. It involves reducing the amount of resources required to describe a large set of data.

At this stage, features from normal tissue and abnormal cancer tissue are extracted. This is because extracting and selecting some essential features is very needful for classification. Thus, a new approach came into existence which uses Gray-Level Co-occurrence Matrix (GLCM) [21]. It deals with the analysis of the texture discrimination capabilities in fundus images to differentiate healthy retinal images from AMD and DR images.

The performance of GLCM along with different classifiers was tested and compared with other texture descriptors. the proposed method is capable of discriminating the classes based on analysing the texture of the retina background, avoiding previous segmentation of retinal lesions. Such lesion segmentation algorithms might be both time consuming and potential inaccurate, thus avoiding the segmentation is beneficial [22]. Five experiments (separating DR from normal, AMD from normal, pathological from normal, DR from AMD and the three different classes) were designed and validated with the proposed procedure obtaining promising results. Blood vessel features such as contrast, correlation, energy and homogeneity values are obtained. The obtained results demonstrate that using GLCM as texture descriptor for fundus images provides useful features for retinal disease screening. This method is suitable for diagnosis aid system for retinal disease screening and preparation of drugs.

F. Classification using Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane.

- In this classification, we are going to train the datasets.
- And also to train the images by the given input images.
- Finally, confusion diffusion matrix is obtained which measures the performance of particular image.

These classifiers are a group of supervised learning methods that can be applied for classification or regression. SVM is used to distinguish the healthier and affected retinal images. It builds a hyperplane or set of hyperplanes in a high or infinite-dimensional space. SVM model maps the training samples that are the points in features space into different categories which are clearly separated with the widest gap in between them [24]. The testing samples are mapped to the same feature space and classified as belonging to any of the classes.

SVM constructs an optimal hyper plane that would maximize the margin of separation between the classes. The feature vectors that lie close to the margin are called the support vectors [25]. The SVM classifier with the optimum hyper plane. A binary SVM finds an optimum hyper plane which separates the feature vectors of the two classes with largest margin from the hyper plane.

The benefits of using SVM are these classifiers are Effective in high dimensional spaces, more effective in cases where number of dimensions is greater than the number of samples and most importantly it uses a subset of training points in the decision function (called support vectors), so it is also memory efficient and versatile. Similarly, the drawbacks of SVM are it does not directly provide probability estimates, these are calculated using an expensive five-fold cross-validation.

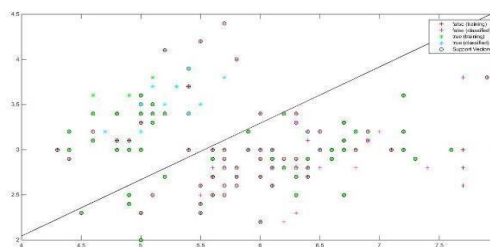


Fig 8. Accuracy measures

Table I. SVM performance measures

Image s	TNR	TPR
1	0.1098	0.1243
2	0.3560	0.6517
3	0.4521	0.1345
4	0.2167	0.5774
5	0.1278	0.3451

Table II. GLCM Features.

Images	Contrast	Correlation	Energy	Homo- geneity
1	6.8731e+03	0.0011	5.1440e-05	0.0443
2	6.5087e+03	7.0462e-04	4.6863e-05	0.0441
3	6.3066e+03	-8.8547e-04	4.9155e-05	0.0447
4	6.7400e+03	5.9267e-04	4.7950e-05	0.0441
5	5.8400e+03	-0.0070	3.7524e-05	0.0449
6	5.3333e+03	-0.0022	5.2950e-05	0.0446
7	6.0480e+03	-7.5030e-04	3.1197e-05	0.0447
8	6.3980e+03	0.0014	6.3704e-05	0.0438
9	3.5851e-05	-0.0032	3.5851e-05	0.0456
10	5.5798e+03	-0.0059	3.6242e-05	0.0454
11	7.1718e+03	0.0015	7.9168e-05	0.0442
12	5.7832e+03	-0.0021	3.2367e-05	0.0452
13	6.3980e+03	0.0014	6.3704e-05	0.0438
14	7.6168e+03	0.0121	9.3065e-05	0.0436
15	5.9035e+03	-0.0017	3.5148e-05	0.0451

III. RESULTS & CONCLUSION

A new approach for AMD and DR diagnosis was presented. It is based on analysing texture discrimination capabilities in fundus images to differentiate healthy patients from AMD and DR images. In future, these diseases will experience a high growth due to diabetes increase. The performance of GLCM along with different classifiers was tested and compared with other texture descriptors. The most important finding is that the proposed method is capable of discriminating the classes based on analysing the texture of the retina background, avoiding previous segmentation of retinal lesions. Such lesion segmentation algorithms might be both time consuming and potential inaccurate, thus avoiding the segmentation is beneficial. The obtained results demonstrate that using GLCM as texture descriptor for fund us images provides useful features for retinal disease screening. This new algorithm does the true vessels classification from the false vessels but the elimination of these false blood vessels can improve the classification accuracy more. This can be a topic for future research.

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